



Oil industry value chain simulation with learning agents

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ARTICLE INFO

Article history:

Received 28 August 2017
Revised 16 December 2017
Accepted 14 January 2018

Keywords:

Simulation
Oil
Agent
Machine learning

ABSTRACT

Simulation is an important tool to evaluate many systems, but it often requires detailed knowledge of each specific system and a long time to generate useful results and insights. A large portion of the required time stems from the need to define operational rules and build valid models that represent them properly. To shorten this model construction time, a *learning-agent-based* model is proposed. This technique is recommended for cases where optimal policies are not known or hard and costly to unequivocally determine, as it enables the simulation agents to learn good policies “by themselves”. A model is built with this technique and a representative case study of oil industry value chain simulation is presented as a proof of concept.

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1. Introduction

Simulation is an important tool to evaluate many systems, but it often requires detailed knowledge of each specific system and a long time to generate useful results and insights. It is necessary to define operational rules and build models that represent them properly. These models need to be verified and validated; usually on a case-by-case basis. Decision makers, nevertheless, may not wait for simulation results if they take too long to be produced.

In this paper, a novel model based on *learning-agents* is proposed to simulate various oil industry value chains. The model:

1. is able to represent arbitrary scopes of oil industry value chains: from single intra-refinery logistics to multi-echelon supply systems with different transportation modes.
2. requires only physical and market properties of the elements as input; there are no system parameters that require calibration or expert input.
3. captures the effects of interaction among the elements without the need to specify complex interaction rules explicitly.
4. considers peculiarities of the oil industry, such as preparation times of tanks.

The main goal is to help define the impact of investments in infrastructure and resources by answering questions such as “how much storage capacity is necessary?”, “what impact does adding a ship to the fleet produces?”, and “does increasing a pipeline flow-rate really improve lead times?”.

The model is described under the agent-based modeling and simulation (ABMS) paradigm and is comprised of interactive and adaptive agents capable of representing components that feature in the systems of interest. This ABMS representation aims to be more useful than other simulation paradigms by making the real world representation more faithful through elements which are more or less in a one-to-one correspondence with the real systems (Macal, 2016). This helps making technical explanations easier and more convincing (van Dam et al., 2009).

The goal of the model is to help with resource planning for *integrated* oil value chains. This means taking into consideration the mutual effects of supply chain echelons and transport modes. Oil industry value chains are usually segmented for study, however, and ignore these effects or only consider them through proxies, such as capacity restrictions or other calibrated input parameters. One common segmentation is to consider only one mode of transportation. For instance, some authors consider various aspects of maritime oil transportation (Al-Khayyal and Hwang, 2007; Al-Yakoob and Sherali, 2012; Bao et al., 2013; Batra, 1980; Cerdá et al., 2015; Chen and Moan, 2004; Chen, 2014; Cheng and Duran, 2004; Christiansen et al., 2013; Du et al., 2011; Feng et al., 2015; Fuller et al., 2013; Hennig et al., 2012; Iakovou, 2001; Jetlund and Karimi, 2004; Korsvik et al., 2011; Lin et al., 2003; Mouret et al., 2008; Nishi and Izuno, 2014; Özelkan et al., 2008; Reddy et al., 2004; Shen et al., 2011; Shyshou et al., 2010; Siddiqui and Verma, 2015) or road oil transportation (Bramakis et al., 2014). Pipelines are mostly associated with the oil industry, but are often studied independently (Banaszewski et al., 2013; Chen et al., 2014; de Souza Filho et al., 2013; Iamashita et al., 2005; Limoeiro et al., 2010; 2008; Lopes et al., 2012; Oliveira et al., 2016; Shen et al., 2011; Wu et al., 2016).

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A large range of techniques are employed in the study of the transportation modes. Taking the previously mentioned papers, *mathematical programming* is employed by Al-Khayyal and Hwang (2007); Al-Yakoob and Sherali (2012); Cerdá et al. (2015); Christiansen et al. (2013); Du et al. (2011); Hennig et al. (2012); Iakovou (2001); Jetlund and Karimi (2004); Lin et al. (2003); Lopes et al. (2012); Mouret et al. (2008); Oliveira et al. (2016); Özalkan et al. (2008); Shen et al. (2011); Siddiqui and Verma (2015); Yüzgeç et al. (2010). *Heuristics* are used by Banaszewski et al. (2013); Chen (2014); Chen et al. (2014); de Souza Filho et al. (2013); Fuller et al. (2013); Iamashita et al. (2005); Korsvik et al. (2011); Nishi and Izuno (2014); Reddy et al. (2004); Shen et al. (2011); Wu et al. (2016). Finally, *simulation* is applied by Batra (1980); Braimakis et al. (2014); Chen and Moan (2004); Cheng and Duran (2004); Feng et al. (2015); Limoeiro et al. (2010, 2008); Shyshou et al. (2010) and is nearly ubiquitous in planning studies. Mathematical programming and heuristics are more closely associated with operational tools.

When multiple modes are covered, such as in MirHassani (2008), supply plans are overviews that aggregate operations over time subject to capacity restrictions. Defining the capacity restrictions is not always straightforward, however, and may disregard mutual effects. For instance: a pipeline may be unable to reach its monthly expected capacity, derived from its flow-rate, because ship deliveries upstream are often late and starve it.

Agent-based approaches have been used for general-purpose supply chains (Swaminathan et al., 1998). The model presented in that paper, however, requires a specialist to define and calibrate input parameters such as inventory levels and lead times. Depending on the model's sensitivity to these parameters, the simulation's output may be excessively reliant on the specialist's opinion.

Gjerdrum et al. (2001) simulate the performance of supply chains with optimal production scheduling, but also rely on pre-defined reorder point and quantity.

An agent-based framework that is less reliant on expert input is presented in Julka et al. (2002a,b). However, it covers a single refinery, whose process is very detailed, but represents other elements through parameters and forecasts.

A simulation-based optimization approach that employs machine learning is presented in Mortazavi et al. (2015). An optimal ordering policy for a 4-echelon linear supply chain is defined by simulating the system while agents test policies and identify the best.

None of the previously detailed papers (Gjerdrum et al., 2001; Julka et al., 2002a,b; Mortazavi et al., 2015; Swaminathan et al., 1998) tries to help determine the necessary infrastructure of the system directly. This is more relevant than ordering policies in oil industry integrated value chains because the product flow is not only *pulled* by demand, but also *pushed* by production, since oil production is continuous and, in almost every case, extremely inelastic in relation to demand fluctuations. This justifies tools, such as the proposed model, to help define storage and transport capacity, as they are responsible for absorbing the fluctuations.

Pitty et al. (2008) present a dynamic model of a refinery's integrated supply chain that match the current goal, but still relies on the user to define policies and decision-making algorithms.

Sha and Srinivasan (2016) deal with resource sizing in a specific chemical industry case. Policies are also left to the user to experiment and choose.

The proposed model will be mainly described in terms of its elements, which are the agents and the environment in which they interact. Some agents follow prescribed behaviors and fall within the definition of agents of Interactive ABMS according to (Macal, 2016), which defines them as agents which are au-

tonomous (i.e. can produce appropriate behaviors in view of the model condition) and interact with other agents and with the environment.

Nevertheless, the behavior of interactive agents need to be defined *a priori* for many conditions and situations. For some agents, this is straightforward and does not vary from scenario to scenario. In such a case, policies known to be optimal should be employed. In other cases, it may be necessary to specify the behavior for each individual case study, which requires new, time-consuming trials, verification and validation. In order to minimize this effort, the definition of model agents that will be valid for all cases of interest is proposed. In order to achieve that, some agents are defined as adaptive agents, which can learn good behavior policies *during the simulation*. This is achieved through the application of a machine learning algorithm to the simulation model, namely a modified R-Learning technique adapted from Sutton and Barto (1998).

The following sections will describe the oil industry value chain as considered in this paper, the simulation and learning techniques applied, the elements that are the building blocks for the model, and a brief, representative case study.

2. Oil industry value chain

Oil is the main international commodity (Hamacher and Ferreira Filho, 2015) and represented, in 2014, 31.3% of primary energy world supply (International Energy Agency, 2016). Crude oil, however, must be transported and converted into a set of derivative products with a broad range of applications. This is done by a value chain that delivers oil, its derivatives and other associated products to their demand locations with adequate quality. Volumes are large, valuable and essential to almost all other economic activities (Fernandes et al., 2010), which underlines the importance of analyzing the value chain. Especially when there are changes in the production environment.

The scope of interest in the oil industry value chain, as far as this paper is concerned, starts where deposits are explored and finishes where products are delivered to consumers. This scope includes storage and transportation of many products and also transformations of these products. Fig. 2.1 shows a schematic example of one such value chain depicting off-shore and on-shore production, ship trade, supply and refining, and distribution. Ships, trucks and pipelines are used to move products and tanks store them.

The broadest scope of interest in this paper covers the process from crude oil input through to product output. Between these, products are stored, transformed and transported; possibly in many stages. Different scopes can be represented following this pattern of input, stages of storage, transformation and transportation, and output. If the scope is a single refinery, for instance, the input may be the distillery production and the output, the delivery of final products to wholesale distributors, with product transfer and mixing in between. If the scope covers from crude oil production to retailing activities, the input may correspond to the wells and the output, the delivery of products to consumers, with many stages of storing and transferring between distant locations.

In order to model oil value chains, it is necessary to identify the basic elements that represent the input and output (I/O) operations and the storage, transformation and transportation, stages. This is presented in the remainder of this section.

2.1. Products

Products are crude oil, derivatives, biofuels and anything else that is moved through the system. When stored, products need time to be mixed, decant contaminants and be quality-checked. This time is part of a product's storage cycle (See Fig. 2.2).

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