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Plant-wide optimization and control of an industrial diesel hydro-processing plant

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ABSTRACT

Diesel hydro-processing (DHP) is an important refinery process which removes the undesired sulfur from the oil feedstock followed by hydro-cracking and fractionation to obtain diesel with desired properties. The DHP plant operates with varying feed-stocks. Also, changing market conditions have significant effects on the diesel product specifications. In the presence of such a dynamic environment, the DHP plant has to run in the most profitable and safe way and satisfy the product requirements. In this study, we propose a hierarchical, cascaded model predictive control structure to be used for real-time optimization of an industrial DHP plant.

1. Introduction

Combustion of sulfur compounds in diesel engines emits sulfur oxides into the atmosphere and causes health and environmental problems. Diesel hydro-desulfurization is an important refinery process which removes the undesired sulfur compounds from the oil feedstock. In order to comply with the new emission standards for better air quality, there is an increasing demand for the production of ultra-low sulfur diesel (ULSD) fuel (<10 ppm). In order to meet this low sulfur demand, refineries are now evaluating alternative revamping and control strategies to improve the operation of their hydro-processing plants (Palmer et al., 2003).

The industrial diesel hydro-processing (DHP) plant which is the subject of this study consists of a series of three subsystems of unit operations: Blending, reactors and fractionation as shown in Fig. 1. The plant is designed to process 4500 cubic meters per day of diesel feedstock. The feedstock is obtained by blending four streams: HD (straight run heavy diesel), LD (straight run light diesel), LVGO (light vacuum gas oil) and an imported diesel. HD and LD streams are obtained from a crude distillation unit, and LVGO stream is derived from a vacuum distillation unit. These streams are blended in order to obtain a desired T95 value (the temperature at which 95% of the distillate is collected e.g. by ASTM D86 distillation) for the reactor charge. The blended feed is mixed with purified recycle hydrogen gas from the fractionation subsystem and makeup hydrogen. Next the feed enters the furnace where it is heated to the required reactor inlet temperature. Reactor subsystem consists of two catalytic hydro-desulfurization (HDS) reactor beds and one hydro-cracking (HC) reactor bed in series as shown in Fig. 1. In the first two HDS beds, the organic sulfur impurities are removed. Hydro-cracking (HC) occurs in the last bed where heavier hydrocarbons are cracked to lower molecular weight petroleum fractions. Inter-stage cooling by quench hydrogen is used in both reactors to control the bed temperatures. In the fractionation subsystem the reactor effluent is next separated into useful end products such as naphtha and diesel. In our earlier work, we developed dynamic, non-isothermal, pseudo-homogeneous plug flow models for the HDS (Aydın et al., 2015) and the HC (Sildir et al., 2012) reactors. These models are trained using industrial data and validated under both steady and dynamic conditions.

Several studies which address the optimal operation of hydro-cracking and hydro-desulfurization processes have been reported in the literature. Bhutani et al. (2006) developed a discrete-lumping model for multi-objective optimization of an industrial hydro-cracking plant. Zhou et al. (2011) studied maximization of diesel or kerosene yield in an industrial hydro-cracking plant which consisted of two HDN (hydro-denitrogenation) and HDS reactor beds followed by four HC beds. Al-Adwani et al. (2005) simulated and

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Nomenclature

T	bed temperature (K)
T_0	reference temperature (K)
TBP	true boiling point (°C)
TBP(h)	highest boiling point (°C)
TBP(lh)	lowest boiling point (°C)
C_p	heat capacity (kJ/kg K)
ΔT	bed temperature difference (°C)
v	average velocity (m/h)
$C(t)$	concentration (kg/kg feed)
$c(k,0,0)$	initial concentration of species at the reactor inlet (kg/kg feed)
$k_{\min 1}$	minimum reactivity of sulfur species in Bed 1 (h^{-1})
$k_{\min 2}$	minimum reactivity of sulfur species in Bed 2 (h^{-1})
k	reactivity (h^{-1})
$D(k)$	species type distribution function
$k_{\max 1}$	maximum reactivity of sulfur species in Bed 2 (h^{-1})
$k_{\min 2}$	maximum reactivity of sulfur species in Bed 2 (h^{-1})
wt	weight fraction
K	maximum reactivity in the hydrocracker (h^{-1})
$\boldsymbol{N}$	number of sulfur species
E_{a1}	activation energy in Bed 1 (kJ/kmol)
E_{a2}	activation energy in Bed 2 (kJ/kmol)
ΔH_1	heat of reaction in Bed 1 (kJ/kg sulfur)
ΔH_2	heat of reaction in Bed 2 (kJ/kg sulfur)
$k_{hc,\max}$	maximum reactivity of hydrocarbon species in the hydrocracker bed (h^{-1})
$E_{a,hc}$	activation energy for the hydro-cracking reactions (kJ/kmol)
c	parameter for the heat of cracking reaction
d	parameter for the heat of cracking reaction
TCP	temperature cut point
a_i	blending parameter for heavy diesel
b_i	blending parameter for light diesel
c_i	blending parameter for light vacuum gas oil
d_i	blending parameter for imported diesel
$D86^{HD}$	ASTM D86 values of heavy diesel (°C)
$D86^{LD}$	ASTM D86 values of light diesel (°C)
$D86^{LVGO}$	ASTM D86 values of light vacuum gas oil (°C)
$D86^{Im.Diesel}$	ASTM D86 values of imported diesel (°C)
$D86^{FEED}$	ASTM D86 values of DHP feed drum (°C)
S_f	feed sulfur weight percent (%)
F_f	feed flow rate (ton/day)
$Feed\ T^{95}$	the temperature at which 95% of DHP Feed by volume boils (°C)
$Diesel\ T^{95}$	the temperature at which 95% of Diesel by volume boils (°C)
$Sconv$	conversion of sulfur
M_{HD}	flow rate of heavy diesel (ton/day)
M_{LD}	flow rate of light diesel (ton/day)
$M_{\mathrm{ImportDiesel}}$	flow rate of import diesel (ton/day)
$T_{in,HDS1}$	inlet temperature of the first HDS reactor (K)
$T_{in,HDS2}$	inlet temperature of the second HDS reactor (K)
$T_{in,HC}$	inlet temperature of the HC reactor (K)
$T_{out,HDS1}$	outlet temperature of the first HDS reactor (K)
$T_{out,HDS2}$	outlet temperature of the second HDS reactor (K)
$T_{out,HC}$	outlet temperature of the HC reactor (K)
C_{HD}	cost of heavy diesel
C_{LD}	cost of light diesel
$C_{ImportDiesel}$	cost of import diesel
P_{Diesel}	price of product diesel
P_{Nafta}	price of product nafta
sp	set point

Greek letters

θ	normalized boiling point
α	the parameter that relates cracking reactivity to normalized boiling point
α_0	the parameter in the yield function
α_1	the parameter in the yield function
β	the parameter that relates HDS reactivity to the normalized boiling point

optimized the performance of residuum hydro-treating reactors. Optimization objective was to minimize the production cost and maximize the monetary benefits of lower sulfur compounds. Optimization used a quasi-steady state model given in Lababidi et al. (1998). These studies did not address the control of HDS plants. Kelly et al. (1988) implemented dynamic matrix control for temperature regulation and energy minimization of a train of four hydro-treating and hydro-cracking beds in a refinery. Sayalero et al. (2012) applied self-optimizing control to a diesel hydro-desulfurization plant for hydrogen consumption optimization. Finally, real-time optimization and control of DHP plants processing ultra-low sulfur has been the subject of several commercial multivariable model predictive control packages (Ikegaya et al., 2004; Yugo et al., 2011).

The DHP plant under the current study processes various feedstocks and large throughputs. Also, changing market conditions have significant effects on the diesel product specifications. In the presence of such a dynamic environment, the DHP plant has to run in the most profitable and safe way and satisfy the requirement that the sulfur content of the diesel product meets its specification (in this case below 10 ppm). In other words, the control system should address both economic and regulatory control objectives. It is well-known that the best way to organize and handle such different plant-wide control tasks is through hierarchical control (Morari et al., 1980). In this study, we propose a hierarchical, cascaded model predictive control structure for the industrial DHP plant. Modeling, optimization and control take into account the steady-state and dynamic interactions present between the blending, reactors and fractionation subsystems. For the reactors we use the models we have developed earlier. For the feed blending and the fractionation units, we develop new empirical models to predict certain important feed and product properties for optimization and control purposes. These models are briefly explained next to help understand the subsequent real-time optimization and control study which constitutes the focus of this paper.

This paper is the first application of the plant-wide optimal control problem to an industrial diesel hydro-processing plant to the best of our knowledge. The proposed hierarchical control strategy includes model predictive control at its core. Model predictive controllers (MPC) have been extensively used for industrial control applications (Qin and Badgwell, 2003). These controllers use an explicit model to predict the future behavior of the process outputs. At each control interval the algorithm estimates the disturbances, corrects the output predictions and calculates the optimal control actions by taking the process constraints into account. MPC's popularity stems from its capability to address multivariable linear or nonlinear systems, constraints, delays and its versatility to utilize different types of process models and performance functions. Because of these characteristics, MPC provides a suitable platform for real-time optimization (Adetola and Guay, 2010; De Souza et al., 2010; Scattolini, 2009).