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Advanced control of a real smart polygeneration microgrid

L.Banta[a], I.Rossi[b], A.Traverso[c], A. N. Traverso[d]

[a] West Virginia University,26505 Morgantown, USA
[b,c,d] University of Genoa,16126 Genoa, Italy

Abstract

This paper presents the development of a control approach for a smart polygeneration microgrid using the Model Predictive Control (MPC) paradigm. The importance of distributed generation systems has increased through recent years and questions of grid stability have emerged in the face of high concentrations of non-dispatchable power sources. Numerous proposals for "smart" distribution systems have emerged, including an architecture called the Energy Hub (E-Hub), which is a smart microgrid where both thermal and electrical power are supplied to customers by a mix of generator systems. The problem deals with a constrained Multi-Input Multi-Output (MIMO) optimization problem. This paper describes work underway on a real E-Hub located at the laboratories of the Thermochemical Power Group (TPG) of the University of Genoa (UNIGE), Italy. The TPG E-Hub is being integrated into a larger smart polygeneration grid under construction on the Savona campus of UNIGE as part of the European Union Resilient project. The proposed control approach aims to optimize the loading of various resources of the E-Hub in response to changing electrical and thermal demands from the campus-wide smart grid. This paper presents some of the results from initial testing of this approach to E-Hub control.

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Keywords: Model Predictive Control ; Polygenerative ; Smart grid ; Energy-Hub

1. Introduction

Driven by legislative measures and market deregulation, electric utility strategies for power production are rapidly evolving. Moving away from centralization and consolidation of large-scale generation facilities to small-sized systems including decentralized generators, utilities face new challenges arising from the need to include non-dispatchable, micro-scale generators in their system planning and control. Since they can be implemented at multiple scales, smart grids are an attractive technology, and many architectures have been studied. At the micro-scale, the Energy-Hub emerges as an attractive option, since it can provide for electrical, thermal and cooling energy thanks to its large use of Combined Cooling Heat and Power (CCHP) systems. The E-Hub offers

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Nomenclature

$P_{1,i}$	Electric power produced by the *i-th* generator [kW]
$Q_{1,i}$	Thermal power produced by the *i-th* generator [kW]
ICE	Internal Combustion Engine
mGT	Micro Gas Turbine
BmB	Biomass Boiler
SPP	Solar Photovoltaic Plant
STP	Solar Thermal Plant

the opportunity for the integration of small-scale distributed generation into utility systems, overcoming safety, reliability and cost issues that have been barriers in the past. Moreover, a real and useful integration between fossil and renewable energy sources is finally possible.

The management of even a micro-scale E-Hub requires complex control processes, since a wide range of objectives, risks, uncertainties and constraints must be considered. This paper describes the development of a Model Predictive Controller (MPC) for the E-Hub facility of the University of Genoa [1]. The MPC approach has been chosen for its ability to optimize system response in the face of nonlinear constraints and uncertainty. Along with its development, this paper describes results obtained by a first-generation MPC tested on the real hardware of the TPG E-Hub. The Energy-Hub used in this work is located on the Savona campus of the University of Genoa, which has been organized as a smart polygeneration grid, where the Energy-Hub is one of the most significant players. It provides electrical energy to the campus, and thermal energy is distributed via a district heating network. In the E-Hub, the thermal grid is arranged with generators connected to both a hot and a cold thermal ring. The hot ring at 75°C takes the water from the generators to customer buildings, while the cold side returns water at 55°C to the generators and their recovery systems. In addition, a 5000 liter thermal storage tank is directly connected to the rings so as to compensate any production mismatches. Finally, 255kW of fan coolers can physically simulate the thermal load of the campus; such fan coolers have been used during the MPC development, described here. Small solar PV and solar thermal arrays are also connected to the E-Hub to simulate the influence of non-dispatchable generators. While their size is small relative to the capacities of the E-Hub hardware, their outputs can be easily scaled in software to simulate the impacts of much larger alternate energy sources. So, E-Hub control strategies for a variety of dispatchable/non-dispatchable generation ratios can be tested. Table 1 summarizes hardware involved in this work.

Table 1: Energy Hub hardware

Model	**Manufacture**	**Electric power [kW]**	**Thermal power [kW]**
T100 PH S3 mGT	*Turbec*	100	155
Tandem T20 ICE	*Energia Nova*	20	55
CS30 BmB	*D'Alessandro Caldaie*	N/A	30
SPP	*Lux Solar*	1	N/A
STP	*SunHeat*	N/A	10
Thermal storage	Capacity:	5000 l	

2. Model Predictive Control

MPC is a model-based control system that uses a dynamic model of the controlled system to estimate future outputs over a *prediction horizon* based on preceding and future actuator commands. MPC is used in many industrial fields, but has not yet been widely applied in energy systems [2] [3]. Differently from other controllers developed for such applications [4] [5], MPC attempts to compute the best sequence of future control commands to minimize some *cost function*, subject to a set of physical or policy constraints imposed on or by the system. For this work, the following cost function [6] was used:

$$S(k) = S_y(k) + S_{\Delta u}(k) + S_u(k) \tag{3}$$

where:

$$S_y(k) = \sum_{i=1}^{P} \sum_{j=1}^{n_y} \left\{ w_j^y \left[r_j(k+i) - y_j(k+i) \right] \right\}^2 \tag{4}$$

$$S_{\Delta u}(k) = \sum_{i=1}^{M} \sum_{j=1}^{n_u} \left\{ w_j^{\Delta u} \Delta u_j(k+i-1) \right\}^2 \tag{5}$$

$$S_u(k) = \sum_{i=1}^{M} \sum_{j=1}^{n_u} \left\{ w_j^u \left[\overline{u_j} - u_j(k+i-1) \right] \right\}^2 \tag{6}$$

These terms represent respectively: a term penalizing error between outputs and setpoints (4), a term suppressing rapid changes in input (5) and a last one (6) penalizing deviation of MVs from their nominal values.

Fuel flow to both the mGT and the ICE is controlled by software supplied by the generator manufacturers. For the ICE, a desired electric power output signal is issued to the engine, and the local controller manages natural gas flow accordingly. For the mGT, the process is somewhat more complicated but with the same effect, i.e. that system dynamic response is managed by the proprietary controller, and is quite conservative to prevent compressor stall/surge cycles. So, in order to maintain a "generic" control architecture, it was decided to keep the manufacturers' controllers intact, building the dynamic model starting from a system identification approach using experimental step response data. The generators were modeled as First-Order Plus Delay (FOPD) or Second-Order Plus Delay (SOPD) systems. Figure 1 shows the mGT model, which is similar to the model for the ICE.

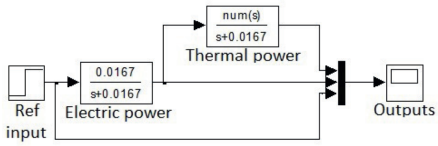

Figure 1: Micro Gas Turbine Model

Thermal storage was modeled as an integrator with a term for mixing and thermal losses. The individual models were then combined in state space form to represent the whole Hub, with its generators and its own thermal system. In the problem at hand, the constraints are the minimum and maximum values for each element, and various operating practice constraints such as start/stop cycle limitations, disturbance input characteristics, etc. The cost functions for the generators consist of capital cost amortization, operation and maintenance costs and distribution losses. Stored energy was given a high value when the storage system was nearly empty and a low value when the storage was nearly full. Other cost functions for the storage are under consideration.

3. Experimental analysis

After the MPC was created and set to obtain a stable controller through simulations, it was tested on the real hardware by connecting it with the hardware of the Energy-Hub. The performance of this or any “optimal” controller is a function of how the weights in the cost function are defined. For example, it is possible to place more importance on tracking electrical demand versus thermal demand or to impose high penalties for rapid fluctuation of generator control inputs. The results shown in Figure 2 represent a case in which electrical tracking error was more heavily weighted. It can be seen that the electrical output matches much more closely the request than does the thermal output. The storage system is used to absorb the difference between thermal demand and thermal supply.

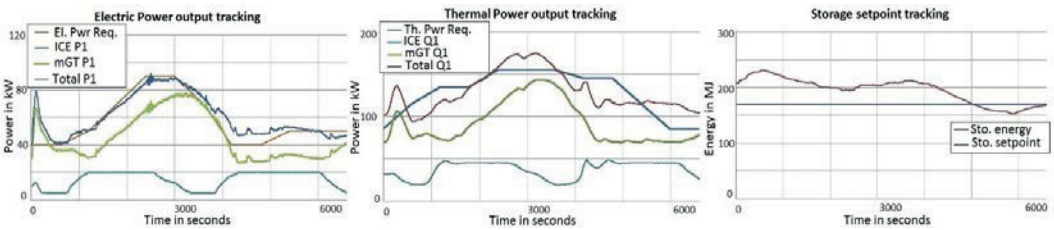

Figure 2: Experimental Results

4. Conclusions

In order to create a reliable and optimizing controller for the E-Hub facility discussed, a system based on the MPC paradigm has been chosen. The first-generation controller has been tested on a real polygeneration system, and has produced satisfactory results. However, for this application, it will be necessary to develop more sophisticated, non-quadratic cost functions including the possibility of negative cost elements to accommodate sales of electricity back to the grid. The extremely slow response of both the ICE and mGT to load changes will also require the incorporation of forward prediction of electric and thermal demand levels, and of expected contributions from solar PV, solar thermal and wind or other alternate energy sources. These refinements are the subject of current research.

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