Computers and Chemical Engineering 99 (2017) 314–324

Contents lists available at ScienceDirect

Computers and Chemical Engineering

journal homepage: www.elsevier.com/locate/compchemeng

Cyclic scheduling for an ethylene cracking furnace system using diversity learning teaching-learning-based optimization

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ARTICLE INFO

Article history:
Received 24 June 2016
Received in revised form
16 December 2016
Accepted 14 January 2017
Available online 20 January 2017

Keywords:
Ethylene cracking furnace
Cyclic scheduling
Teaching-learning-based optimization

ABSTRACT

The ethylene cracking furnace system is central to an olefin plant. Multiple cracking furnaces are employed for processing different hydrocarbon feeds to produce various smaller hydrocarbon molecules, such as ethylene, propylene, and butadiene. We develop a new cyclic scheduling model for a cracking furnace system, with consideration of different feeds, multiple cracking furnaces, differing product prices, decoking costs, and other more practical constraints. To obtain an efficient scheduling strategy and the optimal operational conditions for the best economic performance of the cracking furnace system, a diversity learning teaching-learning-based optimization (DLTLBO) algorithm is used to simultaneously determine the optimal assignment of multiple feeds to different furnaces, the batch processing time and sequence, and the optimal operational conditions for each batch. The performance of the proposed scheduling model and the DLTLBO algorithm is illustrated through a case study from a real-world ethylene plant: experiments show that the new algorithm out-performs both previous studies of this set-up, and the basic TLBO algorithm.

1. Introduction

Ethylene is the most widely-produced organic compound in the world; it is extremely important for the chemical industries and for daily life. Multiple cracking furnaces are employed in industrial ethylene production, to convert various hydrocarbon feeds to smaller hydrocarbon molecules through complex pyrolysis reactions, resulting mostly in ethylene and propylene. The cracked gas is sequentially sent to quenching, compression, chilling, and separating sections to recover the various products. The operating performance of the cracking furnace system plays a crucial role in ethylene plants, since the major product yields are mainly determined in this operation.

A thermal cracking operation is a typical semi-continuous dynamic process, due to the fact that coke accumulates on the inner tube surface of the cracking coils. This increases the heat transfer resistance and the reactor pressure drop, leading to a reduction in both reaction selectivity and productivity. Thus for the sake of production efficiency and plant safety, a cracking furnace must be periodically shut down for decoking (Lim et al., 2006); this means that multiple cracking furnaces are needed in an ethylene plant, so that when one furnace is decoking, other furnaces can continue processing. Due to limited resources for decoking and safety concerns which can arise if downstream processes are disturbed, practical ethylene plants allow only one furnace to be decoked at a given time.

In recent years, the rapid growth of the ethylene demand and volatile raw material and product markets have forced ethylene plants to enhance their manufacturing flexibility to process different types of feeds and effectively arrange their schedules for maximizing operation profitability. These requirements highlight the significance of cracking furnace system scheduling, to satisfy material balance constraints, feedstock and production requirements, and non-simultaneous decoking. We need to determine the optimum allocation of multiple feeds to different furnaces, the optimum processing sequence and time of each furnace, and the corresponding decoking sequence.

Because of the importance of the cracking furnace, this is an active area of research. Riverol and Pilipovik (2007) formulated a fuzzy system for studying operational optimization on the ethane pyrolysis process. Li et al. (2007) constructed an artificial neural network model for the yields of ethylene and propylene and

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http://dx.doi.org/10.1016/j.compchemeng.2017.01.024
0098-1354/

Subscripts

$i = 1, \ldots, NF$ index of different feeds for cracking
$j = 1, \ldots, NC$ index of cracking furnaces
$k = 1, \ldots, NB$ index of batches for each furnace
$l = 1, \ldots, NP$ index of considered key products

Parameters

P_l the price parameter for the product l
$Cs_{i,j}$ decoking cost for the feed i cracked in the furnace j
$\tau_{i,j}$ decoking time used after the feed i cracked in the furnace j
$Coke_{i,j}$ coking scaling factors for the feed i cracked in the furnace j
Flo_i lower bound of the rate of arrival of the feed i
Fup_i upper bound of the rate of arrival of the feed i
$Dlo_{i,j}$ lower bound of the flow rate for the feed i cracked in the furnace j
$Dup_{i,j}$ upper bound of the flow rate for the feed i cracked in the furnace j
$Cotlo_{i,j}$ lower bound of the coil outlet temperature for the feed i cracked in the furnace j
$Cotup_{i,j}$ upper bound of the coil outlet temperature for the feed i cracked in the furnace j
$tup_{i,j}$ upper bound of the processing time for the feed i cracked in the furnace j
$TMTup_{i,j}$ upper bound of the tube temperature for the feed i cracked in the furnace j
$TMT_{i,j}(t)$ the tube temperature function for the feed i cracked in the furnace j
$Y(t)_{i,j,l}$ the yield function of product l for the feed i cracked in the furnace j

Variables

$Feed_{j,k}$ the type of feed assigned to kth batch of the furnace j
$t_{j,k}$ processing time for kth batch of the furnace j
$D_{j,k}$ flow rate for kth batch of the furnace j
$Cot_{j,k}$ coil outlet temperature for kth batch of the furnace j
$S_{j,1}$ starting time point of the first batch in the furnace j
T total cycle time of the scheduling problem
F_i rate of arrival of the feed i

developed a new multi-objective particle swarm optimization method to optimize the operational condition of a naphtha cracking furnace. The validity and reliability of the proposed algorithm were demonstrated through two test functions studied, and actual optimization of operation condition for cracking process. Moreover, the yields of ethylene and propylene were improved. Nabavi et al. (2009) studied the multi-objective optimization of an industrial liquefied petroleum gas thermal cracker by employing an elitist non-dominated sorting genetic algorithm with the jumping gene strategy. Keyvanloo et al. (2010) investigated the effect of temperature, steam-to-naphtha ratio, and residence time and their quadratic and cubic interactions on the yield of ethylene and propylene in naphtha steam cracking. Berreni and Wang (2011) studied the dynamic modeling, simulation and optimization of thermal cracking of propane in a tubular reactor by employing gPROMS; they illustrated that the dynamic optimization can improve operating profit by 13.1%. Xiaoyu et al. (2013) developed a differential evolution group search optimization algorithm to obtain optimal operational conditions of a naphtha cracking furnace for maximizing the sum mass yield of ethylene and propylene. To handle the multi-objective operation optimization for the yields of ethylene and propylene, Wang and Tang (2013) designed a multi-objective parallel differential evolution with competitive evolution strategies. The computational results on practical problems indicated that the operation of an ethylene plant can be enhanced by increasing the yields of ethylene and propylene. Xia et al. (2014) integrated a fuzzy C-means multi-swarm competitive particle swarm optimization algorithm with a radial basis function neural network to study the intelligent optimization control of cracking depth of an ethylene cracking furnace. Yu et al. (2015) presented a self-adaptive multi-objective teaching-learning-based optimization (SA-MTLBO) to determine the optimal control variables for three conflicting objectives: maximization of the yields of ethylene, propylene, and butadiene. The results on one naphtha pyrolysis process showed that SA-MTLBO can obtain a good spread non-dominated solutions and provide more options for decision maker to improve the benefit of cracking furnace.

It is worth noting that the aforementioned work mainly concentrates on the process simulation, advanced control, and operational optimization of a single furnace. Few papers can be found on the production scheduling of a multi-furnace cracking system as the thermal cracking process involves highly complex reactions. Jain and Grossmann (1998) first developed a MINLP (mixed-integer non-linear programming) model for the cyclic scheduling of multiple feeds cracked by multiple furnaces with the exponential decaying functions for product yields. The mathematical property of the designed model was analyzed and a solving algorithm for global optimality was proposed and demonstrated. However, the MINLP model did not consider the non-simultaneous decoking constraint and assumed that the same feed cracked in the same furnace in different batches always has the identical processing time. Schulz et al. (2006) proposed a MINLP model to study the optimal performance of cyclic furnace shutdowns and downstream separation systems. But they assumed that the coke thickness linearly increases with operation time, which is not consistent with the coking mechanism in practical situations (Wauters and Marin, 2002; Jazayeri and Karimzadeh, 2014). The non-simultaneous decoking constraint was also ignored and only one type of feed was considered. To determine optimal decoking policy, Lim et al. (2006) developed a neural network-based scheduling model by employing online information of ethylene and propylene yields, coil skin temperature, and pressure drop to assist the scheduling decisions. They also proposed three alternative solution strategies to solve the developed large-scale MINLP model. However, in this study, the situation of multiple feeds is still not considered and the scheduling is not formed in a cyclic way such that only limited time horizon needs to be designated in advance. Liu et al. (2010) presented a new cyclic scheduling model by considering multiple feeds, multiple cracking furnaces, and non-simultaneous decoking constraints to obtain the best performance of cracking furnace system. However, the operational conditions, such as feed rate and coil outlet temperature, are kept constant during the total cyclic time in their model. Zhao et al. (2010) proposed a new cyclic scheduling model by considering secondary ethane cracking to make the scheduling results more applicable in reality. Subsequently, Zhao et al. (2011) extended the model in a rescheduling framework to dynamically generate reschedules based on the new feed deliveries, the leftover feeds, and current furnace operating conditions. Wang et al. (2014) proposed a novel synchronized scheduling framework to solve the integrated scheduling problem of upstream naphtha inventory management and the related downstream furnace cracking operation. The performance of the proposed integrated framework was demonstrated through a comprehensive case study from a real-world ethylene plant. Very recently, Jin et al. (2015) developed an integrated framework to simultaneously optimize the operational conditions and cyclic scheduling for an ethylene