Journal of Petroleum Science and Engineering 138 (2016) 104–112

Contents lists available at ScienceDirect

Journal of Petroleum Science and Engineering

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

Experimental analysis of drag reduction in the pipelines with response surface methodology

Hamid Reza Karami [a,*], Mohammad Keyhani [b], Dariush Mowla [c]

[a] Department of Mechanical Engineering, University of Alberta, Edmonton, Canada
[b] Department of Chemical Engineering, Faculty of Engineering, Razi University, Kermanshah, Iran
[c] School of Chemical and Petroleum Engineering, Shiraz University, Shiraz, Iran

ARTICLE INFO

Article history:
Received 9 September 2015
Accepted 30 November 2015
Available online 8 December 2015

Keywords:
Drag reduction
luid flow
Friction factor
Response Surface Methodology (RSM)
Statistical analysis
Nomograph

ABSTRACT

Obtaining fundamental variables has critical importance in solving engineering problems, and analysis of experimental data aids more-efficient experimentation. Drag reduction in pipelines is particularly useful in efforts to reduce energy losses. In the present study, statistical procedures are used to analyze some drag reduction experimental data to determine the degree to which each variable and its interactions with the others contribute to drag reduction. The experiments in this study incorporate parameters such as Reynolds number and temperature of fluid, concentration of different drag reducing agents and relative roughness of pipes. A proposed model has been developed by applying response surface methodology to historical data. The statistical analysis shows that the model is statistically acceptable (R^2=96.78%). Results of analysis show that 95% of variation in the friction factor can be described only by Reynolds number and concentration of drag reducing agent and their interactions. Finally for operational applications, a nomograph has been presented to evaluate friction factor simply.

1. Introduction

Adding drag reducing agents (DRAs) to a turbulent fluid flow greatly decreases friction losses. Accurate determination of practical friction losses in dilute drag reducing solutions has been addressed by many researchers. Most studies focus on determining effective parameters for drag reduction (De Gennes, 1986; Hamouda and Moshood, 2007; Joseph et al., 1986; Karami and Mowla, 2012; Lumley, 1969; Mowla and Naderi, 2006; Mysels, 1949; Toms, 1948; Wyatt et al., 2011).

Virk (1975) published a comprehensive study on drag reduction for water flow and proposed relationships for a fanning friction factor. He investigated the performance of different polymer solutions and found a trend to a maximum drag reduction (MDR) asymptote in all cases.

Based on some experimental data, Karami and Mowla (2013) obtained a generalized mathematical model for the friction factor of DRAs in crude oil pipelines. The correlation predicts the drag reduction under different operating conditions such as temperature, flow rate, pipe diameter and roughness, as well as different concentrations of various types of DRAs.

Gallego and Shah (2009) developed a generalized friction pressure correlation for coiled and straight tubing on the basis of the energy dissipation of eddies in turbulent flow fields and shear-rate-dependent relaxation time. They found that their model in straight tubing correlated better than previous models.

Also, Shah et al. (2006) developed new correlations for predicting friction factor values as a function of the solvent's Reynolds number for both straight and coiled tubing using the data for an optimum concentration of polymeric fluid.

Based on the elastic properties of polymers, Sher and Hetsroni (2008) proposed a mechanistic model for turbulent drag reduction using additives, and compared their results with Virk (1975) experiments.

Based on the experimental data obtained for different operating conditions, Mowla and Naderi (2004) proposed a mathematical model for predicting drag reduction by a given polymer for a two phase flow. Their model could also be used for calculating friction and maximum drag reduction as a function of DRA concentration.

As far as we know, there are no statistical analyses of experimental parameters on drag reduction, although these investigations have the potential to increase the efficiency of experiments. When several input variables potentially influence important process specifications, engineering statistics are applied to determine the relations and specifications of the system (Myers et al., 2009). Design of experiment (DOE) and, particularly, response surface methodology (RSM) are two main engineering-statistics

* Corresponding author.
E-mail address: hamidrez@ualberta.ca (H.R. Karami).

http://dx.doi.org/10.1016/j.petrol.2015.11.041
0920-4105/

tools (Khuri and Mukhopadhyay, 2010). Using them, it is possible to design an effective plan of experiments and analysis. But in recent years the analysis of historical data with RSM has also proven useful, yielding highly informative results for virtually no cost (Jeirani et al., 2013a, 2013b). They applied RSM to historical data for modeling and optimizing the composition and viscosity of some emulsions (Jeirani et al., 2013b). Salam et al. (2014) also successfully employed this method for evaluating the bio-corrosion rate of steels.

Applying RSM to historical data is particularly useful when data is abundant, as with the current study. This computer-assisted method helps evaluate friction factors effectively without complex calculations. Based on this analysis a new model has been proposed and validated, and shows good agreement with experimental data. The model has also determined the effect of operational parameters and all their interactions. Based on the parameters of most importance, a simple and useful graphical tool has been developed for practical purposes.

2. Material and Methods

2.1. Experimental data acquisition

To conduct a general analysis of the effect of different parameters, the experimental variables and their levels were selected based on Karami and Mowla article (Karami and Mowla, 2013). In their general investigation on the drag reduction effect on crude oil flow, they carried out their experiments for six concentrations of DRAs (C) in three pipelines with various relative roughnesses (ε/D) under different fluid flowrates (Re). To consider the effect of temperature, four various operating temperatures were employed (T). Generally, the resulting database had 648 data points for three types of drag reducing agents with boiling temperatures of 147.3, 150.8 and 163.2 °C respectively.

To calculate amount of friction factor, they simply measured pressure difference between two specified points of each pipe and then converted it to friction factor using Darcy–Weisbach equation (Karami and Mowla, 2013).

2.2. Semi-empirical model of Karami and Mowla (2013)

Using the experimental data, they developed a mathematical model to predict amount of friction factor based on the employed experimental parameters. The general form of their implicit final equation is as below

$$f^{1/2} = \left(4/n^{0.75} + \xi\right)\log\left[\mathrm{Re}\, f^{1-n/2}\right] - \left(0.4/n^{1.2}\right) - 2.1\xi \quad (1)$$

where n is indicating flow behavior and it is determined experimentally, ξ is slope increment and is defined by Eq. (2)

$$\xi = 0.0917C^{1.162}\theta^{1.48}(\varepsilon/D)^{0.276} \quad (2)$$

The dimensionless parameter θ expressed the effect of the fluid's temperature and the type of DRA, as defined by Eq. (3)

$$\theta = \frac{T_b - T_o}{T_o - T} \quad (3)$$

where T is the operating temperature, T_b is boiling point of each DRA and T_o is reference temperature and here is equal to 100 °C.

Table 1 describes the independent variables and their levels.

2.3. Historical data RSM

When the relationship between a target response and its parameters is unknown, the function can usually be approximated by a low-degree polynomial model. RSM is a group of mathematical and statistical techniques used to develop adequate polynomial functional relationships.

Due to the desirable properties of second order polynomials, such as high predictability, robustness and simplicity, these functions often are used for estimating response value and determining the size of effects. The general form of this function is as below

$$y^{\lambda} = \beta_0 + \sum_{i=1}^{k}\beta_i x_i + \sum\sum_{i<j}\beta_{ij}x_i x_j + \sum_{i=1}^{k}\beta_{ii}x_i^2 + \varepsilon \quad (4)$$

where y is the purposed response; λ (lambda value) is the Box–Cox power transformation value; β_0 is a real constant of regression; β_i, β_j, β_{ij} and β_{ii} values are regression coefficients of the main, interaction and quadratic terms; and x_i values are the ith independent variables of the function. Finally, ε value shows random error. In the present study, using design expert software® (Trail Version8.0.6., Stat-Ease Inc., Minneapolis, MN), the above equation was obtained and all the associated calculations were accomplished. The backward elimination strategy was used to modify the model structure and remove inessential mathematical expressions. However there are enough data to allow the software to determine higher polynomials (such as six order), but a quadratic model is used to compact the equation, because of its simplicity and desirable properties as discussed above. Also comparing linear, quadratic and cubic models suggests that a quadratic model is a better predictor (Table 2). Based on the software results, the cubic model was aliased and made distorted or inaccurate predictions. However the results of cubic model are slightly better, but the suggested model is selected by some indices which are applied by the software. They could be found in the help of the software.

After obtaining an enhanced model using backward elimination, the response can be transformed. A common transformation of responses is the Box–Cox transformation: a general power transformation (Osborne, 2010). To select the correct power law transformation, a Box–Cox Plot provided to determine which form of transformation is both required and acceptable.

2.4. Performance identification of model

After drafting the model, determining its structure and applying all the modifications, it is important to validate the model and employ it to consider system characteristics. This section presents

Table 1
The applied experimental parameters and their levels by Karami and Mowla (2013).

Variable notation	Short description	Levels					
		1	2	3	4	5	6
Re	Reynolds number	19 levels (from 2577.09 to 20427.26)					
ε/D	Relative roughness	0.001811	0.00598	0.011968	–	–	–
θ	Dimensionless temperature	12 levels (from 0.49 to 1.07)					
C	Drag reduction agent concentration (ppm)	25	50	75	100	150	200