

MODEL-BASED PRODUCTION CONTROL

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Abstract

Business environment demands an instant replay to different influences that appear in the production process and in the global market. The synthesis of plant-wide control structures is recognized as one of the most important production-management design problems in the process industries. To develop a production control system, an appropriate model of the production process is needed to evaluate the various control strategies. Within the model different production Key Performance Indicators (KPIs) can be identified which are used to extract the relevant information about the state of the production process. The control systems in production plants are structured hierarchically into several levels. Closed-loop control at the production-management level using production KPIs as controlled variables was implemented. In this article, the procedural model of a polymerization production plant is presented. The plant can be controlled by its input variables, which are *Production speed*, *Raw materials' quality* and *Batch schedule* and the efficiency of the production is determined based on three characteristic KPIs: *Productivity*, *Mean product quality* and *Mean production costs*. These KPIs are used to control the process of the procedural model. To help the manager with the decisions a model predictive controller (MPC) was used. With the controller it is assured to keep *Productivity* and *Mean product quality* indicators at the defined set-points. Preliminary results show the usefulness of the proposed methodology.

Keywords: Production management, Performance measurement, Production control, Closed-loop control, Model predictive control.

Presenting Author's biography

Dejan Gradišar. Dejan Gradisar received his B.Sc. and Ph.D. degrees in electrical engineering from the University of Ljubljana, Slovenia in 2001 and 2006, respectively. He is currently working as a researcher at the department of Systems and Control, Jozef Stefan Institute, Ljubljana. His currently research interests are in the area of information technology in control systems.



1 Introduction

It is very important for every production industry to be efficient, adaptable and flexible in order to be able to deal with competitiveness in the global market. Production is a complex process, consisting of several interconnected operations restricted by various constraints. The production process must deliver products that meet customer specifications consistently, and at the same time respect the imperative of profitability. To be able to control the production process many information has to be handled. Different management support technologies are used to solve those problems.

In the 1970s, Gorry and Scott Morton [3] defined DSS concept by combining the works of Simon [11] and Anthony [1]. Simon [11] classifies needed technology support depending on the type of decisions. Structured processes can use decisions that can be programmed (cost minimization) while with unstructured processes human intuition is often the basis for decision-making. The control systems in production plants are structured hierarchically into several layers, each operating on a different time scale (business-management level, production-management level and process level control) [1]. Only part of the unstructured problem can be supported by advanced decision support tools. Decision support systems (DSS) are interactive computer-based systems, which help decision makers utilize data and models to solve semi- or unstructured problems. In the survey [10] the evolution of DSS technologies and issues related to DSS definition are discussed. Enterprise Resource Planning (ERP) systems which are in first place used in companies for transactional and record-keeping aspects, has to offer also features that support decision making. Holsapple [5] explores the decision-support benefits of ERP systems. Hierarchical control, structured in more levels used in our work is related to the so-called self-optimizing control that was presented by Skogestad [12].

The production manager is usually overloaded with current production process data during his decision-making process and the main problem is how to extract relevant information from this vast amount of production data for fast and correct decisions. One promising way of solving this problem is the introduction of production *Performance Indicators* (PIs) as a means of reducing the amount of data to the most important information about current production process status of the production process. The concept of PIs can take many forms. Folan and Brown [3] have presented in more detail the evolution of the *Performance Measurement* (PM) concept from single PM recommendations, which are a piece of advice through PM frameworks that can be divided into a structural and procedural topology. Those frameworks are basic requirements for PM systems. In the

remaining parts of the paper, the term production Key Performance Indicators (pKPIs) [14] will be used to describe such PMs. Once the pKPIs are defined, they should be utilized in a DSS system.

To study production system properties and to design an efficient control of a production system its (simulation) model is needed. Different computer tools can be used to build and simulate the model. In this document, the modeling procedure of a polymerization plant is presented. To model and make experiments on our polymerization production plant Matlab environment was used, together with toolboxes Simulink and Stateflow. The data are stored in an MS Access Database. Using this model the production control of a polymerization plant is studied.

In the next section, we describe the model of a polymerization production process. Different production KPIs were identified which depict the actual performance of a production process. In the section 3, the control paradigm of a production process using pKPIs is described. This control paradigm used in the polymerization plant is illustrated in section 3. Model-based predictive control (MPC) is used here to help the production manager with decisions. Finally, the conclusions are presented in section 4.

2 The case study

The presented case study addresses the closed-loop control of a production process in a polymerization plant. The chosen batch-production process is representative of typical process-oriented production. First, the production process is described.

2.1 Description of the polymer-emulsions production process

The production process consists of three main reactors and two supplementary reactors, dosing vessels, storage tanks and equalizers that are used for the production of various emulsions. The technological process is defined by a recipe: a sequence of operations that must be performed for the production of a particular product. Various recipes performed simultaneously can share some common resources. To ensure good utilization of the equipment and simultaneously satisfy safety requirements, technological and organizational constraints, there must be proper scheduling of the production jobs.

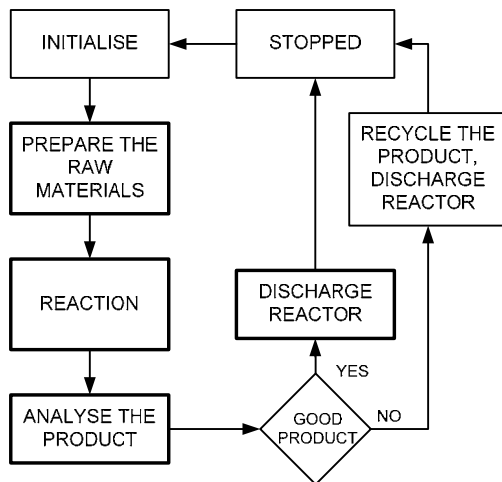


Figure 1: State-transition diagram for the polymerisation process.

The polymerization production process for the production of one batch of emulsion can be represented by the state-transition diagram that is depicted in Figure 1 and consists of three main stages: (i) the preparation of raw materials, (ii) the reaction process and (iii) the product analysis and reactor discharge. The optional stage of product equalization takes place in the equalizator.

The main characteristic of this batch-production process is the production of successive batches using a variety of equipment in which intermediate products appear during each batch stage and must be used in successive stages as soon as possible. In each step certain physical actions (heating, blending) or chemical reactions are involved. Installed DCS and SCADA systems do not handle the production process of a single batch fully automatically, which affects the quality of the product, the duration of a single batch and consequently the utilization of the reactor and the production process. What is particularly noticeable is the influence of manually controlling the reaction temperature on the product's quality. The increased production speed causes the technologists to become busy and their ability to control the temperature is reduced as a result.

The utilization of the whole production process depends on the execution of a list of production jobs (the batch-production process, cleaning the reactor, equalizing a few batches of the same product, etc.), which in the production process is handled manually. The production of batches of equal products together in each reactor reduces the set-up times that is needed in the case when the products from one reactor are mixed (additional equipment cleaning is needed, etc.). If the production speed is increased, some of the phases have to be shortened, which is usually reflected in a reduced quality of the product. If the quality of the raw materials is low or varies, 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 has to be recycled in subsequent batches or discarded. It is obvious that such events have a large influence on the product quality, the production costs and the efficiency.

2.2 Production process model

The model of the polymerization plant should represent the production process and its attributes (utilization of resources, production gain, product quality, production costs, etc) in the form needed for production management. Developed model does not include the mathematical formulation of all chemical reactions involved in the polymerization process as they are too complex and are not necessary at this level of interest. It includes the mathematical representation of temperature, flow and level dynamic as well as a detailed description of the operational sequences. The evaluation of some production processes and the properties of the final product are based on statistical analyses of the production data and on knowledge about the production process obtained by interviewing production operators and technologists. The quality of the product is estimated from the normalized factors representing different quality aspects of production that are contained in one normalized factor for each finished batch, as represented in equation:

$$Q_P = q_{RM} \cdot q_S \cdot q_{RP} \cdot q_{PS} \cdot q_{TC}$$

where:

Q_P - normalized quality factor for a batch of a single product

q_{RM} - the quality of the raw materials

q_S - the of stops in production

q_{RP} - the influence of the reactor's purity

q_{PS} - the influence of the production speed

q_{TC} - the quality of the temperature control

The normalized factor for the influence of the reactor's purity is estimated using this equation:

$$q_{RP} = (1 + 0.02)^{-n}$$

where:

q_{RP} - the influence of the reactor's purity

n - the number of batches since the reactor was last cleaned

The demands of the polymerization-production process model have many specifics that are not easy to implement in commercial modeling and simulation tools. In our case, the model was designed in Matlab

environment, where also toolboxes Simulink and Stateflow were used. The simulated data are stored in an MS Access Database and are available for online and offline processing.

The basic structure of a model is illustrated in Figure 2. Basic models of production items such as buffering tanks, reactors, equalizers, etc. are built in Simulink. Procedural control is performed using Stateflow diagram. It uses different scripts and functions that are defined in Matlab. Global variables are used for data sharing between used tools. All data can also be saved in MS Access.

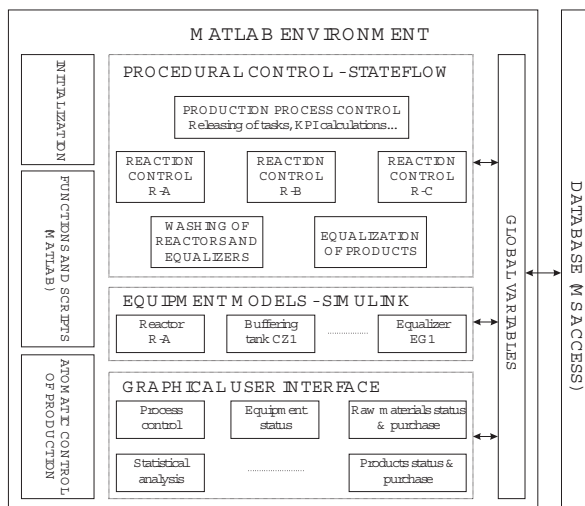


Figure 2: The structure of a model

To supervise and control the process model graphical user interface (GUI) is used (Figure 3). Via this GUI various simulation runs of the polymer production model can be done.

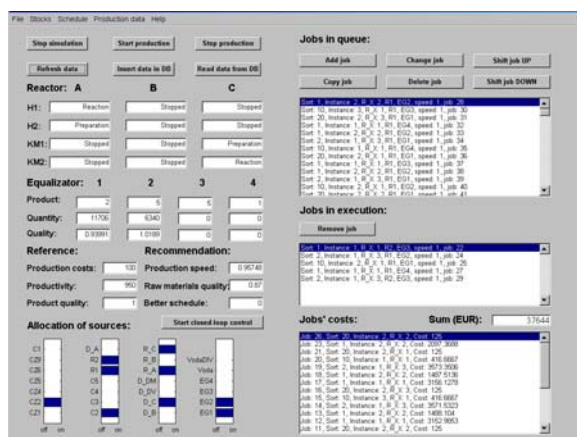


Figure 3: GUI for the polymerization-production process simulator

2.3 KPIs for the polymerization production plant

At the highest hierarchical level the polymerization production plant can be controlled by its input variables, which are *Production speed*, *Raw materials' quality* and *Batch schedule*. The efficiency of the

production process is also affected by disturbances (equipment failures, delays in the production process, variations in the quality of the raw materials, new, high-priority orders, a shortage of raw materials on the market, illness, etc.). Efficiency can be estimated by using the information hidden in a set of current and historical data. This problem can be solved with the introduction of a proper set of production KPIs. pKPIs are chosen according to the specifics of the polymerization production process and the list of general KPIs for the production-management level. Three production KPIs were defined that represents variables that has to be controlled (*Productivity*, *Mean product quality* and *Mean Production costs*).

The procedure for the calculation of the selected KPIs must take into account:

- the calculation frequency that defines how often the KPIs are evaluated T_S and
- the production period (interval) T that defines which production data are used to evaluate the KPIs.

With size of the production period, the dynamics of calculated pKPIs is defined. If production period is increased, the dynamics of pKPIs is decreased.

2.3.1 Productivity

For the described production process, *Productivity* is defined as the amount of all products that were produced in a certain production period, and this amount is defined with:

$$P = \frac{\sum_{i=1}^n k_i \cdot M_i}{T}$$

where:

- k_i represents the correction factor,
- M_i is the batch quantity,
- T is the observed time window and
- n is the number of observed batches.

We take into consideration all the batches that were completely or partly produced in the defined production period and calculate the average amount of products that were produced in an hour. The correction factor defines the percentage of the production time of each batch that fits into the observed production period.

2.3.2 Mean product quality

Another important indicator of production efficiency is the *mean product quality*, which is calculated as the mean value of the quality factors of the batches that were completed in the observed production period. The *mean product quality*, Q , is calculated with:

$$Q = \frac{\sum_{i=1}^n Q_i}{n}$$

where:

- Q_i is the quality of a single batch and
- n is the number of observed batches.

2.3.3 Mean production costs

The production costs indicator consists of *variable costs* such as raw-materials costs, energy costs, and other operating costs and *fixed costs* that are amortization of the equipment, labor costs, etc. The *mean production costs* (per kilogram of final product), C , are calculated as the sum of all the costs related to production in the observed production period divided by the total number of products produced in that production period:

$$C = \frac{\sum_{i=1}^n k_i \cdot C_i + T \cdot C_f}{\sum_{j=1}^m k_j \cdot M_j}$$

where:

- k_i is the correction factor for the job costs,
- C_i is the job cost,
- T is the production period,
- C_f are the fixed costs,
- n is the number of observed jobs,
- M_j is the batch quantity,
- k_j is a correction factor for the batch quantity and
- m is the number of observed batches.

This estimation is helpful for defining the production operating area where the production costs are optimal.

3 The control using KPIs

Production is a complex process, consisting of several interconnected operations restricted by various constraints. The production process must deliver products that meet customer specifications consistently, and at the same time respect the imperative of profitability. To be able to control the production process many information has to be handled.

The control systems in production plants are structured hierarchically into several layers, each operating on a different time scale [1]. On the highest layer, the business-management level, strategic and operational decisions are accepted, that are then sent to the lower production-management level where scheduling, plant-wide optimization and local optimizations are performed, and then further down to the process level control. The automated closed-loop control structures are massively used at the process

level; however, they are less formal and seldom automated at the production level, and almost never automated at the business level. Nevertheless, production managers are performing a feed-back control of the whole production process, although they do not normally directly participate in the production process. Their main mission is to monitor the current performance of the technological process so that they observe the main production-process parameters and make adequate actions. Those parameters can be represented by production KPIs. Here Skogestad's strategy of "self-optimizing control" [12] can be introduced, where the rule is to keep some controlled variables at a constant value. Manager's work now is only to define set-points and some automatic control should be used to assure that set-points. Figure 4 shows the described self-optimizing control scheme [12].

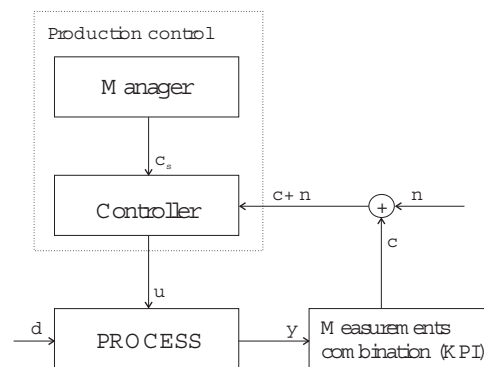


Figure 4: Implementation of the optimal operation of a process with separate layers for optimization and control

Production process can be described as a dynamical system. The values which are used to control the production process (orders, recipes, speed, quality of raw materials...) represents input variables (u). On the other hand performance measurements (pKPIs) represent output variables ($y \rightarrow c$). The system is influenced by different disturbances (d). With the use of the theory of control the appropriate controller can be developed for that kind of dynamical system.

4 Control of a polymerization plant

With a help of the model of a polymerization plant the control of production was designed. The control is based on pKPIs (*Productivity*, *Product quality* and *Production costs*), presented in section 2.3. pKPIs are evaluated every T_s time steps and is calculated based on data for a certain period (T). In our case study, the calculation frequency was 5 hours and the size of the production period was 100 hours. This was chosen empirically on the recommendations of the factory technologists.

The process execution can be influenced with prescription of *Production speed*, *Raw materials*

quality and Batch schedule. Batch schedule is performed manually once per week and for that reason can be assumed as fixed. Let us define the *Production costs* to be the highest priority. Demands from the business-management level are expressed in the *Production schedule* and the desired *Production costs*. The influence of the *Production costs* on the other two production KPIs is known for different types of production schedule (Figure 5).

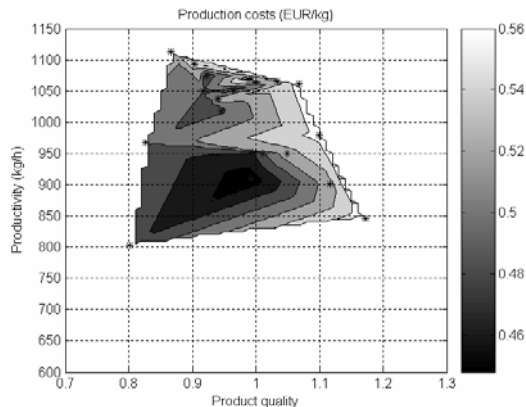


Figure 5: *Production costs* in relation to *Productivity* and *Product quality* for unified production

The production manager can define exact reference values for the *Productivity* and *Product quality* KPIs by choosing the proper KPI dependence (Figure 5) that is relevant for the actual *Production schedule*, and this activity is represented by the outer control loop in Figure 6 – the production manager.

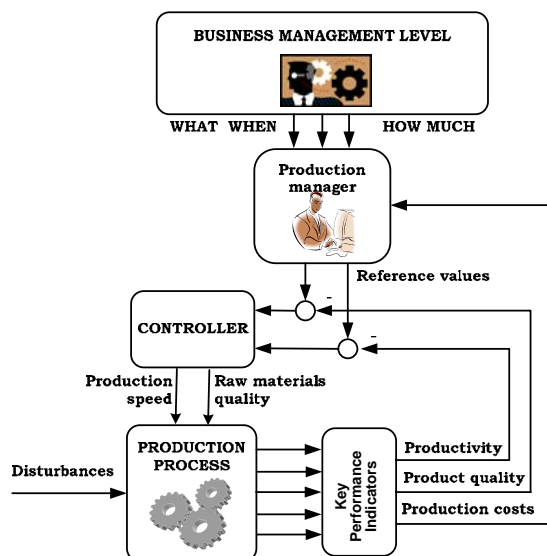


Figure 6: Cascade closed-loop control scheme for the polymerization process

Inner closed-loop is multivariable problem with two input (*Production speed* and *Raw materials' quality*) and two output variables (*Productivity* and *Product quality*). To control these two output variables multivariable controller is needed. Here model-based control strategy was investigated.

This strategy has to operate in an online regime and has to account for any natural physical limitations. The controller has to recognize the interaction between multiple inputs. Model predictive control (MPC) is well suited to solving this constraint problem ([7] or [9]), and multivariable process control using MPC has been thoroughly studied ([6] or [13]). MPC, or receding horizon control, refers to a class of control algorithms in which a dynamic process model is used to predict and optimise process performance.

A simplified, dynamic, first-order process model was obtained by using the identification process over the procedural model of the production process. In the identification process input-output data that were obtained from several simulation runs were used. During the identification process it was assumed that the process is linear. In such a situation an approach where one input is changing 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 the *Production speed* was fixed and the influence of *Raw materials' quality* was studied. The model parameter estimation was made using the identification method in which the least-square criterion was minimized. The input-output dependencies are given with simple first-order models:

$$G = \begin{bmatrix} \frac{31.84}{z-0.938} & \frac{-4.43}{z-0.834} \\ \frac{-0.04}{z-0.932} & \frac{0.052}{z-0.94} \end{bmatrix}, \text{ the } T_S = 5 \text{ hours.}$$

This multivariable model was used for the MPC controller design using the MPC Toolbox in the Matlab environment [1].

The main challenge was the process of MPC controller tuning, so that it was capable of achieving multiple objectives. The MPC toolbox supports the prioritisations of the outputs. In this way, the controller can provide accurate set-point tracking for the most important output, sacrificing others when necessary, e.g., when it encounters constraints. In our case the controller has to consider the input and output constraints as defined by:

$$0.5 \leq \text{Production speed} \leq 1.3$$

$$0.85 \leq \text{Material quality} \leq 1.2$$

and

$$700 \leq \text{Productivity} \leq 1300$$

$$0.87 \leq \text{Product quality} \leq 1.3$$

Different weights were used to prioritise the input and output variables. To solve the optimization problem, a prediction horizon of 100 hours and a control horizon of 40 hours were used. The MPC toolbox uses the Quadratic Programming solver to solve the optimisation problem, where the bounds of the constraints are finite [1].

Closed-loop control was tested in several simulation runs. Figure 7 presents the results of an experiment where the set-point for *Productivity* was changed two times and the set-point for *Product quality* was changed just once. In the experiment a normal batch schedule for the production of three products, each of them produced in one reactor, was used. MPC managed to achieve the prescribed set-points for the controlled KPIs (*Productivity* and *Product quality*). With the increasing set-point for the *Productivity* the *Production costs* is also increasing, and with the decreasing set-point for the *Product quality* the production costs decrease. These trends are in accordance with the production KPIs relationship presented in Figure 5.

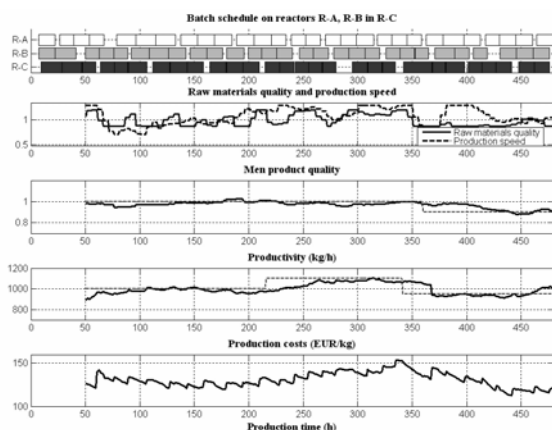


Figure 7: Batch schedule, input and output variables for one simulation run for normal production.

5 Conclusions

To be able to analyze a production system and develop its control the model of production system is needed. In this work, the detailed description of a model of polymerization production plant is presented. Production management must ensure stable production at the technological level as well as at the economic level.

This paper uses approach to measuring and presenting the achieved production objectives in the form of production KPIs and proposes the incorporation of KPIs into closed-loop production-control systems. Developed framework purpose the part of the manager's work can be managed by the controller. Model-based controller is used in this work.

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