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A model predictive control strategy for the space heating of a smart building including cogeneration of a fuel cell-electrolyzer system

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ABSTRACT

The objective of this paper is to analyze the value of energy replacement in the context of demand response. Energy replacement is defined as the possibility of the consumer to choose the most convenient source for providing space heating to a smart building according to a dynamic electricity price. In the proposed setup, heat is provided by conventional electric radiators and a combined heat and power generation system, composed by a fuel cell and an electrolyzer. The energy replacement strategy is formulated using model predictive control and mathematical models of the components involved. Simulations show that the predictive energy replacement strategy reduces the operating costs of the system and is able to provide a larger amount of regulating power to the grid. In the paper, we also develop a novel dynamic model of a PEM fuel cell suitable for micro-grid applications. The model is realized applying a grey-box methodology to the experimental proton exchange membrane fuel cell of the EPFL–DESL micro-grid.

Introduction

In the recent years, flexible demand became of renewed interest as a promising resource to restore the lack of control capacity of the power system caused by the increase of the proportion of energy production from renewable generation. Flexible demand is that part of the consumption that can be shifted in time without compromising the quality of the primary services it is supplying to the consumers. The electric loads capable of flexible operation are said demand side resources (DSRs) and are, for example, the electric thermal loads such as space heating devices and refrigeration units; in this case, the flexibility is given by the associated thermal mass that allows a temporary deferral of the power consumption without causing significant variations of the temperature. The utilization of flexible demand has been proposed to support the primary control of frequency and voltage, and provide regulating power to the grid [1–8].

In this paper, we introduce the concept of *energy replacement* applied to the provision of space heating to a smart building. Energy replacement consists in coupling a traditional source of space heating, i.e. electric radiators, together with combined heat and power (CHP) generation units. The CHP source is a storage system composed by a proton exchange membrane fuel cell (PEMFC), an electrolyzer and tanks for storing the reactants. The control of the energy replacement setup is realized by means of model predictive control (MPC), which achieves to schedule the operation of the energy resources according to a dynamic electricity price and while respecting the temperature comfort of the consumer. From the power grid operation point of view, such a setup is expected to provide larger flexibility because energy can be stored not only in the building thermal mass, but also by producing and storing the reactants of the PEMFC-electrolyzer system. The electricity price reflects the need of regulating power of the grid, and, in general, is meant to act as an economic incentive for the flexible demand to shift the consumption. This approach is known as control-by-price, and is extensively advocated in existing literature as a simple framework to enable demand response, since it relies on a few ICT requirements. We show by simulation that, in comparison with conventional space heating setups [9–11], the proposed predictive control strategy achieves a reduction in the operation cost and is able to manage effectively the extended amount of flexibility provided by the CHP system. The topic of the integration of CHP devices at demand side level with the

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objective of enhancing the performance of demand response was previously considered in [12]. We extend such a development by including dynamic models of the fuel cell and building, showing, as mentioned above, how energy can be stored by means of both producing reactants and exploiting the thermal mass of the building envelope. In the process of developing the energy replacement strategy, we propose a novel dynamic model of a PEMFC suitable for micro-grid applications. The model is realized applying a grey-box modelling methodology and is identified using measurements from the experimental 15 kW PEMFC of the DESL facility at EPFL.

The paper is organized as follows: Section 'Methods' describes the setup of the replacement strategy, the models of the components and the MPC algorithm. In Section 'Results', the simulation results are presented and discussed. Finally, conclusions are stated in Section 'Conclusions'.

Methods

The energy replacement concept

The objective of the energy replacement strategy is to provide heat to a smart building combining the operations of several energy resources while minimizing the total cost of the operation and according to the requirements of the grid, which reflects its need of regulating power into a dynamic price of the electricity. The configuration of the energy replacement setup is sketched in Fig. 1: space heating is supplied by the electric radiators and recovering the waste heat associated to the electrochemical conversions operated by the FC and electrolyzer. From Fig. 1, the reactants required by the FC are produced by the electrolyzer, and are mechanically compressed by electric compressors and stored in tanks. It is worth to note that high pressure electrolysis could avoid the use of the compressors since the reactants are already produced at high pressure [13]. Although, in this setup, the configuration with mechanical compression is chosen because is more general in terms of components.

The control of the energy replacement strategy is realized using the MPC. It consists in an optimization problem that minimizes the associated penalty function, while obeying the constraints of the system. The formulation of the MPC strategy requires the mathematical models of the components in Fig. 1. The model of the FC is identified using a grey-box approach and using measurements from a 15 kW PEMFC: the modelling methodology, the experimental setup and the model are described in Section 'Fuel cell grey-box model'. The models of the compressors and tanks of the reactants are realized using a first principles approach and are described in Sections 'Tank model' and 'Compressor model', respectively. The mathematical models of the electrolyzer and building are from

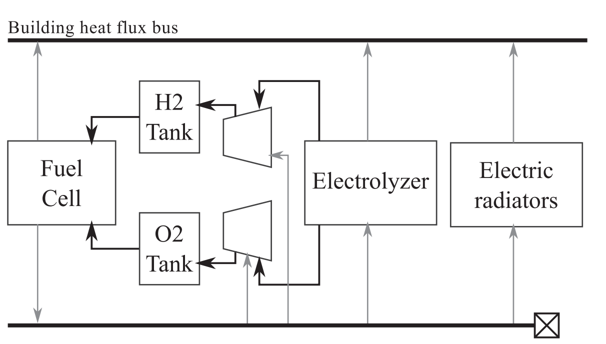

Fig. 1. The setup of the energy replacement strategy. Building space heating is provided by conventional electric radiators, the FC and electrolyzer. The reactants are mechanically compressed and stored in the tanks.

literature and are presented in Sections 'Electrolyzer model' and 'Building thermal model', respectively. The formulation of the MPC problem is described in Section 'Energy replacement model predictive control'.

Fuel cell grey-box model

Stochastic grey-box modelling

The PEMFC model is identified using the grey-box methodology, which is a framework that allows to identify a model incorporating its physical knowledge together with measurements from a real device. The adopted grey-box modelling process consists in formulating a candidate model as a function of unknown parameters that are estimated from measurements using maximum likelihood estimation (MLE). The objective of MLE is determining the parameters of the model that maximize the likelihood of the model, i.e. maximize the probability that the model can explain the set of available measurements. The mean and variance of the 1-step ahead prediction of the candidate model with parameters $\boldsymbol{\theta}$ at the time step k are defined as

$$\hat{\boldsymbol{y}}_{k|k-1} = E[\boldsymbol{y}_{k|k-1}(\boldsymbol{\theta})], \quad (1)$$

$$R_{k|k-1} = \mathrm{Var}[\boldsymbol{y}_{k|k-1}(\boldsymbol{\theta})], \quad (2)$$

respectively, where $\boldsymbol{y}_{k|k-1}$ indicates the prediction of the model provided the information up to $k-1$. The 1-step ahead prediction error of the model is defined as

$$\boldsymbol{\epsilon}_k = \boldsymbol{y}_k - \hat{\boldsymbol{y}}_{k|k-1}, \quad (3)$$

where $\boldsymbol{y}_k$ is the measurement at the time interval k. Assuming that the predictions of the stochastic model are Gaussian distributed, the likelihood function is defined as

$$L(\boldsymbol{\theta}, \boldsymbol{y}(k)) = \left(\prod_{j=1}^{k} \frac{\exp\left(-\frac{1}{2}\boldsymbol{\epsilon}_j^T R_{j|j-1}^{-1} \boldsymbol{\epsilon}_j\right)}{\sqrt{\det(R_{j|j-1})}\sqrt{2\pi}^k} \right) p(\boldsymbol{y}_0|\boldsymbol{\theta}), \quad (4)$$

which is the joint probability of the prediction errors obtained as the product of the single conditional probability density. The parameters of the model are found by minimizing the logarithm of the function in Eq. (4). The MLE routine that is utilized to estimate the FC model is implemented in the software package CTSM [14], which is available as a library for the programming language for statistical computing *R*. In order to capture all the dynamics inherent the system to identify, the device to model should be excited in a wide range of frequency during its operation. This is usually accomplished by controlling the device using a pseudo binary random signal (PRBS), that is a binary signal with a fixed period and duty cycle randomly picked from an uniform distribution. In the case of the FC, the PRBS was replaced by a stepwise signal (shown in Fig. 2) characterized by random durations and amplitude variations. Once the parameters are estimated, the candidate model is validated by means of performing the residual analysis, which allows to determine if the model is able to capture all the dynamics observable in the set of measurements. The FC dynamic model is formulated using stochastic differential equations (SDEs), which allow to obtain, as an outcome of the estimation process, the uncertainties related to both the system disturbances and measurements noise. In general, this is a useful feature since a characterization of the disturbances allows to determine the statistics of the predictions of the model and implement Kalman filtering for state reconstruction and prediction. In the following sections, the experimental setup and the FC model are described.

Experimental setup

DESL laboratory at EPFL in Lausanne implements an experimental micro-grid for studying the interaction between distributed