MODEL PREDICTIVE CONTROL OF A CRUDE DISTILLATION UNIT AN INDUSTRIAL APPLICATION

Serdar Kemaloğlu Emre Özgen Kuzu
Dila Gökçe Özgur Çetin

Turkish Petroleum Refineries Corporation, Izmit 41780
Turkey

Abstract: This paper reviews the application of a model predictive controller algorithm to a crude oil unit in Izmit Refinery of Turkish Petroleum Refineries Corporation as a summary of nearly eight months of practical study. The controller is designed to control the crude heating via process flows followed by furnace heating and distillation column with product strippers. After a process overview, the fundamental control loop considerations are discussed. Steps of determining inferred qualities and step test response tests are outlined. The controller design considerations, constraint handling and economic variables are presented. Finally, a comparison of before and after commissioning in the kerosene quality and rate is tabulated as well as simulation results of the system response for different set point changes in the product qualities.

Keywords: Advanced process control, multivariable predictive control, crude distillation processes, model identification.

1. INTRODUCTION

Model predictive control (MPC) strategies have found a wide range of applications from refineries to food processing and become a standard control algorithm for process industries. In 1999 nearly five thousand applications were reported with an increase of about 80 % in the following years (Qin and Bagdwell, 2003). MPC algorithm utilizes an explicit process model to optimize an open loop performance objective to constraints over a future time horizon, based on current measured variables and the current and the future inputs (Rossitier, 2003).

Turkish Petroleum Refineries Corporation (TUPRAS) is the largest industrial enterprise in Turkey. TUPRAS controls all of Turkey's refining capacity with operating four refineries with a total annual process capacity of 28.1 million tons crude oil. TUPRAS Izmit Refinery is the biggest refinery of four with annual refining capacity of 11.0 million tons of crude oil.

After privatization in 2006, implementation of advanced process control (APC) applications were initiated to increase operational excellence with many other projects. In this paper, an APC application to one of the crude units in Izmit Refinery is presented. After the process overview, base layer control strategies developed to sustain healthy layer for APC studies are explained. The main elements of the controller, controlled, manipulated and disturbance variables are discussed. Following the methods for obtaining inferred qualities, response tests and dynamic modelling strategies are outlined. The dynamic models obtained during tests are used in the commercial MPC algorithm SMOCPro. The control strategies, economic concerns and commissioning issues are discussed in the Section 4. The results of the commissioned plant data is tabulated as well as simulation of the controller for different set point changes in product qualities.

It is desired to give an outline of an industrial MPC application, but also some practical issues on implementation details. Finally, Section 5 outlines the study.

2. PROCESS OVERVIEW AND BASE LAYER CONTROL STRATEGIES

Plant-5 is one of the three crude oil units in TUPRAS Izmit Refinery and its simplified flow diagram is depicted in Figure1.

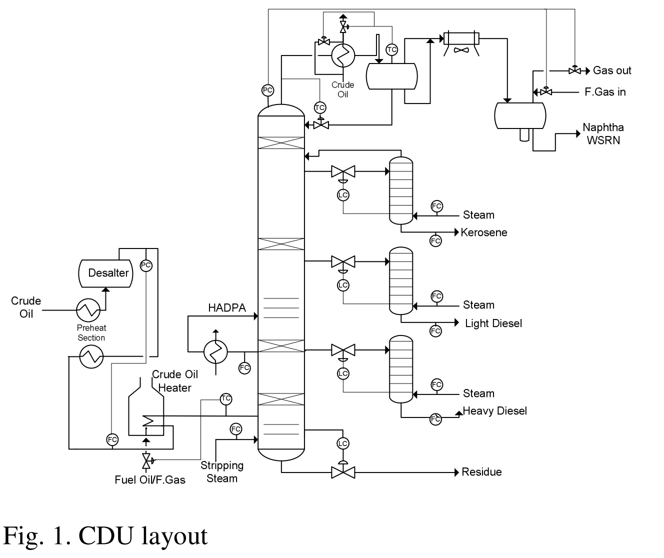

Fig. 1. CDU layout

The crude unit consists of mainly five operations. Advanced control strategies of steps 1,2 and 3 are in the scope of this paper:

1. Before and after desalter operation, the crude is heated via the hot streams available in the plant.
2. The crude is heated at a temperature around 320-350 ºC in two parallel furnaces.
3. The heated crude oil is distilled into products. Kerosene, light diesel and heavy diesel are drawn off after strippers. The bottom product, residue, is the feed to the vacuum unit.
4. The upstream of distillation column, a mixture of LPG, light straight run naphtha and heavy straight run naphtha, is fed to the naphtha splitter column where LPG and light naphtha are separated from heavy naphtha.
5. The liquid product of naphtha splitter upstream is separated into light naphtha and LPG in the debutanizer column.

Before implementation of advanced process control algorithm, a preliminary study comprising a base layer PID-based control is running successfully in normal operation. This study includes check of all instrumentation, checking for sticky valves, process feedback effects, process interactions, noisy measurements, retuning of PID controllers and possible configuration changes in the control strategies. In this scope, 56 regulatory PID controllers were retuned before starting testing.

Two base layer enhancements were carried out in distillation column control. There has been no bottom flow controller in the distillation column. Operators would manipulate the residue flow manually to keep level at operating ranges. This resulted continuous monitoring by operators and also discrete sudden changes in residue flow, which is the feed of vacuum unit as well. In the reviews, a new base layer of a level controller cascaded to the bottoms flow controller is implemented. With an appropriate tuning, the level is controlled while the bottoms flow does not vary significantly to create big disturbances to the vacuum unit.

The overhead drum temperature was manually controlled via bypassing from crude oil preheat heat exchangers at above 102 ºC to avoid corrosion problems. A new temperature controller has been implemented that closes the bypass valve in the line directing overheads product through the overheads cooler / crude preheat exchange.

3. CONTROLLER DESIGN

3.1 Variables

At the beginning of an APC project, the controller design requires selection of manipulated (MV), disturbance (DV) and controlled (CV) variables. These variables in this project:

- 28 manipulated variables are considered, 17 of which are for preheat and 11 for crude distillation column. These manipulated variables are feed flow controllers, furnace coil flow controllers and distillation column pressure, temperature and flow controllers.
- 3 disturbance variables are selected; amount of total feed and inlet flow rates to two furnaces.
- 19 controlled variables, where 4 variables are in preheat section and remaining in the crude distillation column.

Controlled variables for preheat section are desalter temperature and pressure and furnace outlet temperatures for the preheat section.

Some key variables are tabulated in Table 1 at the end of the paper. Distillation column controlled variables can be classified in three categories; inferred qualities, variables of economic importance and operational constraints.

The inferred qualities are the four main product qualities, heavy naphtha, light diesel and heavy diesel 95% distillation points and kerosene flash point. In order to control these qualities, inferential measurements have been developed. All the qualities have been inferred based on statistical regression of empirical data. The data was collected during a test period of two weeks, where manipulated variables and important column dynamics were changed one by one and held constant for two to three hours, while subsequent lab results were gathered. This data was used as a training period and inferential measurements were modelled using RQE Pro, software in the Process Control Technology Package (PCTP) of Shell Global Solutions International BV. Various combinations of process variables were regressed and good fits were achieved. Regular laboratory data of nearly eight months was also used to validate the model. The inferred qualities are mainly functions of pressure compensated temperatures. In some cases, vapour / liquid ratio below the draw-off tray of the product of which the quality was to be inferred. In the online application, the inferred qualities' equations' biases are updated with regular laboratory results. Before defining these qualities as a CV to the controller, several lab results were introduced to obtain a healthy estimation. These results correct any prediction error in the calculation that might arise in a local problem occurred during tests. Reducing the laboratory analysis amount after a certain period is another advantage of this method. Also in the online application, sudden change in bias may result in a change in the predicted quality, hence an aggressive MV output. To overcome this local disturbance, a filter time of thirty minutes to one hour has been applied to smoothen the update mechanism.

Operational constraints are usually the design specifications. Controlling column pressure valve opening prevents any loss of gas during operation. Reflux and heavy diesel pump around amount and top drum level as a CV sustains a safe operation. The level in the strippers is a major constraint where light diesel stripper level can be operated successfully to only a certain amount and is the main drawback of the light diesel amount.

Although they are not a part of the controller, reducing stripping steam amount and transferring the maximum heat from heavy diesel pump around are two economically beneficial CV's. The controller controls the stripping steam / feed ratio and heavy diesel inlet/outlet temperature difference multiplied by heavy diesel pump around amount at certain ranges.

3.2 Response Testing

During the commissioning of a predictive controller, testing and modelling efforts can take up to 90 % of the cost and time (Andersen and Kummel, 1992). Successful modelling engenders controller stability and performance on the predictive capability of the process model used. The most important element of a good modelling is the high quality clean data obtained form response testing. Also it should be noted that data analysis and model identification enhances process understanding and behaviour.

In the APC application in TUPRAS Izmit Refinery crude distillation unit, the response tests were carried out for three weeks in two shifts. For each of the 28 manipulated variables, tests were carried out separately in sequence, groups of six to eight steps were made in each. The sequence was repeated afterwards, obtaining a test data of sixteen to twenty moves for each variable. Repeating sequence allows preventing unmeasured disturbances that might happen in one of the sequences. The step sizes were defined in a way to see clear effects in the other variables, and steps were held for periods of one to one and a half of the settling time. The step sizes were changed sometimes to identify the presence of nonlinearities.

During step testing, it is very important to carefully observe the steps. The correlation of the independent variables, possible operator interventions and insufficient move sizes may result in poor data, hence poor modelling. Good signal-to-noise ratio enables that the effects of test changes in inputs could be clearly visible in process outputs. To overcome possible operator interventions, trainings were carried out before start of tests. Also changes in the regulatory configuration, PID tunings and possible controller saturations must be prevented during the test period.

3.3 Dynamic Modelling

Majority of industrial MPC applications use linear empirical models (Qin and Bagdwell, 2003). While analyzing the plant data, such an empirical dynamic process-modelling tool, AIDAPro –another PCTP software- was used. The results of step tests were analyzed and mathematically fit to obtain predictive process models.

In dynamic modelling, the interactions of all variables are taken into account, hence the effect of intermediate variables and disturbances can be tolerated in identification. Basically, multivariable higher order parametric models were created for each variable. These models are then approximated and reduced to a parametric model on individual relationship basis of two variables. Based on the data analyzed, the process knowledge and step test experience dynamic response of the variables are determined. Numerical representation of these dynamic response curves can be of any degree from first order zero gain to second order beta.

During modelling 31(28 manipulated and 3 disturbance variables) X 19 response curves were fitted. Of these 589 possible independent / dependent variable response curves, 53 responses are identified for the controller design. The other responses are either zero gain or insignificant.

4. CONTROLLER COMISSIONING

4.1 Controller Design

The dynamic models from observed plant data were used to design the controller. Shell Multivariable Optimizing Controller, SMOCPro is used to implement predictive controller in TUPRAS Izmit Refinery Crude Unit. SMOCPro, a part of the Process Control Technology Package (PCTP) of Shell Global Solutions International BV, and its algorithm was summarized by Qin and Bagdwell (2003) :

- An explicit disturbance model described the effect of unmeasured disturbances; the constant output disturbance was simply a special case,
- A Kalman filter was used to estimate the plant states and unmeasured disturbances from output measurements,
- A distinction was introduced between controlled variables appearing in the control objective and feedback variables that were used for state estimation
- Input and output constraints were enforced via a quadratic program formulation

As well as most advanced process control algorithms, SMOC algorithm also follows a reference trajectory by the future outputs on the prediction horizon and penalizes the control effort on the control horizon. General objective function of the controller can be written as

$$\min_{\Delta u(n)\ldots\Delta u(n+C-1)} \sum_{i=1}^{P} \left\| \hat{y}(n+i) - r(n+i) \right\|^2 w_1 + \sum_{j=1}^{C} \left\| \Delta u(n+i-1) \right\|^2 w_2 \quad (1)$$

in which 'u' represents inputs, 'y' is used to define outputs and the superscript ^ denotes the predicted values. Δu is the input variation and r is the reference trajectory of the outputs. In this optimization problem, the first term is used to minimize the error resulting from the difference between predicted outputs and reference trajectory during prediction horizon, P. The second term is the difference of control actions taken at each time step during control horizon, C. Weighting matrices w_1 and w_2 are positive definite matrices, with different magnitudes for all MV's and CV's. These matrices were used in controller tuning. The optimal input sequence's only first input is implemented to the system and the calculations are re-executed in the next sampling time.

The controller was tuned in offline program with simulations. While simulating both control considerations and economic variables, discussed in the next part, were considered.

Increasing w1, CV weights, increases the priority in decreasing the deviation in set point and reference trajectory, in other words makes the control tighter. Low w1 values allow bigger trade-offs. Increasing w2, MV weights, prioritizes minimum input variation and results in smoother moves.

As a base decision, the weights for column pressure, column top temperature and furnace outlet temperature controllers were given higher values than other MV's. The controller was expected to move these MV's smoother. CV weights for kerosene flash point, heavy diesel 95 % distillation and level of light diesel stripper were set higher than other weights to sustain tighter control. The weight tunings were completed by evaluating simulations.

4.2 Economic Variables

A key factor of SMOCPro is the economic function. Economic function is a bilinear function that the controller minimises. As long as the control objectives are met, the controller drives the defined economic function to minimum. Economic function in crude distillation unit consists of:

- Minimizing column top temperature, column pressure and stripping steam ratio to the feed
- Maximizing heavy diesel pump around duty, product draws to stripper level constraints and furnace heater duties. Maximizing the amount of heavy diesel by letting heavier cuts into heavy diesel and leaning to high limit. Maximizing the amount of kerosene by letting heavy naphtha into kerosene and approaching to low limit.

The constants of elements of economic function can be changed based on the plant needs or operational conditions.

4.3 Commissioning and Online Tuning

The controller was commissioned over a three- week period. The controller tunings determined in the offline studies were rechecked to prevent any model-process mismatch. After sustaining successful control, economic variables were commissioned by extending / restricting the limits. Operator trainings were also a major part of the commissioning period. All operators were trained to understand the basics of controller's function and philosophy.

4.4 Results

Over a two months period of controller running, the overall throughput of desired products increased significantly. Figure 2 shows the decrease in the naphtha yield, whole straight run naphtha (WSRN), and increase in the kerosene yield for a five weeks period of pre-commissioning and four weeks period of post-commissioning of the controller. The crude oil density was assumed to be constant, 32.46 and 32.43 API for pre and post-commissioning respectively. As seen from the figure, 11 % increase in the kerosene yield was achieved as a result of decrease in naphtha yield.

The change in the naphtha yield was also observed in the kerosene flash point. The naphtha in the kerosene product decrease the flash point of kerosene and by the high weight in the kerosene quality, the quality approaches to low limit. This approach shown in Figure 3 resulted in very significant economic benefits.

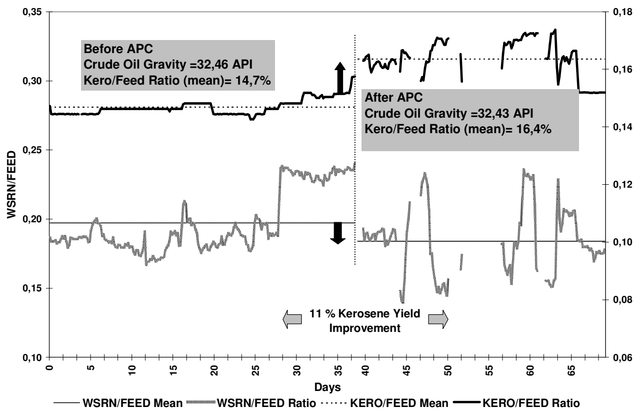

Fig. 2. Change in the naphtha yield before and after commissioning.

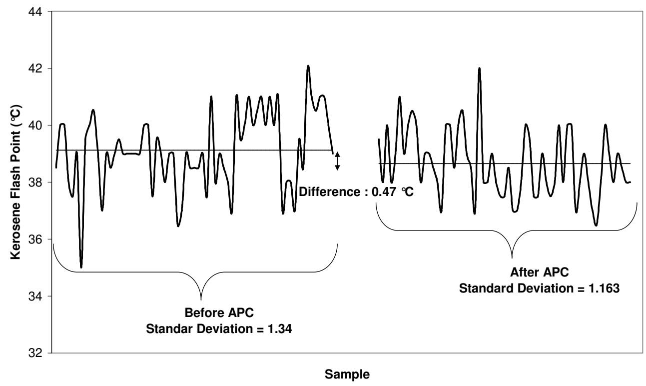

Fig. 3. Change in kerosene flash point before and after commissioning.

To illustrate the controller's performance on different situations, a simulation was studied using real plant data and specifications. When analyzing the results, a few points in controller tuning should be noted. Highest priority was assigned to kerosene and heavy diesel. Controller objective was to keep these qualities to low limit for kerosene and high limit for heavy diesel. On the other hand light diesel was assigned a low priority that its product rate was manipulated mainly in control of heavy diesel quality.

Figure 4 shows the changes in the product quality set points for kerosene flash point, heavy diesel, heavy naphtha and light diesel 95 % distillation points and their responses to these changes. The changes in critical column dynamics were reported in Figure 5. Figure 6 illustrates the product rate changes occurred during these set point changes.

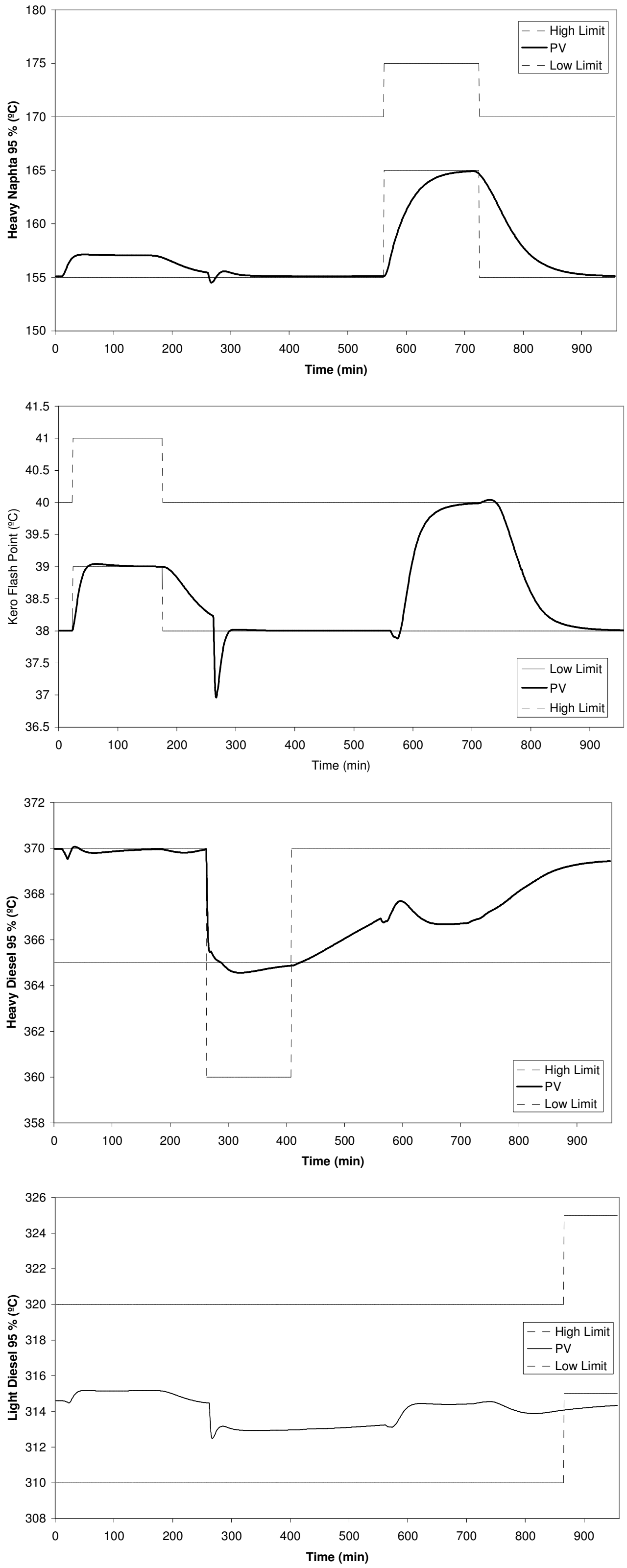

Fig. 4. Controller results in the qualities for the changes in the product quality limits.

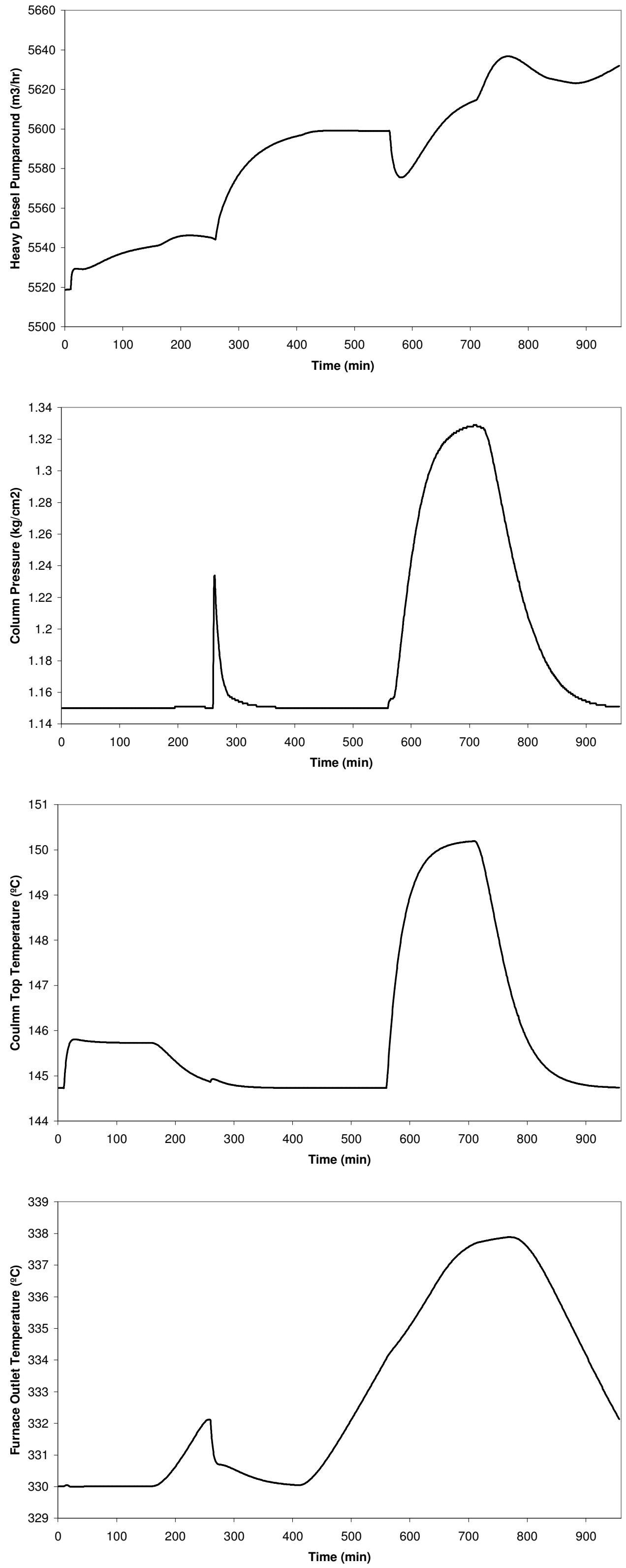

Fig. 5. Controller results in the distillation column critical controllers for the changes in the product quality limits.

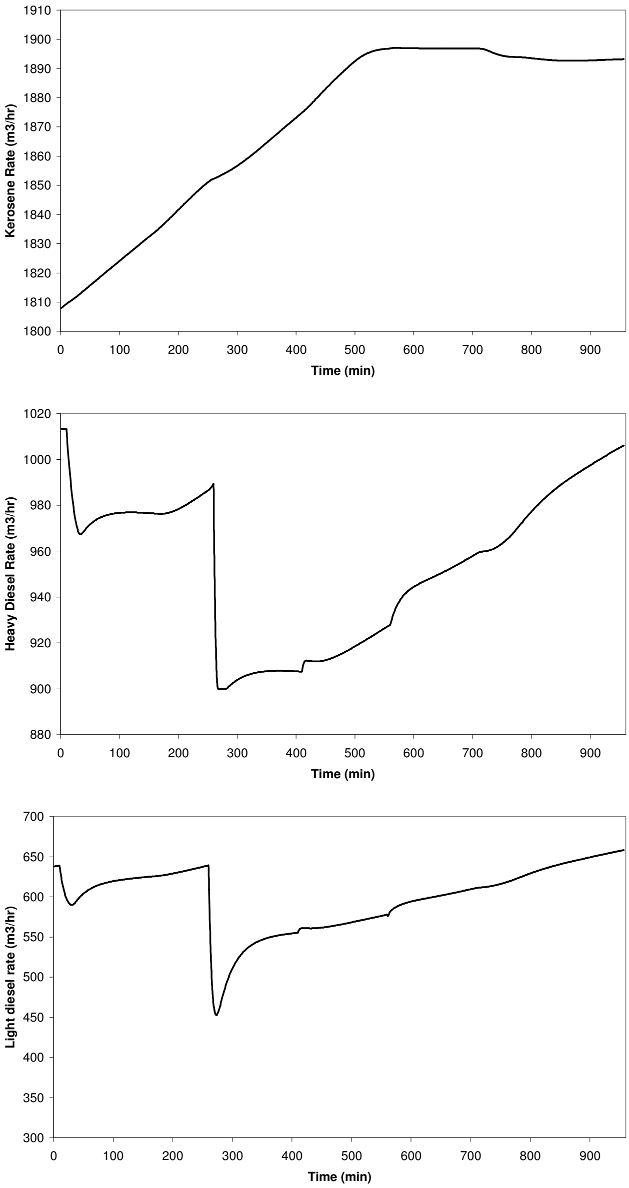

Fig. 6. Controller results in the product flow rates for the changes in the product quality limits.

5. CONCLUSIONS

In this paper, an industrial application of a model predictive controller algorithm has been presented. The controller has been designed for predictive control of crude oil preheat and distillation column of a crude oil unit in Izmit Refinery of Turkish Petroleum Refineries Corporation. A base layer control study has been performed to observe any nonconformity in the present control scheme. Tests have been carried out to obtain a mathematical model of the inferred product qualities. Dynamic step tests have been done for determined 28 manipulated variables. Dynamic modelling showed 53 responses to validate the controller.

Priorities for controlled variables and desired variation limits of manipulated variables were determined and the controller performance was tested using simulations in SMOCPro. Obtained model was commissioned for a three week period. It has been observed that the product throughputs and its economic benefit have been increased significantly.

Table 1. Control Variables of CDU Atmospheric Column

	Loop Description	MV	CV	DV
1	Heater Outlet Temperature	√		
2	Heavy Diesel Pump Around (HADPA) Duty		√	
3	Atm. Column Top Temperature	√		
4	Atm. Column Top Pressure	√		
5	Kerosene Draw-off Flow	√		
6	Light Diesel Draw-off Flow	√		
7	Heavy Diesel Draw-off Flow	√		
8	Stripping Steam Flow	√		
9	Heavy Naphtha 95% Distillation		√	
10	Kerosene Flash Point		√	
11	Kerosene 95% Distillation		√	
12	Light Diesel 95% Distillation		√	
13	Heavy Diesel 95% Distillation		√	
14	Kerosene Stripper Level Control Valve Opening		√	
15	Light Diesel Stripper Level Control Valve Opening		√	
16	Heavy Diesel Stripper Level Control Valve Opening		√	
17	Atm. Column O/H Drum Level Control Valve Opening		√	
18	Atm. Column O/H Drum Pressure Control Valve Opening		√	
19	HADPA Flow			√
20	Stripping Steam Duty		√	
21	Feed to Atm. Column			√

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