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Thermal control via state feedback using a low order model built from experimental data by the Modal Identification Method

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ABSTRACT

This work deals with a closed-loop thermal control problem using a low order model built from experimental data. A metallic plate is heated on one side by a radiative heat source and cooled on the other side by a rack of fans. The heat source is able to move in both directions along the plate. Starting from a steady state corresponding to a nominal configuration of heat power, source position and ventilation level, the objective is to control temperature at 3 chosen points on the rear side when the nominal ventilation level is perturbed. The actuators are the heat source power and its displacements. The originality of this work is threefold: (i) a low order model allows performing state feedback control in real time ($\Delta t = 2$ s) through a Linear Quadratic Gaussian compensator, (ii) the model is identified from experimental data using the Modal Identification Method and (iii) a single heat source with 3 degrees of freedom is used to control temperature at 3 distinct positions. Both thermal regulation and tracking problems have been addressed. The effect of the control time period and the control parameters, have also been investigated. Results show promising future developments involving more actuators and controlled outputs.

1. Introduction

Today, the process control is common in everyday life, in the industrial domain as well as in the domestic one. Numerous control applications are being made in many domains: fluid dynamics, chemistry, biology, power systems, robotics, economics…

The process control field has fascinated many engineers and researchers for many centuries. The scientific literature in this field is rich, hence proposing an exhaustive classification of the methods developed in this domain seems to be difficult.

Our interest in this work is the thermal control of multi-input multi-output (**MIMO**) systems. Let us outline the main techniques suitable for such an application.

One of the most common techniques is the proportional integral derivative (PID) controller. It minimizes an error between a measured process variable and a desired setpoint by adjusting the process inputs. Methekar et al. [1] studied a control strategy to obtain maximum power density from a fuel cell. An analysis of the steady-state relative gain array (RGA) was carried out in order to select suitable process variables for controlling average power density and average solid temperature. Linear PI controllers with fixed gain were implemented in a cascade loop. Furthermore, a ratio control strategy was introduced in order to couple two inlet manipulated variables, which led to a quicker time response of the process control. A simple and practical cascade control strategy was also proposed by Sheng et al. [2] for a molten carbonate fuel cell system. In this numerical application, two temperature variables had to be controlled by three manipulated variables. A master controller and two PID controllers were implemented through a cascade control scheme and satisfactorily brought the temperatures back to their desired setpoints. Hamane et al. [3] used a MIMO linear thermal model and the decoupling PID control strategy. The control objective was to maintain three setpoint errors within ±1 °C by adjusting three manipulated variables. A model identification was performed on the experimental device in an open loop step response experiment for each manipulated variable. This procedure allowed to infer the parameters of each PID controller, without using the trial-and-error tuning.

More recent and sophisticated methodologies consist in using a model-based controller in order to optimize the system performance. Many approaches exist. Let us first cite the model predictive control (MPC). Colclasure et al. [4] and Sanandaji et al. [5] presented this approach combined to a low order model for solid-oxide fuel cell systems. In this study, three actuation commands had to be calculated to guide the system through three desired output trajectories. Due to the slow thermal characteristic times of the temperature regulation compared to the other measured variables, a PID controller was used for this decoupled

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Nomenclature

A	state matrix
B	global input matrix
B_c	input matrix for commands
B_p	input matrix for perturbation
C	global output matrix
C_p	specific heat, $J \cdot kg^{-1} \cdot K^{-1}$
h	convective exchange coefficient, $W \cdot m^{-2} \cdot K^{-1}$
$\mathcal{J}$	objective functional of control problem
$\mathcal{J}_{id}^{(n)}$	objective functional of LOM identification
k	thermal conductivity, $W \cdot m^{-1} \cdot K^{-1}$
K_r	gain matrix of LQR
K_e	gain matrix of LQE
ℓ	parameter used to limit the command magnitude
n	LOM order i.e. size of vector δX
p	dimension of global input vector
q	dimension of global output vector
t	time, s
Δt	time step, s
T	temperature, K
δT	temperature deviation, K
δP	power variation in heating wire, W
δU	global input vector $[\delta P\ \delta x_s\ \delta y_s\ \delta V]^T$
δU_c	command vector $[\delta P\ \delta x_s\ \delta y_s]^T$
δV	ventilation voltage disturbance, V
δX	state vector
$\widehat{\delta X}$	estimate of δX
δx_s	source displacement in x direction, mm
δy_s	source displacement in y direction, mm
δY	global output vector
δZ	output vector for controlled points
δZ^d	desired temperature deviation vector
w_m	temperature measurement noise, K

Greek symbols

α	ratio between standard deviations of measurement and perturbation noises
ε	emissivity
ρ	density, $kg \cdot m^{-3}$
$\sigma_Y^{id,(n)}$	mean quadratic discrepancy corresponding to $\mathcal{J}_{id}^{(n)}$, K
σ_Z	mean quadratic discrepancy between desired and obtained temperatures, K

Subscripts

nom	nominal configuration
z	relative to controlled points

Superscripts

d	desired (for output tracking problem)
m	measured
T	transposition sign

Abbreviations

LOM	Low Order Model
LQE	Linear Quadratic Estimator
LQG	Linear Quadratic Gaussian compensator
LQR	Linear Quadratic Regulator
MIM	Modal Identification Method

SISO system. For the remaining both actuators, an MPC controller was implemented using a low order model that captured the dominant dynamic behavior of the system over the operating range. The system being strongly nonlinear, a linear parameter varying (LPV) structure was used to include nonlinear scheduling functions that blended the dynamics of locally linear models. This low order model, coupled to the Kálmán filter appeared to be suitable for real-time process control.

Secondly, let us mention the artificial neural networks, which have been widely used in control of many practical industrial nonlinear processes. Dinh and Afzulpurkar [6] used an artificial neural network in order to accurately reproduce the behavior of the nonlinear MIMO process of a roller kiln. The neural network is suitable for nonlinear input–output relationships. Hence, the use of neural networks in the place of linear models in model-based controller extends the working domain of the controller. In [6], the feed-forward neural network was implemented through a feedback control diagram and simulation results showed that the neural network controller was reliable in the studied case. Another application using this approach was presented by Scott and Ray [7]. The aim was to control the temperature and the concentration in a highly nonlinear nonisothermal continuous-stirred tank reactor. Different controllers were compared in this study and the neural network one showed better robustness properties with respect to disturbance rejection.

Thirdly, let us cite a few methods relative to low order models (LOMs). Indeed, simpler reduced order models, that capture the dominant time-scale behavior, are needed for control implementation. Zheng and Hoo [8] proposed a novel system identification method for implementable control solutions. The singular value decomposition and the Karhunen–Loève expansion were combined in order to build the low order model. This last one was then successively used in a state feedback loop with the aim of controlling five temperature variables by adjusting three manipulated variables (cooling/heating zones). The same authors provided the theoretical framework to show that their low order model could be implemented in a model-based controller guaranteeing stability of the closed-loop system [9].

Favennec et al. [10] studied a purely numerical temperature regulation problem with a state feedback approach. The objective was to control a temperature profile close to the outlet of a pipe by adjusting two heat fluxes, whatever the disturbance of the inlet temperature. Laminar 2D convective heat transfer was considered. The control was based on a reduced model of the linear unsteady energy equation for a fixed steady velocity field. This low order model was built through the modal identification method. Numerical results showed that the controller was able to reject the disturbance.

Our paper deals with experimental thermal closed-loop control problems: temperature regulation and tracking. A metallic plate is heated on one side by a radiative heat source and cooled on the other side by a rack of fans. The heat source is able to move in both directions along the plate. This problem thus involves several nonlinearities. From a steady state corresponding to a nominal configuration of heat power, source position and ventilation level, the objective is to control temperature at three chosen points on the rear side when disturbances in the ventilation level occur. The actuators are the source heat power and its displacements. The originality of this work lies in the fact that, firstly a low order model, linking up the temperatures to the independent inputs, allows us to perform the state feedback control in real time; secondly this model is directly identified from experimental data with the Modal Identification Method (MIM) [11–15]; and thirdly, only one actuator with its three degrees of freedom is used to control three temperatures. In addition, a study of the influence of control parameters on control results has been addressed, as well as the influence of the time step.