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Optimization of naphtha purchase price using a price prediction model

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ABSTRACT

In order to meet company needs, various models of naphtha price forecasting and optimization models of average naphtha purchase price have been developed. However, these general models are limited in their ability to predict future trends as they only include quantitative data. Furthermore, naphtha price predictions based on fluctuation trends have not been published in the literature. Thus, we developed a system dynamics (SD) model considering time-series data, mathematical formulations, and qualitative factors. The results obtained from our model were compared with the published literature. The best result of the SD is the European naphtha forecasting price model, and the forecasting accuracy percentage shows 92.82%. Furthermore, a nonlinear programming (NLP) model was developed to optimize the purchase price by considering the naphtha price of the forecasting models. In addition, the average optimization value was approximately 45.07 USD/ton cheaper than that of the heuristic approach.

1. Introduction

Naphtha plays an important role in the world economy as it is used to produce widely used products including ethylene, propylene, and butadiene as well as aromatic products such as benzene, toluene, and xylene through thermal cracking. Naphtha price trends tend to follow that of crude oil (Asche et al., 2003). Fig. 1 shows the trends of West Texas Intermediate (WTI) crude oil and naphtha prices from March 1996 to November 2011. This close relationship means that naphtha price forecasting has a great influence on all loss factors in petrochemical industries. For example, the point of purchase of oil has a significant effect on the total profit of oil refiners. If the oil price falls by $1, oil refiners suffer an operating profit loss of $10 billion.

Naphtha price is also affected by the supply and demand for the product as well as ocean freight costs, both of which have political consequences (Chen and Hsu, 2012; Gao et al., 2014; Holland, 2013; Lee et al., 2012; Montroll, 1978; Wen et al., 2014; Wong et al., 2013). Therefore, decision-makers want to reduce the uncertainty of future prices.

However, decisions on the point of purchase of naphtha require the domain knowledge of chemical engineers. General mathematical models including the statistical model (SM), exponential smoothing model (ESM), and artificial neural network (ANN) are well known in the chemical engineering field, but these general models are now being applied to naphtha price forecasting for the first time. In addition, the innovative system dynamics (SD) model is very valuable for determining the point of purchase because it considers integrated data and heuristics. These considerations prompted us to predict naphtha price using the SM, ESM, and ANN forecasting models. An SD model based on a causal loop considering human and psychological heuristics was also applied to naphtha price forecasting. Heuristics is a very important approach for producing decisions at the point of purchase, and their efficacy can affect naphtha purchase. The heuristic approach allows us to reach reasonable solutions for planning decisions.

This paper considers short-term planning for the naphtha purchase problem, which includes the number of naphtha purchases, inventory levels, and running capacity for cracking units. We assume that a naphtha purchase plan is determined by petrochemical industry planning, and this research analyzes the optimization problem to minimize the costs included in spot trading to achieve optimal naphtha purchase planning. Furthermore, we developed a general nonlinear programming (NLP) model to optimize the purchasing unit price and compared its results with the heuristic results. The purpose of this research is to develop a reliable forecasting model. Moreover, the average purchase price was minimized by naphtha procurement planning using the predicted price.

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Nomenclature

FN_{d1}, FN_{d2} past finalized purchases of naphtha
FN_{t+1}, FN_{t+2}, FN_{t+3} amount of naphtha purchased at time $t+1$, $t+2$, and $t+3$
FT_{t+1}, FT_{t+2}, FT_{t+3} level of storage tank at time $t+1$, $t+2$, and $t+3$
$HE1_t$ hedging trading in the first month
$HE2_t$, $HE2_{t+1}$ hedging trading in the second month
$HE3_t$, $HE3_{t+1}$, $HE3_{t+2}$ hedging trading in the third month
P_t, P_{t+1}, P_{t+2} naphtha price at time t, $t+1$, and $t+2$
RC running capacity

The numerical results of this paper verify the effectiveness of the optimization model. In summary, the NLP model can help decision-makers to plan purchase opportunities, so naphtha can be bought at an optimal price.

2. Literature review

Predictions of crude oil prices have been carried out by many investigators all over the world (Fan et al., 2008a, 2008b; Gori et al., 2007; Kang and Yoon, 2013; Lara et al., 2007; Rao and Parikh, 1996; Regnier, 2007; Wei et al., 2010; Ye et al., 2005) but studies on naphtha price forecast are scarce (Lyu et al., 2014; Rao and Parikh, 1996; Sung et al., 2012; Visetsripong et al., 2008). Various approaches to forecasting oil price have used both linear and nonlinear models. Lara et al. (2007) applied a simple linear regression model to predict crude oil prices and stochastic models to calculate patterns of volatility in oil prices. Instead of using a single autoregressive model for all horizons, Kang reported a multi-period-ahead forecasting autoregressive model selected separately for each horizon and found that forecast performance depends on optimal order selection criteria, forecast origins, forecast horizons, and the time series to be forecasted (Kang, 2003).

Kang and Yoon (2013) studied the forecasting potential of the ARIMA–GARCH, ARFIMA–GARCH, ARFIMA–IGARCH, and ARFIMA–FIGARCH models by using the daily spot prices of WTI crude oil. Their results for unleaded gasoline suggested that the ARFIMA–FIGARCH model better captures the long-memory properties of the returns and volatility, even though there was no unique model for all three types of petroleum products. Kang et al. attempted to find the best model to forecast volatility in three crude oil prices (WTI, Brent, and Dubai). They evaluated the volatility of the three crude oil prices using daily spot prices during the period January 6, 1992 to December 29, 2006 by considering the out-of-sample forecasts of the 1, 5, and 20-day forecasting horizons, corresponding to 1-day, 1-week, and 1-month trading periods, respectively. It was found that for Brent and Dubai crude oil, the FIGARCH model was superior to other models (GARCH, IGARCH, and CGARCH) for all three forecast horizons, from 1-day to 1-month. However, in the case of WTI crude oil, the CGARCH model outperformed the other models (Kang et al., 2009). Visetsripong et al. (2008) studied naphtha forecasting using the adaptive neuro-fuzzy inference system (ANFIS) and the statistical method for nonlinear time-series data. It was found that 86% of the comparison tests showed that the ANFIS model forecasting power achieved more accurate results than the exponential smoothing method. It was concluded that the neuro-fuzzy system method is more accurate and more reliable than the statistical method when used to forecast nonlinear time-series data. Wei et al. (2010) compared nine linear and nonlinear GARCH-class models: RiskMetrics, GARCH, IGARCH, GJR, EGARCH, APARCH, FIGARCH, FIAPARCH, and HYGATCH. They concluded that the nonlinear GARCH-class models are capable of capturing long-memory and/or asymmetric volatility and exhibit greater forecasting accuracy than linear ones, especially in volatility forecasting over longer time horizons, such as 5 or 20 days, for WTI and Brent crude oil. Masih et al. (2010) investigated the impact of ethylene prices in the naphtha intensive ethylene markets of the Far East, North West Europe, and the Mediterranean on WTI crude oil price. They observed that the ethylene prices in North West Europe and the Mediterranean were weakly endogenous, but the Far East ethylene price was weakly exogenous, both in the short and long term. It was even found that the results were consistent during the period under review, which had a surge in demand for ethylene throughout the Far East, especially in China and South Korea. However, during the post-sample forecast period, as evidenced in their variance decomposition analysis, the emergence of WTI as a

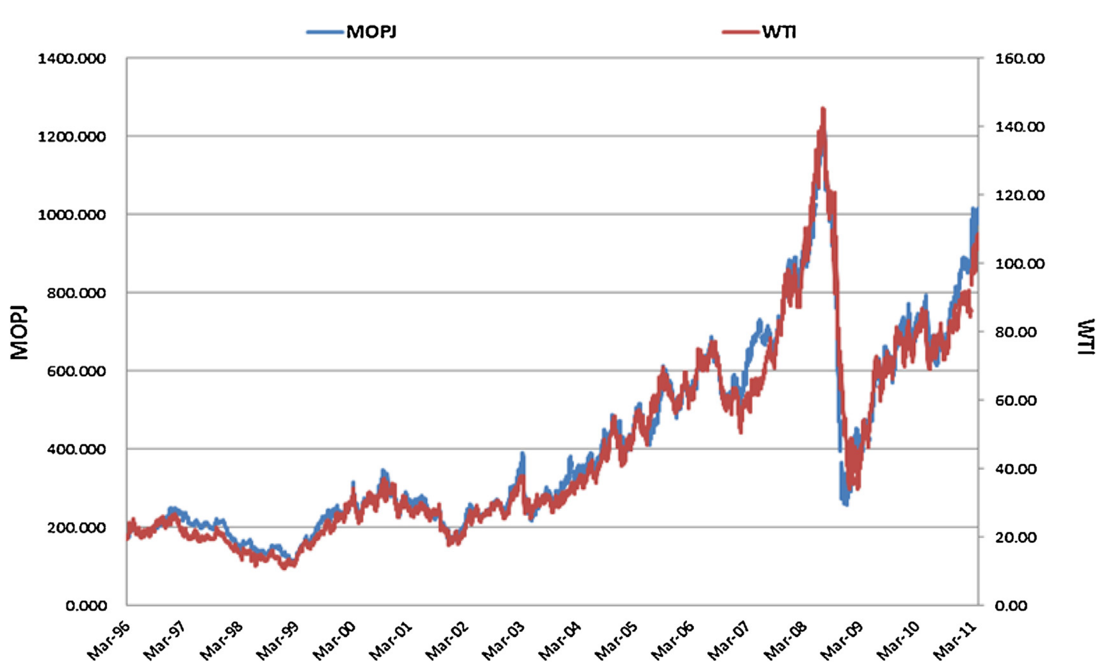

Fig. 1. Crude oil (WTI) and naphtha price trends.