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Corresponding Author: Dr. Jean-Yves Dieulot,

Corresponding Author's Institution: Polytech'Lille

First Author: Jean-Yves Dieulot

Order of Authors: Jean-Yves Dieulot; Frédéric Colas, PhD; Lamine Chalal, PhD; Geneviève Dauphin-Tanguy, Professor, PhD

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Cover letter

Jean-Yves DIEULOT
LAGIS (Control Laboratory)
Polytech-Lille, IAAL
Cité Scientifique
59655 Villeneuve d'Ascq
France
Tel 33 3 28 76 74 95
e.mail jean-yves.dieulot@polytech-lille.fr
Paper CONENGPRAC-D-14-00018R2

Professor A. Kugi
Editor-in-Chief, Control Engineering Practice

Monday, 6 October 2014

Dear Sir,

Please find the final revision of Paper CONENGPRAC-D-14-00018 « Event-triggered variable horizon supervisory predictive control of hybrid power plants» by Jean-Yves Dieulot, Frédéric Colas, Lamine Chalal and Geneviève Dauphin-Tanguy. We replied to some queries by reviewer #2 and added a few related comments in the paper.
We thank you deeply for giving us the opportunity of publishing our research results in Control Engineering Practice, and we are indebted to the anonymous reviewers for their very careful reading of the paper.
Please ask if you need further information.

Yours sincerely

Jean-Yves DIEULOT
Associate Professor.

Highlights

- A new Economic Supervisory Predictive controller for a hybrid power plant is designed
- The techno-economic criterion appears to be in a nonstandard quadratic form.
- The receding horizon is switched to a lower value when the renewable power fluctuates
- A variable receding horizon strategy improves the control performances
- Real-time experiments are performed in a hardware-in the-loop framework.

Event-triggered variable horizon supervisory predictive control of hybrid power plants

Jean-Yves Dieulot[a], Fréderic Colas[b], Lamine Chalal[c], Geneviève Dauphin-Tanguy[d]

[a]*LAGIS UMR CNRS 8219,Polytech-Lille/IAAL Cité Scientifique 59650 Villeneuve d'Ascq France (e-mail: jean-yves.dieulot@polytech-lille.fr, Fax +33 328767401)*
[b]*L2EP,ENSAM ParisTech, 8 Bd Louis XIV, 59800 Lille, France (frederic.colas@ensam.eu)*
[c]*L2EP,Université Lille1, 59650 Villeneuve d'Ascq France (lamine.chalal@univ-lille1.fr)*
[d]*LAGIS UMR CNRS 8219 Ecole Centrale de Lille BP 48, 59650 Villeneuve d'Ascq Cedex, France (genevieve.dauphin-tanguy@ec-lille.fr)*

Abstract

The supervision of a hybrid power plant, including solar panels, a gas microturbine and a storage unit operating under varying solar power profiles is considered. The Economic Supervisory Predictive controller assigns the power references to the controlled subsystems of the hybrid cell using a financial criterion. A prediction of the renewable sources power is embedded into the supervisor. Results deteriorate when the solar power is unsteady, owing to the inaccuracy of the predictions for a long-range horizon of 10 s. The receding horizon is switched between an upper and a lower value according to the amplitude of the solar power trend. Theoretical results show the relevance of horizon switching, according to a tradeoff between performance and prediction accuracy. Experimental results, obtained in a Hardware In the Loop (HIL) framework, show the relevance of the variable horizon approach. Power amplifiers allow to simulate virtual components, such as a gas microturbine, and to blend their powers with that of real devices (storage unit, real solar panels). In this case, fuel savings, reaching 15 %, obtained under unsteady operating conditions lead to a better overall performance of the hybrid cell. The overall savings obtained in the experiments amount to 12 %.

Keywords: Economic model predictive control, power system control, supervisory predictive control, renewable hybrid system, hardware in the loop, variable receding horizon.

1. Introduction

Model Predictive Control (MPC) is a control algorithm that minimizes an objective function over a receding horizon. It is well suited for multivariable or large-scale systems which exhibit large time-constants, long time-delays or middle-range predicted disturbances, and is known to be robust with respect to forecast uncertainties and unmodelled dynamics (Scattolini (2009)).
MPC has been applied in the field of hybrid power cell supervision. It allows to deliver an overall smooth power when intermittent and renewable power sources (wind turbines, solar panels) are combined with conventional sources and storage units (batteries, supercapacitors, etc.). Hence, a predictive supervisor helps to promote the integration of the renewable sources into the grid (Valenciaga and Puleston (2005) , Guerin et al. (2012), Chalal et al. (2012) , Liu et al. (2011a), Qi et al. (2013)). Generating a smooth active power in a short time window, in a time scale around 10-30 seconds, is mandatory for a power cell (see a list of demonstrators in Daguzan and Galland (2012)). To set the context of this supervision in the power generation frawework, the sampling period of local level power converters controllers is below the millisecond (Steinke (1992)). On the contrary, tertiary regulation has a time scale around 15 minutes. The supervisor provides the reference trajectories for the controlled units (in this case a microturbine and a storage unit). Moreover, unlike other algorithms, predictive controllers can consider the planned power reference and a short-time forecast of the intermittent sources powers which generally improves the results. When the predictive criterion is based on economic considerations (e.g. tariff policies, fuel or CO_2 emission cost, storage unit depreciation), it is very easy to tune the supervisor. Moreover, extra components can be integrated into the cell. It is sufficient to consider their dynamical models and to add their economic contribution to the objective function, which can depend on the operating regime as in the case of wind turbines (Chalal et al. (2012), Qi et al. (2013)). Hence, a predictive approach allows for an (economically) optimal and modular way to tune a hybrid power cell supervisor. On the contrary, rule-based algorithms need to be fully designed anew in case of component modification or cell reconfiguration.
The choice of the receding horizon results of a compromise between the intermittent power prediction accuracy, which decreases with the horizon length,

and the benefits of using a long-range control algorithm. Typically, in (Chalal et al. (2012)), this horizon was fixed around 10 seconds. However, whenever an abrupt change of the renewable power occurs, a possible false prediction can hamper the results given by the MPC algorithm. As an example, this could happen for solar panels when it quickly clouds over, or for wind turbines with squally conditions. In this case, it is possible to improve the predictions by using a shorter horizon. The so-called Variable-Horizon model predictive control (VH-MPC) which varies the horizon length according to a constrained optimization problem is well-suited to handle time-varying disturbances. The VH-MPC algorithm drives the system state to a closed set in finite time irrespective of bounded disturbances (Michalska and Mayne (1993) , Scokaert and Mayne (1998), Richards and How (2006) , Shekhar and Maciejowski (2012)) . It is possible to reduce the complexity of the algorithm by setting the variable horizon to predefinite values according to the onset of a disturbance. The horizon is kept to a nominal value when the prediction is accurate enough. Otherwise, it is triggered to a shorter value. This avoids important prediction biases, when the occurrence of a large disturbance is detected (Eqtami et al. (2011)). Note that this policy is quite different from multi-rate predictive control which triggers during a discrete step or uses adaptive step control algorithms (see e.g. Kowalska and von Mohrenschildt (2011) and references therein).
To sum up, such an event-triggered predictive controller has not been used so far for the supervision of a hybrid power cell. This paper presents the design of an Economic Supervisory Predictive (ESP) controller, which original criterion integrates tariff policies, storage units and conventional sources costs, whereas other papers generally propose a standard quadratic criterion. Next, it is shown how predictions can be integrated into the supervisor. Compared with existing papers, the economic tradeoff between the use of a longer horizon which may improve the overall cost and the accuracy of the renewable sources power prediction is evaluated, which shows the relevance of using a variable receding horizon strategy. The design of such an event-triggered variable horizon predictive supervisor, coupled with a detection algorithm is addressed next. Eventually, the algorithm will be applied on a hybrid cell including a storage unit, solar panels and an emulated gas turbine. Real-time experiments in the framework of a Hardware In the Loop platform support the relevance of the proposed approach.

2. HYBRID CELL ECONOMIC SUPERVISORY CONTROL

2.1. Power cell, HIL platform and component models

The hybrid renewable power plant embeds a photovoltaic system (108 modules BP solar 3160 with a power of 160 W each, connected to a 3-phase grid via a Fronius IG30 inverter), a storage unit connected to the grid via electronic converters, and a gas microturbine. This microturbine is emulated by a real time digital simulator RT-Lab which is able to run real-time models on a multi-CPU computer (Fig. 1).

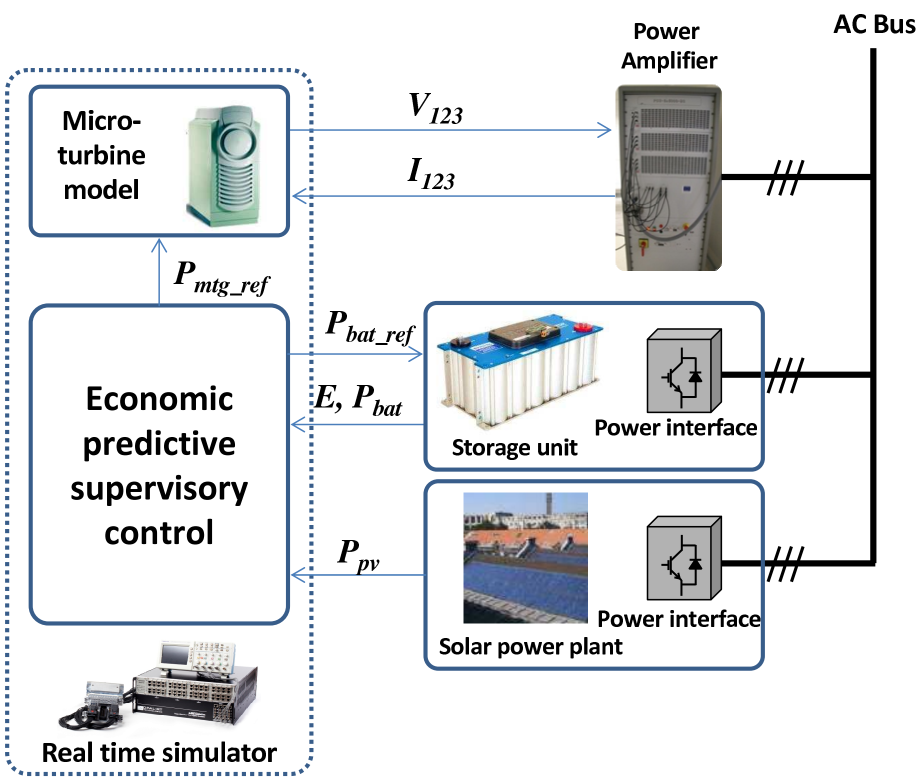

Figure 1: Hybrid Cell and Power Hardware In the Loop architecture

A power amplifier generates a real power signal from a model (e.g. the microturbine). The simulated sources can be blended with real power measurements, achieving the Power Hardware In the Loop principle. Another interest of the real-time simulator is the ability to emulate and reuse a previously measured power (typically here a solar power profile). Hence, a fair comparison of different algorithms is possible (see Chalal et al. (2012) for additional details).

The storage unit allows to absorb the fluctuations of the renewable source power. A simplified model was used to represent the battery storage (Chungpaibulpatana et al. (2002)):

$$P_{bat} = \frac{1}{\tau_p s + 1} P_{batref} \tag{1}$$

where P_{batref}, P_{bat} are the storage unit reference and real powers. It is assumed that the storage unit State Of Charge (SOC) varies (in the working range) as the integral of the power. In case of State Of Charge saturation, if $\int_0^t P_{bat} d\tau > E_{max}$ or $\int_0^t P_{bat} d\tau < E_{min}$, then $P_{bat} = 0$. E_{max} and E_{min} are respectively the maximum and minimum of stored energy. $\tau_p = 5\ s$ is the time constant of the battery.

This model is implemented using a dedicated test bench with supercapacitors. These consist of 6 Maxwell modules in series, the characteristics of each being 48 V, 160 F. The power reference is generated through a power amplifier. The supercapacitors are connected to the grid (Fig. 2) .

The gas microturbine power is generated by a model which features a simplified representation of a turbine in closed loop. The supervisor does not manage the inner control loops and only provides the power references. A gas turbine consists of a gas compressor, turbine, a recuperator, a permanent magnet synchronous generator, and a power electronics interface. In this case, the microturbine works in operating mode. Start-up is discarded and only a turbine speed PID control loop is considered (see details in Chalal et al. (2012)). The torque C_m is a function of the rotor speed N and of the fuel flowrate W_f :

$$C_m(t) = 1.3(W_f(t) - 0.23) + 0.5(1 - N(t)) \tag{2}$$

All variables are expressed Per Unit, allowing scale-up, according to the model in Pai and Hung (2008). The term 0.23 accounts for the need for a significant fraction of rated fuel to support self-sustaining, no-load conditions.

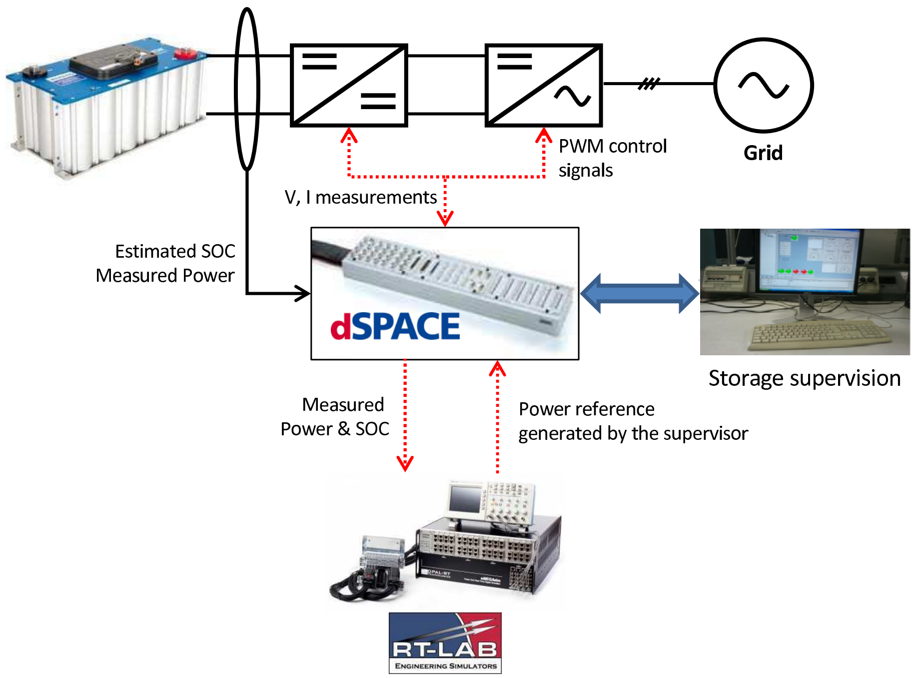

Figure 2: Storage unit test bench

One has the following transfer function:

$$N(s) = \frac{1}{T_l s + 1} C_m(s) \tag{3}$$

$$W_f(s) = \frac{1}{T_f s + 1} \frac{a}{cs + b} VP(s) \tag{4}$$

where the fuel control valve reference position VP is:

$$VP(t) = 0.77N(t).F_c(t) + 0.23. \tag{5}$$

and the speed controller is:

$$F_c(s) = \frac{25}{0.05s + 1}(N_{ref}(s) - N(s)) \tag{6}$$

where F_c is the per unit fuel command per unit speed, the turbine power P_{mtg} is the product of speed and torque. T_l, T_f, a, b, c are respectively the turbine rotor time constant, fuel system time constant, and fuel system transfer function parameters. This model is used for validation and implemented into the real-time simulator. In case of "stiff" turbines, it is possible to simplify the closed-loop model of the microturbine. The model of the microturbine reduces finally to a fourth-order linear model, which is better fitted for Model Predictive Control design:

$$P_{mtg}(s) = \frac{1}{(T_1 s + 1)(T_2 s + 1)(T_3 s^2 + T_4 s + 1)} P_{mtgref}(s) \tag{7}$$

where $T_1 = 0.05\ s, T_2 = 0.15\ s, T_3 = 0.22\ s, T_4 = 0.27\ s$. This coarse linear model shows a good agreement with the full model in the region where the microturbine operates when embedded in the hybrid cell. Simulations can be found in Chalal et al. (2012), showing results which are consistent with that found in the literature (Martinez et al. (2011)).

2.2. Economic Supervisory Predictive control

The design of an Economic Supervisory Predictive controller, presented in Chalal et al. (2012) is recalled. The objective consists of generating the power references of the controllable elements belonging to a hybrid power cell (in this case the storage unit and the microturbine powers P_{bat}, P_{mtg}). This is achieved by minimizing a global cost over a receding horizon H,

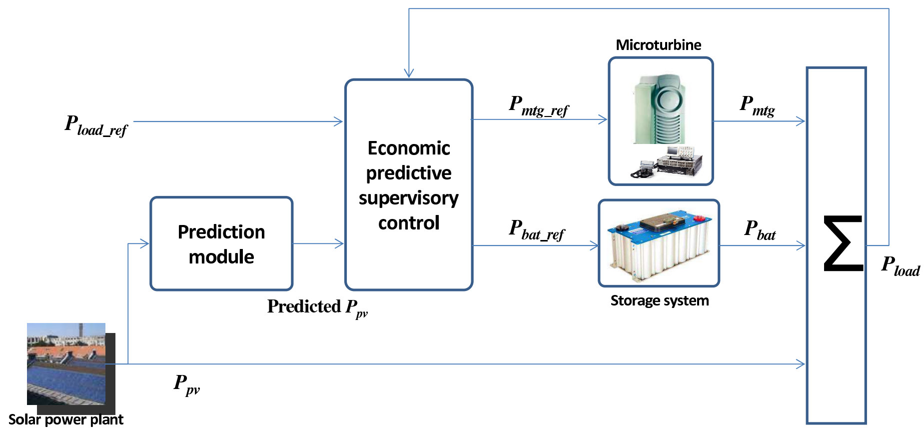

Figure 3: Simplified control scheme

notwithstanding the fluctuations of the renewable power source (here the solar arrays, see Fig. 3).

The time-dependent cost function can be split up into the gas consumption cost C_{fuel}, carbon dioxide emissions tax $C_{emissions}$, the battery cycling cost $C_{cycling}$, and a penalty for not reaching the reference power P_d imposed by the grid manager.

$$J(t) = \int_t^{t+H} \Big(\alpha(P_d(\tau) - \hat{P}_{pv}(\tau) - P_{bat}(\tau) - P_{mtg}(\tau))^2 + ... \\ + C_{fuel}(\tau) + C_{emissions}(\tau) + C_{cycling}(\tau) \Big) d\tau \tag{8}$$

or in a discrete-time fashion:

$$\bar{J} = \sum_k \Big(\alpha(P_{d,k} - \hat{P}_{pv,k} - P_{bat,k} - P_{mtg,k})^2 + C_{fuel,k} + C_{emissions,k} + C_{cycling,k} \Big) \tag{9}$$

α is a penalty term imposed by the grid manager. k corresponds to the k^{th} time period over the time interval $[t, t+H]$.

The delivered power P is the sum of all the components' powers. It incorporates the intermittent solar power predictions $\hat{P}_{pv}$. In our case, these predictions are supposed to be linear functions of time. Their parameters

are estimated by a Least-Square method at every instant t. The predictive control strategy embeds the dynamical closed loop models of the controlled sources' powers and the corresponding operational costs. The cost function is derived only from technical and economic considerations or policies. One can consider marginal costs as in (Edlund et al. (2011)); however, over the short prediction horizon, the parameters are considered to be constant (e.g. fuel pricing does not vary). It is also possible to enrich the criterion with further considerations on power quality. For example, one objective of the MPC controller is to smooth the output power and follow a reference power P_d in the paper. The output power should thus be smoother than if the renewable source was directly connected to the grid. Moreover, in a full scale operation, such a hybrid power cell could participate to frequency support: the reference power could contain a ΔP_d term which comes from a droop in frequency as depicted in (De-Brabandere et al. (2007)) Another possibility would be to add an economic penalty in the criterion.
The cost function of a gas microturbine is assumed to be a linear function of the power P_{mtg} (Dufo-Lopez and Bernal-Agustin (2005)) :

$$C_{fuel}(t) = C_F[BP_{Nmtg}(t) + AP_{mtg}(t)] \tag{10}$$

where C_F is the fuel price (€/l), $A = 0.246$ l/kW and $B = 0.08415$ l/kW are the fuel curve coefficients, P_{Nmtg} is the rated power (kW), P_{mtg} is the generator output power (kW), C_{fuel} is the fuel consumption cost (€).

The emission cost $C_{emisions}$ is assumed to be proportional to the CO_2 emissions weight, with:

$$C_{emisions}(t) = 0.017 * E(P_{mtg}(t)) \tag{11}$$

The volume of these emissions is modelled as a quadratic function of the generator power P_{mtg} (Johansen et al. (1992)), where the $A_i, i = 1, 2$ are constant coefficients:

$$E(P_{mtg}(t)) = A_0 + A_1 P_{mtg}(t) + A_2 P_{mtg}^2(t) \tag{12}$$

The operational cost of the microturbine is a quadratic function of the microturbine power. Battery cycle lifespans vary according to their type and monitoring policy. A mean cycle, with full charge and discharge, is considered, given by the ratio of total cost of the storage unit and the lifespan.

$$\text{cycle cost} = \frac{\text{cost of the battery}}{\text{number of expected cycles}} \tag{13}$$

It is assumed that locally, a portion of a cycle cost corresponds to a linear fraction of the total cost of one cycle. The State Of Charge Q varies linearly:

$$C_{cycling}(t) = \lambda \left| \frac{dQ(t)}{dt} \right| \tag{14}$$

where λ can be calculated from equation (13).

In addition to the cost determination, operational constraints on the power amplitude or power change rate (Liu et al. (2011b)) are considered. The load level of the microturbine should not reach less than 50% for efficiency reasons:

$$15\,kW \leq P_{mtg}(t) \leq 30\,kW \tag{15}$$

Inner-loop constraints on the fuel flowrate F_{mtg} yield in turn:

$$0 \leq F_{mtg}(t) \leq F_{max} \tag{16}$$

The battery operational constraints consider power and capacity limitations:

$$-5\,kW \leq P_{batref}(t) \leq 5\,kW. \tag{17}$$

$$0.5 \leq Q(t) \leq 0.8 \tag{18}$$

and

$$|\frac{dQ(t)}{dt} \leq 0.1| \tag{19}$$

The overall predictive control problem can be put under the following form:

$$\begin{aligned} &\min_{P_{batref}(k), P_{mtgref}(k)} \quad \bar{J}(k) \\ &\text{s. t.} C(k) \forall k \\ &equations(\ 1,\ 7) \end{aligned} \tag{20}$$

where $C(k)$ are the operational constraints. Since the overall criterion is a quadratic function of the states (i.e. the powers), the overall optimization problem is a (QP) quadratic program and can be solved easily. As recommended for most predictive control algorithms, only the first value of the sequence of references provided to the supervisor is fed to the controlled units.

3. VARIABLE HORIZON PREDICTIVE SUPERVISOR

3.1. Event-triggered Supervisory Predictive control

The choice of the prediction horizon H is fundamental for the success of the MPC supervisor. When the horizon is too long, short-term predictions of the solar power become less accurate. If this horizon is too short, the predictive algorithm shows poorer results because of the slow reactivity of the controlled sources (Chalal et al. (2012)). Previous works have shown that the economic criterion can be improved if the predictions are embedded into the supervisor. As was said before, a linear trend was chosen to represent the solar power prediction. For every time t, the relative prediction error is

$$\epsilon_s = (1/H) \int_t^{t+H} \frac{|P_{solar}(\tau) - P_{solar}^{predicted}(\tau)|}{P_{solar}(\tau)} d\tau \tag{21}$$

Table 1 provides an example, for a standard solar power profile, of the mean value of the relative prediction error MRAPE ϵ_s as a function of the horizon. One can see that the forecast errors increase with the prediction horizon, which is quite obvious.

Table 1: Mean relative absolute prediction error for a standard solar power profile as a function of the prediction horizon

Horizon H [s]	3	5	7	9	11
MRAPE [%]	0.4	1.7	4.5	8.6	13.9

The following proposition considers the effects of a time-linear drift in the output. It is assumed that this drift is not compensated by the predictive controller. This case may happen, for example, when there exists a mismatch in the trend of the solar power predictions. The slope of the linear drift is supposed to depend on the value of the horizon and to account for the precision of the predictions. It is assumed to be constant over a time interval $[0...T]$. When the prediction is perfect, it will be assumed that the mean economic criterion is a decreasing function of the horizon H. Indeed, in this case, previous results have shown that using a longer receding horizon yields better results for the supervision of steady solar power P_{pv} profiles (Chalal et al. (2012)).

Lemma 1. *(Leibniz integral rule) Let $f(x,t)$ be continuous over a time interval $[a(x), b(x)]$, then*

$$\frac{\partial \int_{a(x)}^{b(x)} f(x,y)dy}{\partial x} = f(x, b(x))\frac{\partial b(x)}{\partial x} - f(x, a(x))\frac{\partial a(x)}{\partial x} + \int_{a(x)}^{b(x)} \frac{\partial f(x,y)}{\partial x} dy$$

Proposition 1. *Consider a dynamical SISO state-space model $\dot{\mathbf{x}} = \mathbf{f}(\mathbf{x}, \mathbf{u})$, $\hat{y} = \mathbf{h}(\mathbf{x})$ and a smooth control sequence which minimizes, at each time t, the criterion $J(t, H, \hat{y})$ where*

$$J(t, H, w) = \frac{1}{H}\int_t^{t+H} r(\tau)d\tau, t \in [0, T], r(t) = |y_{ref}(t) - w(t)| + g(\mathbf{x}, \mathbf{u}).$$

It is assumed that the real output y obeys, over the time window $[0, T]$:

$$\hat{y}(t) - y = a(H)t, a(H) > 0.$$

Then, one has

$$\frac{1}{T}\int_0^T \frac{\partial J(t,H,y)}{\partial H}dt = \frac{1}{T}\int_0^T \frac{\partial J(t,H,\hat{y})}{\partial H}dt + a(H)/2 + (T/2 + H/2)\frac{\partial a(H)}{\partial H}$$

Proof. Using the lemma, one differentiates the criterion without linear drift

$$\frac{\partial J(t,H,\hat{y})}{\partial H} = \frac{1}{H}r(t+H) - \frac{1}{H}J(t,H,\hat{y})$$

The partial derivative of the criterion with drift is now

$$\begin{aligned}
\frac{\partial J(t,H,y)}{\partial H} &= \frac{1}{H}r(t+H) + \frac{1}{H}a(H)(t+H) - \frac{1}{H}J(t,H,\hat{y}) - \\
&\quad \frac{1}{H^2}\int_t^{t+H} a(H)\tau d\tau + \frac{1}{H}\int_t^{t+H}\frac{\partial a(H)}{\partial H}\tau d\tau \\
&= \frac{\partial J(t,H,\hat{y})}{\partial H} + \frac{1}{H}a(H)(t+H) - \frac{1}{2H}(2t+H)a(H) + (t+H/2)\frac{\partial a(H)}{\partial H} \\
&= \frac{\partial J(t,H,\hat{y})}{\partial H} + (t+H/2)\frac{\partial a(H)}{\partial H} + a(H)/2
\end{aligned}$$

One can now integrate over $[0, T]$, which gives the final result

□

The proposition shows that when the mismatch on the solar power trend is important, the benefits of using a larger horizon are backed by the term which depends on the partial derivative of the slope of the linear trend. It is difficult to have a clear account of the mean value of the criterion without drift. However, as was said before, it is likely to be a decreasing function of the horizon. For unsteady profiles, the precision can be insufficient and a short time horizon will be preferred. Hence, a heuristic controller is proposed, using a decision variable d_v:

$$if d_v < \kappa \; then \; set \; controller \; with \; H = 3\,s \tag{22}$$

$$if d_v > \kappa \; then \; set \; controller \; with \; H = 11\,s. \tag{23}$$

where κ is an appropriate detection threshold. The values of H are chosen according to preliminary simulation results for steady and unsteady profiles.

3.2. Detection methods of solar power change

Different online algorithms allow to detect a change in time series. Some algorithms may detect small variations (e.g. the CUSUM algorithm). However, only high variations are sought in the presented case. This advocates for simple detection policies like Shewhart control charts which are recalled briefly in (Basseville and Nikiforov (1993)). Consider independent variables y_i with a probability density p_θ, where the value of θ changes from θ_0 to θ_1 at some instant, and let the decision function be $S_n = \sum_{i=1}^{n} ln\frac{p_{\theta_1}(y_i)}{p_{\theta_0}(y_i)}$. The algorithm reads simply $\theta = \theta_0$ if $S_n < \kappa$ else $\theta = \theta_1$, where κ is a "well-chosen" threshold. Consider a Gaussian distribution of mean μ, standard deviation σ, and $p_\theta = \frac{1}{\sigma\sqrt{2\pi}} e^{\frac{(y_\mu)^2}{2\sigma^2}}$. When a change in mean occurs, one has $S_n = \sum_{i=1}^{n} \frac{\mu_1-\mu_0}{\sigma^2}(y_i - \frac{\mu_1+\mu_0}{2})$. After a few manipulations, the detection algorithm corresponds, at time k, to:

$$\left| \frac{1}{n} \sum_{i=n(k-1)+1}^{nk} y_i - \mu_0 \right| \geq \kappa \frac{\sigma}{\sqrt{n}}, \tag{24}$$

In this case, some adaptations are needed. The algorithm will be used to detect a change of slope in the solar power signal following a five step procedure:

- differentiate the signal
- at each sample k, estimate recursively the linear trend for the solar power derivative
- use the detection algorithm with a threshold factor $\kappa = 2$
- Set a relaxation time of 200 s to enforce the controller to keep a small horizon for some time after the detection of disturbance to avoid frequent switching
- Reinitialize after detection

Note that differentiation of a signal amplifies the noise. Of course, it would be possible to use low-pass filters instead of changing the horizon; however, changing the horizon allows for a more explicit and discarding policy for handling severe disturbances.

4. EXPERIMENTAL RESULTS

Previous experiments in (Chalal et al. (2012)) have shown that a ESP controller could outperform a rule-based controller used as a standard supervisor for a hybrid cell , and which is not detailed here. The final cost is reduced by more than 30 %. The main goal of the current experiment is to show the relevance of using an event triggered variable strategy for this supervisory predictive control. The solar power profile which is considered is given in Fig. 4. This profile is quite steady, let two negative power disturbances appearing after a time of 450 seconds. After disturbance detection, the event-triggered algorithm will switch the horizon from a high value fit for steady operations, that is $H = 11\,s$, to a shorter horizon $H = 3\,s$. Note that there will be a relaxation time to avoid frequent switching, as that the horizon is set back to $H = 11\,s$ only at a time of 750 seconds. The switching instants are shown in Fig. 4. The κ threshold is chosen by a trial-and-error method as twice the standard deviation of the signal and allows for a rapid detection.

An interesting aspect of the HIL architecture presented in Fig. 1 is that this real solar power profile can be stored and later emulated by power amplifiers, and then reused to allow a fair comparison between the event-triggered strategy, a short-horizon strategy and a long horizon strategy. This allows clearly to a quantitative comparison of different strategies and to provide a fair account of the benefits of using an event-triggered variable horizon predictive algorithm, which would not be possible if different solar power profiles were used for each algorithms.

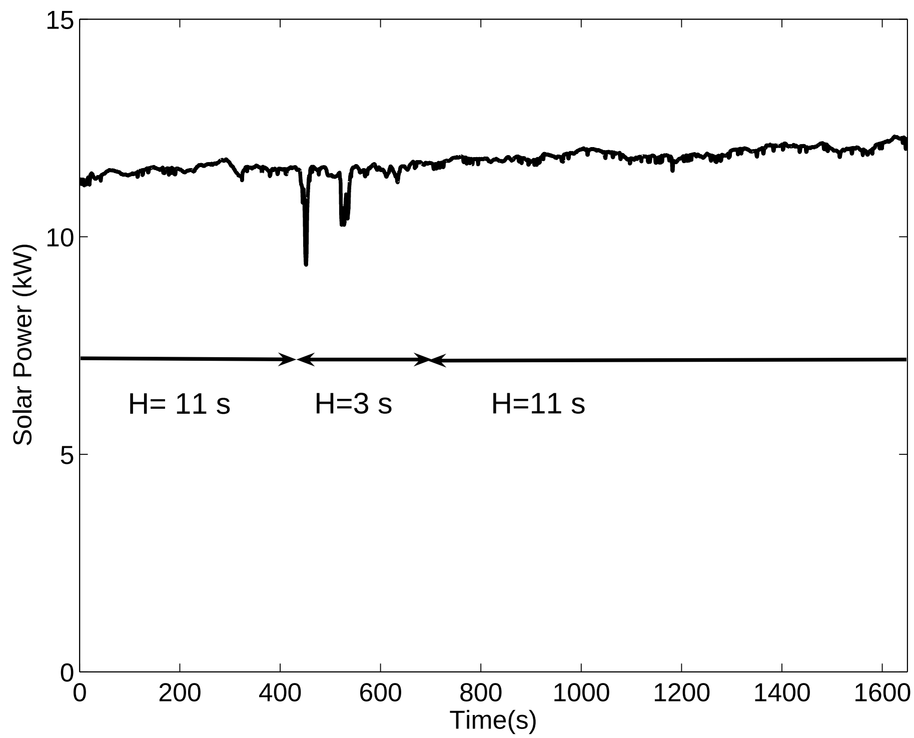

Figure 4: Solar power profile used for real-time experiments

Providing the overall cost for each strategy would be, however, not very useful to the control practitioner, as the weighting of the components of the economic criterion are subjected to a modification of the economic context (e.g. a rise in fuel pricing or a change in tariffs). Table 2 summarizes the different costs (Emission, fuel, cycling and total costs) for a short, long and a variable horizon for the solar profile given in Fig. 4. Before drawing a finer comparison for each strategy, it is necessary to investigate the influence of the horizon value on the behavior of the microturbine and storage unit powers. Specifically, explaining the behavior of the different physical components is important to understand the benefits of using a time-variable horizon.

Fig. 5 shows the profiles of the overall power produced by the cell for a short, a long and a variable horizon strategy. In each case, the optimization of the economic criterion realizes a tradeoff between tracking (corresponding to a tariff policy) and other costs (battery cycling and turbine workout). Hence, the power tracking is never perfect. As could be expected, when using a short horizon, tracking the total power is not very good when the solar power is steady, because predictions are carried out over a short time-window. At the onset of a disturbance, however, the reaction is faster, and prediction errors are not amplified (contrary to the use of a long time-window), even if one can notice power peaks (overshoots)with larger amplitudes. The overall tracking cost is thus not very good for both steady horizon strategies, as can be seen in Table 2. The moving horizon strategy combines the advantages of the two methods, that is, ensure the same tracking performances than the long horizon strategy over steady conditions, and being more reactive during unsteady conditions.

Fig. 6 shows a comparison of the storage unit real-time State of Charge for the three strategies. The microturbine power shown in Fig. 7 exhibits an inverse behavior to that of the battery power profile.
For a long horizon, when the solar power is steady, the storage unit and microturbine powers keep an almost constant value. When the solar power is unsteady, prediction errors will cause the microturbine and storage unit to be called for to maintain the total power close to the reference, hence dramatically increasing cycling and fuel costs.
When the horizon is kept to a low value, the MPC performance is poorer when the solar power is steady, degraded tracking performance leads also to an increase of the control effort. When solar power fluctuations occur, prediction errors are not so important as in the long horizon case, the control is more reactive, leading to an improvement in the monitoring of the microturbine. The storage unit is more called for to smooth peaks or rapid variations of the solar power, hence enduring larger SOC variations which will increase the cycling cost.

To sum up, Table 2 presents the global results obtained for this experiment. Fuel cost is nearly the same for a short and a long horizon; however, it has been shown, through the previous analysis, that the underlying grounds were, in each case, quite different. Making the most of the two strategy by

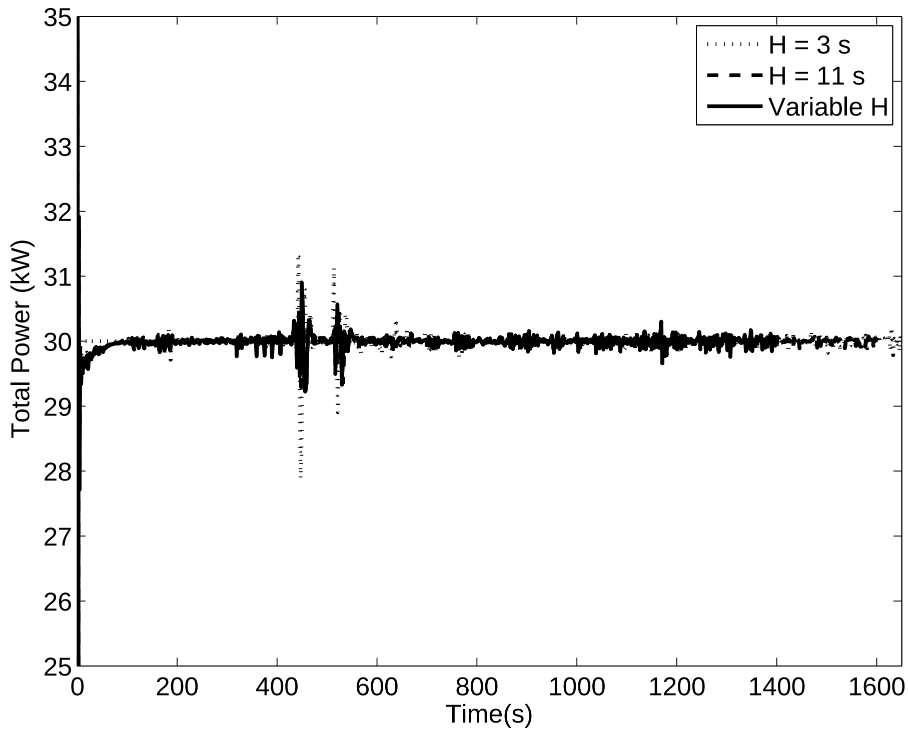

Figure 5: Total hybrid cell power under Predictive supervision with constant and moving horizons

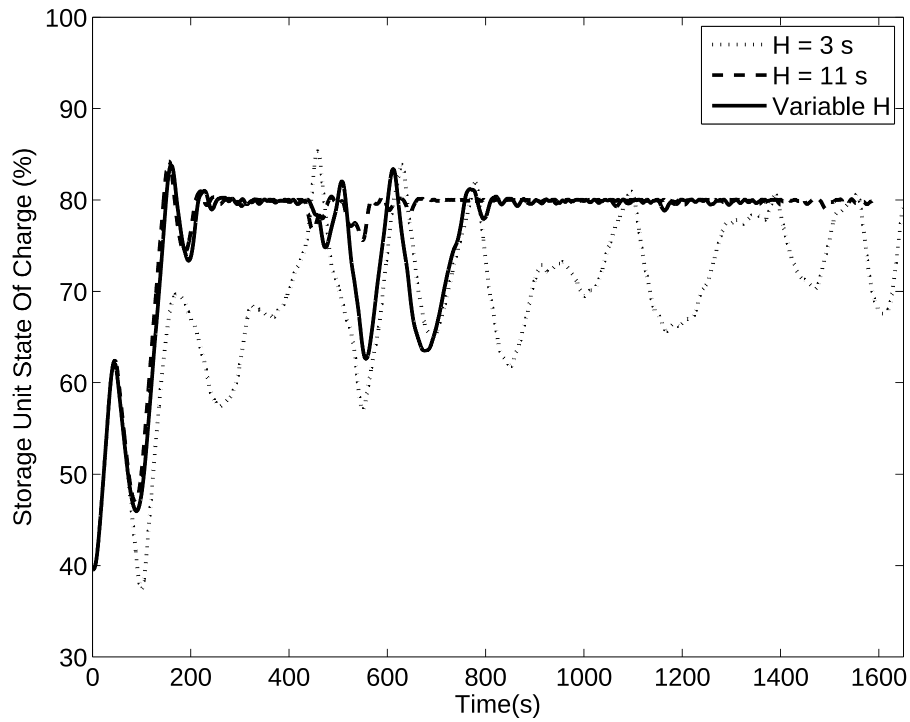

Figure 6: Battery State of Charge under Predictive supervision with constant and moving horizons

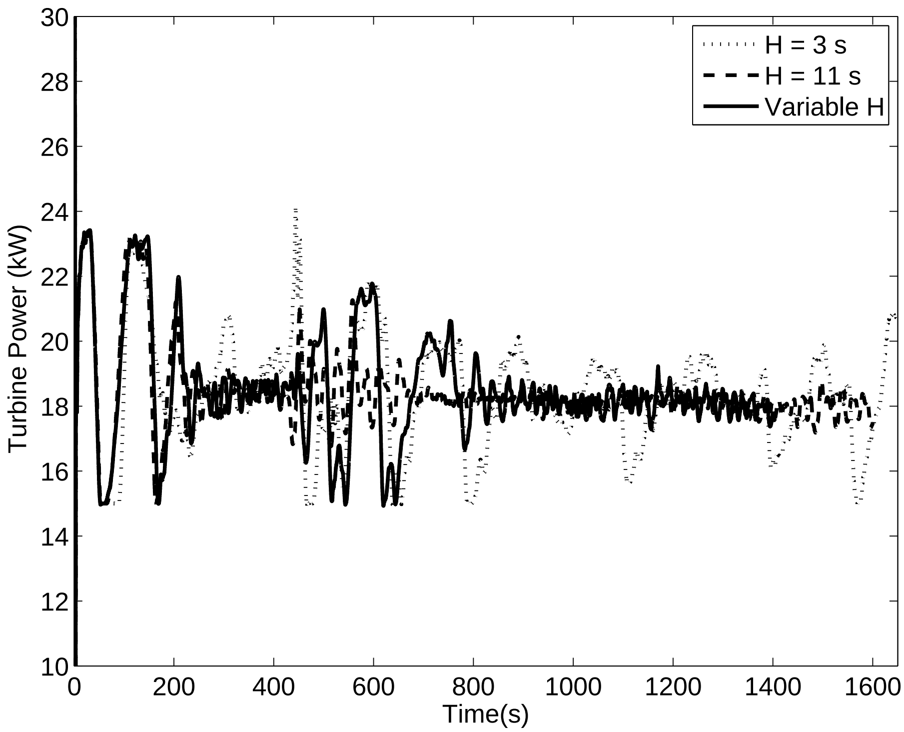

Figure 7: Microturbine power under Predictive supervision with constant and moving horizons

using an adequate switching strategy, the moving horizon algorithm has been able to save up to 15 % fuel and 14.5 % emissions. The battery cycling cost for a moving horizon strategy results in a weighting average between the long horizon periods, where it keeps a lower value, and the short-horizon period, when the SOC of the storage unit fluctuates much more. As a result, the total cost savings can reach 12 %, the shorter horizon being a reference, or 10 % with respect to a long horizon strategy. In any case, the moving horizon strategy proves to be effective.

Table 2: Cost function components as a function of the predictive supervisor horizon value

	H = 3 [s]	H = 11 [s]	Moving Horizon
Emission cost (€)	0.115	0.111	0.098
Fuel cost (€)	1.617	1.569	1.376
Battery cycling cost (€)	0.181	0.079	0.118
Tracking cost (€)	0.047	0.035	0.039
Total cost (€)	1.86	1.794	1.631
Savings (%)	100	96	88

5. Conclusion

A hybrid cell, which consists of a storage unit, a gas microturbine and solar panels is controlled with an Economic Predictive Supervisor. This strategy relies on an economic criterion. This criterion is a function of the grid management policy, the fuel, gas emission and battery cycling costs, all of which have been presented. The overall cost, which is non standard, is optimized over a receding horizon, feeding the battery and storage unit with proper references. The implementation and tuning of such a predictive supervisor is quite easy, since it involves, in this case, the optimization of a criterion at each step time, with any constraints and components of the criterion being based on physical or financial models or considerations. There is no arbitrary weight left to the choice of the user. It has been shown that this controller outperforms a rule-based supervisor by 30 %

However, the results may depend strongly on the prediction horizon of the predictive supervisor. Indeed, when the solar power is well predicted, results are better for a long-range predictive supervisor because the dynamics can be

controlled over a wider time-window. When the solar power is unsteady, the predictions are less accurate and using a shorter horizon avoids to deteriorate the performance. Theoretical results show that the choice of a receding horizon for the predictive supervisor results of a tradeoff between performance and prediction accuracy.
A new moving horizon strategy has been designed which takes advantage of the two situations. When solar power fluctuations occur, the horizon is switched to a lower predefined value. The switching instants are detected through the use of Shewhart charts. Experimental results are obtained using a real-time digital simulator, which allows to emulate virtual components, to blend them will real devices and use the same solar power profiles to get a fair comparison of algorithms. These results have shown the relevance of such an approach, as the overall cost savings reach 12 % with respect to a short horizon and 10 % with respect to a long horizon strategy. Fuel savings are by 15%. This approach remains very simple as only very simple decision algorithms are used along with the model predictive supervisor, and, as the time period is 1 second, no very powerful computation devices are required. A generalization of these results, including a study of the sensitivity to the different cost parameters, will be the topic of future research. Indeed, the methodology can easily be scaled up to a real world application, as welcoming an extra component needs only to know its dynamics and its economic contribution.

Acknowledgements

The authors would like to thank the anonymous reviewers for their in-depths comments and M. Mohit Makkar for fruitful help with the manuscript.

Table 3: List of Acronyms

CUSUM	CUmulative SUM control chart
ESP	Economic Supervisory Predictive
HIL	hardware In the Loop
MRAPE	Mean Relative Absolute Prediction Error
SOC	(Battery) State Of Charge
VH-MPC	Variable Horizon Model Predictive Control

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***Response to Reviewers**

Response to Reviewers, Control Engineering Practice, Manuscript CONENGPRAC-D-14-00018R1
Editor in Chief: Pr. A. Kugi

Please find the following answers to the reviewers' comments.
Yours Sincerely

Jean-Yves Dieulot

Editor: The article is suitable for publication, but the author is requested to consider the further comments of the reviewers. Specific changes are not required but some issues have been raised for the author's further consideration in the final manuscript.

R The authors would like to acknowledge the in-depth and valuable work of the reviewers that helped greatly to improve the paper. We replied to some queries by reviewer #2 and added a few related comments in the paper.

Reviewer #2: This article has clearly been improved in this revision. I do have a few additional comments.

1. Introduction:
- Regarding economic costs, This might more complicated for renewables like wind turbine turbine were operation influences the costs of energy.

R. We totally agree. In the PhD work of Dr. Chalal (unpublished results), we have shown that it was possible to compute the economic cost of a wind turbine, but that one should consider this cost in a different way according to the operating regime, i.e. whether the turbine was operated in MPPT mode or in a sub-optimal (controlled) mode.

3. Variable Horizon Predictive Supervisor
- page 14: detection based on differentiated signals can be problematic in real world applications as it amplifies the noises.
R. In general, this is true. In our study, detection was found effective as noises were small enough.

Reviewer #3: Most of my comments have been satisfactory considered and found errors have been removed.However, I do not think that all weak places have been completely improved. Therefore, my recommendation to publish the papers without further amendments is valid only under the assumption that the others reviewers will be satisfied with all that they asked from the authors to improve. My attitude ls also influenced by the fact that the article may not have any extraordinary scientific value, but it represents for practice useful application of theory. All points in the CEP review guidelines are now tolerable fulfilled and this is the most respectful aspect for publishing in Control Engineering Practice journal

Reviewer #4: This is a revision of a previously submitted manuscript, with extensive changes by the authors. Attention has been given in particular to the motivating sections which were queried in a previous version as the particular power system application was less well motivated than the control theory itself. The theory and application of the variable horizon control itself appear sound.

R. We agree with reviewers #3 and #4 and we think that this paper, while not very theoretical, will be useful to control practitioners. Thanks again to reviewer #3 for his very careful reading of the paper.