# APPLICATION OF DISCRETIZED NON-LINEAR PROGRAMMING TO MINIMIZE MIXED OIL FORMATION IN FLUSHING OPERATIONS OF LUBRICANT PIPELINES

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*Abstract*

The lubricant industries use a complex pipeline system for manufacturing and processing over a thousand unique lubricant blends. The pipelines are therefore reused for multiple operations where the unique lubricant products are processed in batches. To ensure the integrity of the individual product, the lines must be cleaned/flushed between production runs. Currently, the lubricant from a current batch is used for cleaning the residues of the previous batch. This generates commingled oil that does not match in specifications of either of the two batches and is therefore categorized as a downgraded product. The existing flushing operations are based on trial and error leading to long operational downtime and over-flushing/under-flushing case scenarios. Hence, to address this drawback, our work discusses a model-predictive optimization technique for pipeline flushing operations. The proposed method aims at reducing the inefficiencies in the production system. A set of first-order differential equations modeling the pipelines in the lubricant industries have been developed and validated in our previous study. Building upon that background, in our current work we use the discretized non-linear programming solution method to solve our developed optimal control problem. We compare our simulated results against the experimental data and present a platform that will enable the lubricant industries to make more informed decisions for the flushing operations.

*Keywords*

Petroleum Lubricants, Pipeline Flushing, Non-linear Programming, Optimal Control

## Introduction

The unique compositions of lubricant oils produced today, are manufactured, and successively packaged in batches to reach customers. Therefore, the pipeline system referred to as multiproduct pipeline system must be reused for numerous operations. Product quality is extremely crucial to the lubricant industries and hence the lines must be cleaned/flushed between each changeover operation. The existing flushing operation involves the use of a finished product from the current batch to clean the product residues from a previous batch. This results in the generation of mixed/ commingled oil that does not match in specifications of either of the two batches. The operation relies on trial and error and the success of a flush is determined through laboratory testing. The existing mode of operations results in long downtime and must be repeated for multiple iterations, generating large commingled oil volumes. Once commingled, the market value of the products decreases tremendously. In the worst-case scenario, the products are also rendered commercially unviable. To this end, our work addresses these existing drawbacks and optimizes the flushing operations in the lubricant industries through model-predictive optimization techniques.

In recent years, optimization techniques have gained growing interest in the petroleum industry. Mixed-integer linear programming (MILP) and mixed-integer non-linear programming (MINLP) models have been widely used for developing systematic scheduling plans and calculating commingled oil volumes for multiproduct pipelines in refineries (Camponogara and, Grossmann 2021). However, scheduling plans are not sufficient for eliminating the generation of commingled products. Hence, over the years, researchers have reported that the extent of mixing depends on various factors including fluid properties, operating conditions, and flow regimes (Ramanujan 2012). Major oil companies are developing models for calculating the commingled oil volumes ( Chen et al. 2021). These models are based on empirical correlations that are only applicable to their respective pipeline networks. There is no widely accepted correlation that can be used in all actual scenarios (He et al. 2018). To this end, the applications of optimization principles and the developed multiproduct pipeline models in the petroleum industries gave us an idea that we can apply the optimal control principle for optimizing the flushing operations in multiproduct lubricant processing pipelines.

Currently, the flushing time in the lubricant industries is chosen based on the experience of an operator in regard to specific products. At the end of the chosen flush time, samples are collected and sent for lab testing. If the product quality control testing fails, the flush is repeated for the second iteration and the process continues until the desired specification is attained. The laboratory tests include viscosity, density, color, water content, spectrophotometry, emulsions, and miscellaneous. Out of these, viscosity is the primary and most crucial test that confirms the batch purity and success of the flush. The conventional ASTM methods of testing viscosities require a long-running time (approximately 20-30 minutes) leading to extended operational downtime. Hence, our work addresses the existing drawback and enables better in-line controllability of the flushing operations by developing models for predicting the viscosity of commingled lubricants in real-time. We will revisit the optimal control problem of flushing operations developed by Jerpoth et al. (2022). With this basis, we will use the discretized non-linear programming solution method to solve the developed optimal control problem, which will lead us to a new way of controlling the flushing operations and will eliminate the computer-intensive drawback that was experienced in the maximum principal solution method used in the previous work.

## Solution Methodology

We use the viscosity blending correlations proposed by API-TDB for calculating the viscosity of commingled lubricants (lubricant blends). We validate the calculated viscosity values against the experimentally measured values of known blend compositions. The agreement within ±5% error confirms the application of blending correlation for lubricant mixtures. Next, we develop component balance equations for lubricant pipelines and combine them with viscosity blending correlations to build our optimal control problem for flushing operations. Our developed models consisted of a set of non-linear partial differential equations that were solved using the discretized non-linear programming solution method discussed by (Diwekar 2008; Yenkie and Diwekar 2014). Through our simulations, we determine the minimum flush time required to reach the desired viscosity specifications of the new lubricant that is to be processed. We compare our simulated results against the data obtained from plant experiments conducted at our partnered lubricant company.

## Modeling the Flushing Operation

Let us consider that initially, lubricant A was processed through the pipelines. After the processing is completed, it is required to switch the production line to process lubricant B. Hence, the pipelines must be flushed with the lubricant B (new oil) until the desired specifications are attained. The component balance equations for these pipelines are represented by Eq (1) and Eq (2) listed from (Jerpoth et al. 2022).

$$\frac{dx_{A_t}}{dt} = \frac{-x_{A_t}Q_t}{A_c L} \tag{1}$$

$$\frac{dx_{B_t}}{dt} = \frac{x_{A_t}Q_t}{A_c L} \tag{2}$$

Where: $\frac{dx_{A_t}}{dt}$ and $\frac{dx_{B_t}}{dt}$ - change in mass fractions of lubricant A and B w.r.t time, $Q_t$ - volumetric flowrate of lubricant B/flushing oil (changes with every time step or in other words is a state variable), $A_c$ - cross-sectional area, $L$ - pipe length. These parameters were estimated through actual plant measurements from the partnered lubricant facility.

## Viscosity Blending Correlations

Our work uses the viscosity blending correlation recommended by API-TDB (Riazi 2005; Roegiers and Zhmud 2011). The correlation (represented by Eq (3)) calculates the viscosity of the blend of two or more components as the cubic-root average of the individual component viscosities. Furthermore, it gives us an understanding of the mass fraction of the individual components of the blend. Through this equation, we will predict how during a flush the blend viscosity attains the desired specifications of the new lubricant with every time step.

$$\mu_{AB_t}^{1/3} = x_{A_t}\mu_A^{1/3} + x_{B_t}\mu_B^{1/3} \tag{3}$$

Where, $x_{A_t}$ and $\mu_A$- mass fraction and kinematic viscosity of lubricant A, $x_{B_t}$ and $\mu_B$ - mass fraction and kinematic viscosity of lubricant B, $\mu_{AB_t}^{1/3}$ - kinematic viscosity of blend of lubricant A and B.

Note: In the reference Riazi 2005, for the API-TDB blending rule, $x_{A_t}$ and $x_{B_t}$ were reported as the mole fractions of the individual components of the blend. However, for the lubricant blends, studied in this work the mass fractions and the mole fractions had negligible difference and henceforth $x_{A_t}$ and $x_{B_t}$ will be used as mass fractions.

**Validation of Viscosity Blending Correlations for Lubricant Blends**

We conducted experiments to confirm the application of viscosity blending correlation for lubricant blends. In these experiments, we prepared known compositions of blend of two lubricants ranging from mass fraction of 0.1 to 0.9. Each sample was measured for its kinematic viscosity using the ASTM D446 testing guidelines (D02 Committee 2017). Next, we calculated the blend viscosity of each sample using Eq (3) and compared them against the measured values. The validation was done for three different lubricant blends. Figure 1 illustrates the comparison of measured and the calculated viscosities for one such blend. The agreement within ±5% error confirms the application of Eq (3) for lubricant blends.

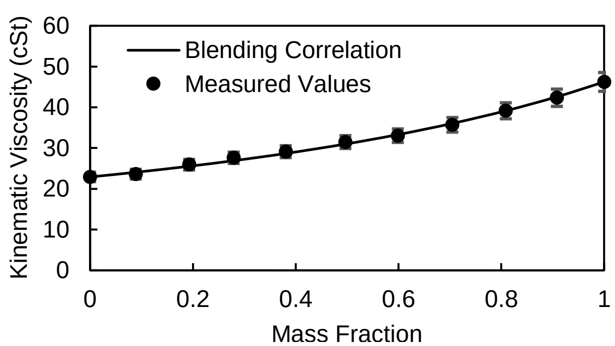


*Figure 1 Validation of Blending Correlation with Experimental Data*

**Solution by Discretized Non-Linear Programming**

Our objective is to have the new lubricant B completely free of the residual lubricant A at the final collection point. Let us consider that a total flush time of 60 seconds was selected by an operator. Hence, the viscosity of the blend at the final time point should be equal to the viscosity of the lubricant B. Mathematically, our objective can be formulated to minimize the difference between the viscosity of the blend and the viscosity of lubricant B by finding an optimum flushing time. Eq (4) represents our objective equation

$$Min\ (J) = \left[\mu_{AB}(t_{final}) - \mu_B\right]^2 \tag{4}$$

Our objective function is subjected to the integrated form of our state equations represented by Eqs (5), (6) and (7)

$$x_{A_t} = exp\left(-\frac{Q_t t}{A_c L}\right) \tag{5}$$

$$x_{B_t} = 1 - exp\left(\frac{-Q_t t}{A_c L}\right) \tag{6}$$

$$\mu_{AB_t} = \left[\left(\mu_B{}^{1/3} - \mu_A{}^{1/3}\right)\left(\frac{Q_t}{A_c L}\right) x_{A_t} t + \mu_A{}^{1/3}\right]^3 \tag{7}$$

The control problem has four parameters $(\mu_A, \mu_B, A_c, L)$, three state variables $(x_{A_t}, x_{B_t}, \mu_{AB_t})$, and one control variable $(Q_t)$. In the discretized non-linear programming (NLP) solution method, the total flush time is discretized into known 'n' equal intervals and the state equations are solved for each interval. Let's consider for an example the total flush time was 60 seconds and we divide the total flush time into 6 equal intervals of 10 seconds each as illustrated in Figure 2. The solution algorithm solves the state equations for each interval.

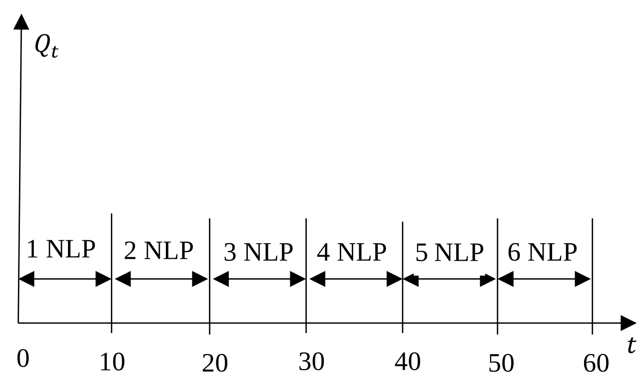


*Figure 2 Discretization of Total Time into Equal Intervals*

We start with an initial guess of the control variable '$Q_t$' and specify the system specific maximum and minimum constraints for our control variable (flowrate of lubricant B). Next, we solve the state equations for the 1st interval to achieve the desired objective function. If the optimality criteria is not satisfied, the flowrate is updated for the next interval such that the updated flowrate profile improves the objective function. The iterations continue for 'n' intervals until the desired optimality condition is achieved. i.e., the difference in the viscosities of the blend and the viscosity of lubricant B is minimized. In other words the desired specifications of the new lubricant B is reached. The choice of our decision variable is based on time because in real world scenario the plant operators at these facilities can provide the input in terms of time. Therefore, we study the optimum flowrate in a given time interval required to conduct a successful flush. Figure 3 depicts the flowchart of the solution approach.

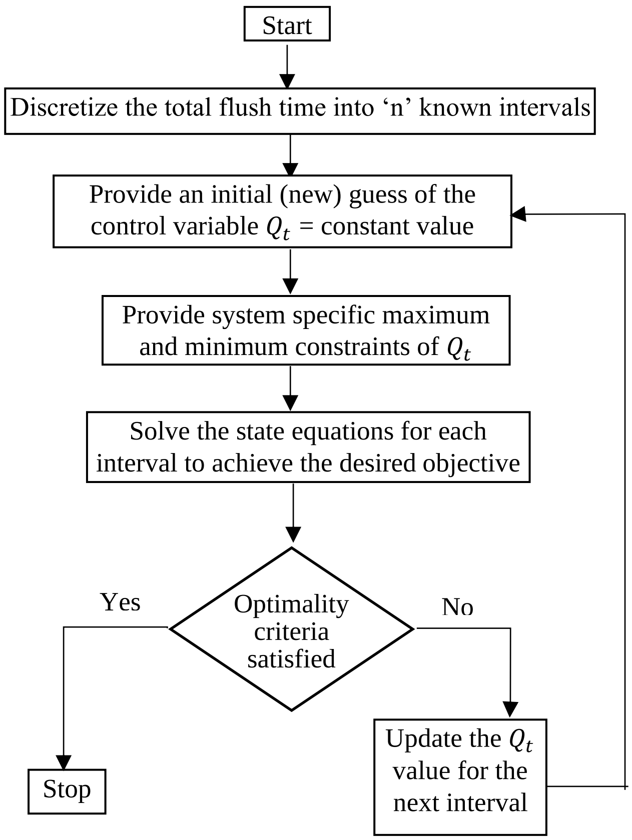


*Figure 3 Flowchart of Solution Technique Using Discretized Non-Linear Programming Solution Approach*

**Plant Experiments**

To validate our simulated results, we conducted well designed experiments at our partnered lubricant industry. In these experiments for different changeover operations for a total flush time selected by an operator (which ranged between 60-300 seconds) we collected samples at an interval of every 10 seconds. We tested each sample for their kinematic viscosity. Furthermore, we recorded initial and final levels of the feed tank that stored the flushing lubricant ‘B’. Next, we calculated the volume of lubricant flushed during the total flush time. Through this we calculated the flowrate of the lubricant B using the total volume flushed and the total time. This flowrate value was the initial guess and maximum constraint for our simulation. Furthermore, we also recorded our parameter values which included, pipe cross sectional area ($A_c$), pipe length ($L$), viscosity of residual lubricant ($\mu_A$) and desired viscosity specifications of the new lubricant/ flushing lubricant ($\mu_B$). We used these measured results to determine at which time interval the desired viscosity was reached. Next, we compared them against the simulated results as discussed in the following section.

**Results and Conclusions**

Figure 4 illustrates the comparison of simulated results against the experimental data for a test case 1. The changeover operation was from a lubricant that had a kinematic viscosity of 12 cSt to a new lubricant of 8.7 cSt. The operator had selected a total flush time of 60 seconds for this respective flush. The scattered plots in Figure 4 represents the experimental data points. As observed the desired viscosity specifications (8.7 cSt) was achieved right for the second sample that was collected at 20 seconds interval. This indicates that the total flush time of 60 seconds was actually unnecessary. Our simulated result represented by the smooth curve is in good agreement with the experimental data. Similarly, we compared our simulated results with the experimental data for a test case 2 (Figure 5) which was a changeover operation from an initial viscosity value of 82.84 cSt for residual lubricant to a required viscosity value of 297 cSt for the new lubricant. The flushing can be stopped if the desired viscosity within ±5% is reached. The operator based upon his previous experience in regards to this respective product, selected a total flush time of 290 seconds. However, from the experimental data (scattered plots) we observed that at a constant flowrate, the required specifications were achieved at the 17th sample for a total flush time of 152 seconds. Furthermore, our simulated results indicate that if the flushing will be conducted at an optimal flowrate profile where the flowrate varies with each time interval, the

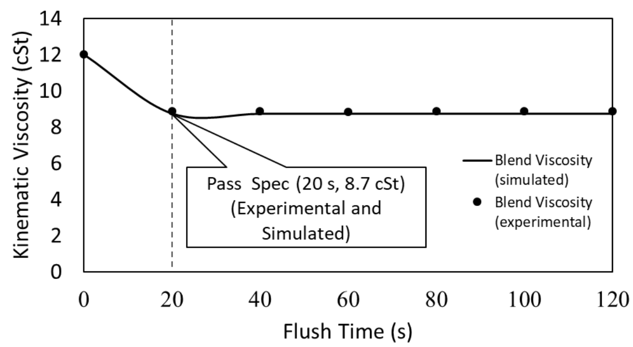


*Figure 4 Validation of Simulated Results for Test Case 1*

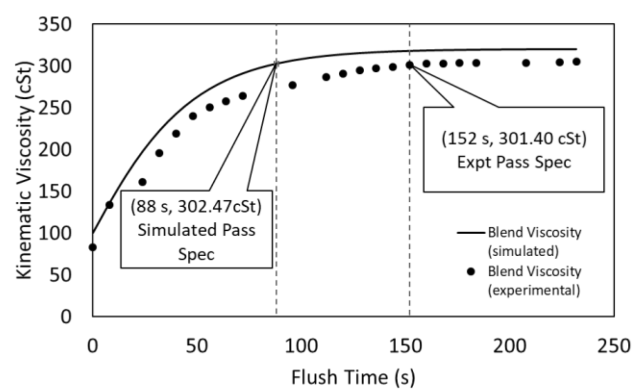


*Figure 5 Validation of Simulated Results for Test Case 2*

desired specifications will be achieved at 88 seconds of flush time (represented by the smooth curve).

In a similar manner we compared our simulated results for 27 such changeover operations and observed that our models slightly over-predicts and under-predicts the flushing time for certain scenarios where there is a large difference in the viscosities between the residual and the new lubricant. For small differences the model validates well within the acceptable limits of the experimental data. Hence, there is a room for improvements and in our future work we are enhancing the existing models to incorporate the parameter for viscosity, frictional losses and diffusion coefficient. Our goal is to develop a product changeover specific flush time guidance computational tool that will help the plant operators and in turn the lubricant industries to predict the necessary flush time for a successful cleaning operation.

We believe that our work can serve as an excellent starting point that will enable these industries to make more informed decisions during the flushing operations. Furthermore, it will enhance the material and energy consumption footprints of these operations. In future our solution strategy can also be applied to other industries that rely on a similar operational procedure such as the paint, specialty food, pharmaceutical, specialty chemicals, adhesives, personal care products, and polymer industries.

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