GRADE-CHANGE CONTROL USING INCA MODEL PREDICTIVE CONTROLLER: APPLICATION ON A DOW POLYSTYRENE PROCESS MODEL

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Abstract: A novel model predictive control architecture INCA® has been implemented on a dynamic model of a Dow polystyrene production facility at Tessenderlo, Belgium. The controller allows for a controlled grade transition and pushes the process towards more profitable operating regions during normal production, subject to prioritized requirements. Results show an excellent tracking of the desired trajectory, together with a large disturbance rejection capability during the grade transition.

Keywords: Predictive control, Model based control, Optimal trajectory, Chemical industry

1. INTRODUCTION

Demand driven process operation allows the chemical process industry to increase their capital productivity. This implies that exactly these products can be produced that have market demand and take price advantage of a scarce market. A flexible production operation is therefore required.

A new process control technology is needed for this purpose. A very important requirement for this technology is to enable optimal control of grade transitions such that these transitions become feasible and economically attractive. Also tight quality control is needed, requiring large bandwidth controllers and inferential sensors. INCA® has been developed for these purposes [Van Brempt et al., 2000]. This controller architecture has been implemented on a dynamic model of a Dow polystyrene production facility at Tessenderlo, Belgium.

Control of grade transitions has been studied by several authors. Lines [Lines et al, 1993] addresses the problem by formulating a NLMPC problem. The original non-linear problem is replaced by a time variant linear problem where models are subject to gain scheduling.
Wang [Wang et al, 2000] integrates the controller with an off-line optimized trajectory. A NLMPC problem is stated using a non-linear model with its linearized version.

Linear model predictive controllers experience problems due to the strong non-linearities over the covered operation region during a grade transition.

The INCA® controller avoids these problems using time-variant linear models and a delta-mode configuration. This configuration integrates off-line trajectory optimization with feedback control. The so-called delta-mode controller compensates for deviations from a given input-output trajectory on both the process inputs and outputs.

The paper is organized along the following three Sections:

In Section 2 a new process control technology INCA® is presented.
In the next section the Dow polystyrene process is shortly introduced.
Finally, Section 4 describes the application of INCA® on a Dow polystyrene process model.

2. INCA®: A NEW TECHNOLOGY

A new technology INCA® is developed and makes flexible operation combined with tight production specifications feasible.

INCA® is a complete family of on-line and off-line components specifically designed to support the industrial application and implementation of control. The engine of INCA® is a generally applicable supervisory model predictive controller that meets current operating requirements for a broad variety of different process industries, e.g. glass industry, chemical and polymer industry.

It therefore incorporates the basic functionality that can be found in industrial model predictive controllers. The control problem is solved basically in three steps:

- Prediction of the future behavior of the process based on assumed future behavior of the process inputs (manipulated variables or 'MV's').

- Minimization of the difference between predicted future steady state process behavior and the desired behavior of the process. The minimization problem is formulated as a ranked constrained quadratic optimization problem: ranked classes are used to give a class of requirements absolute priority above lower ranked classes and at the same time the solution for current class by the solution of the higher ranked classes (*Fig. 1*). Requirements can be both targets and constraints ('zones'). Within one class violation of constraint limits and deviation from target values are traded-off based on a constrained weighted quadratic optimization. The solution for this class is then added to the set of constraints used to solve the lower ranked classes. The ranked specification approach enables the control engineer to specify a control strategy that closely resembles the actual operational hierarchy of the plant or unit.

- In the last step a constrained quadratic optimization problem is solved that brings the process from the current process conditions to the calculated steady state conditions. As in [Muske and Rawlings, 1993] this problem is formulated as a regulator problem.

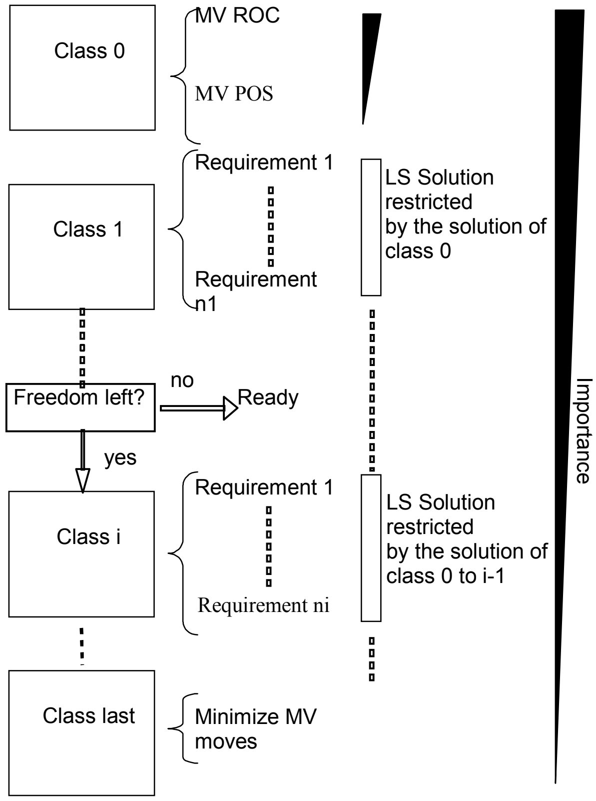

Fig. 1 The MPC minimization problem is formulated as a ranked constrained quadratic optimization problem. This allows the control engineer to specify a control strategy that closely resembles the actual operational hierarchy of the plant or unit.

Besides the functionality described before, extra functionality is added to improve the model predictive controller in order to improve production flexibility, to achieve tight quality control and to reduce total application costs.

Providing a structure for trajectory control enables **production flexibility**, since it allows one to repeat a best-of-history transition at all times. Controlling the process during a grade transition allows for trajectory tracking as well as for disturbance recovery during that transition.

Dynamic economical optimization of the change-over trajectory forms a serious alternative for the use of a best practice trajectory, since it allows you to obtain an optimal transition policy for the current market condition. A specific overall dynamic optimizer, PathFinder, has been developed for this purpose [Van Brempt et al., 2001], but it is not the scope of this paper.

To integrate a grade change-over trajectory with the underlying model predictive controller, an architecture as shown in Fig. 2 is implemented. The model predictive controller is operated in a delta-mode, only correcting for the deviations Δu and Δy from the process input-output reference trajectories u_{opt} and y_{opt} that are given by the best-of-history trajectory.

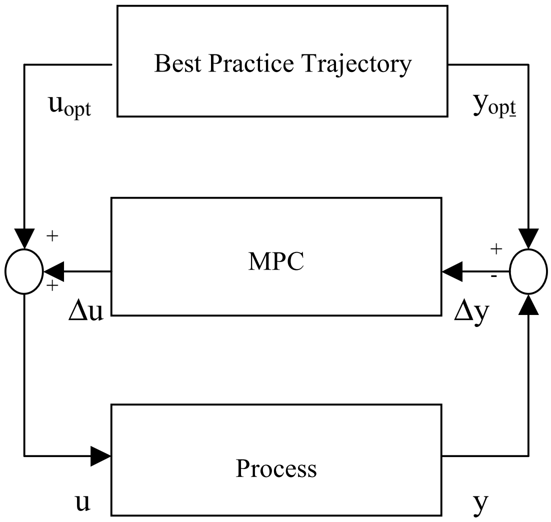

Fig. 2 Integration of a best practice trajectory with the model predictive controller

The delta-mode guarantees a best of both worlds operation. The trajectory has generally been carefully designed with the knowledge of the non-linear process. It would be a pity to have this result overridden by a linear model controller. Therefore this trajectory is applied as such to the process. It puts a curb onto the controller, and the controller is allowed to shift the deviations of the input-output trajectory (u_{opt}, y_{opt}) between the controller input and output. It does not only try to follow as closely the output trajectory, but makes a compromise between deviations from the output trajectory and from the input trajectory.

Since the delta mode controller only considers deviations from a given trajectory, linear models are well suited to be used in this framework. This allows us to use a linear MPC controller with all the advantages with regard to model identification, robustness etc.

The model predictive controller is designed such that it can make use of different linear models according to the current operation point. As such trajectories can be optimally followed. No longer one single, linear dynamic model must be used, but instead adequately tuned sets of linear models can be applied for all the different grades. During transients, the model predictive controller will smoothly switch between the different models of a set of models.

3. THE POLYSTYRENE SOLUTION PROCESS

Polystyrene is mostly produced using a solution process. A simplified layout of a typical polystyrene solution process can be found in Fig. 3.

The process consists of a combination of several plug flow reactors. Styrene, a solvent and in some cases an initiator are fed to the first reactor. Reactors are usually operated at sequentially higher temperatures with a final conversion at 60-90%. Unreacted monomer and the solvent are separated from the polymer under vacuum. The hot melt is then pelletized while the monomer and solvent are condensed and recycled. Additives may be added at different places in the process.

Various polystyrene grades can be produced on the same process using a carefully chosen set of flow, temperature and pressure setpoints (SPi) that we will refer to as a “recipe”. A given polystyrene grade will be characterized by a set of properties (PROPj).

When changing from one polymer grade to another polymer grade, setpoints must be moved from one recipe to the other, driving the process through a zone where off-specification product is made. Typically the transition path for recipe setpoints will be selected to minimize production of low value off-spec product.
Dow developed a rigorous dynamic model for the specific process used for the production of polystyrene at Tessenderlo, Belgium. This validated model is used to demonstrate the application of the INCA® controller to a polystyrene process.

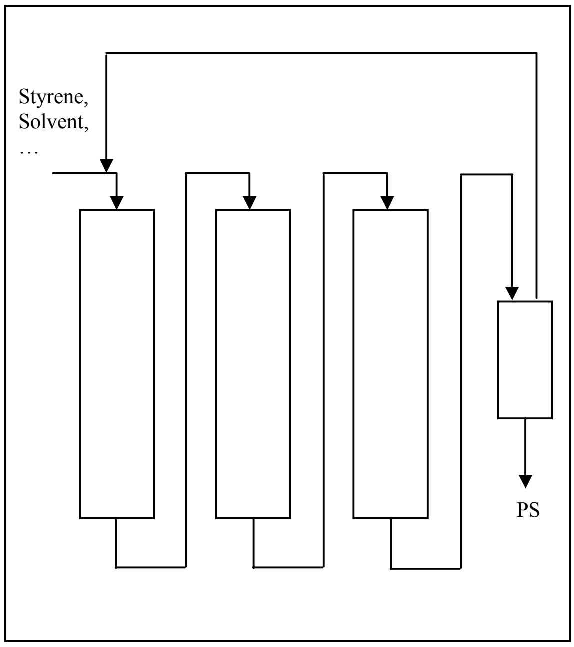

Fig. 3 Schematic description of a typical solution polystyrene process

4. APPLICATION OF INCA® CONTROL ARCHITECTURE

The INCA® control architecture was applied on the Dow polystyrene process model.

The application had the following goals:

- Demonstrate constraint pushing capabilities during normal production, together with a high bandwidth disturbance rejection
- Prove the efficiency of the INCA® trajectory control as it was explained in section 2.

Both goals will be met with one control architecture, such that trajectories can easily be initiated without loosing the general constraint pushing capabilities.

In order to demonstrate the constraint pushing capabilities, the INCA® control architecture was connected to the process model.

As already indicated in the Section 2 the controller treats the various requirements that are imposed on the process in a hierarchical way. Process boundaries (zone constraints) guaranteeing a safe process operation have the highest rank. These zone constraints become only active when the process would leave the specified zone. Otherwise they don't limit the controller freedom. Quality variables are the next ranked variables, guaranteeing a right product property at all times. Next priority is given to the target production level. This could be understood as a general tuning rule: first the safety requirements (zones), next the quality requirements (aim values) and finally the economic requirements.

The economic objective one wanted to achieve is to maximize production, while maintaining a guaranteed safe operation and right product quality. For this purpose the target value of the production is set to a (unachievable) high value. The controller will try to move the process to the desired high production. However, before reaching this value, it will encounter higher ranked process constraints, such as boundaries on MV values and CV values. It moves the process to highest production rate that is feasible within the space that is given by the other boundaries. When a disturbance would enter the process, the active constraint prohibiting the process to increase production could become inactive, but another constraint would take over the limiting role

Results of this constraint pushing are shown in Fig. 4. At time instant 1 the target for the production rate is increased. The target is however not met since some zone boundaries are preventing the process to go further (in this case the temperature in the first reactor zone). If the desired production must be met, one of the boundaries could be loosened. An alternative is presented here: the production target ranking is made more important than the target ranking for the quality parameters. That occurs at time instant 2. Notice how the production target is now achieved, at the cost of releasing the target value for the product properties PROP1 and PROP2. The product properties stay however within their range, since the zone for these is still more important than the target for the production rate.

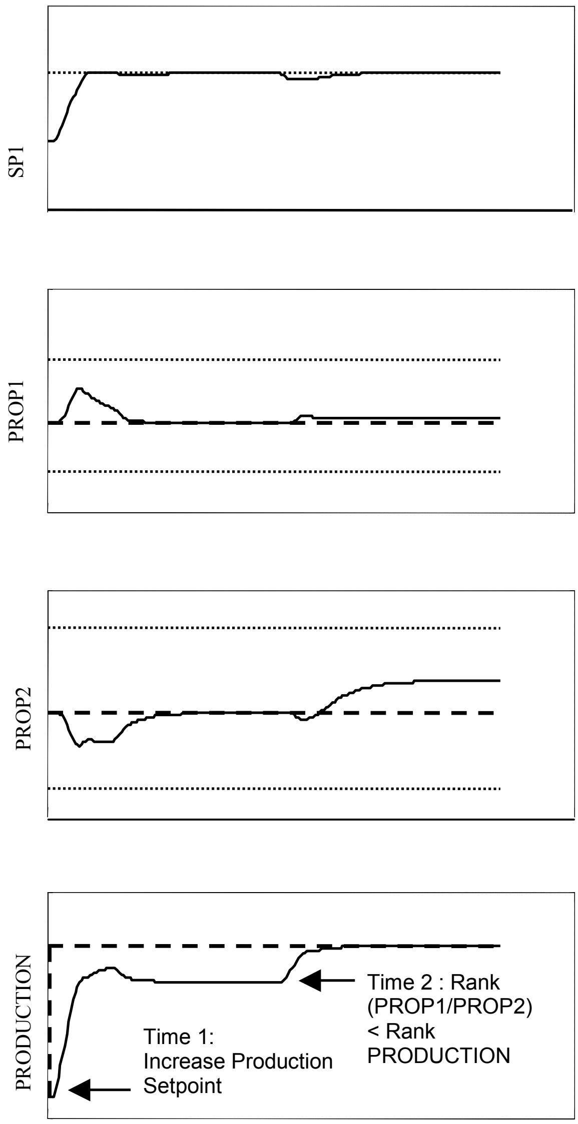

Fig. 4 Constraint Pushing Case: at the first time instant the production setpoint is increased. The target is not achieved due to a zone constraint on the recipe setpoint SP1. At the second time instant the production rate ranking is increased and the target is met, at the cost of a PROP1/PROP2 deviation from their aim value.

The second goal of the project was to prove that the architecture chosen to achieve trajectory control is very well performing. For this purpose Dow selected a known transition between two grades with extremely different specifications. A best practice trajectory was selected.

Both MV and CV transition paths are applied to the process, with the INCA® MPC controller interconnected in delta mode. The controller will thus compensate for deviations from the best practice trajectory. These deviations arise from two sources. At first the given trajectory will not match perfectly with the process. Secondly, when disturbances enter the plant during the transition, the trajectories must be compensated for them such that important process variables remain as close as possible to the original trajectory.

For this purpose the variables are ranked in order of importance. The controller will bring the deviation on highly ranked variables to zero. If there is still controller freedom left, it will bring lower ranked deviations back to zero. The same ranking was applied as in the constraint pushing case.

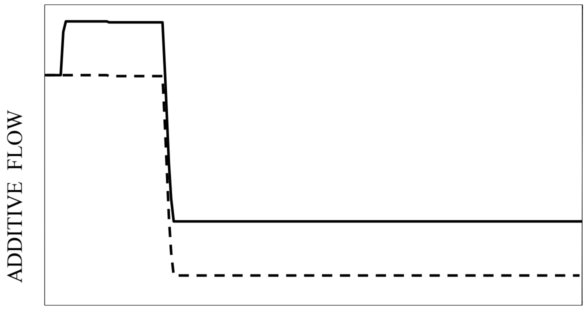

Fig. 5 The trajectory for the additive flow. The original trajectory is shown in dashed The trajectory subject to the disturbance in solid. Notice the stepwise disturbance.

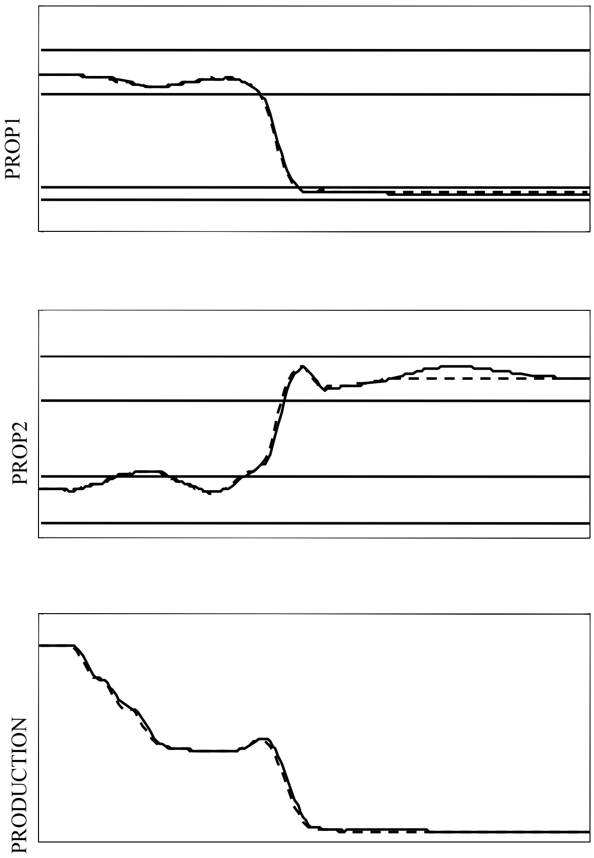

Fig. 6 Controlled Grade change-over trajectories for PROP1, PROP2 and Production rate. The original trajectory is shown in dashed, the controlled trajectory subject to the disturbance in solid. The specification boundaries for the properties are also shown.

A significant persistent disturbance is applied to the process after the trajectory has been started: a 10% extra additive flow is injected into the process (Fig. 5).

In Fig. 6 product properties 1 and 2 are shown. Notice that these properties lie well on the original trajectory despite the large disturbance on the additive they encounter. Also the production rate is well on the targeted trajectory. This is obviously caused by the high ranking of these variables.

The trajectories for 3 manipulated variables (MV1, MV2, MV3) are shown in Fig. 7. The disturbance on the additive flow would have significantly affected the product properties but the controller has taken the appropriate actions on the MV's to compensate for the disturbance and keep the properties and the production rate on the specified transition paths.

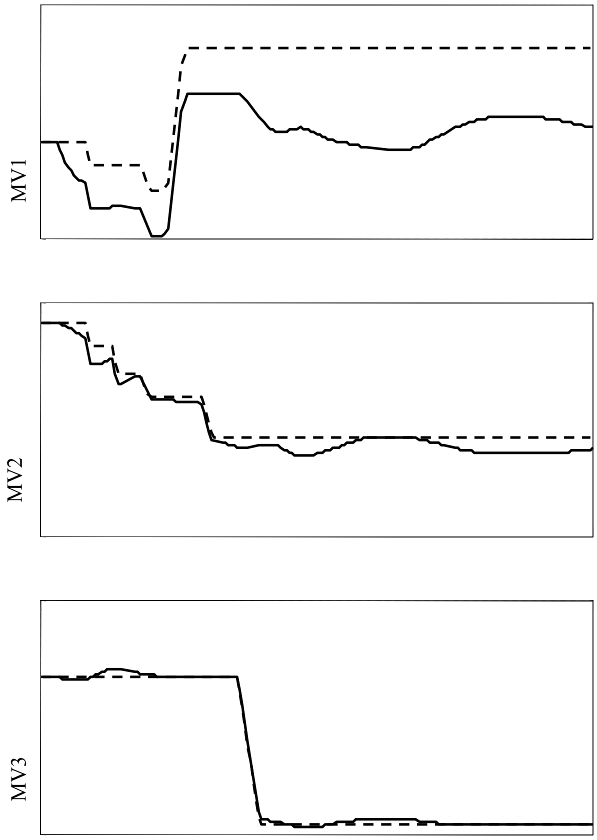

Fig. 7 Controlled Grade change-over MV trajectories for three selevted MV's. The original trajectory is shown in dashed, the controlled trajectory subject to the disturbance in solid.

5. CONCLUSION

A novel MPC architecture INCA® has been implemented on a dynamic model of a Dow polystyrene production facility at Tessenderlo, Belgium. This architecture allows for constraint pushing and trajectory control as well. The application shows very promising results.

6. ACKNOWLEDGEMENTS

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