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Quality Enhancement of Dar Crude Oil Pre-Processing Using Model Predictive Control

Mohamed A. Rahim[a]*, Omnia Hassan[b], Mohammed A.S. Ahmed[c]

aDepartment of Chemical Engineering, University of Bahrain, Sakhir, Kingdom of Bahrain
bChemical Engineering Department, Al-Neelain University, Khartoum, Sudan
c International Sustainability Academy, Hamburg, Germany
maosman@uob.edu.bh

In large-scale industries such as oil refineries and petrochemicals, it is necessary to implement an advanced control strategy. This is of great importance, particularly in separation processes where high energy consumption is required during the operation. Thus, to implement a control system that guarantees high control efficiency with less energy and heat consumption, the first and second-stage separators in Central Processing Facilities (CPFs) operated with conventional PID controllers are replaced with a higher layer of Model Predictive Controller (MPC). In this paper, Aspen HYSYS software is used to characterize the Dar blend in the Sudanese oil field. Later, the existing PID controllers in the separators are simulated to reflect the current operation. The PID controllers are employed to control the liquid level in the first-stage separator and the bulk liquid temperature in the second-stage separator. Then, MATLAB System Identification Toolbox is used to identify the process model to be applied for the MPC controller. Finally, disturbance rejection and set-point tracking are applied for both PID and MPC controllers to assess and compare the performance of each controller quantitatively. The research revealed satisfactory performance in terms of disturbance rejection for both controllers with smoother operation and minimal load on the control valve in the MPC implementation case. Nevertheless, for the set-point tracking, the MPC controller exhibited a remarkably faster response that is nearly half the time required by the PID controller.

1. Introduction

The critical goal of chemical process simulation is to characterize a process of chemical or physical conversion using mathematical models that comprise the determination of mass and energy balances together with phase equilibrium and chemical kinetics equations (Gmehling, Kleiber et al. 2019), (McBride and Sundmacher 2019). These mathematical models also comprised of equipment or process operations and physical or chemical properties represented by differential-algebraic equations, linear and nonlinear equations (Gil Chaves, López et al. 2016, Khayyam, Jazar et al. 2020).
Mathematical models like other types of models that are used in chemical engineering, for design, scale-up/down, optimization, operation of reactors, separators, and heat exchangers (Haydary 2019, Zhao, Cheng et al. 2019, Hashmi, Mali et al. 2022). Mathematical models are similarly applied in the planning and assessment of experiments and for evolving mechanistic understanding of complex processes and they exist as computer programs or sets of mathematical formulas (Alvear, Orabona et al. 2023).
One of the main applications of mathematical models in industry is Model Predictive Control (MPC). The primary idea of MPC is to predict the system behaviour using a predefined mathematical model and optimize this prediction to provide the optimal decision regarding the control moves at present. Hence, mathematical models are the base of all the MPC formulations (S Taheri 2022). Since the initial state is used to determine the optimal control move of the dynamic system in MPC, a fundamental concept is applied to the MPC where the previous measurements are used to decide the most probable initial state of the system (Wang, Zheng et al. 2022). However, the implementation of the MPC has yet to be widely spread compared to the conventional Proportional Integral (PID) Controller.

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Most of the control loops in petroleum refineries and large-scale plants are Multi-Input Multi-Output (MIMO) control loops. However, the problem arises because each controller output does not merely adjust a specific process variable. Instead, it also upsets other process variables in the system. Tuning MIMO PID controllers is a very challenging task in large-scale plants where too many decentralized PID controllers work independently and, subsequently produce a severe degradation in the control performance of the whole plant (Al-Naumani and Rossiter 2017). The MPC approach stands out owing to its capability to provide an optimal control performance to large-scale, nonlinear, complex, and highly interacting multivariable systems. In addition, the MPC framework gives excellent results and is much better than the PID when high noise occurs in the system due to possessing the PID system with the Kalman noise filter (Ibrahim, Kamran et al. 2021). On the other hand, the PID shows more effectiveness in disturbance and gives the systems greater flexibility and relative stability (Okasha, Kralev et al. 2022).
The main objectives of the research are first: to simulate and model the dynamic system of the first and second-stage separators operating with Dar blend in the CPF and secondly, to improve the control performance by replacing the existing PID controllers with a high layer of MPC and ensure stable operation for the plant under multivariable closed-loop system, and finally to quantitatively assess the level of improvement attained in terms of smooth operation, setpoint tracking and disturbance rejection.

2. Materials and Methods

In this section, the separation unit which contains first, second-stage separators and a heater, is simulated in a process flowsheet using Aspen HYSYS. All operating conditions and data to develop the process flowsheet in HYSYS as shown in Figure 1 were obtained from PETRODAR Operating Company, Sudan.

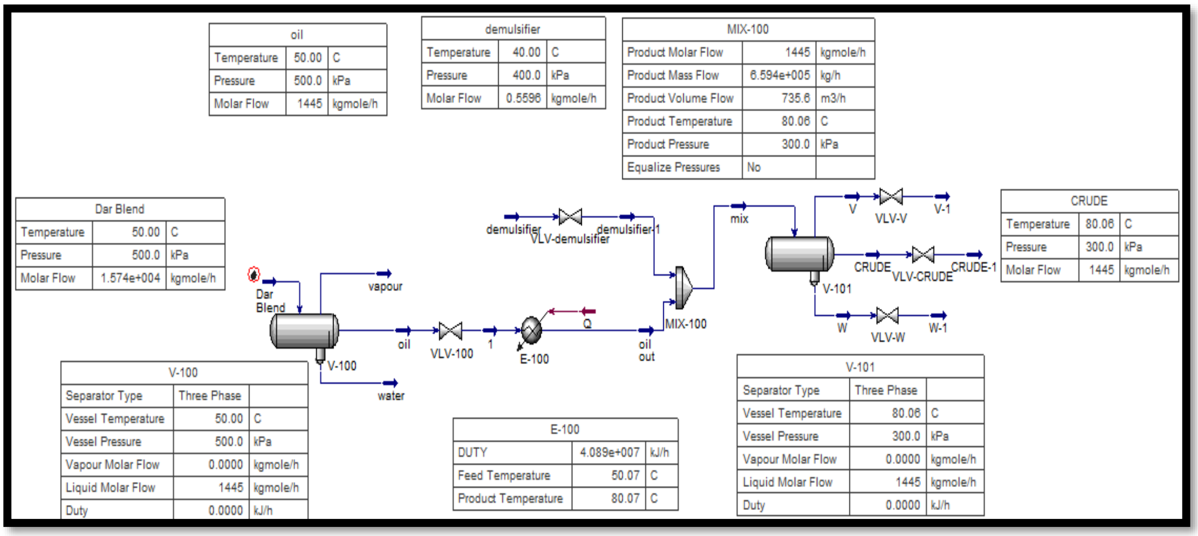

Figure 1: Process Flowsheet

2.1 Oil specification

The following Tables 1 and 2 are used to develop the steady-state mode by first characterizing the assay of the Dar blend using the physicochemical characterization of the blend delivered by the laboratory report from (Central Petroleum Laboratories 2019). The crude assay is stored in the HYSYS data bank, then the blend is calculated and the dynamic state process is constructed.

Table 1. Crude Oil Production

Description	Quantity
Feed (crude oil + water + gas)	150000 bbl/day
Water cut	26% by volume
Associated gas	3.12 % Weight

Table 2. Crude Oil Characteristics of Dar Blend

Test	Method	Unit	Results
Density at 15°C	ASTM D5002	g/cm³	0.8964
Specific Gravity	ASTM D5002	Degree	0.9141
API Gravity	ASTM D5002		23.30
Kinematic Viscosity @50°C	ASTM D445	mm²/s	440.5
Kinematic Viscosity @70 °C	ASTM D445	mm²/s	139.8
Pour Point	ASTM D97	°C	39
Asphaltine Content	IP 143	% Wt	0.27
Total Acid Number	ASTM D664	Mg KOH/g	4.45
Total Sulphur	ASTM D4294	% m	0.1129

To compute the properties and the composition of the feed, the feed is characterized by describing relative crude assays and blends according to the information supplied (Central Petroleum Laboratories 2019).

2.2 Demulsifier

A demulsifier is injected into the mixer as shown in Figure 1 to stimulate the separation of the oil-water emulsion by disrupting the interfacial film between the water and the oil droplets. Different commercial demulsifier species are available in the market. However, in this simulation, a 60% DEGlycol solution in xylene solvent was used. In the simulation, the following operating conditions were considered: 40°C, 400 kPa and 0.56 kmole/hr for temperature, pressure and molar flow, respectively. Then, the volume fraction of DEGlycol is specified as 0.6, m-xylene is 0.24 and o-xylene is 0.08.

2.3 Implementation of PID Level Indicator Controller (LIC) and Temperature Indicator Controller (TIC)

In the LIC controller, as shown in Figure 2, the following parameters were specified: process variable range, PV minimum is 0% and PV maximum is 100%. The controller mode was changed from manual to auto and the set-point was specified and set equal to 70%, while the PID tuning parameters were set to K_c= 3, T_i= 1.5, and T_d= 0.5. This level controller has a direct action, because when the liquid level increases inside the separator and becomes greater than the set point the valve opens more.
To control the temperature in the second separator, PV in the TIC-100 controller is chosen as an object, Bulk Liquid Temperature is chosen as a variable and the operational parameters were set as follows: PV_{min}=50°C, PV_{max} = 90°C, Set-point = 80°C while the PID tuning parameters were set to K_c= 1, T_i= 0.5, and T_d= 0.1.

2.4 Step test for the dynamic model estimation for the MPC

I. The step test is applied to the TIC-100 controller
II. The bulk liquid temperature was defined as a CV while the TIC-100 opening was set as a MV.
III. The set point for bulk liquid temperature was set at 80°C, all the controllers were initially run in automatic mode until reaching the steady state
IV. Then the TIC-100 controller was changed to manual mode and the step test was applied with 12 steps of random input moves
V. The data was stored in Aspen HYSYS historical data and exported to MATLAB Identification Toolbox.

2.5 System Identification (Process Model Estimation)

The collected data of the step test from Aspen HYSYS is used for the process modeling stage by MATLAB System Identification Toolbox. A First Order Plus Time Delay (FOPTD) model was obtained with a process gain - 0.46, process time constant 3.41min and time delay 1.6 min.

2.6 MPC Implementation

A state-space model of the decentralized structure of a plant consisting of *M* subsystems can be denoted using a linear discrete LTI model as follows

$$x_{ii}(k+1) = A_{ii}x_{ii}(k) + B_{ii}u_i(k) \tag{1}$$

Where, $A_{ii} \in \mathbb{R}^{n_{ii}\times n_{ii}}, B_{ii} \in \mathbb{R}^{n_{ii}\times m_i}, C_{ii} \in \mathbb{R}^{z_i\times n_{ii}}$ is a realization for each input-output (u_i, y_i) pair such that (A_{ii}, B_{ii}) is stabilizable and (A_{ii}, C_{ii}) is detectable.

2.6.1 Interaction Models (IM)

The Linear discrete Time Invariant LTI model is implemented to denote the influence of any interacting subsystem $\boldsymbol{j} \in \mathbb{I}_{\boldsymbol{M}}, \boldsymbol{j} \neq$i on subsystem $\boldsymbol{i} \in \mathbb{I}_{\boldsymbol{M}}$

$$x_{ij}(k+1) = A_{ij}x_{ij}(k) + B_{ij}u_j \quad (2a)$$

The equation for each subsystem is formulated as

$$y_i(k) = \sum_{j=1}^{M} A_{ij}x_{ij}(k) \quad (2b)$$

To define the cost function of the decentralized control structure, the controller samples the state of the system $x_{ii}(k)$ at decision instant k, and then solves an optimization problem of the following form to determine the control moves

$$\min_{x_{ii}(k),u_i(k)} J_i(x_{ii}(k), u_i(k)) \quad (3a)$$

subject to: $x_{ii}(l+1|k) = A_{ii}x_{ii}(l|k) + B_{ii}u_i(l|k), k \leq l$ (3b)

$$u_i(l|k) \in \Omega_i, k \leq l \quad (3c)$$

$$x_{ii}(k) = \hat{x}_{ii}(k) \quad (3d)$$

The subsystem cost function in the decentralized MPC structure is

$$J_i(x_{ii}(k), u_i(k)) = \frac{1}{2}\sum_{t=k}^{\infty}[x_{ii}(t|k)'Q_{ii}x_{ii}(t|k) + u_i(t|k)'R_iu_i(t|k) \quad (3e)$$

3. Results and Discussion

The obtained process model was used as an internal model for the MPC controller in Aspen HYSYS. The process variables range was adjusted from 50 °C to 90 °C and the set point was set to 80 °C.

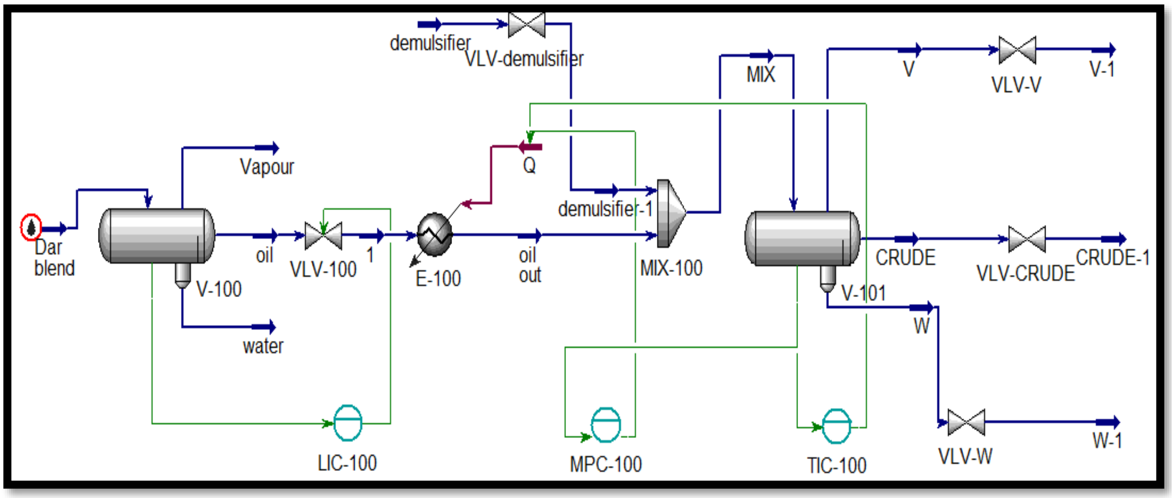

Figure 2: Implementation of the MPC controller

To evaluate the disturbance rejection capability of both controllers, the MPC controller was compared to the PID controller in terms of their ability to maintain the liquid temperature in the presence of disturbances in the feed flow rate. To test the MPC controller, the PID (TIC-100) was deactivated and the MPC was put in auto mode. Under this auto mode, the feed flow rate was changed from 150000 barrels/day to 160000 barrels/day in the dynamic process flowsheet. Then to test the PID controller, the MPC was put in manual mode, and the PID was put in auto mode and the same previous steps were done. The performance of the MPC and PID controllers is shown in Figures 3a and 3b, respectively.

The MPC controller and the PID controller were also evaluated in terms of set-point tracking. The set-point of the liquid temperature in the second separator was changed from the steady-state temperature 80 ºC to 65 ºC, and then it was set back to 80 ºC. This step test was done twice. First by putting the PID controller in auto mode while deactivating the MPC controller and secondly by reversing the setting by deactivating the PID controller and keeping the MPC controller in auto mode. Finally, the response of the MPC and PID controllers to this setpoint change was evaluated and compared as shown in Figures 4a and 4b, respectively.

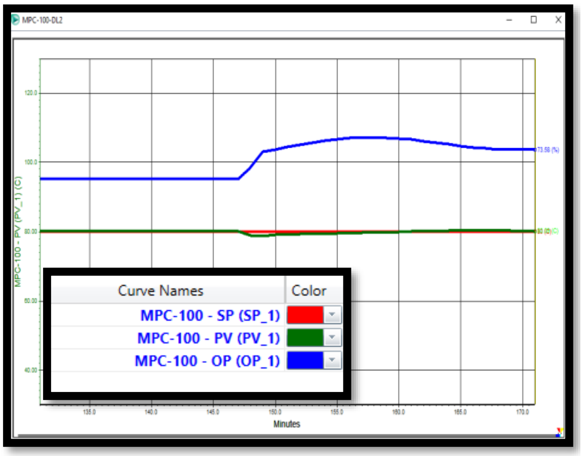

Figure 3a: Response of MPC controller for disturbance rejection

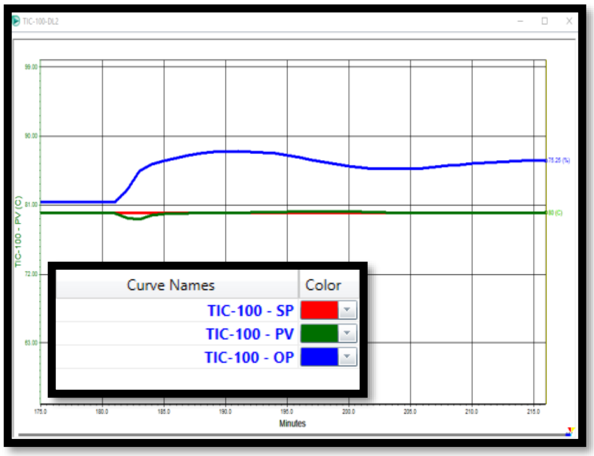

Figure 3b: Response of PID controller for disturbance rejection

MPC and PID controllers show good performance in disturbance rejection. Both controllers took approximately four minutes to bring back the liquid temperature at the second-stage separator to 80 ºC when the feed flow rate stepped from 150000 barrels/day to 160000 barrels/day. However, from Figures 3a and 3b (the blue lines), it is obvious that the response of the MPC is less oscillatory and has less valve opening (73.58) compared to the valve opening of the PID controller which is 75.25%, meaning that there is a minimal load applied on the final control element (the control valve), and subsequently, a smooth operation while maintaining the life span of the control valve.

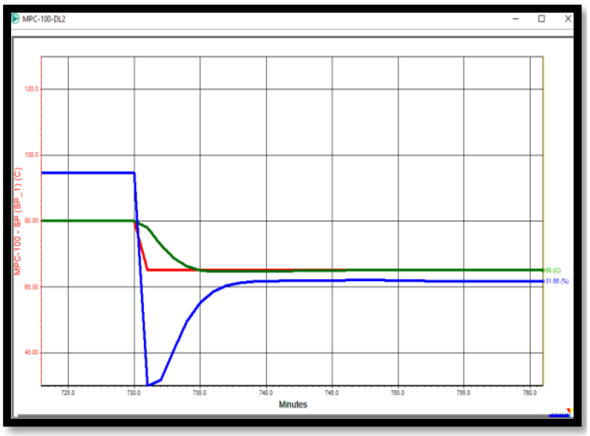

Figure 4a: Response of MPC controller for set-point tracking

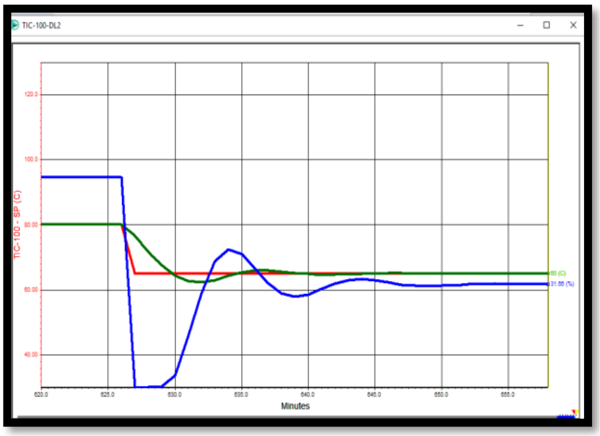

Figure 4b: Response of PID controller for set-point tracking

Figure 4b shows that the PID controller took nearly 11 minutes to track the new set-point. Nevertheless, as seen in Figure 4a, the MPC controller reached the new set-point faster than the PID controller. The MPC shows more superb set-point tracking, taking less than 5 minutes to track the new set-point.

4. Conclusions

This study aims to improve the overall control performance in the CPF plant by obtaining better set point tracking and disturbance rejection. This can ultimately lead to more energy conservation and smooth operation. Toward this end, the existing PID controllers in the CPF are upgraded with a higher layer of advanced control strategy, namely, the MPC controller. After characterizing the Dar blend crude oil, the flowsheets for the first and second-stage separators in both steady-state and dynamic state are developed. Both controllers are implemented in the simulated flowsheet in HYSYS to be compared and evaluated.

The MPC and the PID controllers are compared in terms of their ability to maintain the liquid temperature when disturbances are applied to the feed flow rate. In general, both controllers performed well in the disturbance rejection, yet, the MPC controller performed smoothly while acting on the final control element. This ultimately leads to more energy saving and additional lifetime for the control valve.

In terms of set-point tracking, the MPC controller showed remarkable improvement with less oscillatory response and shorter settling time of about 5 minutes, almost equal to half of the time required by the PID controller, which was 11 minutes.

Nomenclature

A_{ij} - State transition matrix of subsystem *j* to *i*
A_i - State transition matrix of subsystem *i*
B_{ij} - Input matrix of subsystem *j* to subsystem *i*
B_i - Input matrix of subsystem *i*
C_{ij} - Output matrix of subsystem *j* to subsystem *i*
k - Sampling time
$J_i(x_i, u_i)$ Cost function of subsystem *i*
m_i - Input dimension of subsystem *i*
M - Number of subsystems
N - Finite control horizon
p - Iterate of optimization problem
Q_I - Output weighting matrix
R_i - Input weighting matrix
u_i - Input (manipulated variable) of subsystem *i*
u^p - Optimal input trajectory
x_i - State vector of subsystem *i*
x_{ij} - State interaction vector of subsystem *j* to *i*
ε - Slack variable

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