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Process Control

A Composite Model Predictive Control Strategy for Furnaces

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ABSTRACT

Tube furnaces are essential and primary energy intensive facilities in petrochemical plants. Operational optimization of furnaces could not only help to improve product quality but also benefit to reduce energy consumption and exhaust emission. Inspired by this idea, this paper presents a composite model predictive control (CMPC) strategy, which, taking advantage of distributed model predictive control architectures, combines tracking nonlinear model predictive control and economic nonlinear model predictive control metrics to keep process running smoothly and optimize operational conditions. The controllers connected with two kinds of communication networks are easy to organize and maintain, and stable to process interferences. A fast solution algorithm combining interior point solvers and Newton's method is accommodated to the CMPC realization, with reasonable CPU computing time and suitable online applications. Simulation for industrial case demonstrates that the proposed approach can ensure stable operations of furnaces, improve heat efficiency, and reduce the emission effectively.

1. Introduction

Nowadays, oil energy becomes increasingly scarce and the amount of greenhouse gas emissions is getting huge. Technological improvements of control strategies for petroleum refining plants are recognized as potentially effective solutions. Practically, heating various hydrocarbon compounds by burning fuels, tube furnaces consume a significant amount of energy and generate huge exhaust emission. It is reported that two ways are available to improve operational conditions of tube furnaces. One is to maintain or replace old production facilities such as using high efficient heat exchange systems, insulation walls and burners, which is no doubt rather expensive and time consuming [1]. Another is to apply advanced control strategies, which can effectively increase thermal efficiencies of furnaces by the optimization of operation condition.

Kalogirou [2] applied artificial intelligence methods in combustion processes. Mercedes [3] introduced fuzzy cascade control to furnace outlet temperature and achieved good results. Through experiments and case study, Lee and Jou [4,5] presented numerical relationship of flue gas residual oxygen concentration, air preheat temperature and furnace thermal efficiency, pointing out that appropriate excess air oxygen concentration and air preheat temperature can reduce fuel consumption and pollution emissions. Lu *et al.* [6] proposed an intelligent self-searching optimization algorithm for thermal efficiency, giving satisfactory simulations. However, existing optimization methods concerning the thermal efficiency of furnace are usually insensitive to process disturbances, easily leading to malfunctions, or even causing accidents, which discourage their applications.

Being capable of dealing with process dynamics and constraints for multi-input and multi-output systems, nonlinear model predictive control (NMPC) has been widely circulated in academia and industry [7–9]. Tracking nonlinear model predictive control (TNMPC) is commonly used to formulate target tracking problems, in which the cost functions are assumed to be positive definite with respect to a certain set-point or trajectory to be tracked. However, this basic assumption does not hold for all cases, particularly for optimizing process economic objectives [10]. In response, economic nonlinear model predictive control (ENMPC) approaches have been developed, where generic cost functions are used instead. TNMPC demonstrates good dynamic performance and robustness in strongly nonlinear systems such as furnace, but in the absence of optimization information in objective functions, its applications are limited to the traditional two-layer control structure (real-time optimization + model predictive control). In this context, ENMPC is rather competent but suffers complex optimization models, longer control cycles, and slow response to perturbations. Novel control structures for both product qualities and economic objectives are demanded.

Taking advantage of distributed model predictive control (DMPC), communications between different NMPC strategies can be established. Several DMPC methods [11–13] have been circulated in literature, though most relevant articles only highlight DMPC schemes conceptually. Motivated by these observations, this paper introduces a CMPC strategy involving TNMPC and ENMPC based on rigorous nonlinear mathematical models, which is easy to implement, enjoys good stability, and optimizes quickly strongly nonlinear constrained complex systems.

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The CMPC strategy is compared with conventional control performance through an industrial example.

2. Furnace Models

Furnaces are recognized as one of the most crucial facilities in petrochemical plants, which heat hydrocarbon mixtures rapidly to a desired temperature by the combustion of fuel gas or exhaust gas. Fig. 1 shows a schematic of a vertical furnace with a radiation chamber and a convection chamber.

To formulate generic first-principle dynamic models of furnaces, the following assumptions are made.

(1) Flue gas and process variables distribute uniformly in the chambers.
(2) The furnace is a multi-fuel (fuel gas and exhaust gas) burning stove.
(3) Heat loss is negligible.
(4) Flue gas temperature in the convection chamber equals that in the radiation chamber and distributes uniformly.
(5) The mole change of vapor during combustion is negligible.

Models for furnace temperature are based on the feed energy balance

$$C_f\rho_f V_f\frac{dT_{o,f}}{dt}=UA\left(T_{fg}-T_{o,f}\right)-C_f F_{i,f}\left(T_{o,f}-T_{i,f}\right) \tag{1}$$

$$C_{fg}\rho_{fg}V_{fg}\frac{dT_{fg}}{dt}=\gamma Q^{L}{}_{mf}-UA\left(T_{fg}-T_{o,f}\right)-C_{fg}F_{o,fg}T_{o,fg} \tag{2}$$

$$\gamma=\begin{cases}0.4(\alpha-1)+0.8, \alpha\le 1.5\\ 1, \alpha\ge 1.5\end{cases} \tag{3}$$

where ρ_f, V_f and C_f are the density, volume and specific heat of the feed in tubes, respectively, ρ_{fg}, V_{fg} and C_{fg} are those of the flue gas in the chamber, $T_{i,f}$, $T_{o,f}$, T_{fg}, and $T_{o,fg}$ are the temperatures of feed at the inlet and outlet, flue gas in the chamber, and flue gas at the outlet, respectively, F_g, F_{eg}, and $F_{o,fg}$ are temperature–pressure compensated volumetric flow rates of fuel gas, exhaust gas and flue gas at the outlet, respectively, U is the average heat transfer coefficient, A is the heat transfer area of furnace, $Q^{L}{}_{mf}$ represents the low heating value of mixed fuel, γ represents the combustion rate of mixed fuel, and α is the excess air coefficient. Heat capacities $\rho_f V_f C_f$ and $\rho_{fg}V_{fg}C_{fg}$ are adjusted by correcting factors to fit the real time trend. The parameters are obtained by using equipment dimensions and fitting to measurement data.

$$Q^{L}{}_{mf}=K_g F_g+K_{eg}F_{eg} \tag{4}$$

where K_g and K_{eg} denote low heating value coefficients of fuel gas and exhaust gas.

Dynamic characteristics of the fuel gas circuit is

$$\tau_g\frac{dF_g}{dt}=-F_g+F_{s,g} \tag{5}$$

where τ_g is the time constant of fuel gas circuit, and $F_{s,g}$ is the set-points of F_g.

Models for furnace flue gas and air system are as follows

$$C_p\frac{dP}{dt}=F_a+F_g+F_{eg}-F_{o,fg} \tag{6}$$

$$C_O\frac{dO_{fg}}{dt}=21F_a-21A_{mf}\cdot F_{mf}-F_{o,fg}O_{fg} \tag{7}$$

$$\alpha=\frac{0.21F_a}{A_{mf}\cdot F_{mf}} \tag{8}$$

where C_p and C_O are the capacity factor of the chamber at negative pressure and residual O_2 of flue gas, respectively, P is the chamber negative pressure, O_{fg} is the residual O_2 concentration of flue gas, F_a is the volumetric flow rate of air, and A_{mf} is the theoretical air–fuel ratio of mixed fuel, which can be calculated as follows.

$$A_{mf}=Fr_g A_g+Fr_{eg}A_{eg} \tag{9}$$

$$A_f=2.381Y_{H_2}+2.381Y_{CO}+7.143Y_{H_2S}\\ \sum(m+0.25n)Y_{C_mH_n}-Y_{O_2} \tag{10}$$

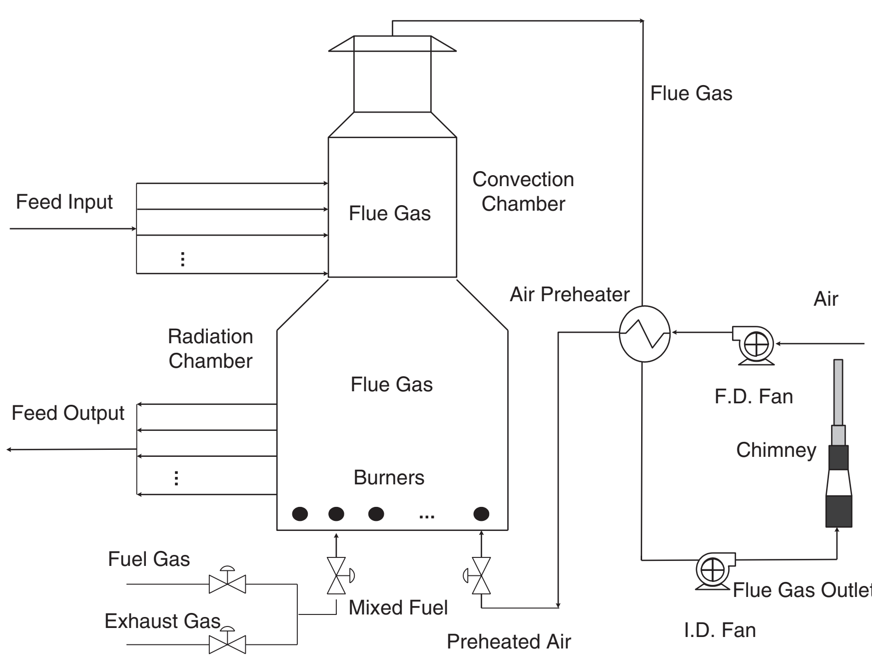

Fig. 1. A simplified schematic of furnaces.