Model Predictive Control Modular Approach for Multi-Source System Management

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***Abstract*—This paper presents a modular approach to model and control multi-source systems or networks. This method derives from an energy-based modeling approach called functional modeling in which predictive functional control algorithms have been implemented. A concept of cost function is introduced and associated to each source. The design of the control has several objectives: remain as generic as possible, satisfy the needs from the consumers and distribute flows in order to minimize the cost functions. This methodology is applied to a use case consisting in the management of an isolated production unit composed of a wind power plant and a backup battery. The system is modeled and controlled in order to ensure the active power balance between consumers needs and sources supplies.**

***Index Terms*—predictive functional control, functional modeling, multi-source systems, wind power integration, energy storage, active power balance, smart grid, energy management**

I. Introduction

The climate change requires the acceleration of the energy transition and the reduction of carbon emissions. A massive development of smart grids is one of the solutions implemented to achieve these objectives. Smart grids are complex networks composed of several consumers and sources, whose main objective is to improve energy management. In a first place, these complex networks need to be modeled to observe their behaviors through simulation. The second step is to design the control of these networks, whose main objective is to optimize electricity production, distribution and consumption while respecting all the constraints. The functional modeling methodology is particularly well suited to develop both the model and the control of a multi-source and multi-consumer system, including smart grids.

The concept of functional modeling has been developed in [1] and [2]. This modeling methodology is inspired from the systemic approach introduced in [3] and the Bond Graph representation, of which an exhaustive overview is given in [4]. Functional modeling is a generic methodology using modular functional blocks, the main ones being fully described in [5], that exchange EMI (energy, matter or information) flows between each other. The specificity of the methodology lies in the fact that each functional element is composed of both a control part and an operation part. The first one determines the EMI needs of the element and sends them to the neighbors. The second one collects the flow needs and supplies information from neighbors to determine the behavior of the functional element. The functional modeling is very useful in the early stages of the system design, because of its relatively easy and quick development. Moreover, its control part can be reused later to control a more sophisticated model ([5], [6]) or the real system.

The main objective of this paper is to extend the genericity of the functional methodology by incorporating some predictive control in it. This integration enables to address new issues, especially in smart grids. Indeed, these networks involve a large variety of sources that have specific characteristics, especially their dynamics, cost, operating range or other constraints that can be taken into account with predictive control. Thus, the objective is to implement a predictive control technique in the control part of the functional elements. The aim is to be able to model multi-source networks by remaining as modular as possible and taking into account the characteristics and constraints of the sources. For different reasons detailed in section II-A, Predictive Functional Control (PFC) seems to be the most suitable technique to achieve this objective.

In Section II, after a brief overview of the different Model Predictive Control (MPC) techniques, the PFC method is presented in more detail and its implementation in functional elements is described. Section III introduces a use case that consists in modeling and controlling a production unit composed of a wind power plant (WPP) and a battery energy storage system (BESS). The model of the system is then simulated and the results are discussed. Finally, concluding remarks and perspectives are presented in Section IV.

II. Implementation of Predictive Functional Control in Functional Modeling

A. Model Predictive Control Overview

MPC is an advanced method of process control. The general concept is to predict the effect of some manipulated variables on the process output thanks to an internal model. The second step consists in determining the sequence of values of the manipulated variables that minimizes a predefined cost function over a moving time horizon. This process is repeated at each time step until the end of the process. MPC includes a large set of different algorithms, such as PFC, DMC (Dynamic Matrix Control) or GPC (Generalized Predictive Control). An overview of these different methods of MPC with their own characteristics, advantages and drawbacks are given in [7] and [8].

B. Predictive Functional Control

Among the methods introduced above, PFC offers some advantages, especially its modularity and its quite ease of implementation. The two main characteristics of PFC technique are:

- The cost function is minimized only on a subset of points called coincident points instead of the whole prediction horizon. This makes the resolution easier and faster.
- The control is build from a set of basis functions. This enables to have quite complex inputs with only a few parameters.

The general principle and formulation of PFC, which are exhaustively described in [9], are detailed below.

1) At each time step, the process output is estimated over a prediction horizon H_p thanks to a model.
2) A reference trajectory corresponding to the desired behavior of the process is defined.
3) The manipulated variable command sequence is calculated in order to minimize the difference between the predicted output and the reference trajectory at the subset of coincident points.
4) The optimal command sequence is applied only over the first sampling time T_s, at which the previous steps are repeated.

Most of the time, PFC uses a state space model to describe the process, as shown in (1).

$$\begin{cases} x_m(n) = F_m \cdot x_m(n-1) + G_m \cdot u(n-1) \\ y_m(n) = C_m \cdot x_m(n) \end{cases} \tag{1}$$

where u is the vector of manipulated variables, x_m is the state vector and y_m is the output. The reference trajectory is defined by (2).

$$y_r(n+i) - c(n+i) = \alpha^i \cdot (y_p(n) - c(n)) \tag{2}$$

where y_r is the reference trajectory over the prediction horizon, y_p the real output of the process, c the setpoint, i a time increment between 0 and H_p and α a coefficient that determines the speed at which the setpoint is wanted to be reached. An auto-compensation term, defined in (3), corrects the output prediction $\hat{y_p}$, by estimating the future error between the model and the real process from the current error.

$$\hat{y}_p(n+i) = y_m(n+i) + \hat{e}(n+i) \tag{3}$$

As seen previously, the future control signal is structured as a linear combination of basis functions, which often corresponds to the polynomial basis given in (4).

$$u(n+i) = \sum_{k=1}^{n_B} \mu_k(n) \cdot i^{k-1} \tag{4}$$

where n_B is the number of basis functions. Assuming the system being linear, the output can be broken down in a free output $y_{m,l}$, which is the response to a null command with the current initial conditions, and a forced output $y_{m,f}$, which corresponds to the response with the current signal command and null initial conditions. This decomposition is detailed in (6).

$$y_m(n+i) = y_{m,l}(n+i) + y_{m,f}(n+i) \tag{5}$$

$$\begin{cases} y_{m,l}(n+i) = C_m \cdot F_m^i \cdot x_m(n) \\ y_{m,f}(n+i) = \sum\limits_{k=1}^{n_B} \sum\limits_{l=1}^{n_S} \mu_{k,l}(n) \cdot yb_{k,l}(i) \end{cases} \tag{6}$$

where n_S is the number of manipulated variables, $yb_{k,l}(i)$ the response of the model to the base function k after the time increment i. The criterion δ to be minimized with predictive control is given in (7).

$$\delta(n) = \sum_{j=1}^{n_h} \left(\hat{y}_p(n+h(j)) - y_r(n+h(j))\right)^2 + \lambda \cdot f_c(u_l, h) \tag{7}$$

where h is the vector of coincident points considered, n_h is the number of coincident points (size of h), f_c a cost function corresponding to the use of the manipulated variables and λ a weighting coefficient between cost and performance.

In a real process, the manipulated variables are often constrained due to physical limitations, security issues, etc. In this paper, we only consider constraints on the manipulated variables. Taking into account constraints on state variables would be possible but much more complex [9]. The limitation values of each manipulated variable are determined for each coincident point and the set of constraints given in (8) must be taken into account to minimize the criterion.

$$u_{l,min}(h) < u_l(h) < u_{l,max}(h) \qquad \forall l = 1 : n_S \tag{8}$$

C. Implementation of PFC in Functional Modeling

The aim of this section is to explain how the predictive control is implemented in the functional elements. We consider an energy node composed of several sources, a consumer and a distributor.

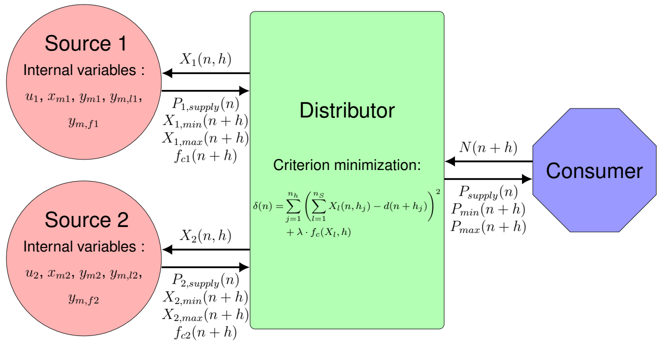

Fig. 1. Power and information flows in an energy node composed of two sources, a distributor and a consumer

- The sources receive an EMI flow need and send back an EMI flow supply according to their limitations.
- The consumer sends an EMI flow need and receives a supply.
- The distributor collects the needs from the consumer and distributes it to the sources according to their limitations. It also collects the supplies and spreads them to the consumer according to its request.

Fig.1 represents such an energy node with two sources.

Assuming a flat error between model process output, i.e. $\hat{e}(n+h) = e(n) = y_p(n) - y_m(n)$, the criterion defined in (7) can be reformulated in a new expression given in (9).

$$\delta(n) = \sum_{j=1}^{n_h} \left(\sum_{l=1}^{n_S} X_l(n, h(j)) - d(n+h(j)) \right)^2 + \lambda \cdot f_c(X_l, h) \tag{9}$$

with

$$X_l(n,h) = y_m(n+h) - y_m(n) \tag{10}$$

$$d(n+h) = c(n+h) + y_p(n) - \alpha^h \cdot (c(n) + y_p(n)) \tag{11}$$

The introduction of the variables X and d provides a good breakdown of PFC between the sources and the distributor, which promotes the genericity of the methodology. As it can be seen in Fig.1, only four parameters are transmitted from sources to the distributor: the power actually provided by the source $P_{l,supply}$, the upper and lower limitations of the source at the coincident points $X_{l,min}$ and $X_{l,max}$ and the cost function $f_{c,l}$ related to the source. The resolution is broken down into two distinct parts:

- The distributor, which does not need to know the prediction models of the sources, solves the criterion minimization problem using the values of the four parameters transmitted by the sources and sends back a power need to them (at each coincident point).
- Each source, thanks to its internal model, determines the control variable sequence that best meets the need it receives (in a least-square sense). The cost and limitations are updated and sent to the distributor.

Fig. 2. Use case system diagram

This division of the problem enables to replace very easily any source by another one or a more complex group of elements (e.g. another network).

III. Application to an Electric Production Unit

One of the most challenging goals of smart grids is the integration of renewable energy power plants to a large extent. The increasing share of intermittent energy sources raises new issues in the control of the grid. An additional storage unit is often needed to ensure power balance between loads and plant production and network stability. There are a lot of publications that deal with the integration of WPP and a BESS into the network and its issues such as power oscillation damping, output power smoothing, frequency regulation or active power support. A review of these issues (and corresponding references therein) is given in [10] and an overview of the different energy storages, their characteristics and their use with renewable energy sources integration can be found in [11] and in [12].

A. System description and modeling

In this part, the methodology presented in the previous section is applied to model and control a WPP and a backup battery. The system is considered to be secluded and not connected to the main network, e.g. on a remote island [13]. Although there is most of the time another backup source (e.g. thermal plant) to ensure production under any weather conditions, only the WPP and the battery will be considered in this paper. This production plant has to provide electric power to several local consumers. The main objective here is to real-time balance the loads (consumer needs) and the electric production (wind plant and battery).

From a functional point of view, the system can be modeled by two sources (the WPP and the BESS), one consumer that corresponds to the aggregation of all real consumers and a distributor that distributes the needs to the sources and concatenates the supplies to the consumer. Fig.2 provides a diagram of the considered system, red arrows representing electrical needs between the elements (supplies in the opposit direction are implicits).

The battery needs to meet some requirements for this application:

- High power density to be able to compensate the mismatch between WPP prediction and real production.

- High energy density to supplement WPP over medium-long time periods (∼1 hour).
- Short dynamic response to avoid frequency variation issues.

According to [12], the BESS type should be either a Lead-acid or a Lithium-ion battery. As the model does not need high accuracy, the battery behavior can be approximated by a first-order model. The parameters of the battery model are given in TABLE I.
The wind turbines in the plant have a variable pitch, which means that their blades angle can be continuously adjusted. Pitch control is often used to maximize the wind turbine power output ([14], [15]) but this technique can also be used to regulate the power output, mainly for frequency regulation issues ([16], [17]). The regulation also avoids to have to shut down wind turbines when the production is too high for the loads, which has an impact on the turbine lifespan when this action is repeated too often. The relationship between the pitch angle and the power output is non-linear but some assumptions are done to simplify this relationship. The wind turbine mechanical power output P_m is given by (12).

$$P_m = P \cdot c_p \tag{12}$$

with c_p the aerodynamic power coefficient and P the power carried out by the wind defined in (13).

$$P = \frac{1}{2} \cdot \rho \cdot A \cdot v^3 \tag{13}$$

where ρ is the air density, A is the rotor swept area and v the wind speed. An empirical expression of the aerodynamic power coefficient, cited in [18] is given in (14).

$$c_p = c_1 \cdot (c_2 \cdot Z - c_3 \cdot \Lambda - c_4 \cdot \beta^x - c_5) \cdot e^{-c_6 \cdot Z} \tag{14}$$

where β is the pitch angle, Λ is the tip-speed ratio (TSR), which is obtained by dividing the speed of the tips of the blades by the speed of the wind. The coefficients c_1 to c_6 and x depend on the rotor type and the expression of Z is given in (15).

$$Z = \frac{1}{\Lambda + 0.08 \cdot \beta} - \frac{0.035}{1 + \beta^3} \tag{15}$$

The wind turbine power output actually depends on both the pitch angle and the TSR. In this use case, we will only focus on three-blades wind turbines, whose TSR is mostly comprised between 5 and 10 according to [18]. Fig.3 shows the influence of the pitch angle on c_p for different values of TSR, where the values of the coefficient c_1 to c_6 have been taken from [18] and are equal to: $c_1 = 0.5$, $c_2 = 116$, $c_3 = 0.4$, $c_4 = 0$, $c_5 = 5$, $c_6 = 21$. As we can see, the curves provided are not linear but in the following, we will assume a linear relationship between the ratio $c_p/c_{p,max}$ and the pitch angle and a range of twenty degrees between optimal angle and the angle that negates power production. In other words, each degree variation in the blade angle leads to a reduction of one

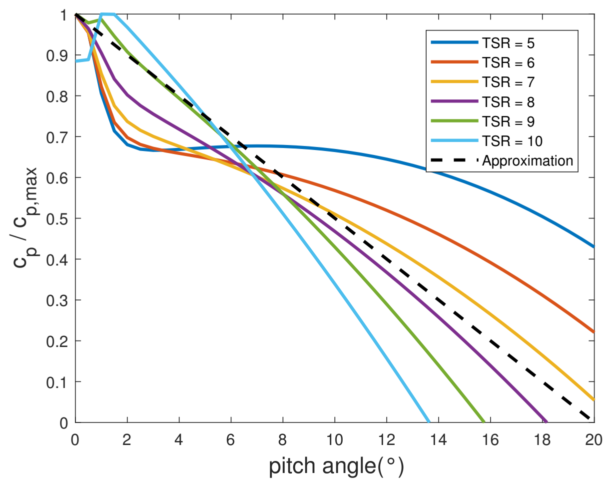

Fig. 3. Influence of the pitch angle on the aerodynamic power coefficient

twentieth of the maximum power. This assumption is strong but as the wind prediction is not accurate, the model does not need to be very precise either.

TABLE I
WIND POWER PLANT AND BATTERY PARAMETERS

Parameter	Value	Unit
WPP nominal power	50	MW
Pitch angle maximal variation	2	°/s
Battery maximal charge power	15	MW
Battery maximal discharge power	15	MW
Battery energy capacity	30	MWh
Battery time constant	0.5	s

B. Simulation Results

This section presents the results of the model simulation for a predefined scenario. The objective is the dynamic power balance between the loads and the production over a quite short time horizon (∼ 30 mn). The consumers needs variations during this period time are often small and the needs will be considered constant. The normalized real maximal production profile and its upstream prediction (used in the PFC) are given in Fig.4.

As the dynamic models of the battery and the WPP are quite simple and their characteristic time is similar (∼ s), only one coincident point is needed to solve the minimization problem introduced in (9). Some requirements that we want to meet in the simulation are listed below:

- Balance between loads and production must be achieved at any cost (priority of performance over cost).
- For lifespan issues, the blade angle should not be changed in an untimely way.
- The battery state of charge (SOC) should remain close to a target value as far as possible, often 0.5.
- To a lesser extent, high frequency variations of battery power should be avoided, especially around the target SOC value.

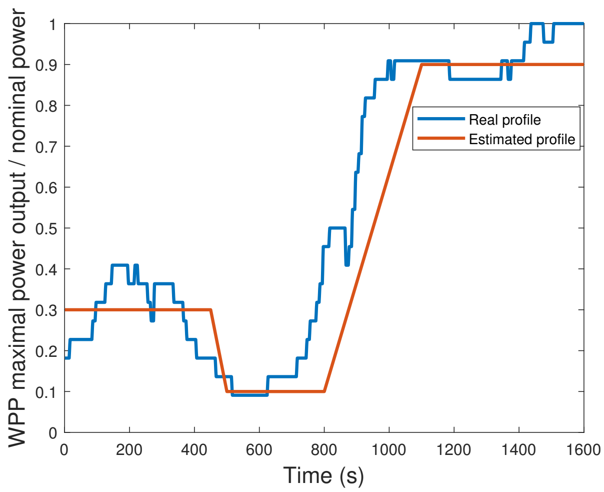

Fig. 4. WPP real (Source: RTE) and estimated production profiles

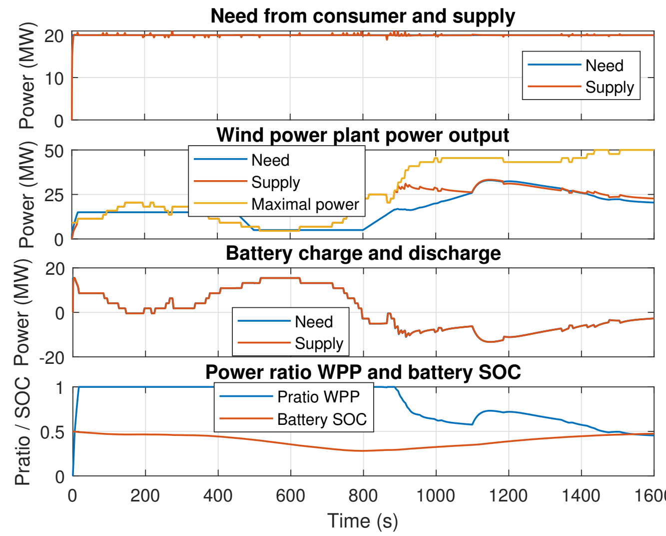

Fig. 5. Simulation results

The first requirement can be met by setting up λ value (see (7)) and the cost functions of each source are defined in (16) and (17) to meet the other requirements.

$$f_{c,WPP} = \alpha_{WPP} \cdot X_{WPP}(n+h) \tag{16}$$

$$f_{c,bat} = \alpha_{bat} \cdot X_{bat}(n+h) + \gamma_{bat} \cdot (SOC_{tg} - SOC) \cdot u_{bat}(n) \tag{17}$$

where α_{WPP}, α_{bat} and γ_{bat} are setting coefficients, which should not affect performance but only power distribution between the sources, and SOC_{tg} the target battery SOC value. In (17), the second term promotes the charge or the discharge of the battery whether the SOC value is too low or too high.

TABLE II
SIMULATION PARAMETERS

Parameter	Value	Unit
h	1	s
SOC_{tg}	0.5	-
SOC_{init}	0.5	-
λ	0.01	-
α_{WPP}	1	-
α_{bat}	0.01	-
γ_{bat}	2	-
Consumers needs	20	MW

The parameters values for the simulation are given in TABLE II and the results are plotted in Fig.5. In the first graph showing the consumers needs and the power that is actually supplied to them, we can observe that both curves are really close. The maximal setpoint overshoot is about 1 MW and the overshoot time is always less than 4 s. In the first part from the beginning to about 800 s, the WPP maximal power output is not sufficient to satisfy the consumers needs and the battery supplements the WPP by discharging. As soon as the WPP produces more than the needs, the battery stops discharging and begins charging to get back to its SOC target value, which is almost reached in the end of the simulation. The profile of the pitch angle, which value is proportional to $Pratio$ (Fig.5, last graph), is quite smooth, which meets the second requirement.

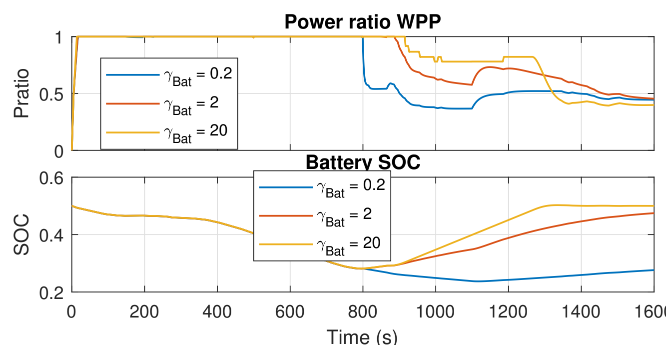

Fig. 6. Influence of γ_{Bat} on the WPP power ratio and the battery SOC

The influence of the parameter γ_{bat} in the battery cost function is then studied. The simulation is run with three different values for this parameter: 0.2, 2 and 20. We can make two main comments from the results given in Fig.6:

- The higher the value of γ_{bat}, the faster the SOC of the battery converges towards its target value and the sharper the profile of $Pratio$ and thus the pitch angle profile.
- The lower the value of γ_{bat}, the longer the SOC convergence and the smoother the pitch angle profile.

This parameter, as well as the target state of charge can be changed during simulation, e.g. in function of long term predictions. The power supplied to the consumers is not plotted here because the profile is identical to the previous one, since the change of the cost functions does not affect performance issues. The use of cost functions associated to each source enables to keep a modular approach, whose complexity is not increased by adding other sources.

IV. Conclusion

This work presents a modular approach, based on the functional modeling concept, to model and control a multi-source system. In order to take into account some characteristics of the sources such as their dynamic response, predictive control algorithms have been implemented in the functional elements. The PFC technique that has been used seems to be the most suitable because of its modularity and ease of implementation. The modeling methodology has been applied to an electricity production system composed of a wind power plant and a battery that must provide power to a consumer. A sensitivity study on the cost functions parameters has been made to highlight their influence.

This study case focused only on the balance of the active power between sources and consumers but the issues concerning frequency, reactive power, power limitations on lines, or even control delays issues have not been taken into account yet and constitute a future improvement.

In this study, the WPP and the battery were considered to be isolated from any grid or any other source. An interesting perspective would be to add another source in the system, e.g. a thermal power plant, with an high cost function to ensure power balance under any weather conditions.

A last objective is the modeling of a more complex grid with several sources and several consumers in which the interconnections between them and the network constraints are taken into account.

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