TECHNICAL PAPER

Reference tracking of membrane distillation with practical nonlinear model predictive control

Autor: M. Bindels, B. Nelemans
Version 1.0

Abstract
In this technical paper the use of model predictive control is introduced. An example is given where practical nonlinear model predictive control (PNMPC) is used to minimize the error between the obtained and the reference distillate production. In PNMPC an objective function is minimized given the constraints of the process. In this case the objective function is to minimize the error between the measured and reference distillate production.

The results indicate the PNMPC can be used for reference tracking. In this case only the reference trajectory was followed. However, the objective function can be very wide, and can even be changed to reduce the operating cost of the whole system. Therefore, PNMPC shows great promise in membrane distillation applications.

aquastill

Introduction

Most membrane distillation processes operate in a steady state manner. However, this is not always preferred. For example, the distillate demand in a chemical plant might fluctuate, or less water might be needed in the night as processes are shut down.

The best method to make sure that the distillate demand is reached, is to use model predictive control (MPC). In MPC, a process model is combined with an optimizer to minimize the objective function given the constraints of the process. The output of the optimizer are the future states of the variables in the process. The constraints can range from the amount of heat available, to the most basic limitation that a tank can not be more than empty. The overall scheme is shown in Figure 1.

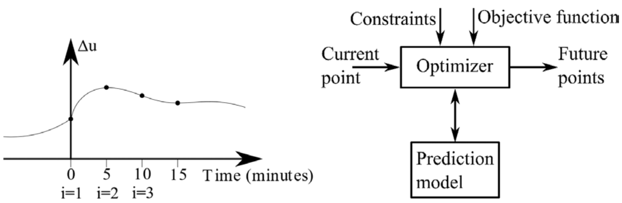

Figure 1 Schematic view of model predictive control. On the left the future control actions. On the right the block scheme of the component used in MPC.

The goal treated in this technical paper is to reduce the error between the reference trajectory and the predicted distillate flux. Therefore, the objective function can be written as:

$$f_{opt} = \sum_{i=1}^{N_{horiz}} \left| J(i) - J_{reference}(i) \right|$$

Equation 1

Most systems are linear for which a linear optimizer, like simplex, can be used. Nonlinear systems, like membrane distillation, need to use nonlinear optimizers which are harder to solve. An example of a nonlinear optimizer is simulated annealing. In practical nonlinear model predictive control (PNMPC) method the nonlinear model is transferred to a linear model, for which a linear optimizer can be used. In this work, the earlier developed model from Aquastill is used [1,2].

Practical nonlinear model predictive control of MD

Practical nonlinear model predictive control (PNMPC) uses an approximation for calculating the output prediction vector, Y, as a linear function of the future control action Δu, along the prediction horizon N [3]. This can be written as follows:

$$Y = F + G \cdot \Delta u$$

Equation 2

F is the response of the system when no new inputs are applied, also called the free forced response. G is a matrix containing the partial differential equations. The method is similar to linearization of polynomial equations. In case of V-AGMD, the feed flow rate, membrane inlet temperature, and condenser inlet temperature can be adjusted during the process. The output vector Y consist here of the distillate flux, J.

In [2] a method was proposed for the approximation of dynamic processes. The same method is applied for obtaining an equation for the AS27 modules, which results in equations below. The coefficients are listed in Table 1. These equations are based on a validated model of V-AGMD. ϕ is the feed flow rate of the MD module.

$$J^i = a_0 + a_1 T_{con,i} + a_2 T_{mem,i} + a_3 \phi_i + a_4 T_{con,i}^2 + a_5 T_{mem,i}^2 + a_6 \phi_i^2 + a_7 T_{con,i} T_{mem,i} + a_8 T_{con,i} \phi_i + a_9 T_{mem,i} \phi_i$$

Equation 3

Coefficient	Value	Coefficient	Value
a_0	-2.554E-03	a_5	1.053E-04
a_1	2.629E-02	a_6	-6.593E-02
a_2	-1.280E-02	a_7	-3.269E-05
a_3	-4.535E-01	a_8	-3.860E-02
a_4	-4.187E-04	a_9	5.103E-02

Table 1 Regression coefficients for equation 3. E^{-b} stands for 10^{-b}, so E^{-5} stands for 10^{-5}.

The equation above can be described in the following form:

$$J_i^{PNMPC} = F_{J,i} + \left[G_{J,Tcon}, G_{J,Tmem}, G_{J,\phi_i}\right] \cdot \left[\Delta u_{T_{con}}, \Delta u_{T_{mem}}, \Delta u_{\phi}\right]^T$$

Equation 4

This way, a linear optimizer can be used, which are computationally more efficient. The free forced response $F_{J,i}$ can be determined by using the process parameters from the current step. The G-values can be determined as in the following equation. Others can be calculated similarly.

$$G_{J,T_{con}} = \frac{\partial J}{\partial T_{con}} = \left(a_1 + 2a_4 T_{con,i} + a_7 T_{mem,i} + a_8 \phi_i\right)$$

Equation 5

The constraints of the system of the system can be written as follows:

$$T_{mem,min} - T_{mem,i} \leq \Delta u_{T_{mem},i} \leq T_{mem,max} - T_{mem,i}$$

Equation 6

$$T_{con,min} - T_{con,i} \leq \Delta u_{T_{con},i} \leq T_{con,max} - T_{con,i}$$

Equation 7

$$\phi_{min} - \phi_i \leq \Delta u_{\phi,i} \leq \phi_{max} - \phi_i$$

Equation 8

The first two constraints are needed to make sure that the temperatures are not higher or lower than allowed. The third constraint depends on the maximum pressure drop, which limits the maximum flow allowed.

In practice, the control algorithm developed above can be used to determine a trajectory of the temperatures and the brine flow. The trajectory is then sent to the MD system where simple PID control can be used for trajectory following. This results in a two-layer control system, where in the upper layer PNMPC is used to for determining the optimal trajectory. And the lower layer is used trajectory following. The two-layer system is shown in Figure 2. The benefit of this architecture is that the current electronics of the MD system can remain simple and robust.

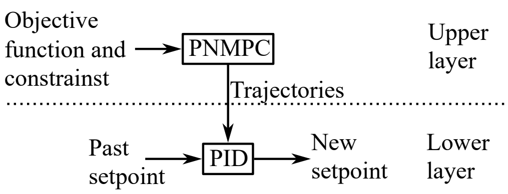

Figure 2 Control architecture that can be used in practice.

Most disturbances can already be accounted for by the current control system. For example, tank levels are automatically controlled, and the maximum brine temperature is controlled by automatic valves. These valves can be employed for reference trajectory.

Not all variables are needed

The gained output ratio (GOR) of membrane distillation depends on the inlet temperature of the condenser and membrane. The GOR is the highest at a membrane inlet and condenser inlet temperature of 80°C and 20°C, respectively. Furthermore, the salinity of the intake water is usually fixed to the salinity of the seawater. Therefore, the condenser and membrane temperature can be omitted from the equations above. This results in a simpler model and reduces the calculation time that is needed.

Case study/example

In the following example the PNMPC method will be employed to follow a fictious sinusoidal reference trajectory, which can be seen on the left side of Figure 3. A noise term is added to simulate the effects of errors on the outputs e.g. valve errors, sensors not measuring perfectly, etc.

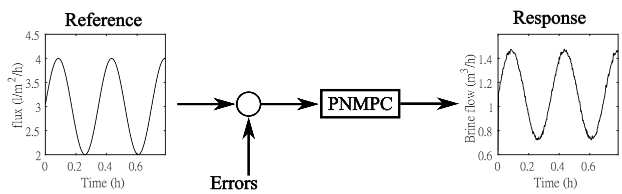

Figure 3 Trajectory shown on the left, and results of the simulation on the right.

The results can be seen in Figure 3. First the response with errors is send to the PNMPC system. Then the optimizer and model select the values which would minimize the tracking error. This is done by changing the brine flow. The flux changes as the brine flow is reduced or increased, which can bee seen in Figure 4. The influence of the noise/errors can clearly be seen in the graph.

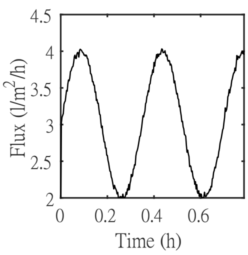

Figure 4 Resulting flux of the simulation

Overall, the PNMPC algorithm follows the flux closely and the PNMPC algorithm can be used in practice. In this case the objective function was quite simple but can be expended to include the complete operating cost of the system. Therefore, the use of PNMPC is very wide.

Conclusion

A steady state flux is not always preferred. Therefore, a method is needed for the reference tracking of the distillate flux. Here, the use of practical nonlinear model predictive control (PNMPC) is used for this purpose. In PNMPC an objective function is minimized given the constraints of the process. In this case the objective function is to minimize the error between the measured and reference distillate production.

The results show that the model follows the pattern closely. A noise term is added to simulate the effect of measurement errors, actuator errors, etc. The effect of the noise can be seen in the results, which indicates that a noise reduction process is needed after the results obtained from PNMPC.

In this case only the reference trajectory was followed. However, the objective function can be very wide, and can even be changed to reduce the operating cost of the whole system. Therefore, PNMPC shows great promise in membrane distillation applications.

References

[1] M. Bindels, N. Brand, B. Nelemans, Modeling of semibatch air gap membrane distillation, Desalination. 430 (2018) 98–106. doi:10.1016/j.desal.2017.12.036.

[2] M. Bindels, B. Medaer, M. Gebrehiwot, B. Nelemans, Approximation of dynamic membrane distillation processes applied to concentration of aqueous sucrose solutions, Desalination. 503 (2021) 114951. doi:10.1016/j.desal.2021.114951.

[3] A. Plucenio, D.J. Pagano, A.H. Bruciapaglia, J.E. Normey-Rico, A practical approach to Predictive Control for nonlinear processes, IFAC, 2007. doi:10.3182/20070822-3-za-2920.00035.