Identification and Control of a Pilot Scale Binary Distillation Column

F. Logist, B. Huyck, M. Fabré, M. Verwerft, B. Pluymers, J. De Brabanter, B. De Moor and J. Van Impe

Abstract— **This paper describes the design and implementation of a model predictive controller (MPC) for a pilot scale binary distillation column containing a mixture of methanol and isopropanol. In a first step experimental data are collected and linear black box models are identified. Secondly, the MPC is configured based on given requirements and restrictions and it is tested offline for several scenarios. Finally, the controller is implemented online and its performance is validated for the different scenarios. Hence, it is illustrated experimentally that the MPC allows a safe and flexible operation leading to enhanced control possibilities.**

I. INTRODUCTION

It is generally known that advanced process control tools (e.g., model predictive controllers) allow to systematically increase the performance and flexibility of chemical plants while ensuring the satisfaction of environmental and safety constraints [1], [2]. Since distillation is still one of the workhorses of the chemical industry [3], it is one of the most interesting processes for the application of advanced process control techniques (see, e.g., [4], [5], [6] and the references therein for general recommendations on advanced distillation control). The aim of the current study is to report on the development of a model predictive controller for a pilot scale packed distillation column, containing a mixture of methanol and isopropanol. It will be illustrated experimentally that it is possible to successfully develop and implement a linear model predictive controller based on straightforward procedures and with a limited effort.

Section II introduces the experimental distillation column set-up, while Section III describes the implementation strategy for the MPC. Section IV presents the obtained results and Section V summarises the main conclusions.

II. DISTILLATION COLUMN SET-UP

The experimental set-up involves a computer controlled packed distillation column (see Fig. 1 and 2). The column is about 6 m high and has an internal diameter of 6 cm. The column works under atmospheric conditions and contains three sections of about 1.5 m with Sulzer CY packing (Sulzer, Winterthur) responsible for the separation. This packing has a contact surface of 700 m^2/m^3 and each meter packing is equivalent to 3 theoretical trays. The feed stream containing a mixture of methanol and isopropanol is introduced into the column between the packed sections 2 and 3. The temperature of the feed can be adjusted by an electric heater of maximum 250 W. At the bottom of the column a reboiler is present containing two electric heaters of maximum 3000 W each. In the reboiler, a part of the liquid is vaporised while the rest is extracted as bottom stream. At the column top a total condenser allows to condense the entire overhead vapour stream, which is then collected in a reflux drum. A part of the condensed liquid is fed back to column as reflux, while the remainder leaves the column as the distillate stream.

In this set-up the following four variables can be manipulated: the reboiler duty Qr, the feed rate Fv, the duty of the feed heater Qv and the distillate flow rate Fd. Measurements are available for the distillate flow rate Fd, the feed flow rate Fv and nine temperatures, i.e., the temperature at the top of the column Tt, the temperatures in the middle of each packing section ($Ts1$, $Ts2$ and $Ts3$, respectively), the temperature between section 1 and 2 ($Tv1$), the temperature between section 2 and 3 ($Tv2$), the temperature in the reboiler of the column Tb, and the temperatures of the feed before and after heating ($Tv0$ and Tv, respectively). All actuators and sensors are connected to a Compact Fieldpoint (National Instruments, Austin) with a controller interface cFP-2100 and I/O modules cFP-AIO-610 and cFP-AI-110. A Labview (National Instruments, Austin) program is developed to control the actuators via PI controllers and to register the variables. There is no online measurement of the concentrations in the distillate and bottom stream, but these properties can be measured offline using, e.g., a refractometer. Thus, online concentration estimates can be derived based on temperature measurements using vapour-liquid equilibrium data and/or experimentally derived inferential relations. Nevertheless, in the current study the actual control of the column will be based on the directly measured temperatures (and not on the inferred concentrations) for controllability reasons.

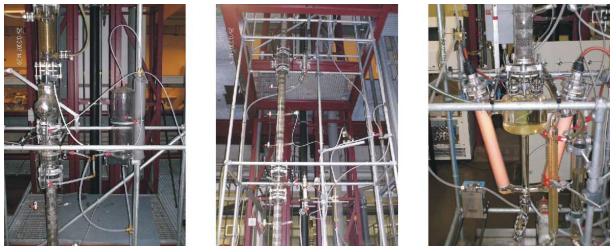

Fig. 1. Pictures of the pilot scale distillation column: condenser (left), packed section and feed introduction (centre), and reboiler (right).

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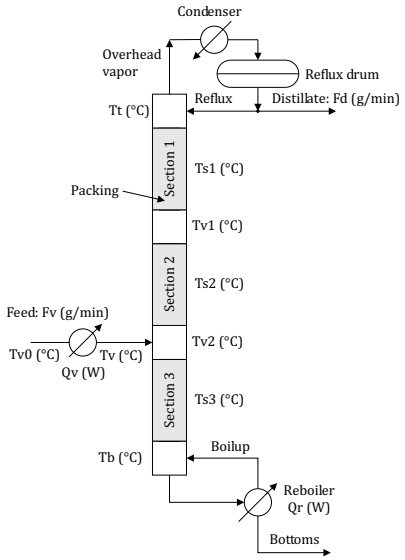

Fig. 2. Schematic overview of the pilot scale distillation column.

III. STRATEGY

The generic strategy for implementing a classic MPC (see Fig. 3) in practice consists of three phases: (*i*) modelling and identification, (*ii*) controller design and offline test, and (*iii*) controller implementation and validation. All steps can easily be performed within the INCA suite (IPCOS, Leuven). See www.ipcos.com/inca for more information.

A. Phase I: Modelling and identification

As the heart of any MPC is the process model, obtaining an accurate mathematical model is the first step. Since linear *black box* models can in general be fitted to given input-output data in a limited amount of time and without excessive experimental efforts, these types of models are employed in the current study. However, the input profiles for obtaining the input-output data should be designed carefully. On the one hand, the input range has to be large enough in order to cover the feasible input space and induce enough excitation in the outputs, but on the other hand, it must not be too large in order not to exit the region of linear input-output behaviour. Based on the experimental data the model type has to be selected and its parameters have to be fitted. Finally, the calibrated model has to be validated, i.e., its predictive performance has to be assessed with respect to new experimental data. This *model identification cycle* [7] has to be repeated until a satisfactory result is obtained.

B. Phase II: Controller design and offline test

Once an accurate process model has been obtained, the controller design phase starts. In the current study a classic moving horizon MPC scheme is employed. The most important controller variables to be specified are: (*i*) the selected setpoints, (*ii*) the boundaries in between which the column operates under stable conditions, (*iii*) the relative importance of the different setpoints and operation boundaries, as well as (*iv*) the length of the control and prediction horizon.

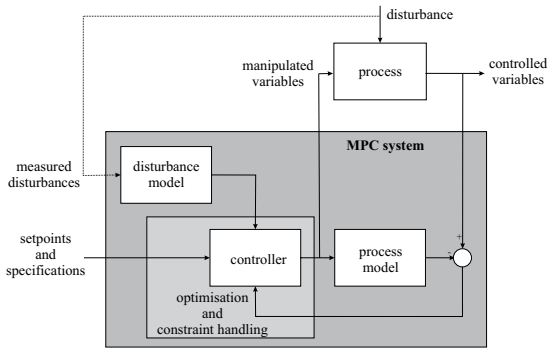

Fig. 3. Schematic overview of a classic MPC scheme. [8]

Before implementing the MPC on the real set-up, it is tested offline. Here, a simulator based on a modified column model replaces the real column. The modified model is derived based on the largest deviations between the model predictions and the experimental data, and, hence accounts for a *worst case* scenario. Typically, several real-life situations (e.g., setpoint changes, disturbances, ...) are mimicked in order to check the stability of the controller and to further tune its parameters.

C. Phase III: Controller implementation and validation

Finally, the controller is coupled to the column and its performance is checked in validation. Experiments based on the scenarios used in the offline tests are performed and the simulated and the real-life behaviour are compared. When the controller causes the column to behave in the desired way (e.g., fast responses without violating bounds), it can be employed during regular operation, otherwise, one must return to one of the previous stages to adjust the controller.

IV. RESULTS

This section describes the results when the above mentioned strategy is applied to the pilot scale binary distillation column. It is assumed that the controller can only manipulate the distillate rate Fd and reboiler duty Qr, but has no control of the feed rate Fv and the feed temperature Tv. Hence, the former two variables are the *manipulated variables* (MVs), while the latter two regarded as *disturbance variables* (DVs). The controlled variables (CVs) are the column temperatures Tt, $Ts1$, $Ts2$, $Ts3$ and Tb, as they relate to the separation quality.

The nominal operation point is given by a feed flow rate Fv of 150 g/min, a feed temperature Tv of 40°C, a distillate rate Fd of 70 g/min, and a reboiler duty of 4500 W. These values have been selected because they give rise to a stable operation, while providing enough space to safely change the inputs. The induced temperature profile varies between 65 to 67°C at the top and 80 to 82°C at the bottom. Since these values are close to the individual boiling points of methanol and isopropanol (i.e., 64.7 and 82.3°C, respectively), it can be concluded that the mixture is well separated.

A. Phase I: Modelling and identification

In this phase 4 x 5 (i.e., 20) models are derived to link each manipulated variable (i.e., distillate rate Fd and reboiler duty Qr) and (measured) disturbance variables (i.e., feed rate Fv and feed temperature Tv)) to each output variable, i.e., the temperature profile determined by Tt, $Ts1$, $Ts2$, $Ts3$ and Tb. Due to space restrictions only the results for the process models are discussed, but similar results have been obtained for the disturbance models.

1) Process model identification:: In the INCA suite different types of input signals can be designed, e.g., step, staircase and pseudo binary random noise sequence signals. For the current study staircase signals around the nominal operation point are employed. The magnitudes of the steps are ± 500 or ± 1000 W for the reboiler duty, ± 5 or ± 10 g/min for the distillate rate, ± 10 g/min for the feed rate and $\pm 5^{\circ}$C for the feed temperature. These values allow to observe the result of different step sizes without leaving the linear region around the nominal operation point. The step length is each time equal to 1 h as this value ensures that a new steady-state is reached. Although all variables are recorded every 50 ms, the experimental data are reduced to one sample every minute by averaging in order to improve the signal to noise ratio.

INCA provides several black box models, e.g., finite impulse response (FIR) and state-space (SS) models. FIR models are described as follows:

$$\begin{bmatrix} y(k) \\ \vdots \\ y(k+N_f) \end{bmatrix} = \begin{bmatrix} u(k) & \dots & u(k-N) \\ \vdots & \ddots & \vdots \\ u(k+N_f) & \dots & u(k+N_f-N) \end{bmatrix} \begin{bmatrix} M_0 \\ \vdots \\ M_N \end{bmatrix} \quad (1)$$

with $u(k)$ and $y(k)$ the in- and output at time k, N_f the measurement length, N the model length, and M_i the model parameters, and they are calibrated by a least squares fit. To avoid too nervous responses, the model can be smoothed by using a Tikhonov regularisation. The general state-space description is the following:

$$\mathbf{x}[k+1] = \mathbf{A}[k]\mathbf{x}[k] + \mathbf{B}[k]\mathbf{u}[k] \quad (2a)$$

$$\mathbf{y}[k] = \mathbf{C}[k]\mathbf{x}[k] + \mathbf{D}[k]\mathbf{u}[k] \quad (2b)$$

with $\mathbf{u}[k]$, the inputs (i.e., MVs and DVs), $\mathbf{x}[k]$, the states, and $\mathbf{y}[k]$, the outputs (i.e., CVs). The actual model calibration uses a subspace identification algorithm.

For the distillation column, three model types are each time considered, i.e., a second order state-space model (SS2), a FIR model (FIR) and a FIR model with a Tikhonov smoothing factor of 5 (FIR05) in order to reduce the noise sensitivity. The experimental results and the identified models for the temperatures Tt, $Ts2$ and Tb with as inputs the distillate rate and the reboiler duty are displayed in Fig. 4 and 5, respectively. These temperatures have been selected since they provide the best indications for the separation quality and the stability.

From Fig. 4 it is seen that higher distillate rates induce higher temperatures. Most variation is observed for the top stream, while the influence gradually decreases towards the bottom. Thus, as could be expected, the top temperature is more easily and directly controlled by the distillate rate than by the bottom temperature. The effect of the input changes is almost instantaneously visible in the output, and, thus, no delays have to be incorporated into the models. These observations comply with the theoretical expectations. Increasing the distillate rate, extracts a larger amount of the light component from the column and decreases the reflux rate, yielding both a less pure top stream. The bottom stream increases, however, in purity as also this stream contains less of the light component. The inverse effects are observed when decreasing the distillate rate.

In Fig. 5, it is observed that higher reboiler duties cause in general higher temperatures. This effect is the most pronounced for the bottom temperature Tb and decreases along the column, resulting in a signal which hardly exceeds the measurement noise for the top temperature Tt. Thus, also here, the controlled variables close to the manipulated variable are more easily controlled than variables further away. Again, the direct response of all controlled variables is clearly visible, and, hence, no delays have to be introduced. The observed behaviour can easily be explained physically. Increasing the reboiler duty, causes a larger amount of the light component to vaporise, resulting in a purer bottom stream and, hence, higher bottom temperatures. The result for the top is more difficult to predict a priori due to the presence of two counteracting forces. On the one hand, more heavy component vaporises due to the increased heat supply. But on the other hand, due to this increased vapour stream, the reflux rate will increase because of the fixed distillate rate, inducing a better separation and a purer top stream. The actual operation point determines which phenomenon dominates. This reason explains why it is hard to derive an accurate model between the reboiler duty (MV) and the top temperature (CV) and why it is important to monitor also the temperature of the packings along the column.

From both Fig. 4 and 5 and Table I, it is clear that the different models describe the experimental data accurately enough. However, there exists a trade-off between the response time and the noise sensitivity. Clearly, the FIR model responds fast to changes in the inputs but it also reacts faster to noise, whereas the state-space model exhibits a smoother evolution. Therefore, state-space models have been selected for all models with as input the reboiler duty, while FIR models have been adopted for all models with as input the distillate rate. Hence, when the models for all inputs and outputs are combined, the final global column model is obtained. Finally, it should also be noted that the models used provide a linear approximation of a nonlinear process, since equal step changes in the inputs do not always lead to equal changes in the output.

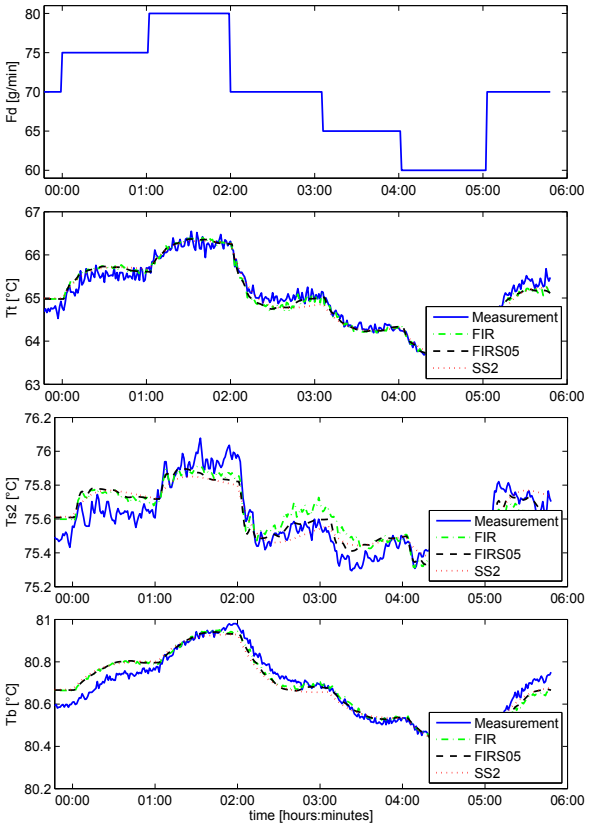

Fig. 4. Model identification: input variable Fd (upper plot); model predictions and measurements for output variables Tt, $Ts2$ and Tb (lower three plots).

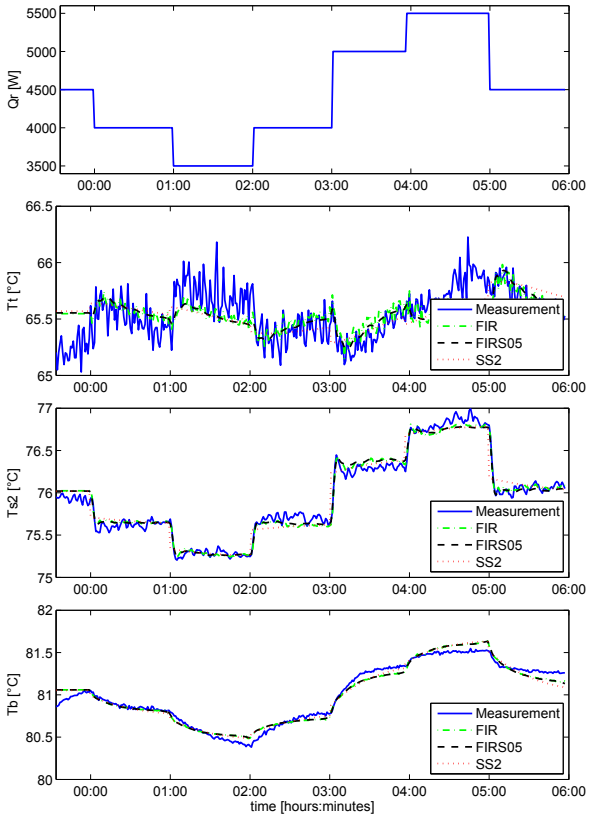

Fig. 5. Model identification: input variable Qr (upper plot); model predictions and measurements for output variables Tt, $Ts2$ and Tb (lower three plots).

TABLE I

SUM OF SQUARED ERRORS DIVIDED BY THE NUMBER OF SAMPLES.

	Estimation		Validation
	Qr (SS-model)	Fd (FIR-model)	
Tt	0.036	0.022	0.137
Ts2	0.012	0.013	0.014
Tb	0.005	0.002	0.015

2) Process model validation:: To check the predictive quality of the derived column model, the model predictions and experimental results are compared for a carefully designed validation test signal, in which both inputs are changed simultaneously. Here, modifying the inputs at the same time gives rise to easier and more difficult changes. Counteracting phenomena, e.g., increasing the distillate flow rate and decreasing the reboiler duty have counteracting effects on the bottom purity, are more difficult to predict than synergistic effects, e.g., increasing both the distillate flow and the reboiler duty.

The resulting measurements and predictions are displayed in Fig. 6. Although, the general trends for the top temperature are well predicted, fast modifications of the flow rate are not captured well. The quality of the predictions of the middle packing temperature $Ts2$ is high. In addition, since most of the separation is performed in this part of the column, this temperature $Ts2$ is attractive to control the column and its stability. Finally, also the bottom temperature is quite accurately predicted despite the propagation of errors originating from difficult to predict counteracting control changes. Table I depicts for these variables the Sum of Squared Errors (SSE) divided by the number of samples. As can be seen, the validation SSE of $Ts2$ is comparable with the estimation SSE, whereas for both Tt and Tb, the validation SSE is one order of magnitude larger than the estimation SSE. However, the model is believed to posses enough predictive power in order to be employed within an MPC scheme.

B. Phase II: Controller design and offline test

In general, the distillation column has four inputs, i.e., distillate rate Fd, reboiler duty Qr, feed rate Fv and feed temperature Tv, of which only the first two can be manipulated, and five outputs (i.e., top temperature Tt, bottom temperature Tb and three intermediate temperatures $Ts1$, $Ts2$ and $Ts3$. Consequently, for the controller design, the distillate rate Fd and reboiler duty Qr are used as *manipulated variables*, while the feed rate Fv and feed temperature Tv) are regarded as (measured) *disturbance variables*. To accurately control the separation quality and the stability of the column, the top, bottom and middle packing temperature $Ts2$ are considered as the most important *controlled variables*.

The classic receding horizon MPC controller employed has a prediction and control window of 150 and 90 min, re-

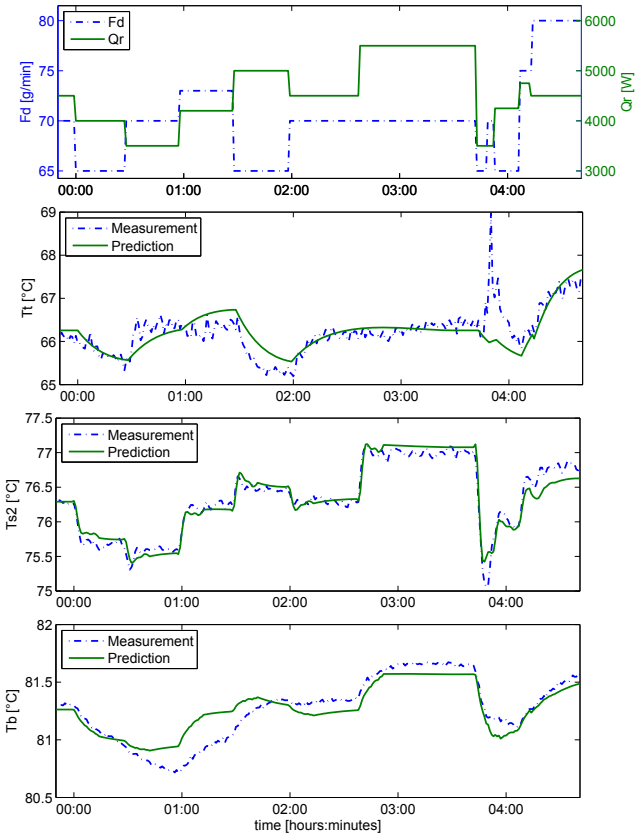

Fig. 6. Model validation: manipulated variables Qr and Fd(upper plot); model predictions and measurements for controlled variables Tt, $Ts2$ and Tb (lower three plots).

spectively, and updates its control action once every minute. For practical reasons the operating range of these MVs is bounded, i.e., between 3500 en 5500 W for the reboiler duty and between 60 en 90 g/min for the distillate rate. In addition to prevent the actuator hardware from too large (and too fast) variations, maximum step changes are imposed, i.e., 300 W and 5 g/min. The two MVs introduce two degrees of freedom, which can be used to satisfy two additional requirements. Typically, *operational* requirements (e.g., stability and safety) have the highest priority, followed by *product* requirements (e.g., purity constraints) and economic requirements (e.g., energy consumption). Requirements of equal importance are finally traded off based on given weights.

To check the performance of the controller offline several scenarios are examined based on simulations. Here, the real plant is replaced by a model, which is based on the largest deviations between the identified process model and the measurements. Successfully passing this *worst case* test is required to proceed to the implementation of the controller on the real process. Two scenarios are tested. Case 1 examines the capability of the controller to reject disturbances in the feed stream. Both the feed flow rate Fv and the feed temperature Tv change every 10 min (see Fig. 7), while the aim is to maintain constant value for the top and bottom temperatures.

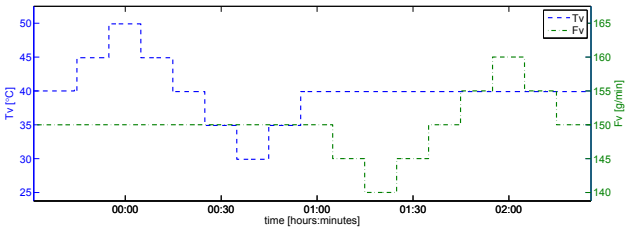

Fig. 7. Case 1: disturbances in the feed stream: flow rate Fv and temperature Tv.

Case 2 checks the controller's capacity for tracking setpoints for the top temperature. Hereto, the setpoints are changed by 0.5°C every 1.5 h. These scenarios correspond to real-life situations since in practice the feed stream properties can often not be controlled, and differing customer demands involve switches in the purity of the top stream. It is observed that the controller performs well. However, due to space restrictions the resulting figures are not displayed here, but together with the controller validation results (Fig. 8 and 9). It should also be noted that before the addition of the MPC scheme to the column, setpoint tracking of the column temperatures was not possible. Hence, the MPC introduces additional control possibilities.

C. Phase III: Controller implementation and validation

Finally, the MPC controller is implemented on the column itself and it is tested experimentally for the two scenarios. Fig. 8 and 9, display the results for both scenarios.

1) Case I: disturbance rejection:: The first scenario involves fast disturbances in the feed stream. As can be seen from Fig. 8, the MPC controller counteracts the disturbances by adjusting the distillate flow and the reboiler duty. Although the actual controller actions do not always coincide with the ones from the simulated worst case test case, it is seen that the top and bottom temperatures are maintained closely around their setpoints and that the actual deviations are smaller than the simulated ones. In addition, it is seen that the temperature of the middle packing remains within the specified bounds and does not exhibit major fluctuations, which indicates the stable operation of the column.

2) Case II: setpoint changes in Tt:: In the second scenario a staircase trajectory is requested for the top temperature Tt, while the bottom temperature Tb has to be kept constant. From Fig. 8 it is seen that the controller accurately steers the process to the desired setpoints. Clearly, the evolution of the top temperature follows closely the evolution in the distillate flow rate, while the bottom temperature is predominantly kept constant by adapting the reboiler duty. Hence, the model predictive controller acts in the intuitive and expected way. Also a stable operation is guaranteed as the middle packing temperature $Ts2$ hardly fluctuates.

Based on the experimental results for both scenarios, it can be concluded that the designed MPC enables a flexible, efficient and stable operation of the binary distillation column under study.

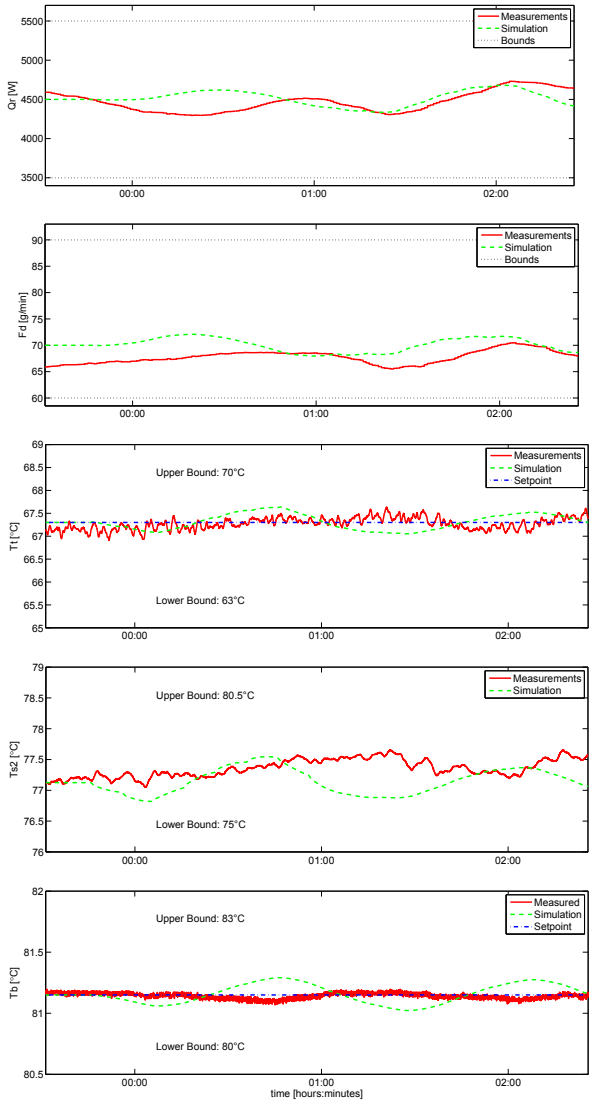

Fig. 8. Controller validation case 1: manipulated variables Qr and Fd (upper two plots); simulated behaviour and measurements for controlled variables Tt, $Ts2$ and Tb (lower three plots).

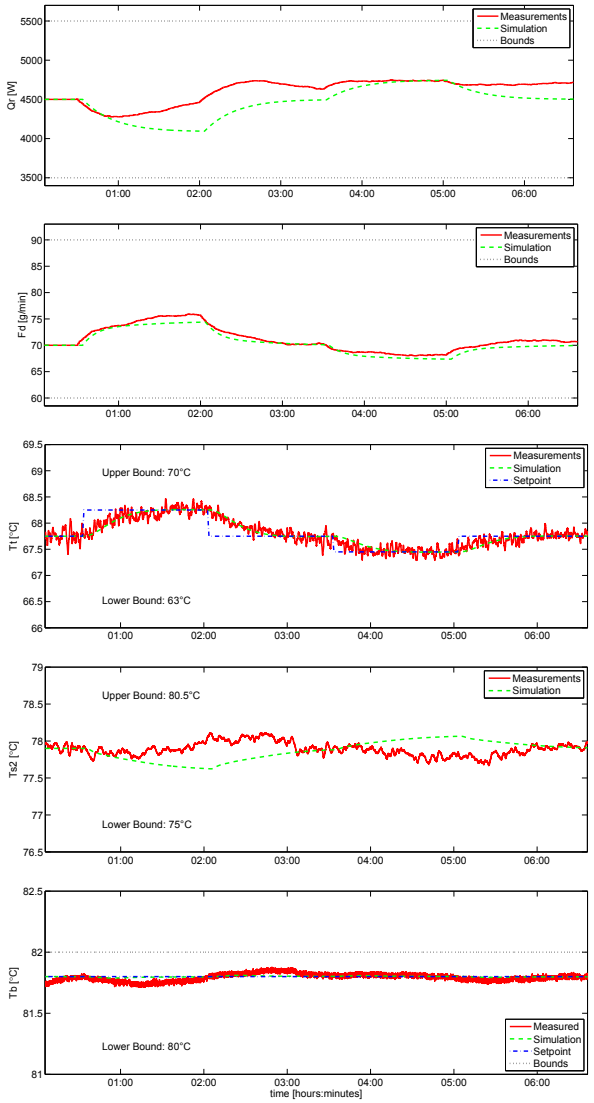

Fig. 9. Controller validation case 2: manipulated variables Qr and Fd (upper two plots); simulated behaviour and measurements for controlled variables Tt, $Ts2$ and Tb (lower three plots).

V. CONCLUSIONS AND FUTURE WORKS

In the current study a linear black box MPC controller has been implemented on a pilot scale packed distillation column for the separation of a mixture of methanol and isopropanol. Hereto, a plant model has been identified and validated based on step tests in a first phase. In a second phase, a controller has been designed and it has been successfully tested offline based on a worst-case scenario. Finally, the MPC has been applied to the practical set-up and its performance has been validated experimentally. The experimentally tested scenarios involved the rejection of disturbances in the feed stream and the tracking of setpoint changes along the column. It has been shown that the MPC is able to safely and efficiently fulfil the requirements of the different scenarios. Possible directions for future research involve the comparison of the current black-box approaches to more physically inspired white-box methodologies.

VI. ACKNOWLEDGMENTS

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