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A Decision Support System for consumption optimization in a naphtha reforming plant

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ABSTRACT

In a naphtha distillation process, the natural objective is to perform an entire process maximization of the production rate while meeting required product qualities by searching for an optimal operating condition by manipulating the operating variables. The objective of this paper includes performing an energy process optimization. Not only is an adequate production rate met with the required product qualities but the operating cost is also minimized through a data mining approach. The study of the influence of all process attributes in the defined Energy Efficient Indicator (EEI) allows the construction of a multivariate linear model to aid human experts in the recovery of energy losses. A canonical discriminant function carried out the data prediction step. The quality of the Decision Support System framework is illustrated by a case study considering a real database. Also, a commercial software supported by this mining framework is presented.

1. Introduction and bibliographical review

The goal of simulating the performance of an expert is to help human workers solve real-world problems by expertise, a specific domain of knowledge (Shiau, 2011). There are diverse problems which need to be solved in the real world. Thus, the use of an expert system (or a similar artificial intelligence framework) becomes prolific in many fields (Liao, 2005). One of the complex problems for the control in which a computational intelligent approach is amenable is a crude oil distillation unit. In a crude distillation process, the first objective is to perform an entire process optimization including high production rate with a required product quality by searching for an optimal operating condition of the operating variables (Frenkel, 2011; Ouattara et al., 2012). In the previous decade, there was considerable research concerning the optimization of crude distillation processes (Ghashghaee & Karimzadeh, 2011). In Seo, Oh, and Lee (2000), the optimal feed location on both the main column and stabilizer is obtained by solving rigorous "a priori" models and mixed integer nonlinear programming. The sensitivity to small variations in feed composition is studied in Dave, Dabhiya, Satyadev, Ganguly, and Saraf (2003). Julka et al. propose in a two-part paper (Julka, Karimi, & Srinivasan, 2002; Julka, Srinivasan, & Karimi, 2002) a unified framework for modeling, monitoring and management of supply chain from crude selection and purchase to crude refining. In addition to analytical non-linear models, computational intelligence techniques such as neural networks (Gueddar & Dua, 2012; Liau, Yang, & Tsai, 2004) and genetic algorithms (Motlaghi, Jalali, & Ahmadabadi, 2008) are used for the same purpose. Alhajree, Zahedi, Manan, and Zadeh (2011) cite several Artificial Neural Network research studies for the control of processes in petrochemicals and refineries. From cited papers, most of the nonlinear controllers require the feedback of state information for effective control and close monitoring of a process. In practice, however, the complete online information about the present state of the industrial process is rarely available. If the real-world values are not provided to the algorithm on time, the control algorithm becomes formally invalid. In practice, it recovers from the situation, at the price of reduced quality control (i.e., worse product), so such situations should be avoided (Metzger & Polakow, 2011).

The scope of this present study is concerned with a part of the crude oil distillation called the platforming unit. It is made up of two subunits: the catalytic reforming or reaction unit and the distillation unit or train distillation. Most of the cited references are focused on optimizing the production rate of the distillation unit (Iranshahi, Bahmanpour, Paymooni, Rahimpour, & Shariati, 2011; Meidanshahi, Bahmanpour, Iranshahi, & Rahimpour, 2011), but if the focus is the heat recovery, 80% of the energy consumption (67% of the energy invoicing tasks) corresponds to the fuel consumption in the boilers of the previous task (the reaction unit).

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At present, research is not only focused in the rise of the production rate but also in making customized products (Frenkel, 2011) and in the improvement of product quality (Rahimpour, Vakili, Pourazadi, Iranshahi, & Paymooni, 2011). In this sense, classic applications of linear control theories on the distillation unit are widely available in the literature (Jabbar & Alatiqi, 1997). Also nonlinear state estimation research (Jana, Samanta, & Ganguly, 2009) and optimal planning strategy research (Kuo & Chang, 2008) are available. The main objective of these papers was to remove impurities in the distillate (i.e., C_5^+ in the debutanizer column) and maintain the minimum possible amount of product (butane) in the bottom residual fuel oil to maximize the yield of the product.

The energy management (de Lima & Schaeffer, 2011; Kansha, Kishimoto, & Tsutsumi, 2011) and the energy efficiency (Chiwewe & Hancke, 2011) become important problems. The objective is to perform a complete plant energy process optimization, including an adequate production rate with the required product quality while minimizing operating costs (fuel consumption in boilers) through a data mining approach. Several research endeavors have treated consumption analysis as a knowledge discovery problem using intelligence techniques (Li, Bowers, & Schnier, 2010). Both forms of learning, supervised and unsupervised, have been adopted in these studies (Hippert, Pedreira, & Souza, 2001; Metaxiotis, Kagiannas, Askounis, & Psarras, 2003). In Hippert et al. (2001), the unsupervised learning based on the SOM algorithm for the three tasks, namely classification, filtering and identification of customer load pattern, is proposed. The intelligent control algorithms applied to the control of combustion processes have produced satisfactory results and show a great potential for growth. Previous research has shown that boiler efficiency can be optimized with data-mining approaches (Miyayama et al., 1991; Ogilvie, Swidenbank, & Hogg, 1998). In Kusiak and Song (2006), the authors proposed an optimization with clustering-derived centroids. In Song and Kusiak (2007), the authors develop a data mining approach for optimizing the combustion efficiency of an electric-utility boiler subject to industrial operating constraints. The latest cited papers offer interesting researches about single boilers. These studies encourage the authors of the current paper to offer a mining approach to optimize the efficiency of a complete distillation plant, regarding the operating and economical constraints.

Since close monitoring of the process is, in practice, rarely available, only information collected in a historical database and the data mining software tools were used. The expert's performance is hidden in the collected dataset. This valuable knowledge feeds the proposed Decision Support System (DSS) framework. The global plant control model does not need to be reconfigured. The expert's information can simply be extracted.

The questions that emerge are: is it possible to extract expert information from the limited amount of data collected in the historical database, searching in past data optimal cost operating conditions? And, is it possible to improve energy efficiency result by the estimation of new operating condition with a DSS software tool? The feasibility and benefits of the proposed framework are demonstrated with a real case study reported. The proposed framework-based pilot commercial software is also presented.

The paper is organized as follows: in Section 2, the refinery platforming unit process is described. In Section 3, the data mining-based DSS framework is presented. It is divided into four subsections: the nature of the data set, the data preprocessing (cleaning and filtering), the data transformation and discretization and finally, the data reduction and prediction. In Section 4, a solution to increase the plant energy efficiency is proposed. Section 5 illustrates the quality of the framework by a case study considering a real database. In Section 6, a framework-based commercial software is presented. Section 7 outlines future directions and concluding remarks.

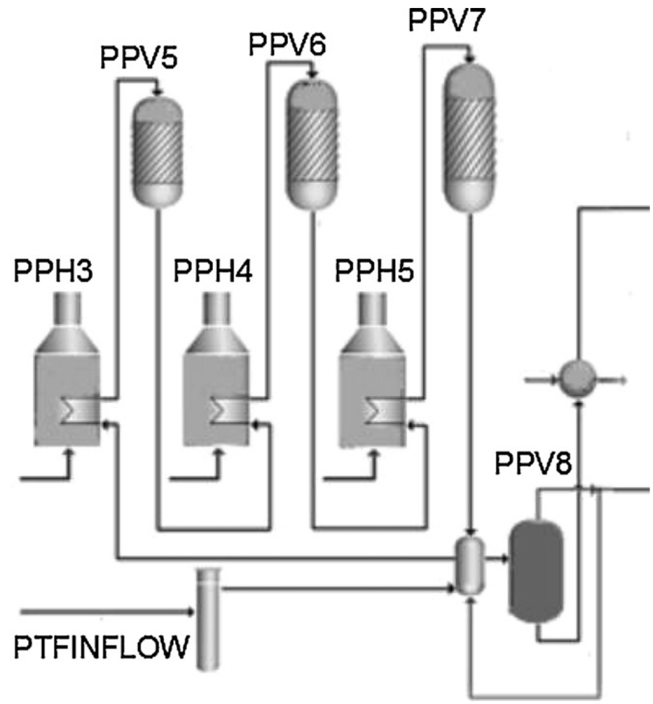

Fig. 1. Process flow diagram of the catalytic reforming plant.

2. The refinery platforming unit process

Refineries are composed of several operating units that are used to separate fractions, improve the quality of these fractions and increase the production of higher valued products like gasoline, jet fuel, diesel oil and home heating oil. The function of the refinery is to separate the crude oil into many kinds of petroleum products. This paper pays special attention to the Platforming Unit. This unit is constituted of two basic units: the catalytic reforming or reaction unit and the distillation unit or train distillation.

The conventional catalytic naphtha reforming process has been described in previous studies (Iranshahi, Rahimpour, & Asgari, 2010; Rahimpour, Iranshahi, & Bahmanpour, 2010). The process consists of three adiabatic reactors containing inter stage heaters to increase the reaction rates. The main idea of the process is to convert paraffins and naphthenes into aromatics (Fig. 1). The feed to the naphtha reformer is a crude oil fraction from the refinery crude unit with a boiling range between 100 °C and 180 °C. This process is adiabatically carried out at high temperatures, building up gasoline with a high octane number, LPG, hydrogen, fuel gas and coke, in three reformers. The coke deposits on the spent catalyst surface causing its deactivation. To recover its activation, the catalyst with coke is regenerated after a certain running time.

In the first reactor, the major reactions such as dehydrogenation of naphthenes are endothermic and very fast, causing a very sharp temperature drop. For this reason, this process is designed using a set of multiple reactors. Heaters between the reactors allow an adequate reaction temperature level to maintain the catalyst operation.

The effluent from the last reactor (PPV7, Fig. 1) is cooled partly by heat exchange with the reactor charge. The stream then enters the product separator and some of the light hydrocarbons are produced. The separator liquid product is pumped into the distillation unit. The function of the distillation unit is to separate the input product and to produce the aromatic fraction, i.e., benzene, toluene, $C8^-$ and $C9^-$ aromatics.