1st September 2016 Hans Aalto, Martti Larinkari, Jaakko Nauha

FACE LIFT OF REAL TIME OPTIMIZATION TO TRULY DYNAMIC

On-line, real-time optimization by computers has been developed and practised since the 1960's with varying success within the process industry. Typically optimization is based on existing rigorous process models, which assume steady state operation. However, processes rarely run in conditions, where the models explain the process behaviour at best. This paper will outline improved methods of on-line real-time optimization including a comparison with the traditional approaches. A dynamic real-time process optimization (DRTO) is introduced, which leverages conventional model predictive control (MPC) applied in advanced process control (APC) towards economically driven, fully functional real-time on-line optimization.

Optimization and process models

One of many *optimization tasks* related to design and operation of process plants is the calculation of *optimum* flow rates, temperatures, pressures, and chemical compositions etc. of individual major units of equipment such as chemical reactors, distillation columns, compressors and steam/heat generators. This task, sometimes called "process simulation", is done by advanced software including rigorous mathematical models and requires many work hours by experienced specialists, even if it is common to limit the task to some fixed, constant conditions of the process to be designed and it is ambient. Normally, these calculations assume *steady state operation* of the process, where all variables attain constant values, i.e. they do not vary as a function of time. This calculation task involves investigation of the process behaviours, for instance in different temperatures, but the transition from one (design) temperature to another (design) temperature is omitted, because it would involve a function of time. This reveals one of many idealisations seen on the process designer's desk: in reality, transitions between different process conditions are very frequent, but they are normally left away from process optimization calculations. Process equipment related to transitions, like tanks, are dimensioned by rule of thumb, but there is an increasing trend towards using *dynamic simulators* for more demanding cases or for optimizing the process with respect to process dynamics.

Going on-line

It is quite rational to think of re-using the rigorous models developed during the process optimization calculations mentioned above in *real-time optimization* of the process. On-line, *real-time optimization* (RTO) can be built around the developed process models by applying appropriate *optimizer* software which finds the maximum of a benefit function related to the process while respecting the behaviour of the process described by the models. For example, if the optimizer considers extracting more production from a distillation column for more benefit, the model defines how the product quality approaches its purity specification limit.

The rigorous model applies for the process in steady state conditions, i.e., when all flows, temperatures, pressures, raw-material and product qualities are at their fixed values. Because processes in reality always are subject to fluctuations, the results provided by using the model are not correct. In RTO, this challenge is handled by the software, which looks at the historical behaviour of relevant process variables and flags an approximate steady state condition, when the variance of those variables fall below given limits. Consequently, this launches the real-time optimization cycle.

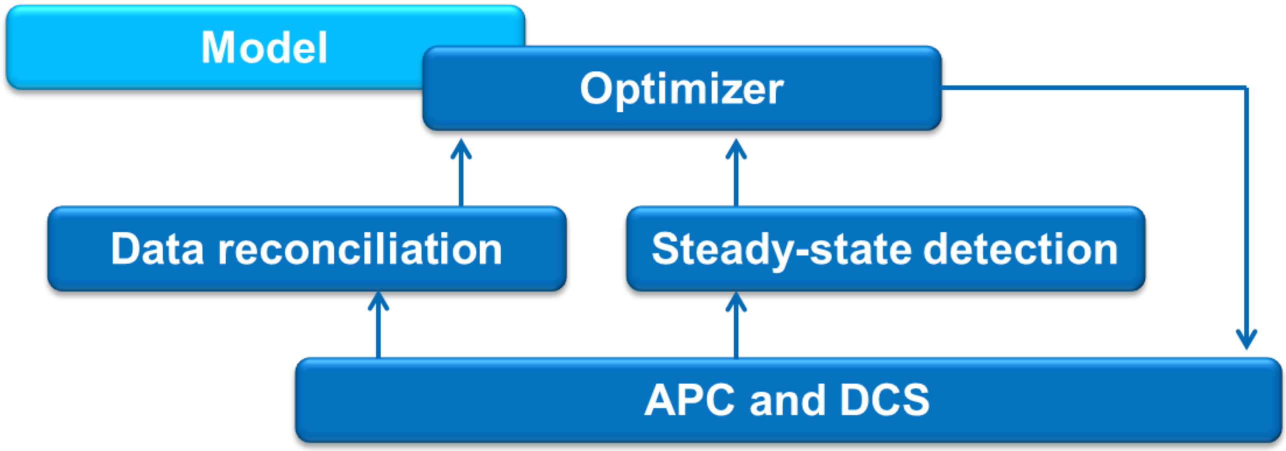

Figure 1. Building blocks of RTO. The data reconciliation and steady state detection blocks may be seen as "interface to the real world". The output of the optimizer are "commands" automatically sent to an underlying APC or directly to the process control system.

It is mandatory for RTO to use measured process data in order to reflect the true situation of the process as closely as possible. Typically, RTO systems incorporate software for *data reconciliation*, which applies small corrections to the average values of measured variables over a past time period in order to make the corrected values to close material, energy and chemical component balances. In addition, data reconciliation compensates for measurement errors.

When the real-time optimization cycle is finally launched, it typically requires several minutes or even hours for completion. Due to the iterative nature of the calculations, some ill-conditioned data input (although checked for steady-state and reconciled) may cause convergence problems leading to prolonged calculation times or even failures, which might prevent obtaining new optimization results for this cycle.

Conclusively in spite of its sound basic idea, RTO based on rigorous steady state models do have drawbacks, which relate to built-in complexity and a certain failure probability. In particular, processes with frequent changes in raw-materials, operating conditions, ambient conditions and product quality specifications (or grades) may not be able to run RTO at all, if they seldom come close to steady state operation.

There is no such thing as steady state

Saying this categorically may be an over-statement, but in fact processes rarely operate in steady state. This led us to develop *Dynamic real-time optimization* (DRTO) to tackle previously mentioned issues of traditional RTO. One of the initiatives for the development came from the excellent track record of *model-predictive control* (MPC), which is the most commonly used methodology for advanced process control (APC) within the process industries. The properties of MPC may be crystallized as follows:

- It uses experimental, simple process models derived from true, measured process behaviour
- These models are used to predict the expected deviation in controlled variables with respect to their targets
- The deviation is formulated as a cost function, which is minimized at every control cycle
- The control cycle is short and at every cycle true process measurements are obtained and incorporated in the control deviation minimization
- MPC honours and, on the other hand, exploits the process constraints

MPC is based on feedback control, which does not rely on steady state conditions. Respectively, short cycle times and frequently updated measurements eliminate the need for data reconciliation.

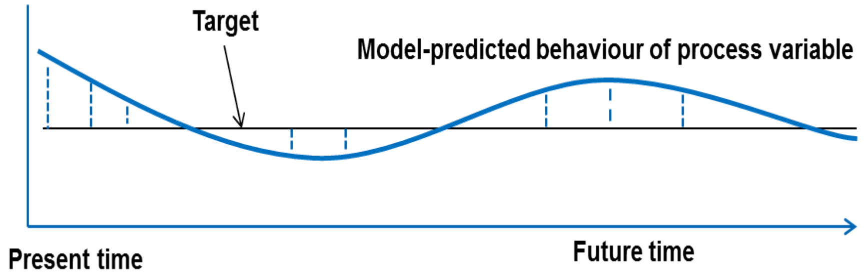

Figure 2. MPC minimizes control deviation i.e. squared differences between predicted process variable values and target

The development steps from MPC to DRTO exploits the fact that MPC already incorporates optimization in terms of minimizing a cost function as depicted in Figure 2. The following steps define the actual DRTO development on a principal level:

1. Replace the control deviation cost function of MPC with an economically meaningful cost function or benefit function, which then shall be maximized
2. Define limits for process variables and update the constraint set already existing within MPC with new constraints reflecting the process control requirements

However, substantial amount of advanced engineering work is remained related to handling of the enlarged constraint set and more irregular cost/benefit functions compared to the smooth control deviation cost functions of MPC.

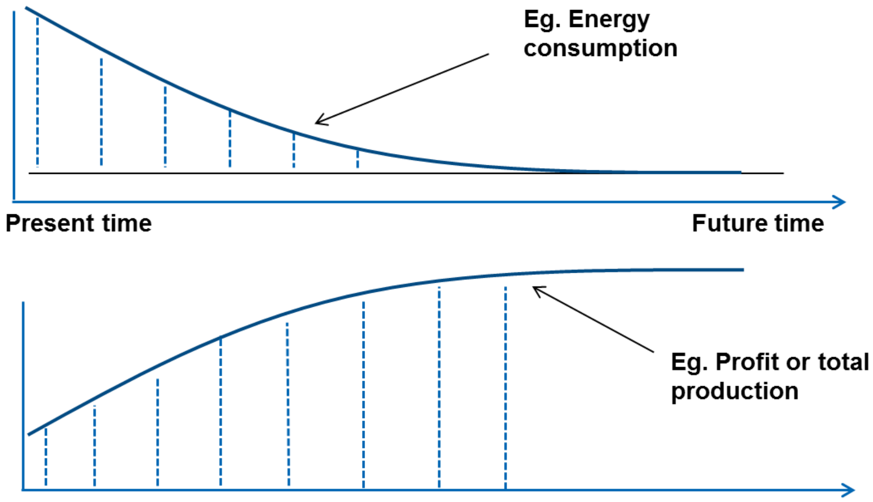

Figure 3. DRTO minimizes an economical cost function or maximizes an economical benefit function

Having done this, we observe that DRTO inherits the good properties of MPC such as low sensitivity to measurement and model error. Also, the practicalities of "tuning" DRTO for performance are very similar to that of MPC which saves a lot of specialist work. What is *not* borrowed from MPC is the typical feature that MPC is typically built separately for process units, but DRTO may easily encompass a whole process complex consisting of multiple units.

NAPCON

Some more math

A little more mathematics is in order to shed some more light on the DRTO concept.

Assume that we wish to maximize a benefit function

$p_1 * P - p_2 * R - p_3 * E$,

where P is the flow rate of product, R is flow rate of raw material and E is power consumption and p_1 , p_2 and p_3 are corresponding prices. This is of course a simplified setting because we have only one product and one raw material but it will be descriptive anyhow. P, R and E all depend on a set of *manipulated process variables* x_1, x_2, x_3, … x_N, all of which affect the P, R and E due to their own characteristic behaviour including larger or smaller delay (the dynamics!).

P = flow rate of product
R = flow rate of raw material
E = power consumption
p_1 , p_2 and p_3 = corresponding prices
x_1, x_2, x_3, … x_N =manipulated process variables

Now, RTO strives to find optimum fixed steady-state values for the set of variables x_1 , x_2 , x_3 , … x_N , for a future time period of several hours ahead until the next optimization calculation which may be severely delayed because of process not achieving steady state.

DRTO basically uses the same benefit function as above but does not restrict to fixed values of the variables during the future time period which we may denote as "0...T" where zero means the present time and "T" a time several hours ahead, the end of the so called optimization horizon. We may change the notations from above in order to underline the fact that DRTO honours the behaviour of the process as dependent on time and does not assume steady state operation:

Rewrite benefit function:

$p_1(0…T)*P(0…T) - p_2(0…T)*R(0…T) - p_3(0…T)*E(0…T)$

(with point-wise multiplication) and the set of process variables $x_1(0…T)$, $x_2(0…T)$, $x_3(0…T)$, … $x_N(0…T)$.

In purely mathematical terms the variables are now re-defined from being *scalar-valued* to being *vector-valued*. Note, that the re-formulated benefit function also includes the prices as functions of future times. This means that if we have price forecasts, we can just plug in them in the benefit function and DRTO will run the process optimally to prepare (look ahead) for an upcoming price change. RTO does not include this 'look ahead' feature, and it needs to do a re-optimization at the time of the price change, if possible, i.e. if the process happens to be in a situation close enough to steady state.

Neste Jacobs offering

Our company is devoted technology-intensive process development and engineering as well as performance improvement. The various optimization tasks mentioned in the introductory section above are available from us including dynamic simulation for advanced process design and dynamical studies. In particular, we want to emphasize our NAPCON process control technologies including NAPCON Controller model-predictive control and NAPCON Optimizer Dynamic real-time optimization.

One of our most successful NAPCON Optimizer projects was for an ethylene cracker, which is described in the article in Hydrocarbon Processing from October, see list of literature below.

Literature

Hydrocarbon Processing, October 2006, J. Vettenranta, S. Smeds, K. Yli-Opas, M. Sourander, V. Vanhamäki, K. Aaljoki, S. Bergman and M. Ojala, Dynamic real-time optimization increases ethylene plant profits

Hydrocarbon Processing, April 2014, *M. Rönkä, M. Palosaari, J. Vettenranta*, *S. Bergman, K. Yli-Opas, S. Karlsson, A. Frejborg* , Case history: Optimization of aromatics complex