Production Control of a Polymerization Plant using a Reduced Set of Control Variables

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***Abstract*—The specifics of process manufacturing have a great influence on production management, and the focus of process-production control is to maintain stable and cost-effective production within given constraints. The synthesis of production-control structures is thus recognized as one of the most important design problems in process-production management. This paper proposes a closed-loop control structure with the utilization of production-performance indicators (pPIs) as a possible solution to this problem. pPIs represent the translation of operating objectives, such as the minimization of production costs, to a reduced set of control variables that can then be used in a feedback control. The idea of production-feedback control using production PIs as referenced, controlled variables was implemented on a procedural model of a production process for a polymerization plant. Some preliminary results demonstrate the usefulness of the proposed methodology.**

***Keywords*—Production control; Productivity, Closed-loop control, Model-based control**

I. Introduction

Competitiveness in the global economy has changed the basic method of production from planned production to order-driven production. This has introduced new demands related to flexible production, increased production efficiency, fast responses to customer demands, and a high and uniform quality of products and services [1], [2].

Production is a complex process, consisting of several operations, interconnected by material, energy and information flows, and restricted by the time available as well as organizational, technological and other constraints. At the production-management level at least two essential activities are performed:

(i) the transformation of a company's objectives into results and

(ii) the optimization of production.

To fulfill these two basic tasks successfully, a production manager's decisions must be based on accurate and online information. A production manager makes decisions on the basis of online production data (plans, the availability of technological equipment, human resources and materials, capacity, the consumption of energy, stocks, quality assurance, and ecological measurements), as well as on the basis of a subjective assessment and experience. However, the quality of the manager's decision making is limited because of the need to adopt a decision in real time, the availability and accuracy of existing production data, insufficient knowledge of the requirements, and the restrictions dictated by the production environment. Of course, this still omits the cost-benefit aspect of production, the inability to make the right decision in terms of long-term benefits, subjective decisions, etc. All this may result in non-optimal decisions, differing management strategies, and non-optimal production control from the point of view of optimization of the overall operation of a company.

The problem of reliable production control is given greater exposure in the *process industries* than in the assembly industries, i.e., the process industry has several specifics compared to the discrete industry [3], [4]. These specifics make process manufacturing both *complex* and *uncertain* [5], [4]. The complexity of the production process arises primarily from the required linking of various sub-processes, each of which affects the quality of the final product. The uncertainty of the process industry is expressed above all in actual product quality and achieved production rate. The non-uniformity of the quality of basic raw materials, chemical reactions involved, deviations in process parameters, failures of technological equipment, outages in energy supply, and often also combinations of various indeterminate reasons render any prediction of the level of both quality and production rate a risky job.

During the past ten years, or even longer, a number of information-technology products have been developed to collect and process a vast amount of production data. Today, online production data, by various MES (*Manufacturing Executive Systems*), are available to a production manager for use in cost-effective production control. In 2001, reference [6] discussed the need for information flow and the redistribution of management responsibility among all the management-structure entities in order to achieve highly efficient levels of production. The first research results on *Decision Support Systems* (DSS) for the production-management level began to appear after 2000. Reference [7] proposes and discusses a methodology for the conceptual design and implementation of a production DSS, and place this system in the context of an overall enterprise-management structure. Reference [8] in 2002 defines the principal measurements used to indicate current short-term production efficiency. In the past few years, articles describing implemented DSS have also appeared.

However, the production-management-level functions are covered only partially (e.g. production quality and energy consumption). The problems regarding a production manager's decision-making process that still remain are:

- how to extract the relevant information from a vast amount of disposable production data in order to make the correct decision;
- how to design a plant-wide production-control system that is capable of maintaining near-optimal production and eliminating a production manager's/operator's subjective assessments.

The weakness of today's form of production control is often in the subjective perception of global production aims, the subjective decision making, and also in the vast amount of data that are not properly classified according to their importance in the decision-making process. The indefinite current status of production and the lack of unambiguous reference values for significant measures of production efficiency, production-plant productivity, mean product quality, etc., mean that the production-control activity is still influenced by a strong human-factor impact. The main problem lies in the fact that the most important global production objectives (such as profitability, production efficiency, plant productivity, and product quality) are often so-called *implicit objectives* (as they can usually only be expressed implicitly as functions of the measurable and manipulable variables) and they cannot be directly estimated from current production data.

For this reason their translation into a set of output production-process variables should be provided. The transformation of implicitly expressed global production objectives into measurable output production-process variables (subsequently termed "*production-performance indicators*", pPIs), the definition of their reference values and the proper choice of a set of input (manipulable) production-process variables are the bases of the design of an efficient production-control system. To enable near optimal production, a model of the production incorporating a-priori knowledge about the behavior of the production process is of great help. As profitability is usually the most important production parameter a model should incorporate both the cost aspects of production as well as production-process dynamics and constraints.

This paper is organized as follows: Section 2 briefly describes the basics of the pPI methodology and presents a closed-loop paradigm of production management. Section 3 describes the proposed concept for utilizing pPIs in production management in the process industries using the case study of a polymerization production process and gives some preliminary simulation results of closed-loop MPC-based production control. Section 4 presents the conclusions.

II. Design of a Production Control System

A production process involves several business and technical activities on and around the factory floor. Its effectiveness can be assessed using information hidden in a set of current and historical production data. The problem of extracting the relevant information from a vast amount of production data for fast and accurate decision-making can be solved by introducing *production-performance indicators* (pPIs) as a reduced set of production parameters, calculated from directly measurable production-process outputs, which show a relevant, current production status.

Recently, a balanced set of general pPIs for the production-management level was introduced [9] and five principal pPIs for process-oriented productions were defined:

(i) *Safety and environment*: number of accidents at work, number of hazardous alarms, fresh-water consumption, wastes generated before recycling and number of penalties due to releasing waste into the environment.

(ii) *Production efficiency*: efficiency of employees/infrastructure, raw materials used, energy consumption, unit production time, quality of internal and external services, and production shutdowns.

(iii) *Production quality*: percentage of final products/raw materials that do not meet quality criteria, production losses, and quality of internal and external services.

(iv) *Production-plan tracking*: percentage of production orders finished late, number of penalties and percentage of production orders finished ahead of time.

(v) *Employees' issues*: complete job satisfaction of employees, lost workdays due to injury and illness, turnover rate, and employees' proposals for improvements and innovations.

As was already stated, the weakness of the enhanced role of the production manager is in the subjective perception of global production goals and in the large amount of production data that are not properly defined with regard to their importance for the decision-making process.

To resolve this problem it is necessary to define uniform global production goals derived from actual production plans and strategy [10]. The global production objectives can be defined as the reference values $\boldsymbol{c}_s$ for significant measures $\boldsymbol{c}$ (pPIs) of, e.g., plant efficiency, production-plant productivity, mean product quality and others (see Figure 1).

The controlled variables $\boldsymbol{c}$ are often called implicit as they usually can be expressed only implicitly as functions of the measurable variables [10].

Since implicit variables $\boldsymbol{c}$ are not directly measurable, the estimation of their current values using the disposable production process variables $\boldsymbol{y}$ should be provided. These output production-process variables $\boldsymbol{y}$ should have the following properties [11]:

(i) They should be more easily measurable;

(ii) It must be possible to maintain their set-point values by proper adjustments of manipulable production process variables $\boldsymbol{u}$;

(iii) When maintained at the desired optimal set-points through the feedback-control subsystem, they should inherently contribute to the overall profitability of a production process.

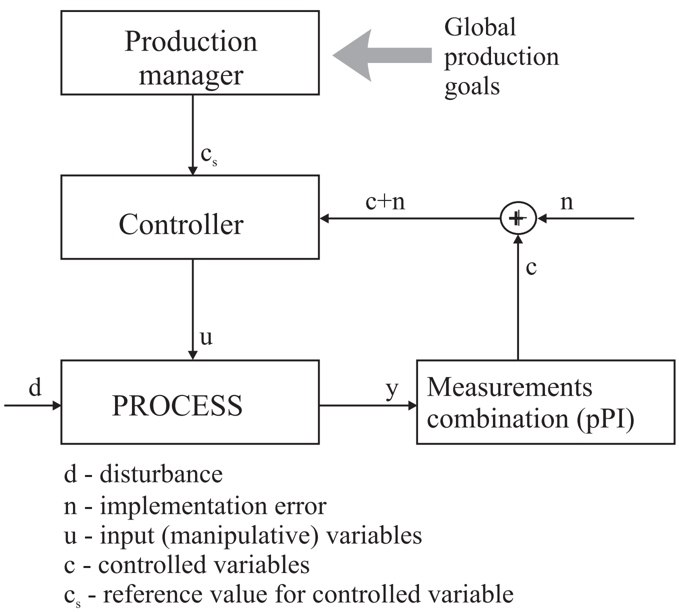

Figure 1: Optimal production-control system with separate layers for optimization and control [12]

Neither pPIs $\boldsymbol{c}$, nor their reference values $\boldsymbol{c_s}$ are static; the reference values need to be re-evaluated on the optimization layer according to modifications in the production processes or production strategy [13], [14.

An evolution of the general production-control system scheme from Figure 1 is given in Figure 2.

To improve the behavior of the production-control system two models are included into the control scheme. As the profitability is usually the most important production parameter the production-*cost model* $\mathcal{CM}$ calculates the current production costs.

The second model, called the *process model* $\mathcal{M}$, is used for calculations of the parameters of the production-control algorithm. Both the production-cost model and the process model can be constantly improved by using current production data.

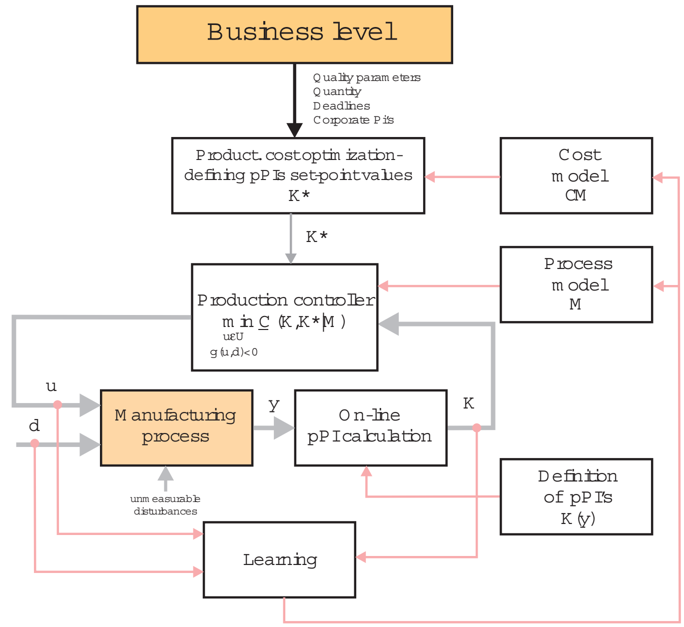

Figure 2. General scheme of a model-based production-control system

III. The Case Study

A. Polymer-Emulsion Production Process

The polymer-emulsion batch-production process is a typical representative of process-oriented production. The production effectiveness, to a large extent, relies on the quality of the production-control system. The production layout consists of several reactors, dosing vessels, storage tanks and equalizers, which are used for the production of different products.

The technological process is defined with a recipe, i.e., the sequence of operations that have to be performed for the production of a particular product. Installed DCS and SCADA systems handle the safety, regulatory control and monitoring functions successfully, but often the non-uniform quality of raw materials, the chemical reactions involved, process down-time due to failures, prolonged operation at non-optimum points, long periods of switch-over from one mode of operation to another, prolonged operation with off-spec products, a mismatch between the business production plans and those achieved by the plant, make the final product quality, yield and duration of a single batch variable, which renders the entire production process non-optimal.

The production proceeds in successive batches on different equipment where at each batch stage intermediate products appear and have to be used in successive stages as soon as possible. In each step some physical actions (heating, blending) or chemical reactions are involved that have a significant influence on the final quality of the product. If the production speed is increased, some of the phases need to be shortened, which is usually reflected in a lower product quality. If the quality of the raw material is low or variable, or if the production process is not stable (due to energy failures or inadequate regulation) then the quality parameters of the product achieved may not satisfy the prescribed quality requirements and the product may need to be recycled in subsequent batches or eliminated.

A procedural model for the case-study production process has been developed to facilitate experimentation and verification of the closed-loop control structure ([15], see also Figure 3). The model was designed in the academically established *Matlab*, *Simulink* and *Stateflow* simulation environments. The simulated data are stored in a *MS Access* database and are available for various forms of online and offline processing.

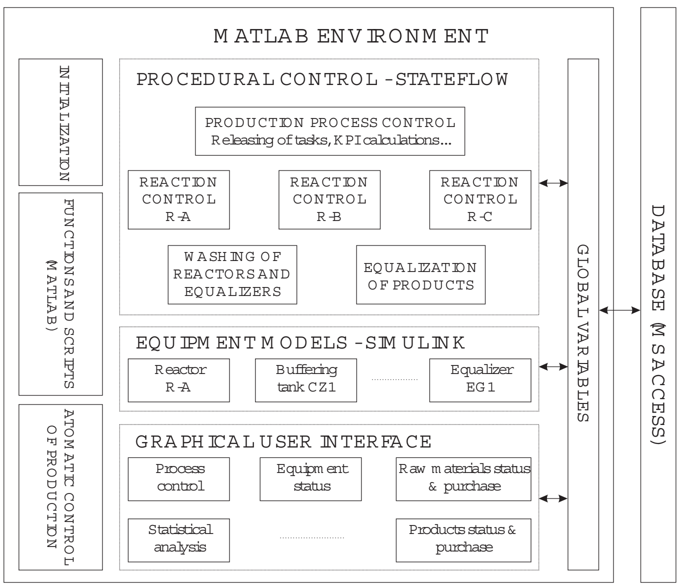

Figure 3: The structure of the procedural model of producton

B. Closed-loop production control

For the case study of the polymer-emulsion batch-production process the chosen production-performance indicators (pPIs) were *Productivity* (also denoted as the actual production rate or production yield), *Product Quality* and *Production Costs*.

These three pPIs represent the output (controlled) variables $\mathcal{K}$ in Figure 2. None of them are directly measurable, but an estimation of their current values can be made using a combination of the directly measurable production-process variables y (e.g., production rate, temperature profiles, quantity of final products, number of production stops, etc).

Maintaining the predefined set points $\mathcal{K}^*$ for the chosen pPIs $\mathcal{K}$ can be achieved by the proper adjustment of some process variables $\boldsymbol{u}$, which in this case were *Raw Material Quality, Production Speed and Batch Schedule* (all direct inputs in the production process).

The cost model $\mathcal{CM}$ was used to calculate the current production costs, while the process model $\mathcal{M}$, which incorporates the case study's production-process dynamics and constraints, was used for the adjustments of the model-predictive-control algorithm's parameters.

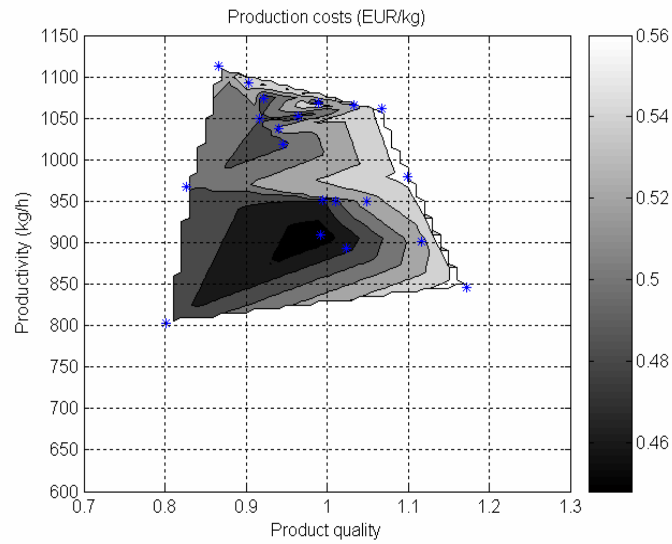

Figure 4. *Production costs* in relation to *Productivity* and *Product quality pPIs* for a fixed batch schedule

The results obtained from the production-cost model $\mathcal{CM}$ in Figure 4 show how *Production costs* pPI are related to *Productivity* and *Product quality* pPIs. In the Figure 4, the global minimum, where the production costs are a minimum, can be identified. While the dependence of the *Production costs* on the other two production pPIs for a chosen type of production schedule is known *a priori* (from the cost model $\mathcal{CM}$), a production manager can define exact reference values $\mathcal{K}^*$ for *Productivity* and *Product quality* p*PIs* that have to be maintained by the production controller (the inner control loop).

The inner production-control loop is based on the model predictive controller. Model predictive control (MPC) is well suited to solving this constraint problem [17] and [18] and multivariable process control using MPC has been thoroughly studied [19] and [20].

The process model $\mathcal{M}$ was identified and analyzed using input-output data, gained from several simulation runs. It was supposed that the process is linear. In this situation an approach where one input is tested while another one is fixed can be used.

In the first experiment the *Raw materials quality* was fixed and the influence of *Production speed* on the outputs of the system (*Productivity* and *Product quality*) was studied. The same experiment was repeated, but in this case *Production speed* was fixed and the influence of *Raw materials quality* was studied.

The model-parameter estimation was made using the identification method, where the least-square criterion was minimized. The input-output dependencies were given with first-order models (equation 3.1).

$$\mathcal{M} = \begin{bmatrix} \frac{31.84}{z-0.938} & \frac{-4.43}{z-0.834} \\ \frac{-0.04}{z-0.932} & \frac{0.052}{z-0.94} \end{bmatrix}, \quad (3.1)$$

where the sampling time was 5 hours.

This multivariable model was then used to design the MPC controller using the MPC Toolbox in the Matlab environment [16].

The main challenge was to tune the obtained MPC controller in order to achieve multiple objectives. The MPC toolbox supports the prioritizations of the outputs. In this way, the controller can provide an accurate set-point tracking for the most important output, sacrificing others when necessary, e.g., when it encounters constraints. In our case the controller had to consider both the input and output constraints (equation 3.2).

$$0.5 \leq Production \quad speed \leq 1.3$$
$$0.85 \leq Material \quad quality \leq 1.2$$

and

$$\begin{aligned} 700 \leq Productivity \leq 1300 \\ 0.87 \leq Product \quad quality \leq 1.3 \end{aligned} \quad (3.2)$$

Different weights were used to prioritize the input and output variables. To solve the optimization problem, a prediction horizon of 75 hours and a control horizon of 20 hours were used. The MPC toolbox uses a Quadratic Programming solver to solve the optimization problem, where the bounds of the constraints are finite [16].

The closed-loop control was tested in several simulation runs. Figure 5 presents the results of a simulation run where both the set points for *Productivity* and *Product quality* were changing inside the period of approximately 20 days. The increase in the *Productivity pPI* set point was reflected most in the related increase of *Production costs pPI,* as seen in Figure 4.

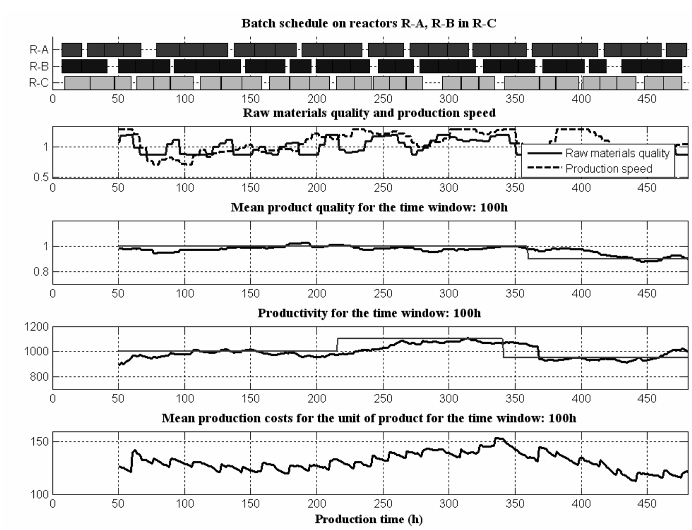

Figure 5. Batch schedule, input and output variables for a single simulation run.

IV. Conclusions

The ideal plant-wide control system should ensure that the production process is constantly working in an optimal manner. As a result of the plant-wide focus, a plant-wide control problem possesses certain characteristics that are not encountered in the design of control systems for single units, such as the following [10]:

(i) The variables to be controlled by a plant-wide control system are not as clearly or as easily defined as for single units;

(ii) Local control decisions, made within the context of single units, may have long-range effects throughout the plant;

(iii) The size of the plant-wide control problem is significantly larger than that for the individual units, making its solution considerably more difficult.

This paper proposes an approach to measuring and presenting the achieving of production objectives in the form of introducing production-performance indicators as a reduced set of control variables that are further used in a feedback control.

Using this approach the implicit production objectives can be translated into measurable and controlled values. In this way the production-control concept and the role of the production manager are slightly changed; instead of monitoring and controlling several tens and hundreds of process variables at a low production level, the production manager monitors and controls only a few major production pPIs with the aim of achieving the most important implicit production objectives, e.g., predefined product quality, high productivity and minimal production costs.

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