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Production Control of a Polymerization Plant Based on Production Performance Indicators

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The specifics of process manufacturing have a great influence on production management. 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 article proposes a closed-loop control structure with the utilization of production-performance indicators (pPIs) as a possible solution to this problem. Suggested concept takes into account also economic issues of production. 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 pPIs as controlled variables was implemented on a procedural model of a production process for a polymerization plant. Preliminary results demonstrate the usefulness of the proposed methodology. At the implementation stage we must be aware that appropriate IT system has to be available which ensures needed online production data.

Keywords: Production management, Production Control, Production performance indicators, Model-based control.

1 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 (Holt 1999; Dangelmaier et al., 2005). 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 organisational, technological and other constraints. At the production-management level many activities are performed. The transformation of a company's objectives into results and the optimization of production are one of the most essential.

To fulfil 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 optimisation 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 (Jovan, 2001). These specifics make process manufacturing both *complex* and *uncertain* (Scherer, 1995).

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, Forza et al. (2001) 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. Vicens et al. (2001) propose and discuss 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. Ahmad et al. (2002) define 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 means 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 production objectives (such as profitability, production efficiency, plant productivity, and product quality) cannot be directly measured from current production data. For this reason their translation into a set of output production-process variables (subsequently termed "*production-performance indicators*", pPIs) should be provided (Neely et al., 1995). The concept of PIs can take many forms. Folan and Brown (2005) 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, which can be divided into a structural and procedural topology. These frameworks are the basic requirements for PM systems. There are many methods to define and implement PIs in production. In Ghalayini et al. (1996) an integrated dynamic performance measurement system (IDPMS) that integrates the management, the process-improvement teams and the factory shop floor is presented. Suwignjo et al. (2000) developed quantitative models for PM systems (QMPMS) that can be used to identify the factors affecting performance and their relationships, structure them hierarchically, quantify the effect of the factors on performance, and express them quantitatively. Another method to design and establish a PI system is defined with ECOGRAI (Tatsiopoulos and Panayiotou, 2000).

Many researches have been done in the field of plantwide control system design. As Stephanopoulos and Ng (2000) have stated, plantwide control possesses certain characteristics which are not encountered in the design of control systems for single units. Plantwide control deals with the structural decisions of the control systems, including what to control and how to pair the variables to form the control loops. Morari (1980) introduced the formulation of the problem of synthesizing control structures for chemical processes. Decomposition is the underlying principle, leading to the classification of the control objectives (regulation, optimization) and the partitioning of the process for the practical implementation of the control structures. Larsson and Skogestad (2000) have made a review of plantwide control and proposed new design procedure. The first issue of a control is stabilization and then keeping the operation within given constraints. Some degrees of freedom are used for stabilization, while others can be used to optimize the operation. Different kinds of solutions are possible. In practice hierarchical feedback implementation is preferred, where *optimization layer* computes set-points c_S for the controlled variables c, and *control layer* implements this in practice, with the aim of achieving that (Skogestad 2002).

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.

In the next section we describe closed-loop production management paradigm that is organized in two hierarchical layers. In section 3 the case-study is given, which discuss the control of a production process in a polymerization plant. After the production process description its procedural model is briefly represented. Section 4 explains the control of the polymerization plant. The control is divided on production cost optimization and production control on the lower level. Finally, the conclusions are presented in section 5.

2 Closed-loop production-management paradigm

In the management system of a process-production enterprise, 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. At the production-management level, the main mission of a production manager is to monitor the current performance of the technological process by observing the most important production-process parameters (pPIs), e.g., the utilization of production capacities, the quality of the raw materials and the product, the stocks, etc. In the case when the pPIs deviate from reference values, production managers have to make on-the-spot adjustments to the direct inputs in the production process so as to achieve the desired global production goals, i.e., they control the process.

In this work the production control system is proposed, which is divided into two hierarchical layers: the *optimization layer*, where production costs are optimized and the reference values for the pPIs are defined, and the lower *production control layer*, which is responsible for maintaining the current pPIs values close to their reference values. The idea of hierarchical control levels is related to the so-called self-optimizing control that was presented by Skogestad (2000; 2002). In attempting to synthesize a feedback optimizing control structure, our main objective is to translate the economic objectives into process control objectives. Generally speaking, for most of the systems we have available degrees of freedom (decisions), u, that we want to use in order to optimize the system operation. With the proper selection of the controlled variables, c, which when held constant, leads automatically to the optimal adjustments of the manipulated variables u, and with it, the optimal operating conditions, and neutralization of disturbances (d) and implementation errors (n). With this approach the complex optimization problem can be translated to a simpler control problem. Figure 1 shows the described self-optimizing control scheme.

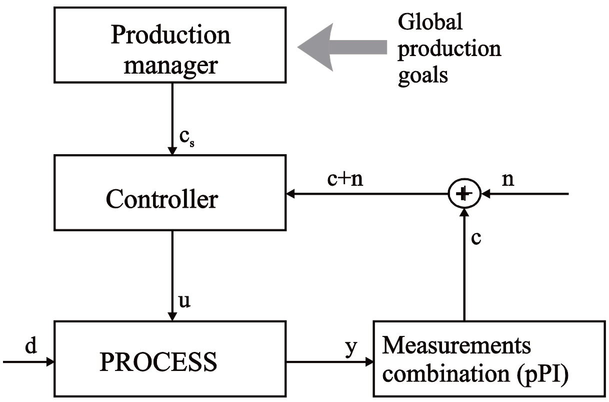

Figure 1: Self-optimizing control divided on optimization and production control layer.

Figure 2 presents the generalized, hierarchical control-loop scheme for the whole production process based on the self-optimizing control approach and pPIs. On the optimization level, represented by the upper control loop, the production manager optimizes the production process by selecting appropriate reference values (c_S) for the pPIs in the control loop on the lower production-control level. The production manager's choice of proper pPIs set-point values depends on her/his experiences and skills, the demands from a higher business-management level and on the current state of the production process. The process of defining the set points can be improved by using the production DSS, where an estimation of the current production costs can be made using a mathematical model of the production and the online production data. Once the reference values for the pPIs are defined, they are maintained by the production controller. The described control structure reduces the complexity of the control problem; while the upper control loop is managed manually by the production manager's decisions about the set-point values for the chosen pPIs (e.g., on a daily basis), the lower control loop is managed automatically by the production controller more frequently (e.g., on a hourly basis). It is important to note that the time constants of the lower control loop are significantly shorter than in the higher control loop.

As the control problem is decomposed on two hierarchical levels, it follows that two different models of production usually need to be developed. On the optimization level a production-costs model (CM) has to be developed to support the production managers' decisions for the most suitable set-point values of the observed pPIs. Also, the design of the production controller (e.g., model-based control) on the lower control level usually needs a process model (M).

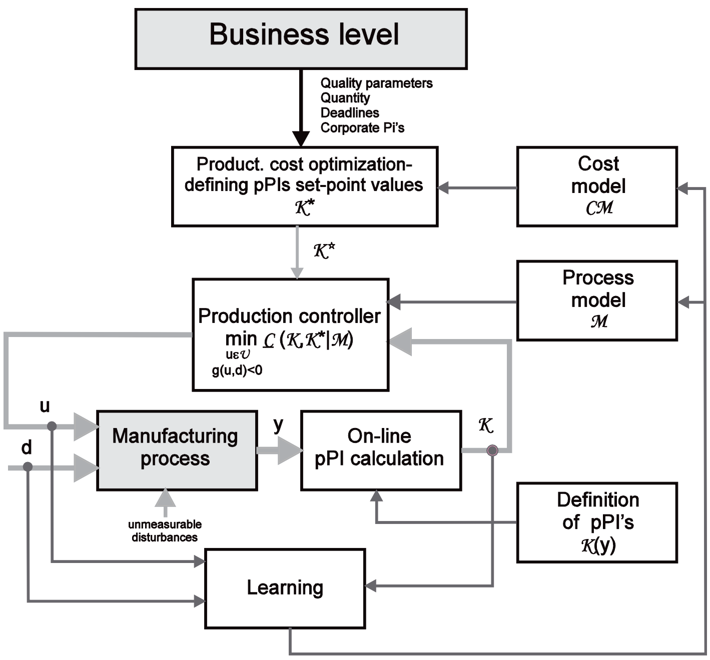

Figure 2: General scheme of a model-based production-control system.

3 Case-study production process

Case-study discussed in the paper addresses the closed-loop control of a production process in a polymerization plant. The chosen batch-production process is a typical representative of process-oriented production. As the installed DCS and SCADA systems do not handle the production process completely automatically, and not all the production-process variables are available online for use in a control system, a procedural production-process model of the case-study production process was developed.

3.1 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 polymer-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 and proper scheduling of the production jobs must be defined.

The polymerization process for the production of one batch of emulsion 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 the 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. As already mentioned, the installed control equipment does not handle the production process completely automatically, which affects the quality of the product, the duration of a single batch and, consequently, the utilization of the reactors and the production process itself. The increased production rate can cause an operator to become too busy and his/her ability to control the production efficiently can be reduced.

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 appear in the case when the products from one reactor are mixed (additional equipment cleaning is needed, etc.). Speed of production and quality of raw materials has a large influence on the product quality, production costs and efficiency.

3.2 Procedural production process model

The main purpose of designing the procedural production-process model was the capability of simulating the execution of scheduled jobs in production and of investigating and verifying the plant-wide control algorithms (Gradišar et al., 2007). The demands on the procedural model of the case-study production process have many specifics that are not easy to implement in commercially available modeling and simulation tools. To avoid this trap, academically well-established Matlab, Simulink and Stateflow simulation environment were used. The simulated data are stored in an MS Access Database and are available for online and offline processing.

The developed production process model of the polymerization plant represents the production process and its attributes (utilization of resources, production gain, product quality, production costs, etc) in the form needed for production management. This means that we have modeled physical realities of the process as well as production costs and quality aspects of the process. The model is structured in six logical units that are interconnected as depicted in Figure 3.

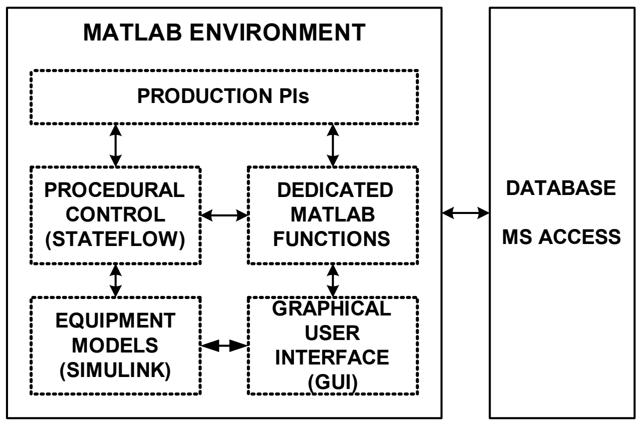

Figure 3. The structure of the production process model

The *equipment models* are created with simple Simulink models that incorporate I/O control signals. The Simulink models of the chemical reactors do not include the exact mathematical formulation of the chemical reactions involved in the polymerization process (they are too complex and, at this level of interest, they are not necessary), but they do include the equations of temperature, flow and level dynamics.

Procedural control of the equipment is done by the Stateflow toolbox. *Dedicated Matlab functions* are used to evaluate other properties (e.g., the product quality) of the chemical reactions. These functions were designed and calibrated on the basis of statistical analyses of the production data and on knowledge about the production process obtained by interviewing production operators and technologists.

The production jobs are scheduled according to the demands from the business management level (due times, desired product cost and quality, etc) and other production constraints (production rate, availability of resources, etc). Job schedule represents an input variable in the production-process model. The other two input variables that define the production process are the *Production speed* and the *Raw materials' quality*, and these are described in more detail in Section 4.1.

The *GUI* enables the user to simulate the production process; the user can manipulate online the job schedule, the *Production speed* and the *Raw materials' quality*. On the other hand, the GUI presents the current state of the equipment (reactors, equalizator, etc) and enables statistical analyses and a visual representation of the historical production data as well as the pPIs.

For the case-study production process presented in this article the *production Performance Indicators* (*Productivity*, *Product Quality* and *Production Costs*) were selected to obtain information about the current status of the production process. None of these pPIs is directly measurable, but an estimation of their current values can be made using the combination of the measurable output production-process variables.

The procedure for the pPIs calculation has two characteristic parameters:

- The pPIs' calculation frequency f_{PI}: this defines the time frames in which the pPIs are evaluated.
- The pPIs' calculation window T_{PI}: this time window defines which production history data are used for the evaluation of the pPIs.

These two parameters have a special effect on the evaluation of the pPIs. For example, if the calculation window T_{PI} is increased, the dynamics of the calculated pPIs are decreased and vice versa. In our case the simulation runs were performed with a calculation frequency of one evaluation per 5 hours, and with the size of the calculation window being 100 hours. These time constants were chosen empirically, on the recommendations of the factory technologists and on the basis of simulation results.

For the described production process, *Productivity*, *P* (*kg/h*) is defined as the amount of all products that were produced in a certain production period. We take into consideration all the batches that were completely or partly produced in the defined calculation window and calculate the average amount of products that was produced in an hour. Another important indicator of production efficiency is the *Product Quality*, Q_P (no unit), which is calculated as the mean value of the normalized quality factors of the batches that were completed in the observed calculation window T_{PI}. The quality of product is defined with more parameters: viscosity, non-volatile portion, solid particles, pH and concentration of monomers (Aller, 2007). The production costs consist of variable costs (raw-materials costs, energy costs, and other operating costs) and fixed costs (amortization of the equipment, labour costs, etc). The mean *Production Costs*, *C*, (EUR per kilogram of final product) are calculated as the sum of all the costs related to production in the observed production period divided by the total amount of products produced in that production period.

4 Control of the polymerization plant

To control the modeled process a control system was designed, with the control being performed on different levels of decisions. The minimization of production costs is the highest priority, and the majority of control actions are made to fulfil this demand. The demands from the business-management level are expressed in the production schedule and the desired production costs. The production jobs schedule represents an input variable that has a significant impact on the pPIs, but it is performed manually once or twice a week, and for that reason there is no need to use it in a direct closed-loop control.

Figure 4 represents an adapted version of the basic hierarchical control structure from Figure 2. On the process-optimization level the cost optimization is performed by the production manager, who is using the current value of the *Production Costs* indicator, the job schedule and a production cost model to define the optimal set points for the *Product Quality* and *Productivity* indicators. The production costs' model is constantly updated with current data and its simulation runs can provide vital information for defining the appropriate reference values for the chosen pPIs. Thus, a production costs' model acts as a kind of decision support system (*DSS*) for the definition of references for the pPIs. Once the pPIs' reference values are defined they are maintained by the production controller, which controls the execution of the production jobs' schedule by adjusting the available degrees of freedom for the chosen production processes, which are *Production speed* and *Raw materials' quality*.

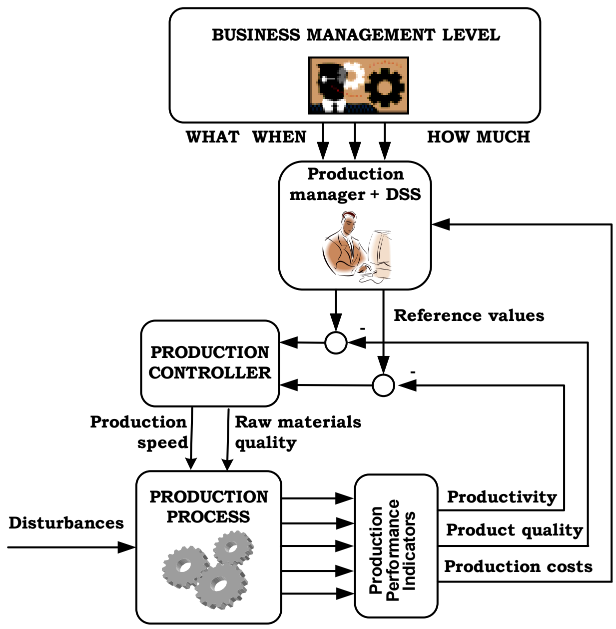

Figure 4. Hierarchical closed-loop control scheme for the polymerization

Production-process control logic was implemented using Stateflow charts, and with them the I/O control signals are simulated.

4.1 Production cost optimization

To be able to define a production costs' model, a sensitivity analysis of the pPIs has to be made. Figures 5 and 6 describe the dependence of the *Product Quality* and *Productivity* pPIs on the process input variables (*Production speed* and *Raw materials' quality*) for a fixed batch schedule. The pPIs were evaluated at 20 working points and connected together by extrapolation. The *Production speed* defines the production rate, and is normalized. During normal production there is enough time for all the production cycles to be finished in the required time. An increased production speed represents an increased production rate, where some production phases (e.g., vacuuming) have to be shortened, and this normally decreases the product quality and increases productivity. When the production speed is increased, the productivity is increased, but on the other hand, the operator's ability to control the reactor temperature is decreased, which normally decreases the product quality and vice versa. The efficiency of the production process is also affected by disturbances; the most significant are 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. Some of these disturbances are included in the model as random events. The *Raw materials' quality* is also presented as a normalized entity, where the value 1 represents a quality of raw materials that is most suitable in relation to cost/performance aspects. Good *Raw materials' quality* (1.2) enables the production of products with sufficient quality in worse production conditions, which are normally represented during an increased production speed. Extreme working conditions, like high *Production speed* (1.2) and low *Raw materials' quality* (0.8), can result in batches of insufficient quality, which then have to be recycled. This introduces additional analyses and work that are connected with delays in the production process, increased *Production Costs* and, consequently, lower *Productivity*, as can be seen in Figure 6.

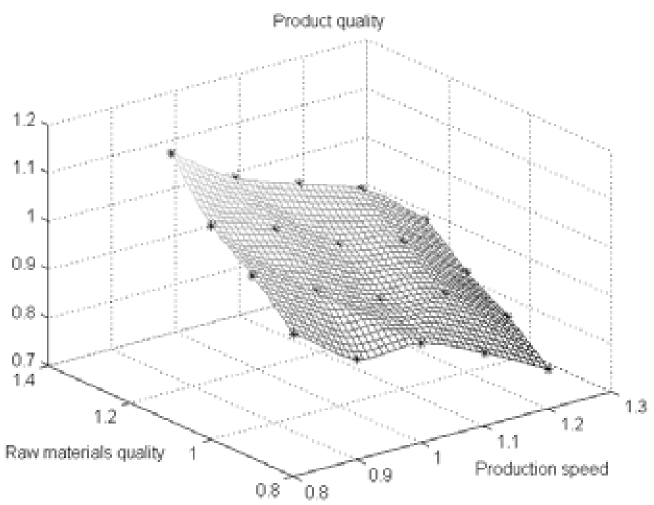

Figure 5. Product Quality PI in relation to Raw materials' quality and Production speed.

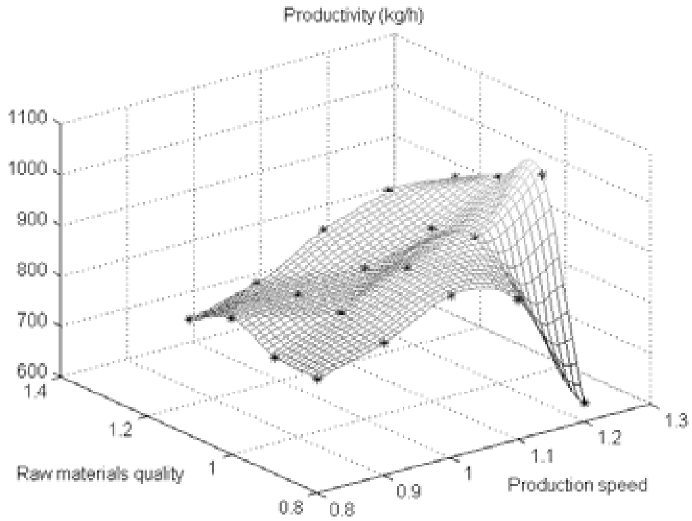

Figure 6. Productivity PI in relation to Raw materials' quality and Production speed.

Figures 7 and 8 show the relation between *Production Costs*, *Product Quality* and *Productivity* pPIs, i.e. the dependence of the *Production Costs* regarding *Productivity* and *Product Quality*. Figure 7 shows the results for unified production (a production where a series of batches of the same or similar final products are performed on each reactor – production for stock) and Figure 8 shows the results for mixed production (a production where products are changing from batch to batch on each reactor – production on demand). The production of batches of equal products together in each reactor reduces the set-up times that appear in the case when the products from one reactor are mixed (additional equipment cleaning is needed, etc). Both figures exhibit a noticeable global minimum where the *Production Costs* are minimal. In the unified production the *Productivity* pPI value ranges from 800 to 1100, whereas in the mixed production it ranges from 650 to 1050 kg/h. The region with low *Product Quality* and *Productivity* is not well defined because it is

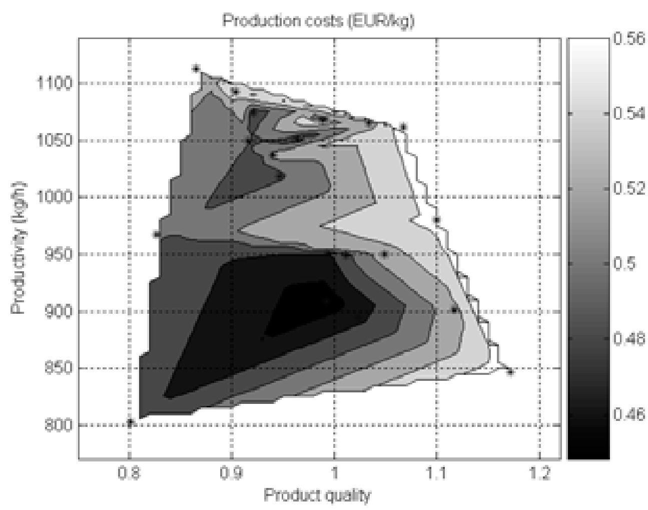

Figure 7. Production Costs in relation to Productivity and Product Quality pPIs for unified production.

connected with the frequent production of bad batches and represents a working region that has to be avoided during normal production.Performed PI sensitivity analysis support the idea of closed-loop control based on pPIs. These dependences can be further used to suggest production manager defining exact reference values for the *Productivity* and *Product Quality* indicators. This is done by proper PI dependence that is relevant for the actual production schedule, and this activity is represented by the upper control loop in Figure 4.

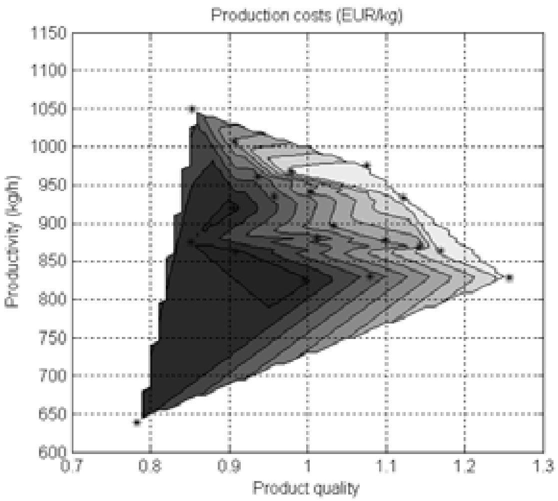

Figure 8. Production Costs in relation to Productivity and Product Quality pPIs for mixed production.

4.2 Design of the production controller

As mentioned previously, optimal operating conditions can be ensured if selected pPIs (*Productivity* and *Product Quality*) are being controlled at a predefined referenced value. The production controller performs the monitoring and controlling of these two pPIs to the reference values, defined by the optimization level.

The production controller is placed in the lower hierarchical control loop in Figure 4. To design a controller a model of the production process is needed. The part that has to be controlled is a multivariable system that can be linearized for a commonly used working area. It has two input variables (*Production speed* and *Raw materials' quality*) and two output variables (*Productivity* and *Product Quality*). In the remaining part of the paper, two controllers will be presented:

- A controller based on look-up tables,
- A multivariable predictive controller (MPC).

A controller based on look-up tables simulates the production managers' control actions in one working region of the production process. The controller consists of two look-up tables, the first manipulates *Production speed* (*S*), and the second one manipulates *Raw materials' quality* (Q_{RM}) according to the control error (Figure 9). Indicator for *Productivity* is labeled as *P* and *Product Quality* as Q_P. The control scheme also includes control disturbances that are always present in real systems. The look-up tables G_1 and G_2 were defined on the basis of a sensitivity analysis of the production-process model and on the expertise of experienced technological staff. P_R and Q_{PR} are reference values for controlled pPIs. The first diagram in Figure 10 shows the batch schedule for the production of *Product 1* in *Reactor R-A*, *Product 2* in *Reactor R-B* and *Product 3* in *Reactor R-C*. The spaces between batches represent reactor cleaning procedures and bottlenecks. The second diagram shows the trace of the manipulated variables during the experiment and the remaining three diagrams show the traces of the controlled pPIs.

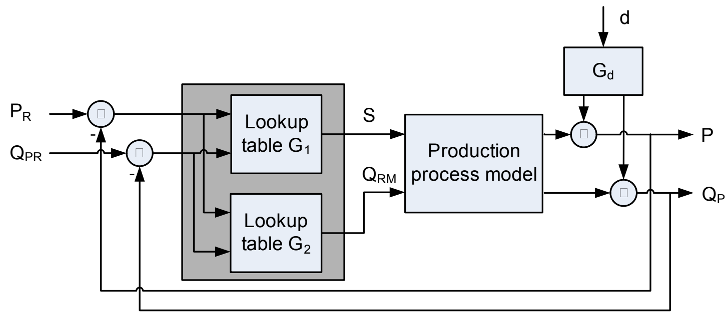

Figure 9. Internal closed-loop control scheme based on look-up tables.

The main drawback of the presented controller is the control error in steady state, which can be observed in Figure 10 when the set-point for the *Productivity* pPI is different from 1000 kg/h. This is a consequence of the property of the presented controller that is in fact a P-controller with variable gain.

In the next step, the *model-based control strategy* was developed. This model-based 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 (Morari and Lee 1999, Qin and Badgwell 2003), and multivariable process control using MPC has been thoroughly studied (Maciejowski, 1989). MPC, or receding horizon control, refers to a class of control algorithms in which a dynamic process model is used to predict and optimize process performance.

The designed production-process model, presented in Section 3, is not suitable for the MPC construction, and for that reason a simplified, dynamic, linear process model was obtained by using the identification process over the earlier developed production-process model. 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

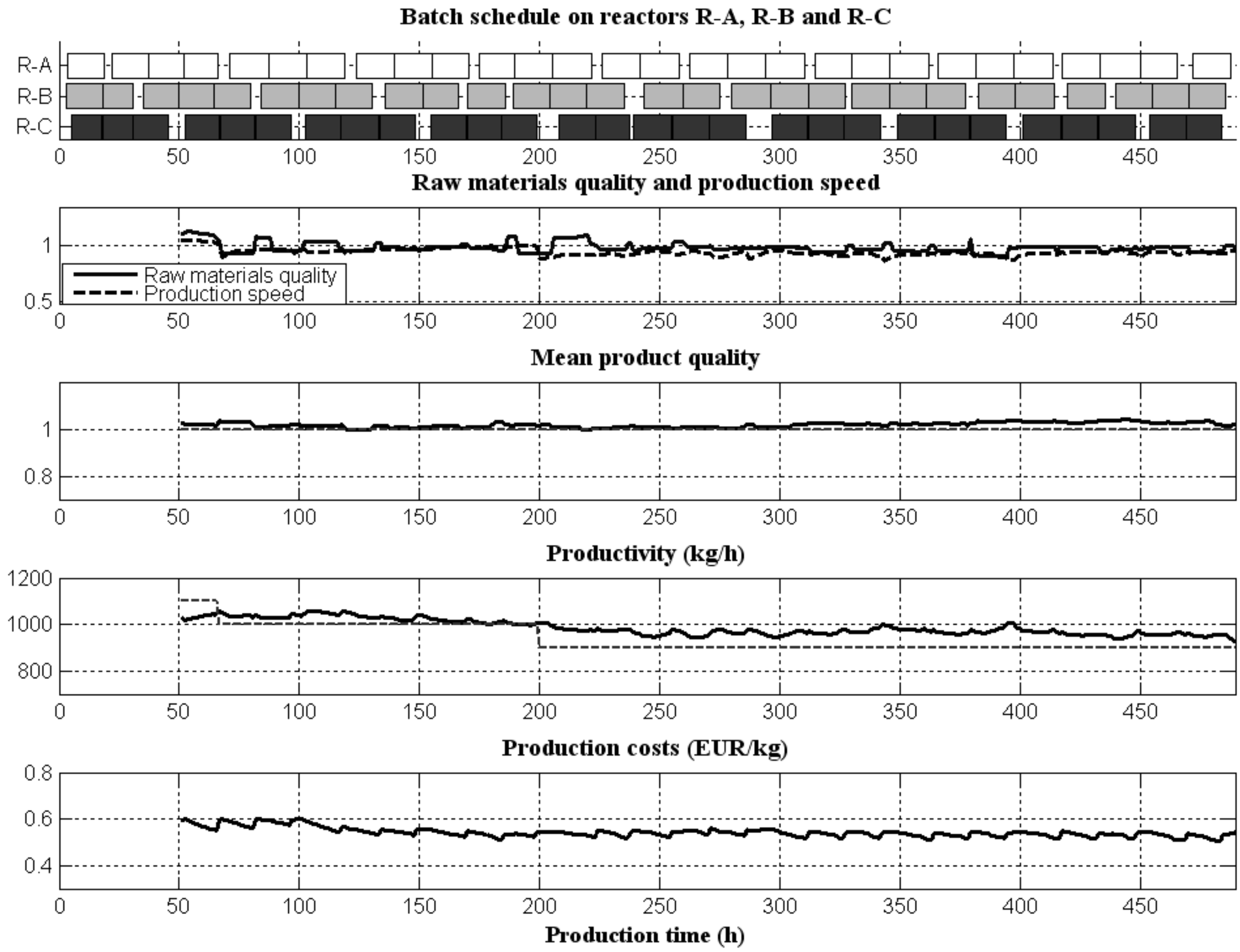

Figure 10. Production PIs' control using a look-up-table-based controller

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 therefore given with first-order models , where the sampling time T_S was 5 hours.

$$G = \begin{bmatrix} \dfrac{31.84}{z-0.938} & \dfrac{-4.43}{z-0.834} \\ \dfrac{-0.04}{z-0.932} & \dfrac{0.052}{z-0.94} \end{bmatrix}, \qquad T_s\text{=5 } h$$

This multivariable model *G* was used for the MPC controller design, where the MPC Toolbox from the Matlab environment (Bemporad et al., 2006) was used.

The main challenge was the tuning of MPC controller's cost function parameters. The MPC toolbox supports the prioritizations 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 Equation (4.2). In order to eliminate the production of batches of insufficient quality we had to constrain the lower limits of the Raw materials quality and *Product Quality*. *Production speed* and *Product Quality* represent physical constraints of the production process.

$$\begin{matrix} 0.5 \le S \le 1.3 \\ 0.85 \le Q_{RM} \le 1.2 \end{matrix} \quad \text{and} \quad \begin{matrix} 700 \le P \le 1300 \\ 0.87 \le Q_P \le 1.3 \end{matrix}$$

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 (Bemporad et al., 2006).

Closed-loop control was tested in several simulation runs. Figure 11 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

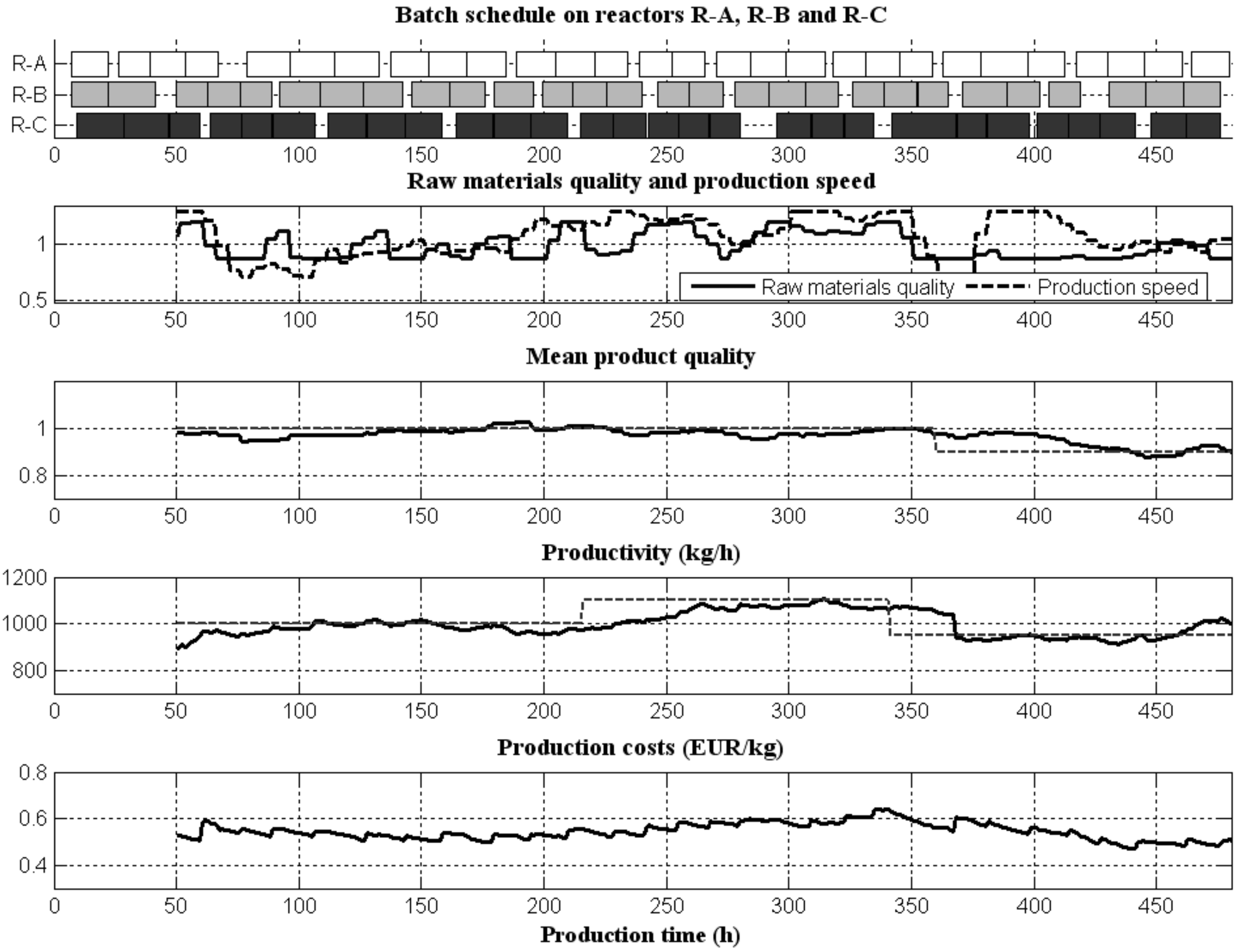

Figure 11. Batch schedule, input and output variables for one simulation run for normal production.

prescribed set-points for the controlled pPIs (*Productivity* and *Product Quality*). With the increasing set-point for the *Productivity* pPI the *Production Costs* pPI is also increasing, and with the decreasing set-point for the *Product Quality* pPI the *Production Costs* decrease. The *Production Costs* pPI is not as smooth as the other two pPIs, which reflects the influence of the stops in production on the *Production Costs*. With an increased time horizon for the pPI evaluation such leaps in the pPI values are reduced, but also the pPI's dynamic is reduced, and consequently the performance of the MPC controller is also reduced. From the pPI responses on changed set-points for *Product Quality* and *Productivity* pPIs the time constant of such a pPI model can be estimated at around 50 hours.

Figure 12 presents the situation when the production schedule is changed during the simulation. In the middle of the experiment the *Productivity* set-point is very high and an extremely mixed production is applied to the production process. Even in the case when the *Production speed* is at a maximum for almost all the time the *Productivity* pPI cannot reach the prescribed set-point. A closer look at Figure 8 reveals that the set-point for the *Productivity* pPI is set far outside the manageable working region. The MPC controller managed to reach the set-points for the controlled pPIs in the remaining part of the experiment. The presented results show that the designed MPC controller is robust enough to control the production of different types of batch schedules.

5 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. The variables to be controlled by a plant-wide control system are not as clearly or as easily defined as for single units. Local control decisions, made within the context of single units, may have long-range effects throughout the plant. Also the size of the plant-wide control problem has to be considered which is significantly

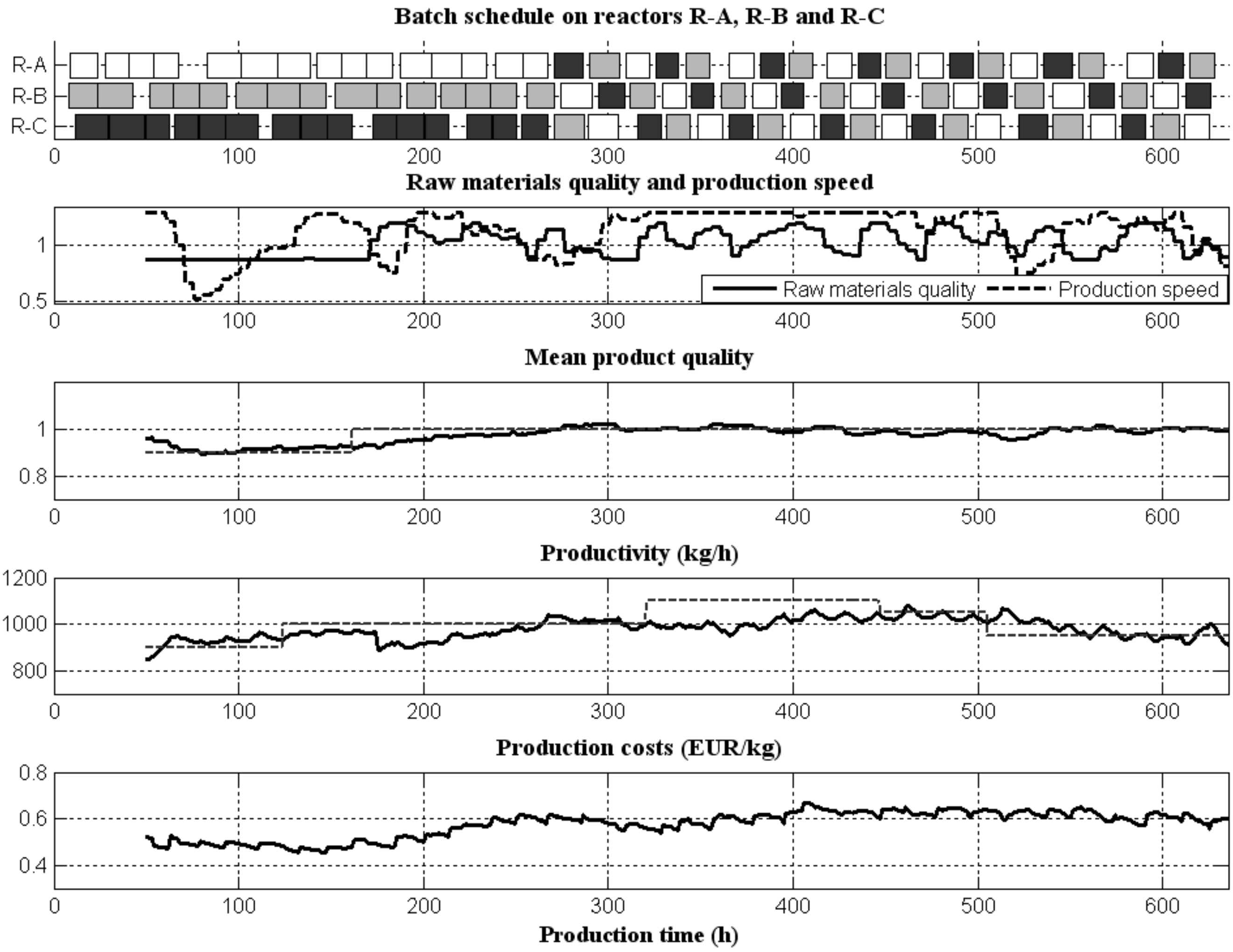

Figure 12. Batch schedule, input and output variables for the case when the production schedule is changed during the simulation run.

larger than that for the individual units. This makes its solution considerably more difficult.

This article presents an approach to measuring and presenting the achieved production objectives in the form of production PIs as a reduced set of control variables and proposes the incorporation of those indicators into closed-loop production-control systems. The framework used in this work makes it possible to automate part of the manager's routine work. In the hierarchical closed-loop control structure two types of control strategies were tested: a controller based on look-up tables and model-based controller (MPC). The control system was developed and tested for the model of a polymerization production plant. The promising results of this study suggest that the approach can further be successfully implemented in real industrial plant.

Profitability is the criteria by which the vast majority of decisions are made in production management. The proposed concept uses online observations of production costs and enables production managers for on-line and adequate response, when defining the production parameters. The weakness of the implementation of that kind of system is that the system needs online data, which are most commonly not available in the real industrial plant. In this case appropriate IT system has to be implemented first.

6 Literature

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Vodenje proizvodnje polimerizacije z uporabo proizvodnih kazalnikov učinkovitosti

Posebnosti procesne industrije imajo velik vpliv na vodenje proizvodnje. Poudarek vodenja proizvodnje v tovrstnih industrijah je na vzdrževanju stabilne in stroškovno učinkovite proizvodnje znotraj danih omejitev. Načrtovanje strukture sistema vodenja proizvodnje tako predstavlja enega izmed najbolj zahtevnih problemov. Kot možna rešitev omenjenega problema je v prispevku predlagan koncept zaprtozančnega vodenja z uporabo proizvodnih kazalnikov učinkovitosti (pPIs). Predlagan koncept upošteva tudi ekonomski vidik proizvodnje. Uporaba kazalnikov učinkovitosti omogoča prevedbo doseganja globalnih ciljev proizvodnje (npr. minimizacijo proizvodnih stroškov) v ustrezno izvedeno zaprtozančno vodenje izbrane podmnožice procesnih veličin. Ideja zaprtozančnega vodenja, kjer kazalnike pPI uporabimo kot regulirane veličine, je bila preizkušena na proceduralnem modelu proizvodnega procesa polimerizacije. Preliminarni rezultati kažejo na uporabnost predlagane metodologije ob predpogoju,, da je v fazi implementacije potrebno zagotoviti ustrezno informacijsko podporo za zagotavljanje vseh potrebnih podatkov za vodenje proizvodnje.

Ključne besede: Upravljanje proizvodnje, Vodenje proizvodnje, Proizvodni kazalniki učinkovitosti, Prediktivno vodenje.