Computers and Chemical Engineering 106 (2017) 309–321

Contents lists available at ScienceDirect

Computers and Chemical Engineering

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

A piecewise McCormick relaxation-based strategy for scheduling operations in a crude oil terminal

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ARTICLE INFO

Article history:
Received 24 January 2017
Received in revised form 2 May 2017
Accepted 7 June 2017
Available online 15 June 2017

Keywords:
Bilinear terms
MINLP
Piecewise McCormick envelopes
Blending
Crude oil scheduling

ABSTRACT

The petroleum supply chain can be divided into three segments: upstream, midstream and downstream. This work studies the scheduling of operations in a crude oil terminal within the midstream segment. The first challenge consists in deciding how the crude oil that arrives in vessels should be uploaded to the storage tanks. At the same time, the operations engineer must decide which storage tanks will feed the pipeline connected to the refinery in order to satisfy its demand. This work concerns the crude oil terminal of the national refinery of Uruguay. To schedule terminal operations, this work proposes an iterative two-step MILP-NLP algorithm based on piecewise McCormick relaxation and a domain-reduction strategy for handling bilinear terms. For small instances for which an optimal solution is known, the proposed strategy consistently finds optimal or near-optimal solutions. It also solves larger instances which are, in some cases, intractable by a global optimization solver.

1. Introduction

The supply chain of the petroleum industry is arguably one of the most complex and economically relevant of today's society. According to Sahebi et al. (2014), the oil supply chain can be divided into upstream, midstream and downstream segments. Functions such as petroleum exploration, production (Silva and Camponogara, 2014) and transportation (de Assis and Camponogara, 2016) of crude oil to the refineries belong to the upstream segment. Major components of the infrastructure are production platforms, transportation vessels and crude oil terminals. The midstream portion is concerned with the reception of commercial crude oil grades in terminals and conversion of the petroleum into refined products at refineries and petrochemical plants. Finally, the downstream segment includes storage, primary and secondary distribution, and wholesale and retail market of refined products.

One of the main challenges of the midstream segment concerns the schedule of operations at crude oil terminals. In general, the problem can be described as follows. After reaching the mooring buoy, a vessel unloads crude oil through a pipeline to the tank farm, which is composed by storage tanks. Crude oil can be pumped between tanks and to the main pipeline that connects the crude oil terminal to the refinery. Although mixtures of crudes with similar properties (e.g., specific gravity and sulfur concentration) are allowed in the storage tanks, they are not recommended in order to provide more flexibility to satisfy the demands of the refinery.

The main decisions of the scheduling problem are: (a) determine the volume and quality of crude oil to be transferred from a vessel to each storage tank; and (b) the volume and blend of crudes to be sent to the main pipeline in order to satisfy the refinery demands.

Blending equations are one of the most common constraints that appear in crude oil scheduling. These equations involve bilinear terms, which are non-convex functions, thereby, potentially giving rise to multiple local solutions. Algorithms can make use of the fact that, in a MINLP minimization problem, an MILP relaxation provides a lower bound on the original problem, while any feasible solution provides an upper bound (Castro, 2015). If these bounds are within a given tolerance, the global solution is achieved.

Standard McCormick envelopes (McCormick, 1976) provide the tightest possible linear relaxation for bilinear terms. In this approach, the bilinear term $x_i x_j$ is replaced with a new continuous variable w_{ij} and four sets of linear constraints are added to the formulation. In order to strengthen the relaxation, one can partition the domain of one variable (x_j) involved in the bilinear terms

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http://dx.doi.org/10.1016/j.compchemeng.2017.06.012
0098-1354/

into n disjoint regions. Then McCormick envelopes are constructed in each disjoint region and new binary variables are added to the formulation to select the best partition of x_j. This approach, known as piecewise McCormick (with univariate partitioning), was first proposed in the work of Bergamini et al. (2005), presenting uniform partitions and a linear increase of the binary variables with the number of partitions. Gounaris et al. (2009) present a comprehensive study on piecewise under- and over estimators for bilinear terms.

To our knowledge, Wicaksono and Karimi (2008) and Hasan and Karimi (2010) were the first to apply bivariate partitioning, which means partitioning the domain of both variables x_i and x_j. In the latter work, bivariate partitioning is applied to a benchmark process network synthesis problem, obtaining stronger relaxations than univariate partitioning. The former one achieved better relaxation using bivariate partitioning than univariate in moderate-size problems such as column sequencing for nonsharp distillation, integrated water use and treatment systems, generalized pooling problems on wastewater treatment networks;, and synthesis of heat exchanger networks.

The remainder of this paper is organized as follows. A review of the literature on crude oil scheduling is presented in Section 2. The problem statement is given in Section 3. Section 4 introduces the proposed mathematical model. The solution algorithm based on piecewise McCormick envelopes is discussed in Section 5. The computational results and analysis are reported in Section 6. Finally, Section 7 presents conclusions and suggests directions for future research.

2. Literature review

Scheduling problems are challenging optimization problems, both in terms of modeling and algorithmic solutions (Mouret et al., 2009). Of concern in this work, crude oil scheduling is a crucial part of the petroleum supply chain. To satisfy the demand for crudes in refineries, optimal or near-optimal decisions regarding the scheduling of crude oil operations can represent significant economic gains for companies. However, the problem of scheduling crude oil operations leads to a large non-convex mixed-integer non-linear programming (MINLP) model (Cerdá et al., 2015), which is hard to solve with commercial solvers, usually requiring tailored algorithms. Thus, this problem has received significant in the literature.

2.1. Discrete and continuous time models

Discrete- and continuous-time models are the two major approaches for modeling crude oil scheduling problems. Discrete-time models (Lee et al., 1996; Reddy et al., 2004a; Hamisu et al., 2013; Chen et al., 2014) are based on fixed duration of time intervals. The main advantage is the simplified modeling of material balance and flow constraints. The drawback is the large number of time intervals to correctly represent the problem, resulting sometimes in intractable problems. On the other hand, in continuous-time models (Reddy et al., 2004b; Karuppiah et al., 2008; Mouret et al., 2009; Castro and Grossmann, 2014; Cerdá et al., 2015), the duration of time intervals is treated as continuous variable in the optimization model. Major advantages lie on the smaller size of the problem and the complete use of the time domain (Karuppiah et al., 2008). However, for this time representation it is more difficult to keep track of material balances. In addition, it is not obvious how to define a-priori the number of time events that are needed. Floudas and Lin (2004), Chen et al. (2012) and Mouret et al. (2011) present formulations and comparisons between continuous- and discrete-time models.

2.2. Physical arrangements

Two types of topology for physically describing the system appear in the literature. The first one considers two sets of tanks: storage and charging tanks. In that case, storage tanks receive crude oil from vessels and charging tanks receive crudes from several storage tanks to produce the mixture demanded by the refinery. Finally, each distillation unit (CDU) is fed by only one charging tank at a time. This approach is used in the works of Lee et al., 1996. When no charging tanks are used (Reddy et al., 2004a,b; Li et al., 2012; Cerdá et al., 2015), multiples storage tanks can feed a particular CDU at the same time. A different approach is presented by Zimberg et al. (2015), which considers the operations in a crude oil terminal, excluding charging tanks and CDUs.

2.3. Solution approaches

Several solutions approaches have been studied for crude oil scheduling problems. Lee et al. (1996) propose a discrete-time mixed-integer linear program for short-term crude oil scheduling. Bilinear terms in mixing equations are avoided by a linear approximation, which replaces the non-linear terms with individual component flows. Reddy et al. (2004a) identify the periods of the planning horizon over which the composition in each tank does not change (before receiving crudes from a vessel or another tank), which results in an MILP without composition discrepancy. For the remaining periods, mixing constraints are dropped. This strategy proved to be attractive by producing near-optimal solutions in reasonable time. An extension of this strategy to deal with a continuous-time model is presented by Reddy et al. (2004b). A discrete-time MILP is proposed by Zimberg et al. (2015), where discrete values of crude proportion are chosen from a discrete set by the optimization solver, transforming the non-linear mixing equations into linear terms.

The work of Karuppiah et al. (2008) presents an outer-approximation algorithm for solving a continuous-time nonconvex MINLP. First, the original MINLP is relaxed using McCormick envelopes, which results into an MILP capable of producing a lower bound on the original problem. The solution of this relaxation is used to obtain an upper bound for the MINLP. At each iteration, cutting planes derived from Lagrangean decomposition are added to the MILP. The process continues until the difference between the lower and upper bounds is within a given tolerance.

Mouret et al. (2009) propose a new continuous-time formulation for crude oil scheduling, denoted as single operation sequencing. For this approach, the solution schedule is represented as a single sequence of operations, which reduces the number of time slots required. Symmetry-breaking constraints are added to the model in order to avoid searching multiple equivalent solutions. In addition, a simple two-step MILP-NLP procedure is used for solving the original MINLP.

Li et al. (2012) develop a robust continuous-time MINLP formulation under demand uncertainty. The authors propose a branch and bound global optimization algorithm to solve the deterministic robust counterpart optimization model.

A resource-task network is used in the work of Castro and Grossmann (2014) for modeling a continuous-time crude oil scheduling problem. The solution strategy is based on a two-step MILP-NLP algorithm, whereby the MILP relaxation is obtained via multiparametric disaggregation.

Cerdá et al. (2015) present a continuous-time MINLP model based on global-precedence sequencing variables for loading and unloading operations in tanks, and synchronized time slots for modeling the sequence of feedstock for each CDU. A two-step MILP-NLP, which reduces non-linear constraints with bounding constraints and valid cuts, is proposed as the solution algorithm. For