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The importance of first-principles, model-based steady-state gain calculations in model predictive control—a refinery case study

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Abstract

This paper addresses the development and application of a first-principles, steady-state modeling framework in multivariable control applications. A rigorous approach based on detailed nonlinear models calibrated with reconciled online measurements is presented. Sensitivity analysis of this model is then applied in order to generate steady-state gain (inferential) models used in a DMC-based control application of a refinery unit. The benefits of using open-equation based inferential models to account for online product quality control are demonstrated in the context of a real-time model predictive control system, applied to a refinery. Finally, the direct economic impact of this application is assessed in a detailed quantitative manner and offered along with the relevant business process changes and operational practice recommendations for sustaining the benefits achieved.

Keywords: Model-predictive control; First-principle modeling; Large-scale optimization; Inferentials

1. Introduction

The fierce increase in competition over the last few years combined with large oil price fluctuations has forced most oil and petrochemical companies to find ways to streamline and optimize plant operations. At the same time increased computing power combined with improved modeling tools has provided the opportunity to use rigorous modeling for generating accurate product quality predictions. Those predictions are invaluable in the context of advanced multi-variable control strategies, especially since traditional quality control via laboratory testing is no longer practical or acceptable due to the time-scale differences (order of seconds for a controller cycle versus a few hours for lab data). A linear model predictive control (MPC) algorithm (DMC in this particular application, as described in Cutler and Ramaker (1979) utilizes this information in the context of an optimizer that solves for the control trajectory over a future time horizon based on a dynamic model of the process. This general control methodology has been successfully employed for solving constrained multiple-input/multiple-output (MIMO) problems, which are often encountered in the process industries (see VanDoren (1998) for a review). Currently there are over two thousand online applications of MPC in the chemical process industry, mainly in the refining, petrochemical, and chemical industries as well as in pulp and paper and food processing (Qin & Badgwell, 1997).

Inferential product quality control (IFQ) has elevated traditional quality control to a higher level of total quality management. In the traditional approach, plant operators monitored product quality behavior as a sequence of discrete points lagging real-time by 4 h and being 4 h apart of each other. This operating paradigm is not particularly relevant or useful in the context of advanced control applications where both the control applications cycle every minute and the process

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dynamics are fast. The new IFQ based approach provides operators with the capability of observing product quality (inferred) on a minute-by-minute basis and therefore enabling them to monitor and analyze plant constraints, plant performance and the associated economic considerations.

In the last decade, a number of approaches to property prediction and inferential calculations have been developed in the contexts of advanced control and regulatory monitoring operations. These approaches range, in terms of rigor, from empirical correlations, to "black box" neural networks, to simplified "short-cut" models, to first principles and rigorous auto-calibrated models. Although the advantages and disadvantages of the above have been debated, it is generally accepted that as confidence in our ability to develop adequate representations of plant behavior has grown, there has been a trend to move towards more rigorous and detailed implementations. This fact is only compounded by the ever-increasing availability of low cost high-powered computing.

There is a long tradition in the process industries of using fundamental knowledge captured in the form of mathematical models to aid plant operations (Varvarezos, 1994). Recent advances in open-equation based modeling technology, in the context of real time optimization (RTO), have provided the foundation for generating inferential model calculations of high quality comparable—in some cases—to that of hardware analyzers. Those first principles based models (Aspen Plus®), with the embedded capabilities of equation oriented data reconciliation and parameter estimation (RT-Opt®), and the power of state-of-the-art, SQP-based (Han, 1977), large-scale nonlinear optimization engines (DMO), form the backbone of this technology (Lowery, McConville, Yocum, & Hendon, 1993). The fact that these models incorporate analytic derivative information for all model variables and equations makes sensitivity analysis possible for any pair of variables in the process.

This paper presents the methodology for creating those inferential calculations; it describes the implementation details and provides an account of the benefits derived from such an application in a refinery crude unit. All the above are presented in the context of a project at the Petronas Melaka refinery along with insights on the tangible and intangible benefits achieved in the project implementation lifecycle. The contribution of this work is two-fold. First, it provides a demonstrated success story of first principles model based steady-state gain calculations. Although the concept of utilizing an engineering model for MPC has been used before (Gillette & Prett, 1979), this work introduces the methodology and relevant issues associated with the model validation and data reconciliation of a large scale model in the context of an MPC application. It is also presents an analytic way of generating the steady-state based inferential calculations in a simultaneous fashion. The second contribution of this paper lies in the detailed quantitative and qualitative assessment of the economic benefits associated with this work, since it highlights the technical and economic importance of such a modeling approach in large-scale advanced control applications, as well as the important interplay between advanced control and closed-loop real-time optimization.

The rest of this paper is devoted to developing the above ideas and is organized as follows. The second section deals with the problem definition and description of the project requirements. In the third section, we offer a description of the advanced control model formulation along with the associated processes for constructing such a model. In particular, we discuss the assessment of laboratory data quality and the plant testing procedures. In Section 4, the rigorous process model is detailed along with a powerful approach to inferential model development. In Section 5, we outline the benefits derived through this advanced control strategy. Special attention is given to the lessons learned that have an impact at the refinery organizational level and involve business processes and human factors. Finally, in Section 6, we discuss the conclusions of this work and the resulting technical and operational recommendations.

2. Problem statement

This work was primarily motivated by an advanced control project for the crude unit complex (CDU) at the Petronas Panipisan Melaka refinery. The goal of this project was to effectively and optimally control the CDU operations. The CDU was designed to process 100,000 barrels per day of crude oil and condensates, and it is typically operated at 10–15% over the design capacity.

There are three different types of feed processed at this refinery. They are Tapis crude, Bintulu and Terranganu condensate. Normally Terranganu and Bintulu condensate are processed at the condensate tower where mid-distillate product and condensate naphtha are produced. The bottoms of the condensate tower are fed to the CDU via the FC004 flow meter. The Terranganu condensate and Tapis crude are fed to the CDU combined with the condensate tower bottom product.

The combined crude feed to the CDU is passed through two parallel preheat trains which consist of several heat exchangers, desalters, pre-flash towers and furnaces. The two parallel preheat trains are then combined to feed to tray #4 of the atmospheric tower.

A graphic description of the process with all the flows and their respective prices are shown in Fig. 9.

3. Advanced control formulations

The PSR1-CDU optimization project started with a detailed study to determine the potential economic benefit of implementing a multivariable control and optimization system in the CDU complex at the Petronas Penapisan Melaka refinery. The study identified a potential benefit of approximately US$685,000 per year for implementing the advanced control and optimization system (DMCplus). The timeline for the project was as follows. After the approval of the benefits study results in February, the kickoff meeting and pre-test was started and completed by the end of March. A detailed design of the controllers was issued for review and approval in May. Initial plant test was successfully completed a month later. Preliminary analysis of the data collected during the plant test revealed that there may be a need for additional data to obtain better models. Further analysis and the second plant test were conducted in July. Final data analysis and model identification was completed in August. Throughout this time, Petronas control engineers and operation personnel were actively involved in the model building and data analysis activities. This has greatly contributed to the success of the implementation of the project for reasons that will be outlined later in this paper. Controller commissioning was started in September and completed by the end of the month. Minor improvement for the inferential work was performed during the month of November. The controllers then ran on-line without any major problem.

There are three controllers running on the DEC/Alpha 4100 server machine. The controller for the main crude fractionator (CDU), the controller for the condensate tower (CND), and the controller for the gas recovery plant (GRP).

From an operational standpoint, the refinery mainly runs under two distinct modes of operation: *maximum diesel* mode and *maximum kerosene* mode. The difference between the two modes of operation is the significant change in the diesel and kerosene product specifications and product prices.

Inferentials for product qualities were developed from a rigorous real-time optimization (RT-Opt®) model of the crude fractionator. There are a total of 13 inferential qualities provided for control purposes. They form part of the control variable (CV) list for all three controllers. Table 1 details the list of inferential properties developed for this project.

The objectives of the overall control strategy are to:

- Maintain safe plant operation.
- Maximize crude charge to the unit (throughput).
- Maximize incremental product yields for optimum benefit.
- Improve equipment reliability and operational stability.

Table 1
List of inferential properties

Inferential properties	Controller
HNN 95% distillation Point	CDU
Kerosene 95% distillation point	CDU
Kerosene flash point	CDU
Kerosene freeze point	CDU
Diesel flash point	CDU
Diesel 95% distillation point	CDU
Diesel pour point	CDU
AGO pour point	CDU
AGO 95% distillation point	CDU
LSWR pour point	CDU
Condensate naphtha 95% distillation point	CND
LNN RVP	GRP
Medium naphtha 95% distillation point	GRP

These objectives were achieved by the three separate DMCplus controllers one on each of the CDU, CND and GRP units. In conjunction with the three controllers, extensive efforts were involved in developing rigorous, model-based, steady-state inferentials for side stream product quality predictions and control.

4. Rigorous nonlinear steady-state modeling

4.1. Overview

The methodology for developing inferential estimates based on first-principles models involves the following steps:

- Develop a steady state model of the process from engineering principles. In this particular case it involved detailed mass and energy balances for tray-by-tray distillation involving non-ideal thermodynamics and non-ideal liquid–vapor equilibrium calculations. This model involves over 100,000 variables and equations. There are over 1,000,000 non-zero entries $\frac{2}{3}$ being nonlinear. The solution times vary (based on the particular data instance) and are typically less than 3 min elapsed time on a current computing platform.
- Employ a solution analysis methodology to obtain the sensitivity ($\mathrm{d}y/\mathrm{d}x$) of any property of interest (dependent variable, y) with respect to any model variable of interest (independent variable, x), using the *analytic derivatives* (Jacobian) of the entire steady-state model to obtain the total derivatives as indicated in Eq. (1):

$$\frac{\mathrm{d}y}{\mathrm{d}x} = \sum_{i=1}^{N} \left(1 \Big/ \frac{\partial h_i}{\partial y} \right) \frac{\partial h_i}{\partial x} \tag{1}$$

This calculation is done in *one step* for all the variable pairs of interest (x, y) and does not involve any numerical perturbation of the model. An important property of this methodology is that it is designed to be independent of the optimum active set (the bounds that the variables may encounter at the optimal solution of the steady-state model), which frequently changes during the course of the control optimization executions. This is particularly important since it is not known a priori which constraints will be active at the control level at any given time. This "unconstrained" (independent of the optimum active set) sensitivity is achieved by performing the sensitivity analysis at the beginning of the optimization cycle (where the degrees of freedom are not "saturated") and not at the end (where several variables are at their bounds).

- Use the information above to develop an understanding of the correlation between product properties and independent variables selected differently for each property. The selection of independent variables for each property is performed using the understanding of the process unit operations, the particular parametric modeling context (i.e. quality of related measurements and updated parameters) and longtime project experience in developing such specifications. It is interesting to note here that a "poor" selection of independent variables typically results in an ill-conditioned steady-state problem.
- Add the lab update module to maintain consistency between measured and estimated values.

This methodology offers significant advantages over the other methods proposed for modeling major refining processes. The main disadvantage of these other methods is that statistical, empirical, and neural network based models tend to behave very erratically when significant changes in operating conditions occur. For instance, when the unit is processing a new crude slate or is operating in a new domain in the space of temperature, pressure and/or composition, historical data used in the context of these models are grossly inadequate to predict all properties. First principles models, on the other hand, have the capability to predict the properties accurately in as yet unobserved regions of the operating space since all of the major inputs, such as crude properties, are included as independent variables in the model. Therefore, even if plant operations are moved to a new domain the models are still valid. This is the result of using a detailed fundamental model combined with a robust parameter estimation strategy (the latter is necessary in order to match the reconciled plant measurements).

The Lab bias update module makes sure that the models are sufficiently correct to predict the actual properties. The measured properties were the distillation D86ASTM percent cut-points for all products. The quality of the models was demonstrated using the lab repeatability of the measured properties plus a tolerance of 0.5 °C to 1 °C. The exact inferential performance repeatability is described in the following equation:

$$I_R = L_R + \varepsilon, \tag{2}$$

where I_R is the inferential repeatability, L_R the lab repeatability and ε the tolerance.

The tolerance (dead-band) for each property varies between 0.5 °C and 1.0 °C.

4.2. Rigorous model development

Prior to this MPC control application, a steady state model of the crude and condensate units was developed for the purpose of debottlenecking the plant. For the optimization benefits study, the model was modified to incorporate the following capabilities:

- Selection of feed by crude assay name.
- Side-stream product qualities specified as convergence criteria.
- Elimination of the use of product back-blending.
- Removed the condensate tower model for faster convergence.

Tapis Crude, Bintulu condensate, and Trengganu condensate assay data were entered into the modeling system. Product distillation D86ASTM 95% cutpoints specifications were added. As a result, the rigorous model was reconciled to match data taken from the plant with the same feed source and mode of operation.

Once the model parameters were identified through least-squares reconciliation, the new model was saved as a base case for the study. Key operating variables were each perturbed at least three or four times to establish a relationship between them and the overall plant operating profits.

4.3. Base case model results

Table 2 compares the simulation results and the actual plant test data. From this table, it can be seen that the simulation results fit very well against the original plant data collected during the test runs with the exception of the flash zone temperature and the tower bottom temperature. It was noted that the pour point for the LSWR stream does not match well with the lab data. This is because the pour point property curve was not available for the CTB stream assay.

4.4. Assumptions

The following assumptions were used in this work:

- 78,000 barrels per day (KBP) throughputs.
- Test run plant data for the base case.

Table 2
Base case simulation results

Description	Units	Price	Actual	Simulation	% Diff
Tower temperature and operating conditions					
OVHD condenser (tray 1)	°C		46	48.70	5.87
Tower top temperature (tray 2)	°C		102	100	−1.96
Top pumparound draw temp (tray 5)	°C		120	119	−1.67
HN draw temperature (tray 17)	°C		150	147	−2.00
Kero draw temperature (tray 27)	°C		187	186	−0.53
Diesel draw temperature (tray 35)	°C		260	260	0.00
AGO draw temperature (tray 43)	°C		304	306	0.66
Flash zone temperature (tray 49)	°C		323	339	4.95
Bottom crude tower temperature (tray 54)	°C		311	326	4.82
TPA flow rate	m^3/h		635	630	−0.79
TPA duty	mm kcal/h		−13.50	−13.50	0.00
TPA return temperature	°C		67	68.10	1.64
HN pumparound flow rate	m^3/h		529	530	0.19
HN PA duty	mm kcal/h		−10.70	−10.70	0.00
HN PA return temperature	°C			101.70	0.00
Diesel pumparound flow rate	m^3/h		224	220	−1.79
Diesel PA duty	mm kcal/h		−9.10	−9.10	0.00
Diesel PA return temperature	°C			181.50	0.00
AGO pumparound flow rate	m^3/h		105	100	−4.76
AGO PA duty	mm kcal/h		−5.40	−5.40	0.00
AGO PA return temperature	°C			210.77	−0.01
Atmospheric heater overflash	%			2.50	0.00
Atmospheric condenser pressure	kg/cm^2		0.66	0.60	−9.09
Atmospheric bottom stripping steam	kg/h		1650	1650	0.00
Kero stripping steam	kg/h		1500	1500	0.00
Diesel stripping steam	kg/h		1170	1170	0.00
AGO stripping steam	kg/h		198.70	198.70	0.00
Atmospheric heater outlet temp.	°C		334	334	0.00
Product flowrates and qualities					
OVHD gas	T/h	193	0.58	0.58	0.00
OVHD liquid	m^3/h	18.75	188	184	−2.13
HN	m^3/h	22	21	21.80	3.81
Kerosene	m^3/h	25.5	134	130.20	−2.84
Diesel	m^3/h	24.5	91	93.30	2.53
AGO	m^3/h	24.5	24	24.20	0.83
LSWR	m^3/h	17	71	74.10	4.37
HNN 95%	°C		144	149	3.47
KERO 95%	°C		243	240	−1.23
KERO flash point	°C		44.50	49.40	11.01
KERO freeze point	°C		−52	−58.60	12.69
DIESEL 95%	°C		347	340	−2.02
DIESEL cloud point	°C		N/A	1.40	N/A
DIESEL pour point	°C		N/A	−13.30	N/A
AGO 95%	°C		410	390	0.98
AGO pour point	°C		17.70	20.20	14.12
LSWR 95%	°C		N/A	721	N/A
LSWR pour point	°C		41.25	27	−34.55
Feed to the units					
Tapis crude	$/BBL	20.5	50 900	50 900	0.00
Condensate to crude unit	$/BBL	19.3	24 039	24 039	0.00
CTB	$/BBL	19.4	4800	4800	0.00
Total feed to the unit	m^3/h		531.59	531.59	0.00
Total feed cost	$/day		1 600 522.70	1 600 522.70	0.00
Utility cost	$/day		15 813.37	15 813.37	−0.29
MP steam	T	7.5	813.37	813.37	0.00
LP steam	T	7			
Fuel gas					−0.65
Electricity			15000	15 000	0.00
Total product flow rates	m^3/h		529.58	528.18	−0.26
Total product revenue	$/day		1 716 977.77	1 710 925.27	−0.35
Total profit	$/day		100 641.70	94 589.20	

- Current operating constraints.
- Current product and crude pricing as supplied by planning operations.

4.5. Economic objective function

In order to evaluate the improvement in profitability due to changing operating conditions in the simulation, an objective function calculates a "unit profit" which is the total product value minus the feed and utility costs. The objective function (to be maximized in this case) was formulated as follows:

$$\Phi_{Economic} = \sum_{i=1}^{NProd} C_i P_i - \sum_{j=1}^{NFeed} C_j F_j - \sum_{k=1}^{NUtil} C_k P_k, \qquad (3)$$

where C_i is the product price C_j the feed Cost C_k the utility cost, P_i the product flow rate F_j the feed flow rate U_k the utility flow rate.

For the online objective function, the following objective function, Φ, is recommended. This function accounts for the amount of product drawn and also penalizes the production of off-specification product (Δs is the absolute value of the quality deviation from the specification). The steady state gains $\mathrm{G_i}$ could be inferred during model development after the plant test. For the benefits study this formulation is not being used since off-specification product does not occur in the simulation.

$$\Phi_{Online} = \sum_{i=1}^{NProd} C_i(P_i - G_i \Delta s) - \sum_{j=1}^{NFeed} C_j F_j - \sum_{k=1}^{NUtil} C_k U_k, \qquad (4)$$

where Δs is the |quality – specification| G_i the gain of quality vs. product draw.

4.6. Data reconciliation objective function

The data reconciliation objective function is used to minimize an L2 norm of the difference between measured data and model predictions around key process measurements. In addition, the reconciliation objective function includes a second group of weighted least squares terms that allow feed characterization by allowing a refinement around a base feed profile (known). This is achieved through the minimization of deviations from a characteristic TBP analysis curve for the processed crude. The need for this type of augmented objective function becomes particularly important for crude unit optimization where feed composition is constantly changing due to a number of reasons including mixing and stratification. The nonlinear least-squares weighting strategy involves individual weights on measurements based on standard deviation, as well as an overall weighting factor for the feed characterization portion of the objective, as described in (5).

$$\Phi_{\mathrm{Recon}} = \sum_{i=1}^{NMeas} w_i (y_i - y_i^{meas})^2 + \alpha \sum_{j=1}^{NFeeds} \sum_{k=1}^{NTBPpts} (x_{jk} - x_{jk}^{ref})^2, \qquad (5)$$

where y_i is the model prediction for variable i, y_i^{meas} the actual measurement for variable i, w_i the weight factor for measurement i, x_{jk} the model value for TBP point k of feed j, x_{jk}^{ref} the assay reference value for TBP point k of feed j, and α the overall weight for the feed characterization term.

Prior to the parameter estimation phase, there is a gross-error detection step by which few, selected measurements are identified as "unreasonable" and are discarded.

5. Benefit calculation

5.1. Standard tangible benefits

The standard economic benefits are outlined in Table 3 and are derived from the calculation of the profit function as described in Table 4 and the off-specs product re-run as outlined in Table 5 (annual off-specs product). These benefits are true measures of the real savings that were obtained in the Petronas Melaka crude unit operation since implementing this control and optimization strategy. The product and feed flows were obtained during the post-audit exercises where the

Table 3
Advanced control benefits summary

Description	CDU controller	CND controller	GRP controller
Average profit when controller is ON (US$/HR)	$1298	$76	$407
Average profit when controller is OFF (US$/HR)	$1245	$49	$401
Incremental economic benefit (percent)	4.3%	55.1%	1.5%
Incremental economic benefit (US$/HR)	$53	$27	$6
Total profit for implementing DMCplus (US$/YR)	$465,607	$237,335	$49,732

Table 4
Profit function calculation

Description	Formulae
CDU Profit =	P11*11FC002 + P12*11ZFC004 + P13*11FC062 + P14*11FC050 + P15*FC049*P16*11FC047 + P17*11FC048 + P18*11FC053
CND Profit =	P21*11FC501 + P22*11FC502 + P23*11FC518 + P24*11FC514 + P25*11FC507
GRP Profit =	P31*11FC518 + P32*11FC062 + P33*11FC068 + P34*11FC522 + P35*11FI071 + P36*11FC072 + P37*11FC077 + P38*11FC083

Notes:

P11 = −89.32 Tapis crude cost ($US/M3)
P12 = −83.02 Bintulu condensate cost ($US/M3)
P13 = 69.2 stabilizer feed product price (use light naphtha price) ($US/M3)
P14 = 90.57 HNN product prices ($US/M3)
P15 = 96.86 kerosene price at Max KERO mode ($US/M3)
P16 = 89.32 diesel Prices at Max KERO mode ($US/M3)
P17 = 96.23 AGO product prices ($US/M3)
P18 = 64.16 LSWR product prices ($US/M3)
P21 = −83.02 Bintulu condensate price ($US/M3)
P22 = −81.77 Terrenganu condensate price ($US/M3)
P23 = 78.0 condensate tower OVHD (use light naphtha price) ($US/M3)
P24 = 91.83 condensate naphatha product prices ($US/M3)
P25 = 83.02 condensate bottoms product prices ($US/M3)
P31 = −78.0 condensate tower OVHD (use light naphtha price) ($US/M3)
P32 = −69.2 stabilizer feed product price (use light naphtha price) ($US/M3)
P33 = 64.16 crude stabilizer OVHD to SAT gas plant ($US/M3)
P34 = 64.16 condensate stabilizer OVHD to SAT GAS ($US/M3)
P35 = 86.8 medium naphtha to tank ($US/M3)
P36 = 86.8 medium naphtha product to HDS unit ($US/M3)
P37 = 69.19 light naphtha to storage ($US/M3)
P38 = 64.16 IC5 to storage ($US/M3)

Table 5
Product off-specs annually

Description	With DMCplus	Without DMCplus
Total kero to slop (bbl)	12,532[a]	66,012
Total diesel to slop (bbl)	12,365[a]	49,084
Total AGO to slop	0	11,553
Total LSWR to slop	0	6371
Total LPG to slop	0	25,853
Heavy naphtha	0	118
Medium naphtha	0	71,731
Light naphtha	0	90,856
Ic5	0	58,199
Total off-spec product loss profit (US$)	24,897[b]	379,777

[a]Denotes the annual generalization based on 3-month data.
[b]The total incremental benefit for reduction of off-specs product is 379,777–24,897 = US$354,880.

controllers were turned ON and OFF alternately every shift. The product and feed prices were obtained from the planning department to reflect the true economics of operating the refinery. A total benefit of over US$1,131,000 is obtained by running the advanced control system on-line annually. It is worth mentioning that this figure is larger than the originally predicted benefit of about US$685,000 (initial study). The detailed post-audit analysis results (where the new controllers were alternating between ON and OFF at randomly predetermined intervals) are presented for each controller in Figs. 1–3, respectively. In addition, a significant improvement in product quality by means of reduced variation was also observed and is shown in Table 8. The significant reduction in product property standard deviations is an indication of improved operation. Reduction in product quality variation allows us to operate closer to product quality limits, resulting in more valuable products.

The above benefits are achieved as a result of moving the manipulated variables in the controller while observing the process safety constraints and product quality specifications. Typical movements from key manipulated variables in the controllers are tabulated in Table 6. Contributions from the movements can be inferred with reference to the estimated benefits as shown in Table 7. In that study (prior to this project), the benefit of implementing this control and optimization strategy was estimated to be about US$685,000. Note the manipulated variable (MV) movements shown in Table 6 are similar to those shown in Table 7. While it is difficult to separate the contribution from individual manipulated variable to the overall benefit, the similarity is a clear verification of the understanding in the benefit study. The MV movements in Table 6 indicated

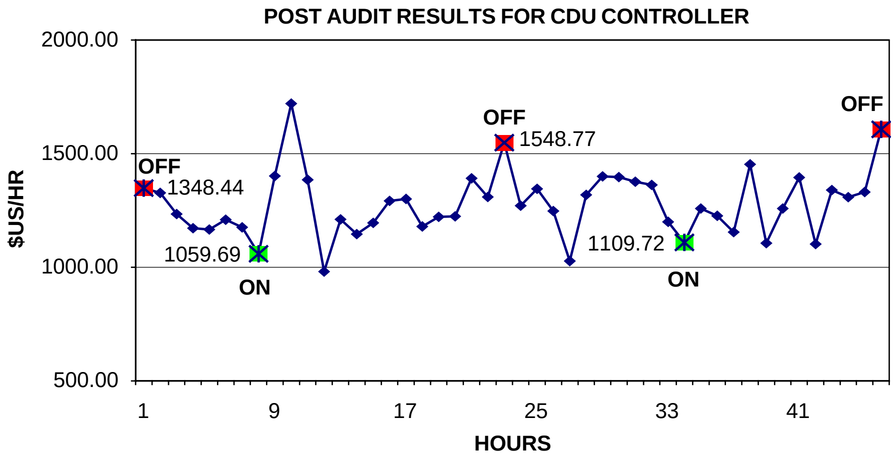

Fig. 1. CDU controller performance.

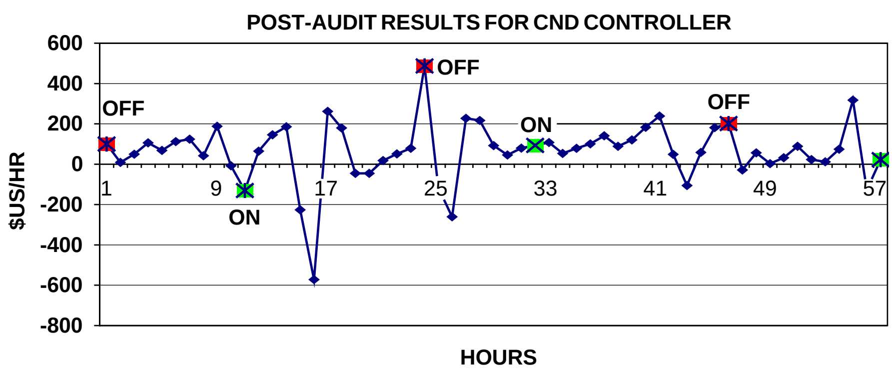

Fig. 2. CND controller performance.

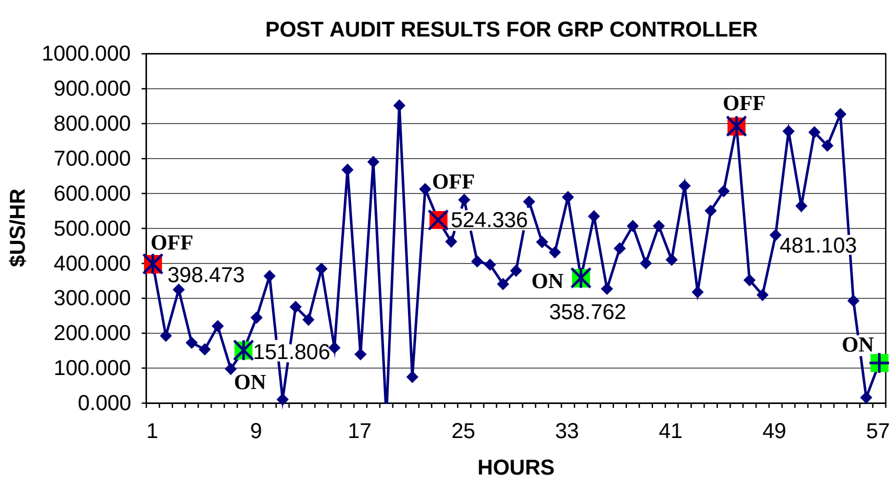

Fig. 3. GRP controller performance.

almost the same understanding as in the benefit study report. The only exception, as denoted by (**), was that the AGO pumparound was expected to increase rather than to decrease. This difference occurred because the controller had to cut AGO pumparound to maintain Diesel and Kerosene qualities. Note the LP cost tuning was changed to make the controller more robust when the crude slate varies significantly. Since the AGO

Table 6
Benefit contributors.

Manipulated variable	Tag name	DMC ON	DMC OFF	Direction
TPA pumparound	11FC006	753.14	782.16	DOWN
HN pumparound	11FC037	601.93	613.96	DOWN
Diesel pumparound	11FC038	82.48	82.45	UP
AGO pumparound	11FC035	195.8	201.95	DOWN**
CDU bottom stripping steam	11FC033			N/A
Kerosene stripping steam	11FC043	0.705	0.955	DOWN
Diesel stripping steam	11FC041	2	2.08	DOWN
AGO stripping steam	11FC040	2.00	2.08	DOWN
Throughput Max., COT	11TC089	328.4	327.9	UP
Kerosene cupoint	11SRK95B	236.16	236.04	UP
Diesel cutpoint	11SRD95B	346.38	347.36	DOWN

Table 7
Benefits estimated from benefit study report

Manipulated variable	Change by	Benefit in US$	Direction
TPA pumparound	10%		DOWN
HN pumparound	10%		DOWN
Diesel pumparound	10%		UP
AGO pumparound	5%		UP
Total pumparound benefit		$105,200	
CDU bottom stripping steam	5%		DOWN
Kerosene stripping steam	10%		DOWN
Diesel stripping steam	10%		DOWN
AGO stripping steam	0		DOWN
Total stripping steam benefit		$149,850	
Throughput maximization, COT	2 °C	$175,000	UP
Kerosene cutpoint	3 °C		UP
Diesel cutpoint	1 °C		DOWN
Total product cutpoint benefit		$255,000	
Total estimated benefit		$685,050	

pumparound was constrained, it was important to allow the controller to search for optimum solutions that release these physical constraints.

5.1.1. Reduction of off-specs products to slop

Data were collected during a six month period when PSR1-CDU implemented advanced control systems. The information collected was used to calculate the amount of off-specs product to slop for rerun. Since the implementation of the controllers, there was only one observed incident where the products were sent to slop for a period of 4 h. This incident occurred as the result of lack of training by the operator to properly maintain the inferential calculation in the controller. Additional training on the use of inferential to lab bias update program was performed. The results have been extremely favorable since the additional training.

It is important to emphasize that the inferential needs to work well to ensure that the product quality specifications are met. The controllers will manipulate all independent variable to its optimum conditions while maintaining the product specifications and process safety constraints.

5.2. Intangible benefits

In addition to the tangible benefits discussed in the above section, significant additional benefits were obtained upon implementing the advanced control system at the Petronas Melaka refinery as discussed below.

5.2.1. Ease of operation

The operation of the crude unit complex is much smoother, with fewer alarms as recently reported by the operators. The capability of the controller to continuously monitor important process constraints while pushing the units to optimize the economics of operation has been confirmed by a significant reduction in the number of nuisance alarms. Mode switch has been implemented in the controller and provides easy options that allow operator to swing the operation in a quick and efficient manner.

5.2.2. Reduction in sample analysis

All important product properties are predicted on-line from the rigorous inferential calculations. The accuracy of the inferential has helped to increase the performance of the controller and had a major impact in the reduction of non-routine laboratory samples. A custom program was written in the TDC3000 system to allow the bias update from the routine laboratory analysis and thus improve the prediction of the inferential calculations. Since the proper implementation of this program, the inferential calculations have been reported to perform well and the non-routine samples have been drastically reduced. Figs. 4–8 show that the inferential calculations have performed well and met all the requirements for acceptance as stated in the benefit study. These figures show the laboratory analysis results, the inferential predictions and the upper and lower inferential acceptance limits (Fig. 9).

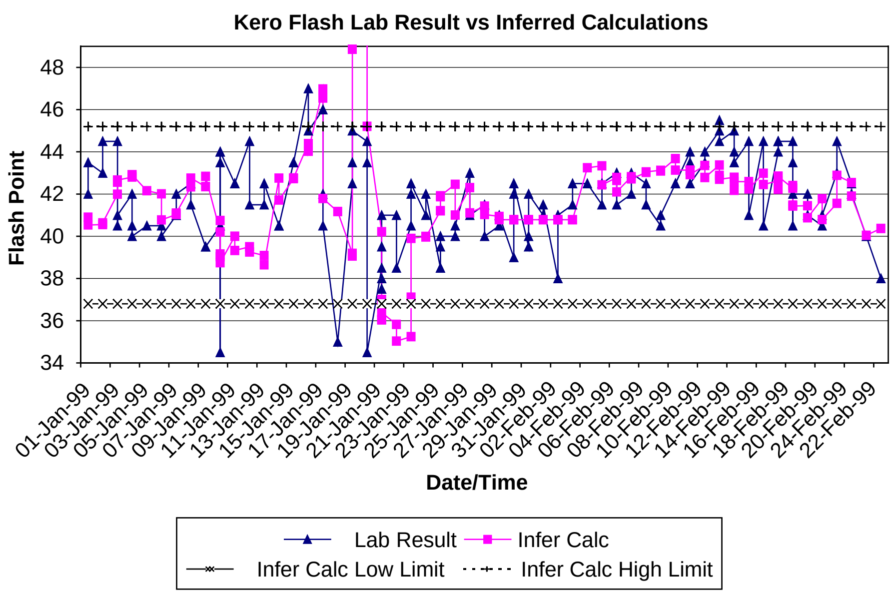

Fig. 4. Kerosene flash point.

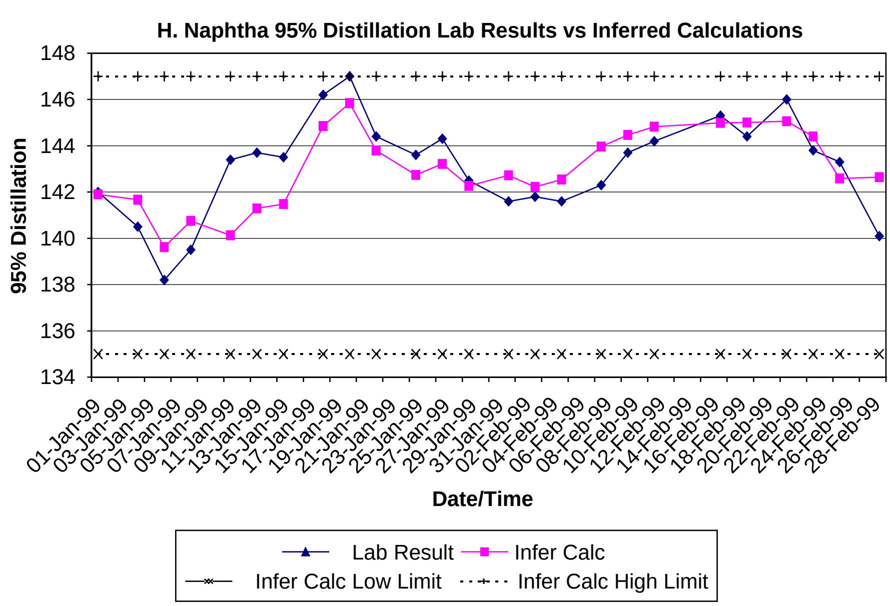

Fig. 5. Heavy naphtha cutpoint (95%).

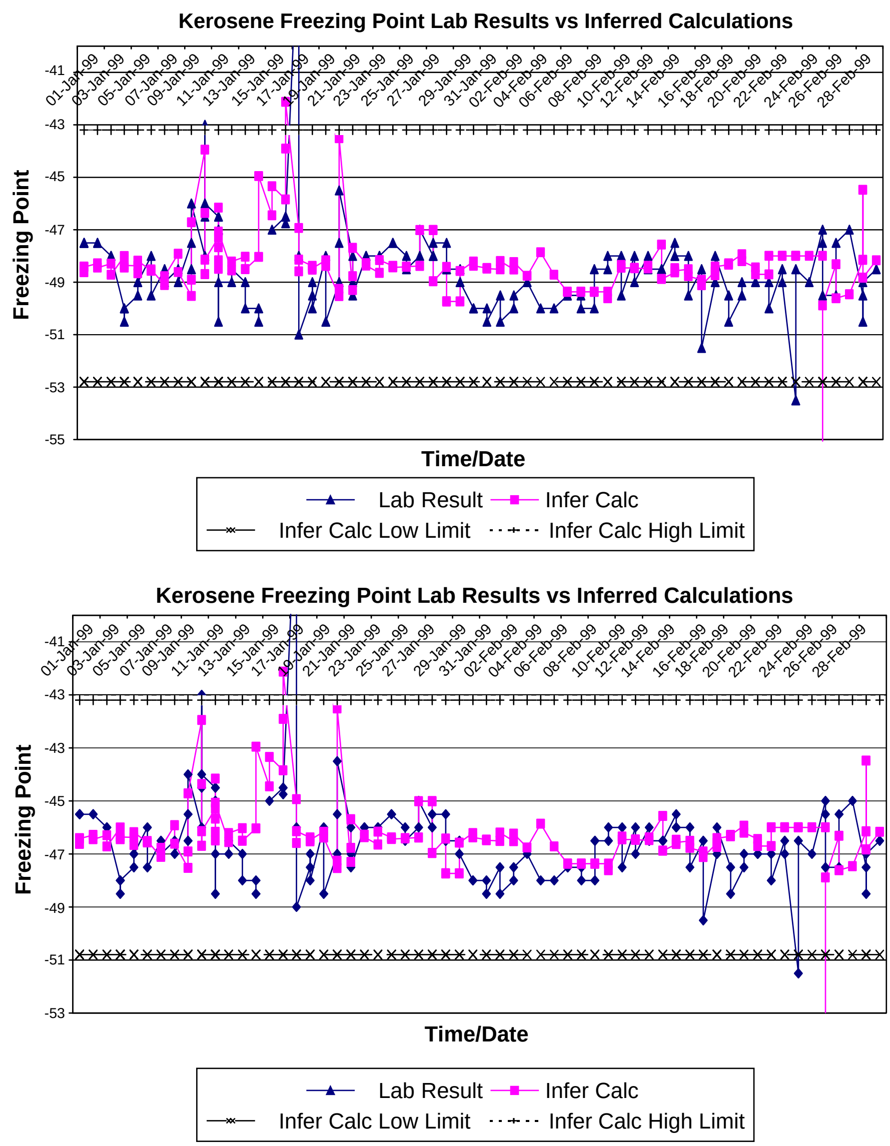

Fig. 6. Kerosene freeze point.

5.2.3. *Reduction in product qualities standard deviation*

Data were collected for the period from January to March after the controllers were implemented in PSR1-CDU. Standard deviations of all key product properties were calculated and tabulated in Table 8 (product quality standard deviation). The standard deviations of all key properties as given from the benefit study report were used for the reference to the standard deviation before implementing the advanced control strategy as described above.

As shown in the table, there are significant reductions in the product quality variations when controllers were running on-line. Most of the property standard deviation was reduced by a significant amount of almost 40–50%.

6. Conclusions and recommendations

6.1. *Conclusions*

The results presented in this study have shown an enormous amount of benefit attained by implementing a multivariable constraint controller in the CDU complex. This is because the controller has the capability to move several manipulated variables simultaneously and in cooperation in order to maximize profits in real time

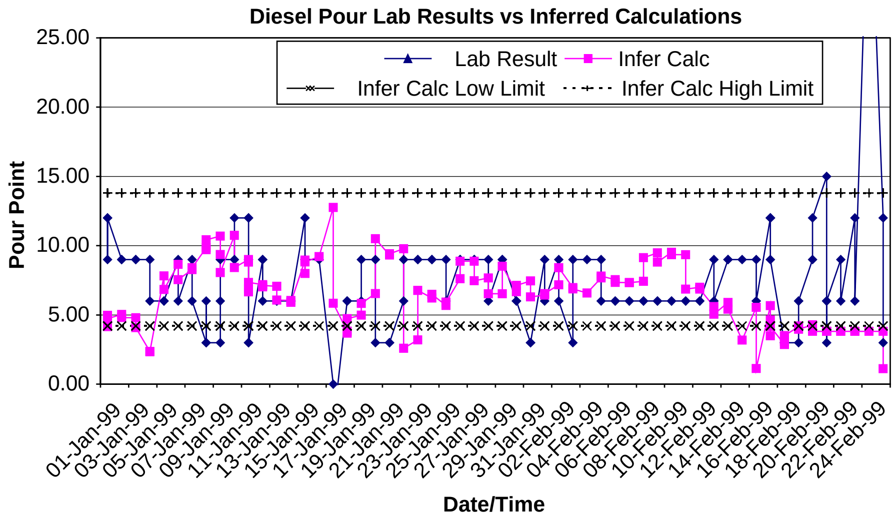

Fig. 7. Diesel pour point.

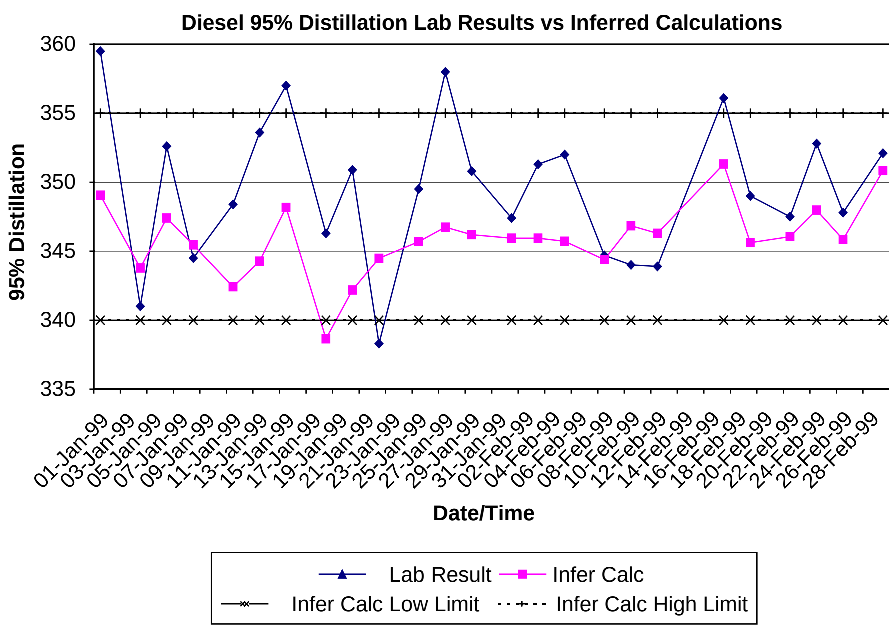

Fig. 8. Diesel cut point (95%).

while continuously observing the process safety constraints. It continuously searches for the optimum solution. In order, however, for this optimum to be meaningful it should be based on the correct, first-principles-based, auto-calibrated inferential calculations. Although a direct comparison between the benefits of this approach and a "standard" DMC controller application (where empirical data are used for the steady-state inferential calculations) was not performed, it should be noted that the discrepancies observed between empirical gains and first-principles gains can differ significantly in size and often in direction (derivative sign). The above supports the assertion that a controller based on partially incorrect steady-state gains can have significantly lower economic benefits.

Finally the accomplishments of this work can be summarized as:

- The establishment and confirmation of the benefits obtained from implementing the advanced control strategy using first-principles-model derived gains. From the results of the post-project audit outlined in the previous section, it is clear that the benefits

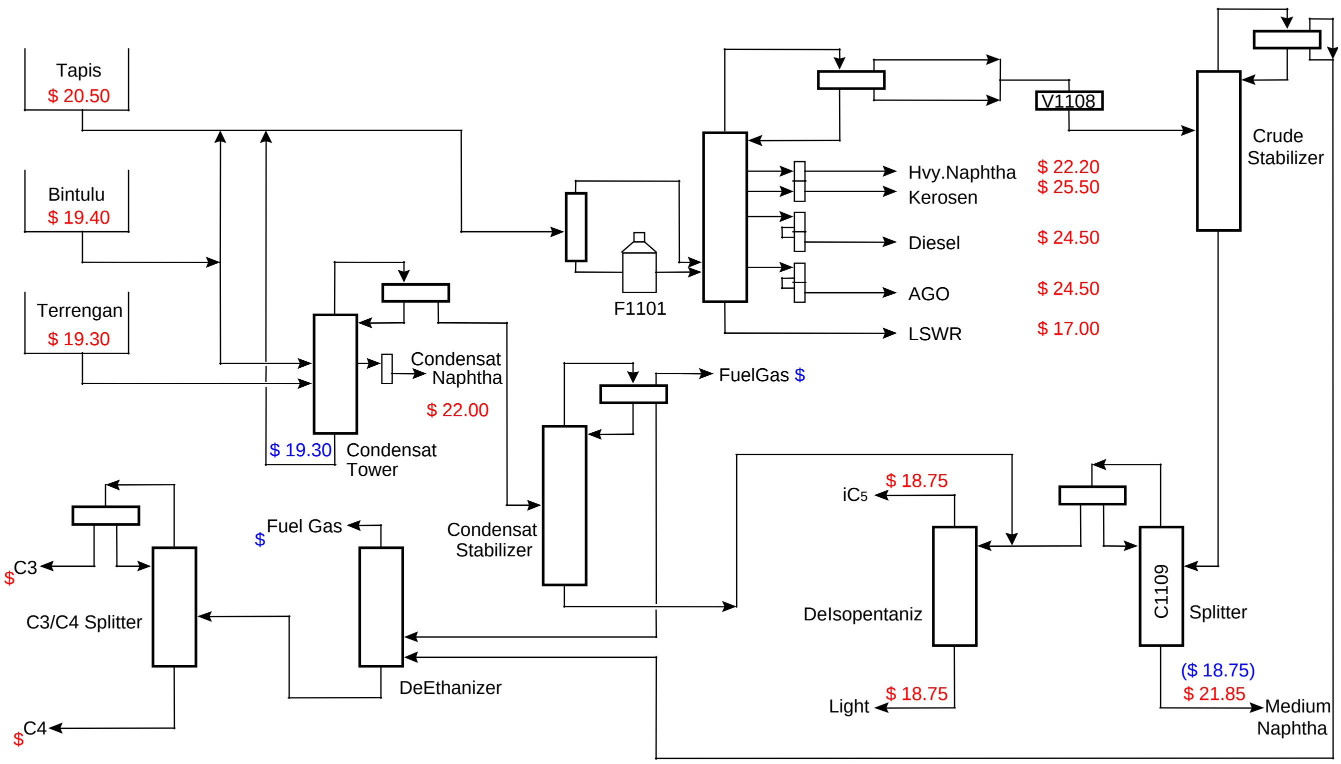

Fig. 9. Process flowsheet and product pricing.

Table 8
Product quality standard deviation

Description	Before DMCplus (°C)	After DMCplus (°C)
SRK freezing point S.D.	3.0	1.3
SRK flash point S.D.	1.4	1.4
SRK 95% point S.D.	3.1	2.2
Diesel pour point S.D.	3.0	2.6
Diesel 95% point S.D.	2.9	2.5
AGO pour point S.D.	3.0	2.3
AGO 95% point S.D.	6.1	4.9
LSWR pour point S.D.	3.0	1.7
HN 95% point S.D.	0.8	0.8

achieved at the Petronas PSR1 refinery using the controllers and the proposed methodology far outweigh the implementation costs. The project payback time was *less than 8 months*.

- The establishment of the required business process changes to help Petronas personnel maintain the controllers on-line. It is very important to understand that the benefits can only be sustained when the controllers are well maintained. A summary of the necessary procedures will be described in the recommendations section.

6.2. Recommendations

As discussed in the previous section, it is recommended that the following procedures and plans be adhered to, in order to ensure a high on-line rate for the controllers, thus ensuring that the achieved benefits are sustained.

(i) Continuously provide training/support to the operators to ensure that all MV/CV limits are loosened. Opening the limits is critical for the linear programming algorithm to find a feasible solution and thus ensures optimum solutions that maximize the profits of operating the unit.
(ii) Work with the operators to ensure that the routine laboratory sample analysis is entered into the system. This is critical to the success of the inferential estimates and thus the controller performance.
(iii) Continuously monitor the performance of the inferential estimates to ensure that the results are consistent with the laboratory analysis.
(iv) Ensure adequate support from the advanced process control engineer to the operational staff. This is to increase the confidence level of the operators. The authors' experience indicates that

when operators have more confidence and knowledge in the control strategy, they are more likely to keep the controller running on-line.

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