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Model-based Production Control

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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 simulation 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.

Key words: production management, performance measurement, production control, closed-loop control, model predictive control.

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 [4] defined DSS (Decision Support System) concept by combining the works of Simon [10] and Anthony [1]. Simon [10] classifies needed technology support depending on the type of decisions. Structured processes who refer to routine, repetitive problems with standard solutions, 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. A number of information-technology products have been developed to collect and process a vast amount of production data. However, the production-management-level functions are covered only partially. 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; and 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.

In general, an appropriate model of a production process is needed in order to cope with its behavior and to build a control system. However, this behavior is often extremely complex. When the behavior is described by a mathematical model, formal methods can be used, which usually improve the understanding of systems, allow their analysis and help in implementation. Within the changing production environment the effectiveness of production modeling is, therefore, a prerequisite for the effective design and operation of manufacturing systems.

It this paper the control of the polymer-emulsion batch-production process is presented. The polymerization process consists of three main stages: preparation of raw materials, the reaction process and the product analysis. Batches are produced successively using variety of equipment. Simulation model of this production-process was designed in order to simulate the execution of scheduled jobs in production and to investigate and verify the plant-wide control algorithms. The demands on the simulation 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, Matlab, Simulink and Stateflow simulation environment were used.

Usually the most important production objectives cannot be directly measured from current production data. For this reason, their translation into a set of output production-process variables should be provided. 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 [8]. 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 production control system. 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 [12]. Decomposition of the problem 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. Hierarchical feedback implementation of a control is used here, where *optimization layer* computes set-points for the controlled variables and *control layer* implements this in practice, with the aim of achieving the predefined setpoints [5, 11]. For each level of a control, different model is needed. On the optimization layer, production costs' model is used to optimize the production costs, and on the control layer usually model based control (MPC) with in built process model is used.

In the next section, we describe the simulation model of a polymerization production process. Different pKPIs 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 4. Model-based predictive control (MPC) is used here to help the production manager with decisions. Finally, the conclusions are presented in section 5.

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.

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 equalizer.

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

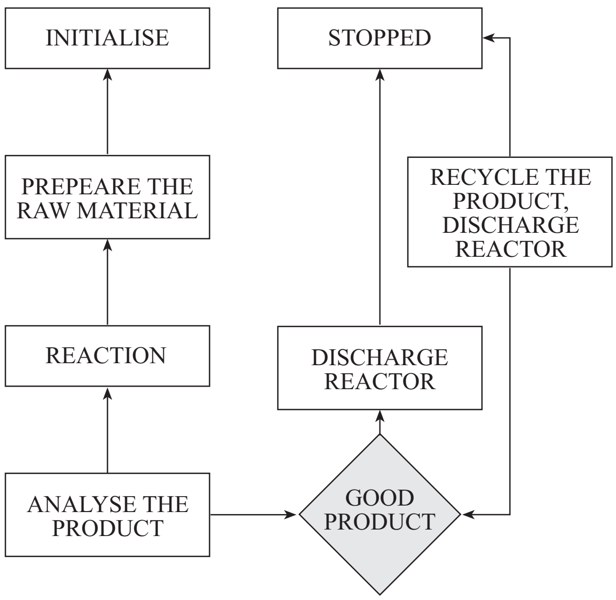

Fig. 1 State-transition diagram for the polymerisation process

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 manual control of 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 efficiently is 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 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 itself together with 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 Q_P for each finished batch, as represented in equation:

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

Factor q_{RM} is defined here as a mean value of raw materials' quality, multiplied by influence factor k_i.

$$q_{RM} = \frac{1}{n}\sum_{i=1}^{n} k_i \cdot q_i$$

The factor for the influence of the reactor's purity on the final product's quality q_{RP} is estimated using next equation (where n denotes the number of batches since the reactor was last cleaned):

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

The influence of the production speed q_{ps} in described with $q_{ps}=1-s_p$, where s_p denotes production speed. The quality of the temperature control q_{TC} is evaluated using the integral of the square error between measured temperature and defined temperature profile. The influence of the stops in production q_S is defined in the same way as the influence of the reactor's purity; only that in this case n represents the number of stops.

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 are 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.

To supervise and control the process model graphical user interface (GUI) is used (Figure 3).

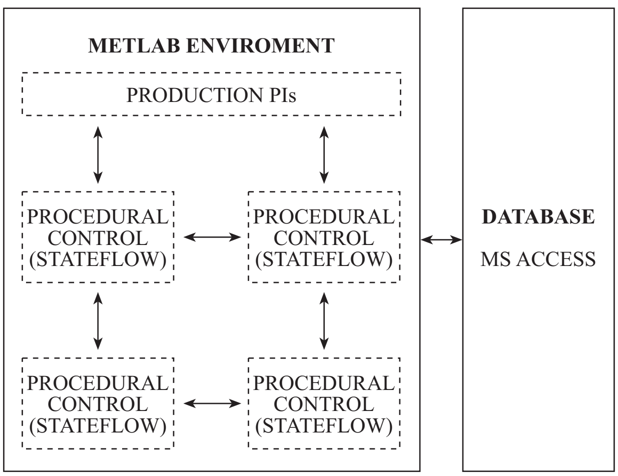

Fig. 2 The structure of a model

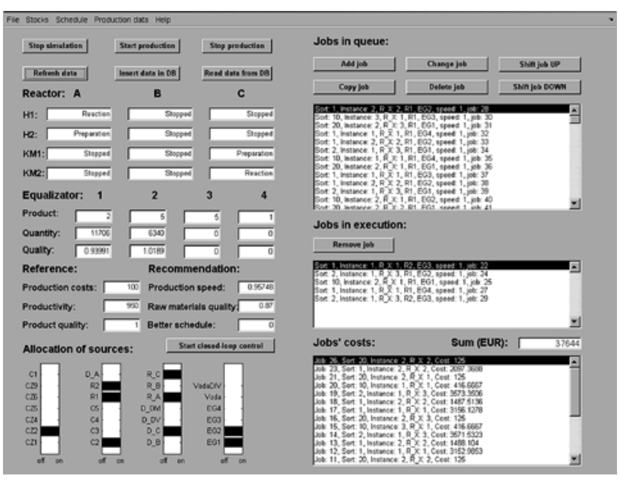

Fig. 3 GUI for the polymerization-production process simulator

Via this GUI various simulation runs of the polymer production model can be done.

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 pKPIs

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 pKPIs.

The idea of hierarchical control levels is related to the so-called self-optimizing control that was presented by Skogestad [11]. Generally speaking, for many 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, and the set-points, c_s, for these variables it is possible to operate in a near-optimal regime just by preserving these variables at defined set-points. With this approach, the complex optimization problem can be translated to a simpler control problem. 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.

The control is separated in two levels and for this reason two models are needed. 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 – cost's model. Once the set-points for the pKPIs are defined, they are maintained by the production controller. At this level, the 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 control variables (u). On the other hand performance measurements (pKPIs) represent output variables ($y \rightarrow c$). The system is influenced by dif-

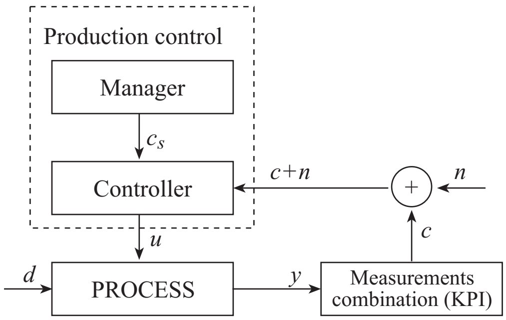

Fig. 4 Implementation of the optimal operation of a process with separate layers for optimization and control

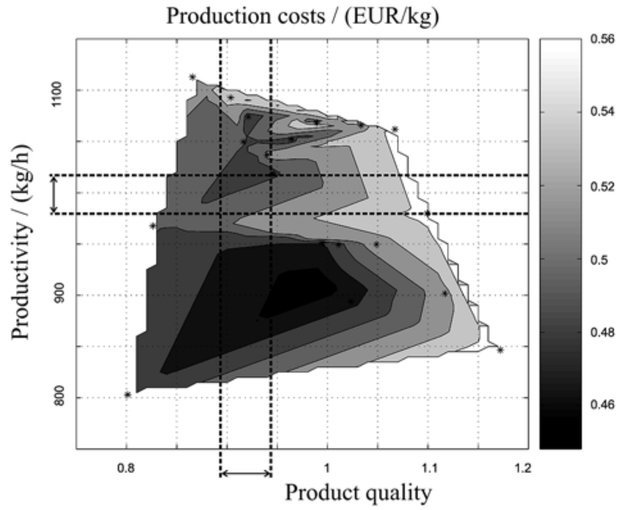

Fig. 5 Cost's model – Production costs in relation to Productivity and Product quality for unified production

ferent disturbances (d). Denotation n is used to describe the influence of an implementation error. 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

In this section, the design of a control system for a polymerization plant production is presented. 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*. Sensitivity analysis of the pPIs was done in order to get the production costs' model. The pPIs were evaluated at 20 working points and connected together by extrapolation. Figure 5 shows the relation between *Production costs*, *Product quality* and *Productivity* pPIs, i.e. the dependence of the *Production costs* regarding *Productivity* and *Product quality*. These are dependencies for the case for unified production, i.e., a production where a series of batches of the same or similar final products are performed on each reactor. Another cost model would be achieved for different production.

With a help of a cost model the production manager can define exact reference values for the *Productivity* and *Product quality* indicators that are relevant for the actual *Production schedule*, and this activity is represented by the outer control loop in Figure 6 – optimization layer.

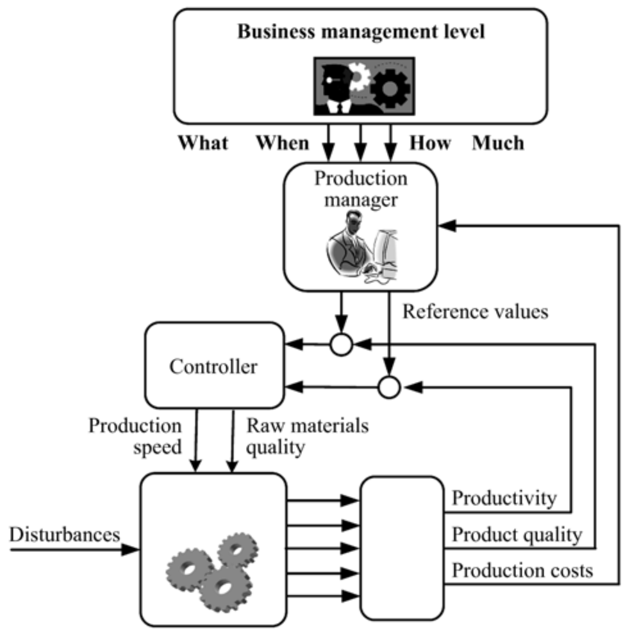

Fig. 6 Hierarhichal closed-loop control scheme for the polymerization process

Inner closed-loop (production control level) 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 take into account all process constraints. 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:

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

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

The main challenge was the 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:

$$0.5 \le \textit{Production speed} \le 1.3$$
$$0.85 \le \textit{Material quality} \le 1.2$$

and

$$700 \le \textit{Productivity} \le 1300$$
$$0.87 \le \textit{Product quality} \le 1.3$$

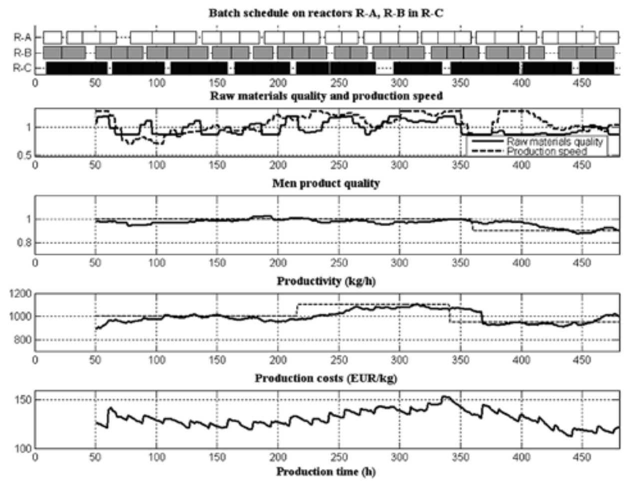

Fig. 7 Batch schedule, input and output variables for one simulation run for normal production

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 pKPIs relationship presented in Figure 5.

5 CONCLUSIONS

Simulation model of a polymerization plant in the form needed for production control is presented. 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. The framework used in this work makes it possible to automate part of the manager's routine work. In the hierachical closed-loop control structure a model-based controller (MPC) is implemented. 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.

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Upravljane proizvodnjom zasnovano na modelu. Poslovno okruženje zahtijeva trenutni odgovor na razne utjecaje proizvodnog procesa i globalnog tržišta. Sinteza sustava upravljanja cjelokupnim proizvodnim pogonom prepoznata je kao jedan od najznačajnijih problema procesne industrije. Za razvoj sustava upravljanja proizvodnjom nužan je odgovarajući model proizvodnog procesa za vrednovanje raznih struktura upravljanja. Razni proizvodni Kjučni Indikatori Kakvoće (KIK) mogu se identificirati u okviru modela i koristiti za izlučivanje relevantnih informacija o stanju proizvodnog procesa. Sustav upravljanja proizvodnim postrojenjem strukturiran je u nekoliko hijerarhijskih razina. Na razini upravljanja proizvodnjom izvedeno je upravljanje u zatvorenoj petlji s proizvodnim KIK kao upravljanim varijablama. U radu je prikazana simulacija polimerizacijskog proizvodnog postrojenja. Tim se postrojenjem može upravljati pomoću njegovih ulaznih varijabla, koje su: *brzina proizvodnje*, *kakvoća sirovine* i *slijed šaržnog procesa*. Učinkovitost proizvodnje određuje se na osnovi sljedeća tri KIK: *proizvodnost*, *očekivana kakvoća proizvoda* i *očekivani proizvodni troškovi*. Ovi su KIK korišteni za upravljanje proceduralnim modelom procesa. Primijenjen je modelski prediktivni regulator za pomoć menadžerima u donošenju odluka. Regulator održava proizvodnost i očekivanu kakvoću proizvoda na zadanim vrijednostima. Preliminarni rezultati ukazuju na korisnost predložene metodologije.

Ključne riječi: upravljanje proizvodnjom, kakvoća proizvodnje, upravljanje u zatvorenoj petlji, modelsko predikvino upravljanje

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