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ProOpter: An advanced platform for production analysis and optimization

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ABSTRACT

This paper presents the prototype of an advanced platform for production analysis and optimization, referred to as ProOpter. The platform was developed to support the recently derived concept of holistic production control (HPC), which relies on model-based control. The prototype is comprised of a set of off-line and on-line modules. The off-line modules support the definition of key performance indicators (KPIs), the selection of the most influential input (manipulative) variables, and the identification of a simple production model from historical data. The on-line modules enable KPI prediction and suggest actions to the production manager, employing model-based production control and/or optimization techniques. In this way, a new decision-support reasoning based on historical production data can be introduced. ProOpter has a modular design and can be used as an add-on to existing production IT systems since it relies on established industrial communication standards. The use of the platform is validated on the well-known Tennessee Eastman benchmark simulation process and on two industrial case studies.

1. Introduction

Production, as the main activity inside an industrial plant, is a very complex activity. The main reasons for this complexity are complicated and unstable economic conditions, market globalization and the increasing demands of customers for customized and qualitatively high level products. As such, the production process needs to adapt to this situation with shorter innovation cycles, the production of individualized/personalized products, the effective utilization of resources, etc. In order to answer all these challenges and to gain a key competitive advantage, production companies must constantly strive for improvements.

Increasing productivity has been an issue for many years. Lean-management, parameter optimization and other paradigms were frequently used to boost productivity in the past. In this context organizational advancements in Japanese manufacturing have a long tradition dating back to the 1980s, with Just-in-Time manufacturing and lean production [14]. Nowadays, when high production flexibility and low-volume production are the main focus of companies, the classic approaches do not fully address all the production problems. For these reasons the data-oriented approach is increasing in its significance, with particular attention being given to the successful integration of new IT technologies into production processes.

A number of initiatives have emerged recently, with the goal being to establish a framework for the continuous improvement of production efficiency using the latest technological advancements. In Europe, the best-known example is probably Germany's Industry 4.0 initiative [15]. It proposes employing the Internet of Things paradigm on the factory floor and derive intelligent, intercommunicating, autonomously operating production units, i.e., the so-called cyber-physical systems. This should result in a flexible and efficient Smart Factory, with a consideration of ergonomics and customer needs, and the integration of supply-chain partners along the value chain [2].

A similar initiative in North America is known as the Smart Manufacturing Leadership Coalition [24]: a coalition of companies, manufacturing consortia and consultants working on Smart Manufacturing. This has been defined as the dramatically intensified application of 'manufacturing intelligence' throughout the manufacturing and supply-chain enterprise [4].

These initiatives tend to improve the organization of the production process and establish a decision-support framework with an improved insight into the current state of production and its performance. In this context the obvious step in production support is to employ sophisticated data analysis and

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system-modelling methods that would make it possible to predict the effect of production-control measures on future performance. In this way a decision-making process at the production-control level could be substantially improved by the possibility to pre-evaluate the various decisions. Such an approach would also provide a solution to one of the main problems of today's industrial IT systems, i.e., they are collecting a vast amount of unstructured production data that are seldom used for production analysis and decision support.

In recent years some progress has been made in these fields of research. In order to connect shop-floor systems and the enterprise resource planning (ERP) layer and make today's factories smarter, manufacturing intelligence (MI) systems are being developed. The key functions of MI are data aggregations, contextualization, analysis, visualization and propagation [13]. In addition, data mining has emerged as an important tool for knowledge acquisition from manufacturing databases [3,18].

MI support systems are currently still in the phase of gaining recognition in everyday practice. In the near future, the rapid evolution of MI solutions is expected [1,25], where new functionalities and the increased diversity of software providers can be expected. Currently, the largest support for MI solutions is being offered by major business-software companies, which aim to extend their Business Intelligence (BI) solutions to include the production level (e.g., SAP, Oracle).

In contrast to this trend we are following the idea of taking the control solutions used at the lowest level of the control pyramid, i.e., at the process-control level, and employing them at the production-control level. With this in mind we have introduced and further elaborated the concept of holistic production control (HPC) (see [9,10,28]), which relies on the well-known, model-based, process-control paradigm. However, the developed ideas and methods are of little value if they are not supported by an appropriate tool.

The aim of this paper is to introduce the prototype of a tool, referred to as ProOpter, that enables the analysis of production dynamics and supports advanced production-control methods that are based on embedded models. Preliminary results were published in [22]. The proposed prototype is a relatively simple and flexible add-on tool that extends the functionality of classical Manufacturing Execution Systems (MES). It could also serve as a platform that can be used to test and validate various methods needed for production control in a real industrial environment, which could later be included into the solutions of well-established MI providers.

In the next section we describe the architecture and the particular modules of the prototype ProOpter. In Section 3, the functionality of the tool is demonstrated using a selection of results from case studies, which include a simulation benchmark as well as historical data from actual industrial production. Finally, the discussion and conclusion are presented in Section 4.

2. The architecture and modules of ProOpter

The proposed tool is aimed at supporting the concept of holistic production control (HPC), which was introduced in Zorzut et al. [28], and further elaborated and extended in Glavan et al. [10] and Glavan et al. [9]. The concept is schematically shown in Fig. 1. It suggests using current key performance indicators (KPIs – K), their desired business plans (K^*) and KPI predictions ($\hat{K}$) when looking for the optimized production process settings (U), Eq. (1). The process settings U comprise the production variables that can be employed to manipulate the production process (e.g., production parameters, actuator settings, and low-level control references). Here, an appropriate model (*KPI model – M*), describing the behaviour of the process as seen through KPIs is required, and it is

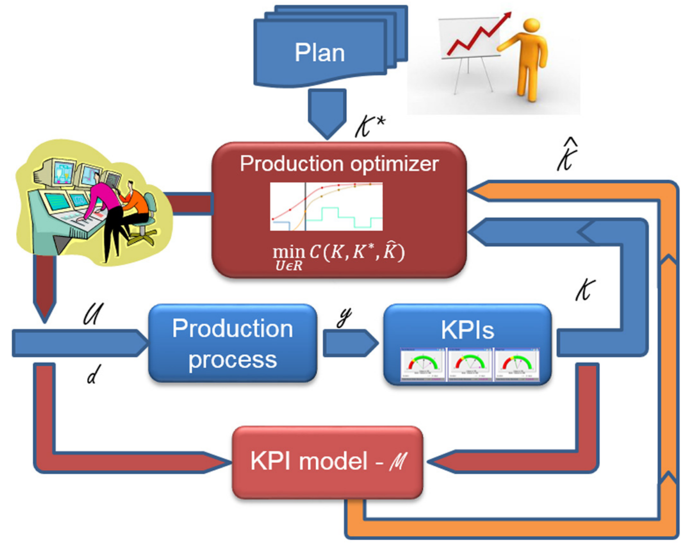

Fig. 1. The concept of production optimization.

expected to be derived from historical measurements of the process settings (U), the disturbances (d), and the archived KPIs that were determined from the measured production data (y). The KPI predictions ($\hat{K}$) are determined based on the model M, using current and past values of U, d and past measured KPI values (K_{past}), as shown with Eq. (2).

$$U = \underset{U \in R}{\operatorname{argmin}}\, C(K(y), K^*, \hat{K}) \tag{1}$$

$$\hat{K} = M(U, d, K_{past}) \tag{2}$$

2.1. ProOpter architecture

The concept of production optimization is realized with the modular structure of ProOpter shown in Fig. 2. Each of the modules takes care of its own task, while their integration enables the realization of all the tasks that must be resolved in the design and application of the HPC concept (Fig. 1). Here, the *KPI definition module* is used to determine K, the *Influential variable selection* and the *Modelling module* are used to determine the model M, the *KPI prediction* and *Optimization module* are used to calculate the

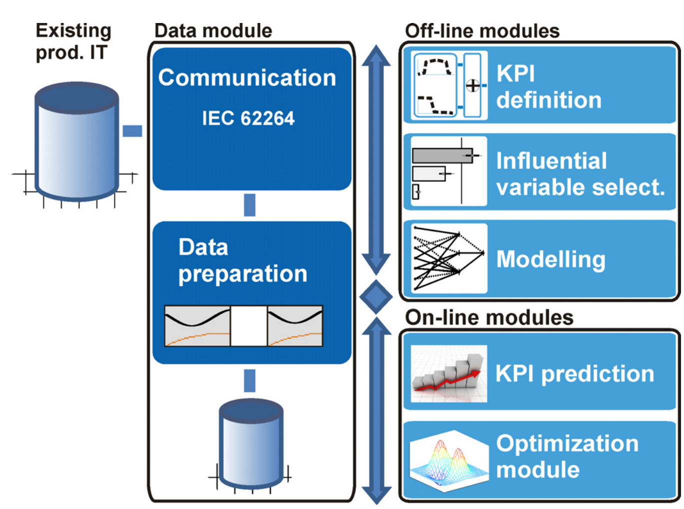

Fig. 2. ProOpter architecture.

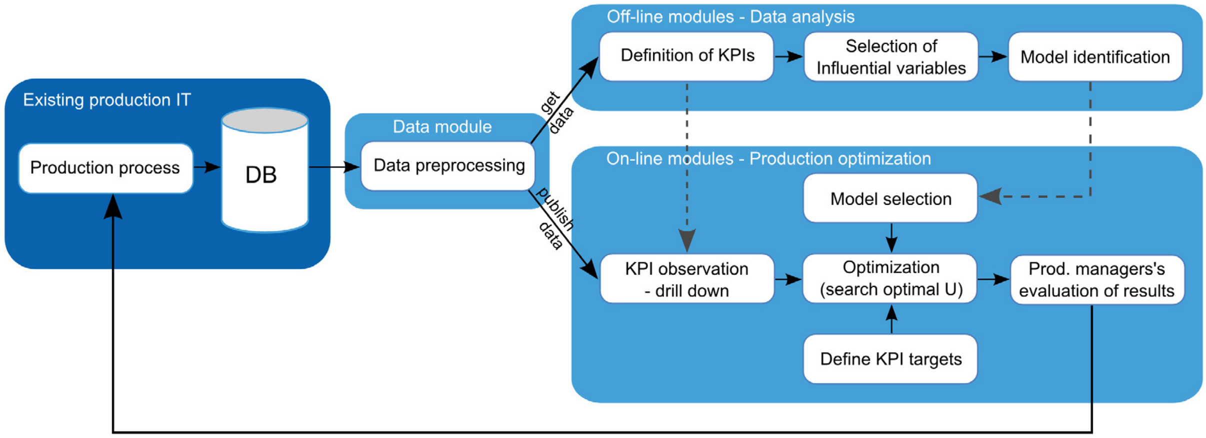

Fig. 3. ProOpter software workflow.

optimized solution, while the supporting modules *Communication* and *Data preparation* are used to integrate all the modules. The open architecture of the tool enables the subsequent development of new modules using different programming languages, the integration of various subsequently developed methods and algorithms, and distributed operation on various systems.

The modules shown in Fig. 2 are divided into three major categories:

- Data integration (*Data module*),
- Support for production modelling (*Off-line modules*),
- Support for optimization (*On-line modules*).

The ProOpter workflow is illustrated in Fig. 3, where the darker outline (*Production process* and *DB*) denotes the existing production IT infrastructure to which ProOpter is connected. From there the production data are obtained and pre-processed (*Data module*). Off-line modules support the simplified production-modelling procedure, where first the KPIs have to be defined (*KPI module*), then influential variables need to be selected (*IVS module*) and based on these the production models are identified (*Modelling module*). On-line modules provide an insight into the production performance through the *KPI observation*, as well as supporting the production manager in determining the optimized production settings (*Optimization*). The optimization is based on the KPI targets and selected, previously identified, models.

2.2. Data module

ProOpter is designed as an add-on to the existing production management information systems. Connectivity to the external databases is established with *Data module*, which takes care also about production-data pre-processing and the integration of all the ProOpter modules (Fig. 4).

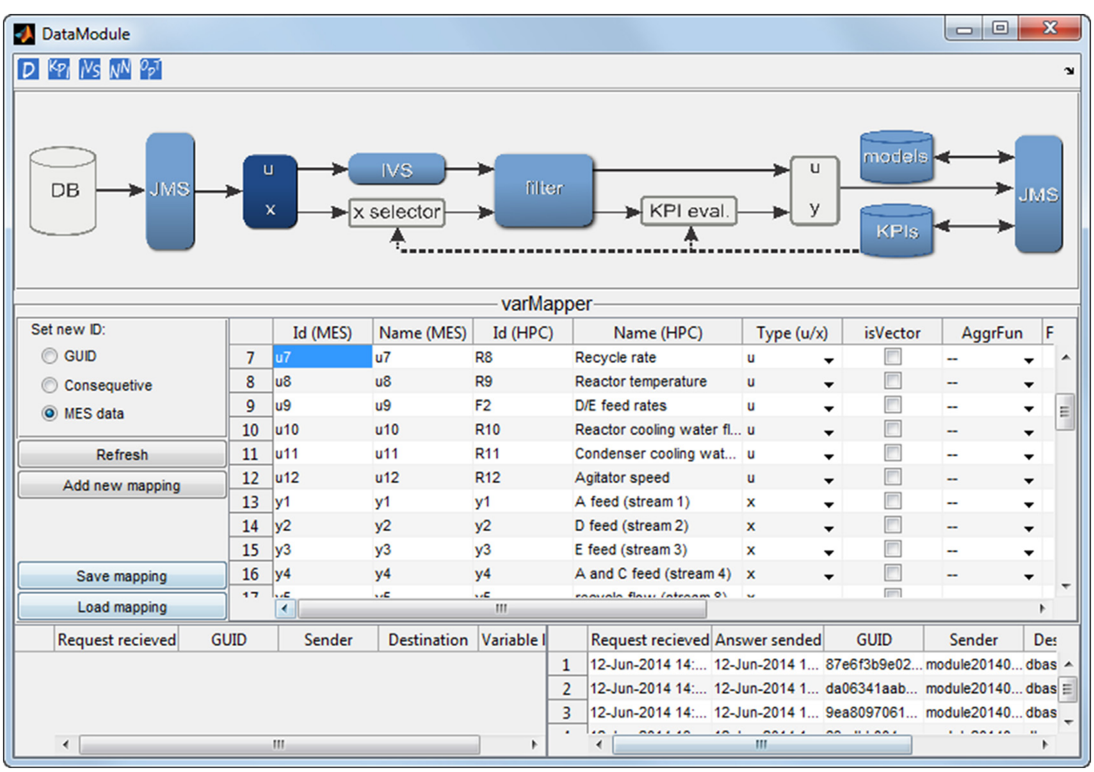

Fig. 4. ProOpter data module.

2.2.1. Data integration

One of the main requirements for such an add-on is to support established industrial standards in being able to connect and integrate into the existing information-communication infrastructure. These typically consist of ERP and MES systems on the higher levels, which are connected to SCADA systems, PLCs and other automation equipment on the factory floor.

ProOpter's integration is achieved by supporting the standardized data-interchange message format, which is typically used for communications among business-planning and production-control applications. Equally important is the use of standardized communication messages among tool modules. This enables the simple addition or removal of the functional modules as well as their upgrading, without compromising the functionality of the rest of the system.

Therefore, the following standards were considered and used in the development of the software tool:

- the B2MML schema [26], defined by standard IEC 62264 (ISA 95) [16], is used for messages about production data.
- the OpenMath schema [27] is used for mathematical description of production KPIs.
- the PMML schema [5] is used to describe empirical production models.

The use of the described standards for inter-module communication within ProOpter is illustrated in Fig. 5.

2.2.2. Communication

The use of unified communication protocols within a production information system is of great importance. The use of communication standards guarantees the long-term stability of developed applications as well as an easier integration with the existing information infrastructure. In compliance with IEC 62264 [16], two standard methods of data transmission are used within ProOpter:

- *Pull model* – the data user requests the data from the data supplier, which sends the data upon request. This is a point-to-point communication.
- *Publish model* – the data supplier sends data to the recipients that are subscribed to specific data. The communication is carried on according to the publish-subscribe principle.

The use of the MOM (Message Oriented Middleware) infrastructure is best suited for such an asynchronous XML message exchange among several clients. It supports both the point-to-point and publish-subscribe communication principles. MOM enables distributed communication among loosely coupled clients, meaning that the communicating applications do not necessarily all have to be active within the network, nor do they all have to be aware of each other.

Within ProOpter, the MOM communication was implemented using the JMS (Java Message Service) specification. Even though JMS originates from the Java environment, its specification is general and open to use with clients that are designed within other development environments and platforms.

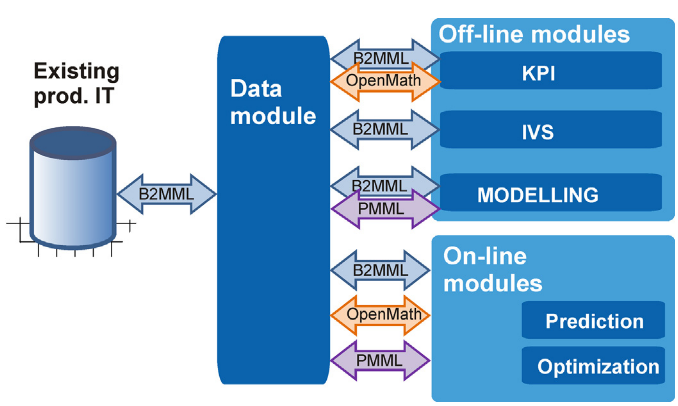

Fig. 5. ProOpter standard messages.

2.2.3. Data preparation

Special attention is needed when data from a historical production database are used. From the vast amount of data, the informative portions have to be identified. These data segments should cover the interesting dynamics of the KPIs, for which we would like to determine the future behaviour. Furthermore, any outliers or missing data (due to the weakness of the data acquisition, deadlocks or other unusual process states, output influences, noise, etc.) need to be properly analyzed. To cover all the operating conditions of a process, a diverse data distribution is needed.

For all these reasons, advanced data-processing techniques are necessary. Data-cleaning procedures can be applied to detect and remove any outliers present in the data. As pointed out in [23], nonlinear, data-cleaning procedures are recommended. We can find many filters in the literature proposed for this task: the Martin–Thomson filter, the FIR-median hybrid (FMH) filter, the Hampel filter, etc.

The data module checks the production data received from the external databases for various anomalies (outliers, missing data). It helps the user to correct these anomalies using a variety of techniques.

In certain production situations efficiency measures are calculated based on the data series being measured. This is common in batch production, where several production variables are continuously sampled and, therefore, we typically have a range of corresponding variable values for a batch. On these occasions it is necessary for such values to be aggregated into a single data point. In order to achieve this a set of standard data-aggregation functions is provided within the *ProOpter Data module*, e.g., average, min, max. Alternatively, a user can define customized aggregation functions.

2.3. Off-line modules – production modelling

ProOpter's offline modules are used to analyze historical data records and to develop a production KPI model using these data.

Modern manufacturing systems are, in many cases and for various reasons, too complex to be accurately described analytically from first principles. Instead, we can assume that the relationship between the inputs and the outputs can be described by a stochastic, high-dimensional model from a class of generally nonlinear model structures.

The production model has to include enough details of the production process to reflect the dynamics for production control. This model should be relatively simple in comparison to the models used for the process-control level, yet because of the overall complexity and the limitations of testing the process, this task is extremely complex. Production control usually requires the model to be easily adapted online as well. Therefore, the main objective is the development of the concept of identifying a relatively simple input–output model of the production. A short overview of each step supported by ProOpter is given in the following subsections.

2.3.1. KPI definition module

The KPI module is used to define the performance-measurement metrics that evaluate the production and the company's overall success. The production objectives are usually aggregated with the key production performance indicators [8]. Although there exists a standard collection of KPIs [17], the specifics of each

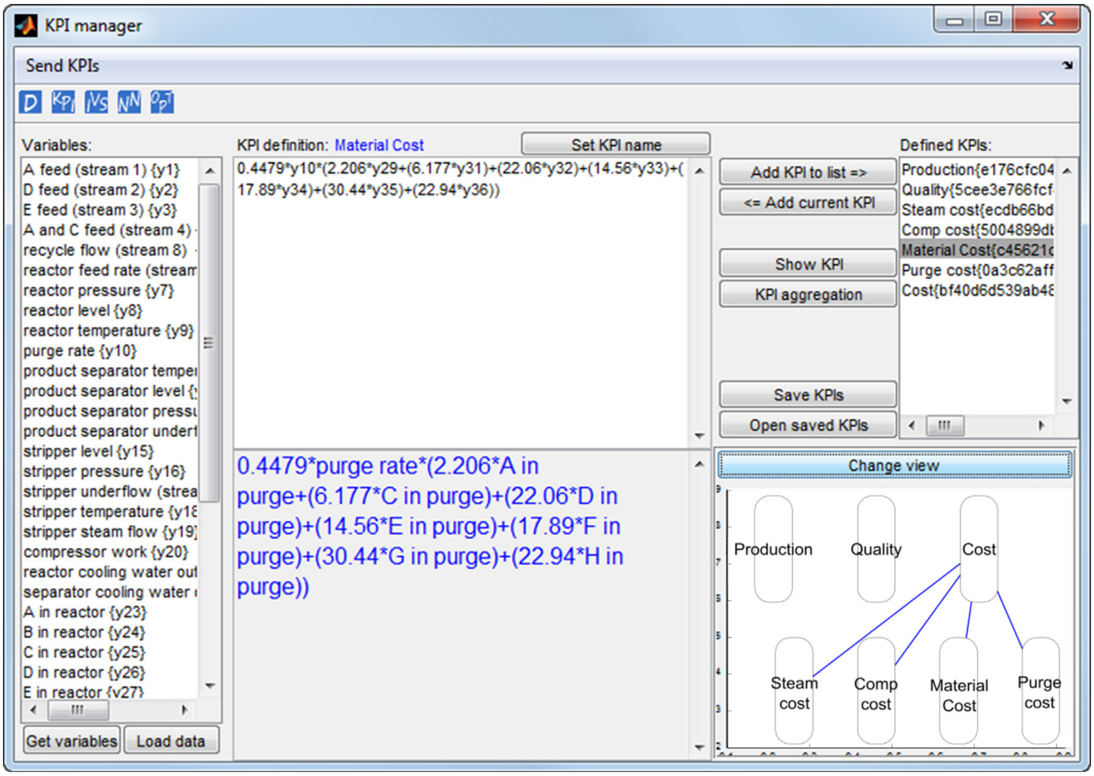

Fig. 6. GUI for KPI definition.

production and individual business objectives need to be considered manually. Here, the production expert's knowledge is needed to properly alternate the standard KPIs and connect their definitions to the considered production process. The ProOpter's supporting tool allows the production manager to define the structure of a production process's KPIs and give him/her the possibility to critically evaluate the illustrative KPI values.

Fig. 6 depicts the GUI of a developed KPI module. In the central white area there is an equation editor, where the operator can compose the KPI. All the available measured variables, listed on the left-hand side of the GUI, can be included in the KPI definition.

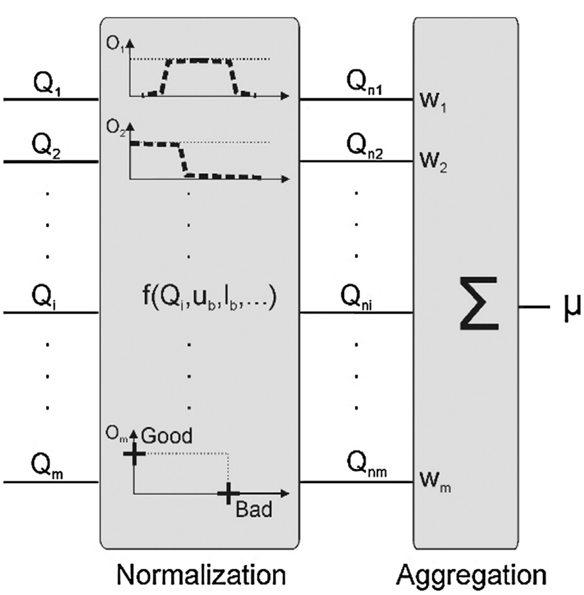

Fig. 7. Aggregated KPI composition.

The equation can also be defined with delayed values – in this way the performance-indicator dynamics can be defined. The lower right-hand side of the GUI shows the defined structure of the KPIs, which can be saved and distributed to other modules using the OpenMath XML schema.

The main advantage of the KPI module is in its integrated support for the formalization of the currently used expert's practice to evaluate the production performance. This can be achieved using the *KPI aggregation* function that can aggregate different measurements/KPIs to a newly defined KPI. The aggregation is utilized using two basic operations. Firstly, the *normalization* can be performed for a mutual comparison of different measurements. Then, the common estimate is achieved with the *aggregation* of separate, normalized measurements, as illustrated in Fig. 7.

Measurements can be normalized in different ways, using a general normalization function given by Eq. (3). Different normalization types are possible and are shown in Fig. 8. The normalization functions can be adjusted later using the relevant parameters. Here, the parameters *lb* and *ub* determine the desired range of the production parameter, while others are used to set (or tune) the transformation function (see Fig. 8).

$$
\begin{aligned}
Q_{ni} &= f(Q_i, ub, lb, \ldots) \\
&= \begin{cases}
0 & \text{if} \quad Q_i \epsilon (-\infty, T_{\min}) \\
\dfrac{T_{1low}}{lb - T_{\min}} \cdot Q_i - \dfrac{T_{1low}}{lb - T_{\min}} \cdot T_{\min} & \text{if} \quad Q_i \epsilon [T_{\min}, lb) \\
\dfrac{1 - T_{1top}}{T_{opt1} - lb} \cdot Q_i + T_{1top} - \dfrac{1 - T_{1top}}{T_{opt1} - lb} \cdot lb & \text{if} \quad Q_i \epsilon [lb, T_{opt1}) \\
1 & \text{if} \quad Q_i \epsilon [T_{opt1}, T_{opt2}] \\
\dfrac{1 - T_{2top}}{T_{opt2} - ub} \cdot Q_i + 1 - \dfrac{1 - T_{2top}}{T_{opt2} - ub} \cdot T_{opt2} & \text{if} \quad Q_i \epsilon (T_{opt2}, ub] \\
\dfrac{T_{2low}}{ub - T_{\max}} \cdot Q_i + T_{2low} - \dfrac{T_{2low}}{ub - T_{\max}} \cdot ub & \text{if} \quad Q_i \epsilon (ub, T_{\max}] \\
0 & \text{if} \quad Q_i \epsilon (T_{\max}, \infty)
\end{cases}
\end{aligned}
\tag{3}
$$

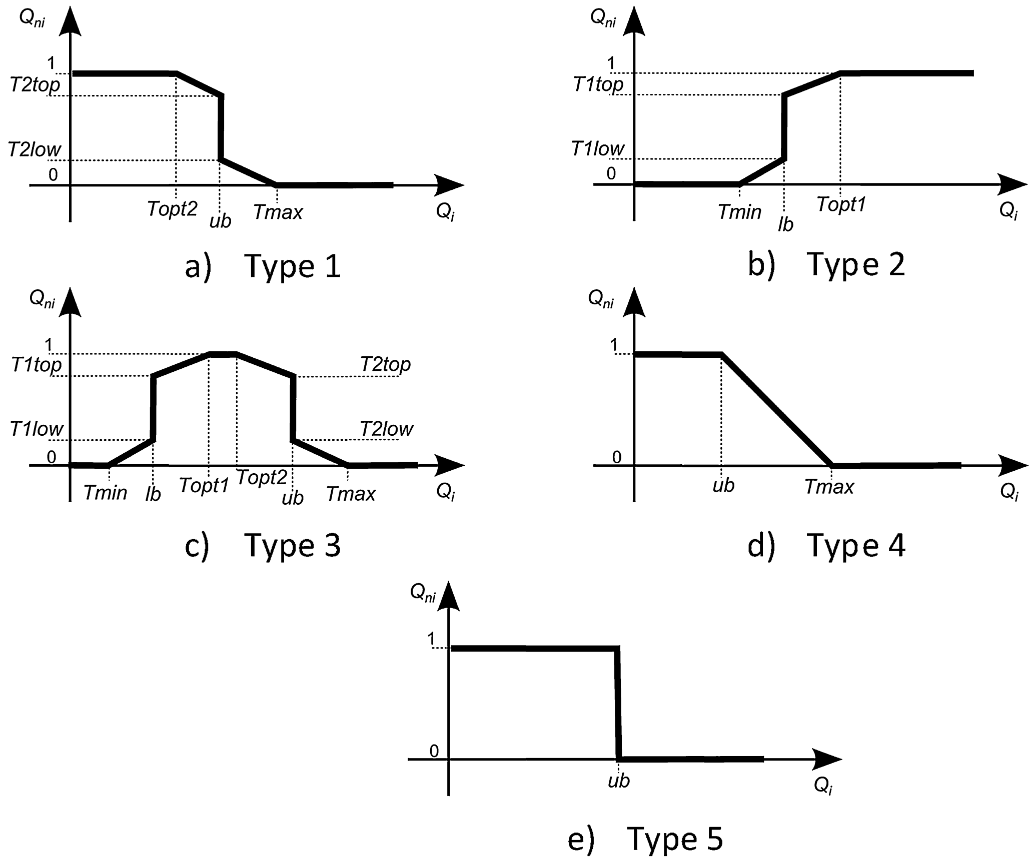

Fig. 8. Predefined normalization types.

Finally, the m normalized measurements are aggregated into a KPI, $\mu(Q)$ using the weighted sum (4), as shown in Fig. 7.

$$\mu(Q) = \frac{1}{m}\sum_{i=1}^{m} w_i f_i(Q_i, ub_i, lb_i, \ldots) \tag{4}$$

under the conditions for weights w_i that guarantee KPI values are in the range [0, 1]:

$$\sum_{i=1}^{m} w_i = m \tag{5}$$

$$w_i > 0 \quad \text{for all} \;\; i \in [1, m] \tag{6}$$

The KPI module supports the procedure for fine-tuning the normalization and aggregation parameters. In this way the production operator can directly see the influence of the parameters and adjusts them in such a way as to integrate his/her working practice.

2.3.2. Influential variable selection module

Variable selection represents an important step for HPC design, as many potential variables are usually available in production processes. Furthermore, since aggregated KPIs are connected with more process variables, it often happens that some a priori excluded inputs are later found to be significant, and vice versa.

The IVS module is used to rank the impact of various input parameters on selected performance measures (KPIs). In this way, only the most relevant manipulative variables are selected, which simplifies the KPI models, enhances their robustness and reduces the optimization problem (1). The analysis is based on the historical production-process data, where several standard and advanced variable-selection methods are embedded and the result is given based on the combined analysis.

In the literature, three major principles for variable selection are used [12], i.e., feature construction, variable ranking and variable subset selection. Different variable-ranking methods are contained in the IVS module, such as: (partial) Correlation, (partial) Mutual Information, Gamma Test, ANOVA, Non-Negative Garrote, LASSO, etc. For a detailed discussion and an evaluation of the integrated methods, see Glavan et al. [9]. Note, that the list of supported methods is not strictly closed, as new methods can easily be added to the module. The main uniqueness of the IVS module is the way it represents the final results to the user. The final result is obtained as a combination of the results of several IVS methods, where the dispersion of the results additionally informs the user about the reliability of the given result for each candidate input.

As we are dealing with dynamical systems, the current values of the production performance indicators do not depend only on the current input values, but also on their time-delayed values. The input-selection problem is therefore augmented by the selection of lagged inputs and outputs that are used as regressors. The regression vector for ith KPI is defined as:

$$\begin{aligned}\phi_i(t) = [&K_i(t-1)\ldots K_i(t-n_a), U_1(t-n_k)\ldots U_1 \\ &(t-n_b-n_k+1), \ldots, U_{nu}(t-n_k)\ldots U_{nu}(t-n_b-n_k+1)]^T\end{aligned} \tag{7}$$

where n_a and n_b denote the number of past outputs and inputs used for determining the prediction, n_k denotes the time delay for the input variables and n_u indicates the number of different input variables.

The GUI of a module for influential variable selection is shown in Fig. 9. This window is used to define the input/output data and

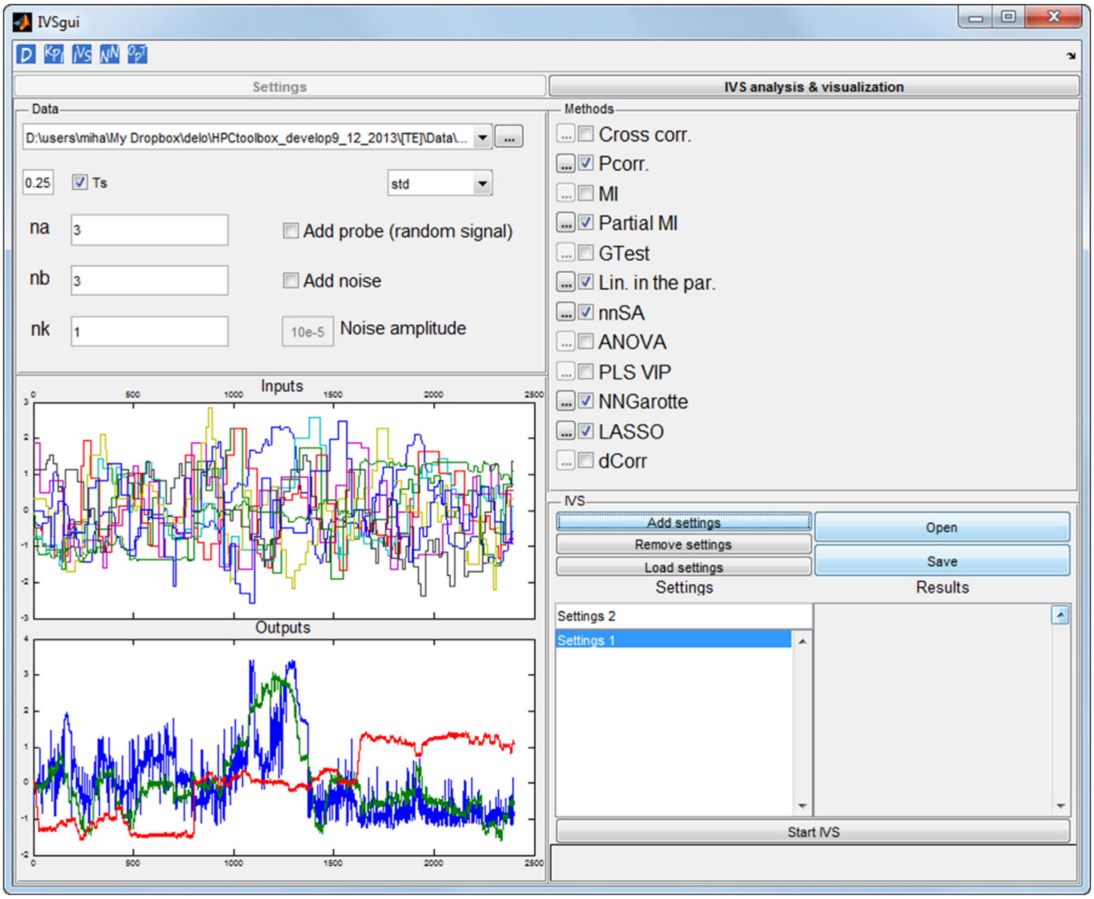

Fig. 9. GUI for determining the most influential manipulative variables.

other settings for the analysis. After the analysis is finished, we can observe the results in the window called *IVS analysis & visualization*.

2.3.3. Modelling module

Within ProOpter there is also a module that can be used to define a production model based on historical production data, for defined KPIs and inputs with the largest influence. It offers a simplified procedure of black-box modelling and for this reason it can also be easily used by a production manager who is not usually an expert in modelling.

The main idea of parametric black-box modelling techniques is to trim some universal input–output functions, with a fixed number of parameters, to accurately represent the true process dynamics, Eq. (8) [20]. The goal is to minimize the mismatch $e(t)$ between the true process response $K(t)$ and the model prediction $g(.)$, where the trimming is performed solely on the basis of the process input–output data pairs $Z^N = [U(t), K(t)]_{t=1}^{N}$.

$$K(t) = g(\phi(t), \vartheta) + e(t) \tag{8}$$

ProOpter's *Modelling module* makes it possible to use two different modelling approaches. We can build a model using neural-network modelling techniques [9], or using a fuzzy modelling approach [6]. In Fig. 10 we can see the GUI of the module for modelling with neural networks.

The main idea of the *Modelling module* is to use the characteristic production datasets for learning and validating the identified models. As different parameters need to be tuned to find a model with good generalization capabilities, the modelling module identifies several models with alternative parameter settings. Then, with different validation scenarios and validation datasets the optimal model is indicated. Model regressors (model inputs) are automatically selected with the application of the IVS module results. In this way, dynamic and static models can be identified, with little or no prior knowledge. If the process characteristics were to change during the use of the production model, new process data should be analyzed and a better model has to be extracted. The cyclical generation and validation of new models enables a rather conservative adaptation of the model-in-use to long-term changes in the production. The developed models are described with PMML schema and are shared in this form with all the other modules of ProOpter.

2.4. On-line modules

On-line modules give the user the possibility to monitor the performance of the production process and support him/her with the decisions on parameter settings in order to control the production process more efficiently. Actual and previous KPI values can be examined on-line, where the user can drill-down to any detail of the production process. The prediction is based on models that are identified in a previous step using off-line modules.

Advanced decision-support options are available with the use of two sub-modules. The first one is used for efficiency prediction while testing different production settings and second one implements the model-based production control. With the GUI depicted in Fig. 11 we can use both sub-modules.

2.4.1. KPI prediction module

The *KPI prediction module* uses KPI models, defined with the *Modelling module*, to predict and analyze the KPI dynamics. In this

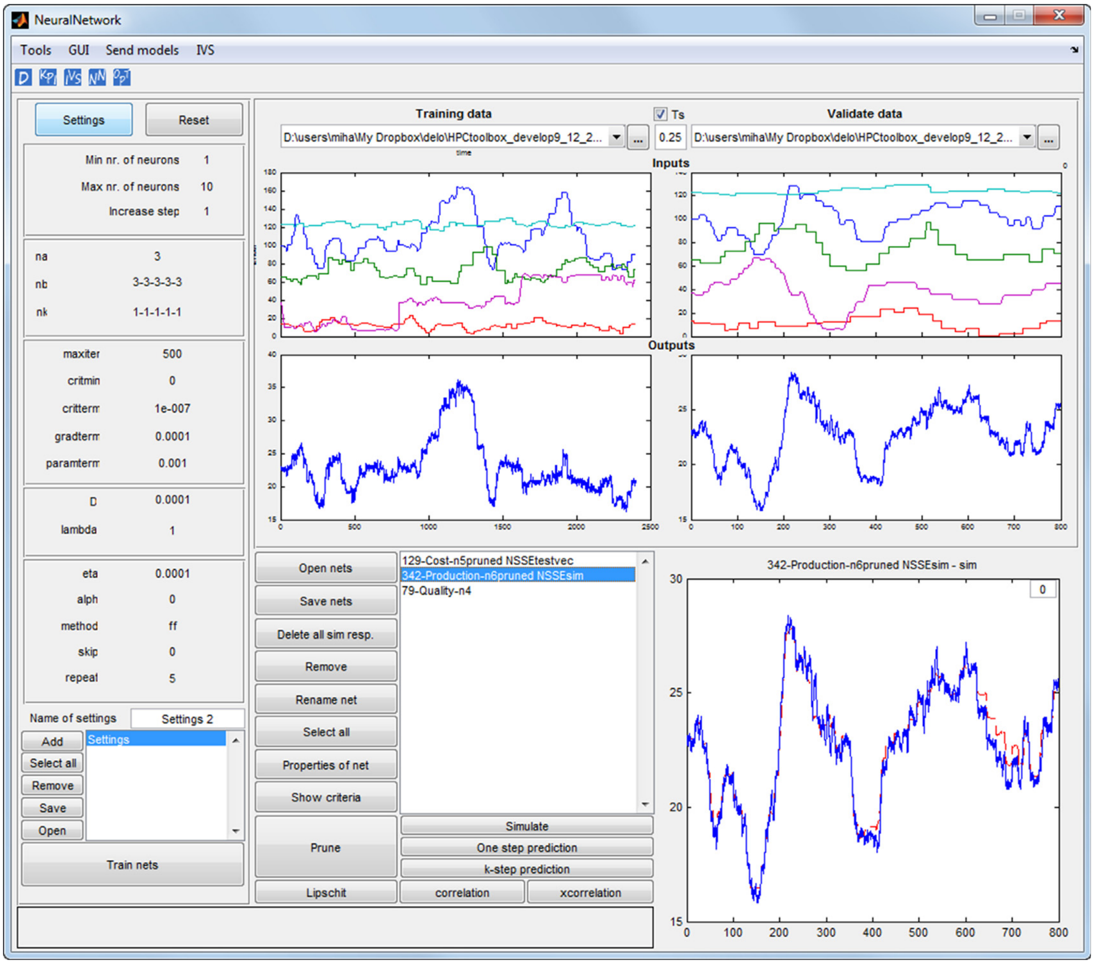

Fig. 10. GUI for modelling with neural networks.

way, various production parameter settings (scenarios) can be simulated and evaluated.

The method used for the long-term prediction of the model depends on the applied model structure. For model identification the non-recursive structures (e.g., FIR, NARX) are usually applied, as their applications are, in general, more straightforward than the use of recursive alternatives (e.g., NOE, NBJ, NARMAX) [20]. The most widely applied non-recursive structure is the NARX model

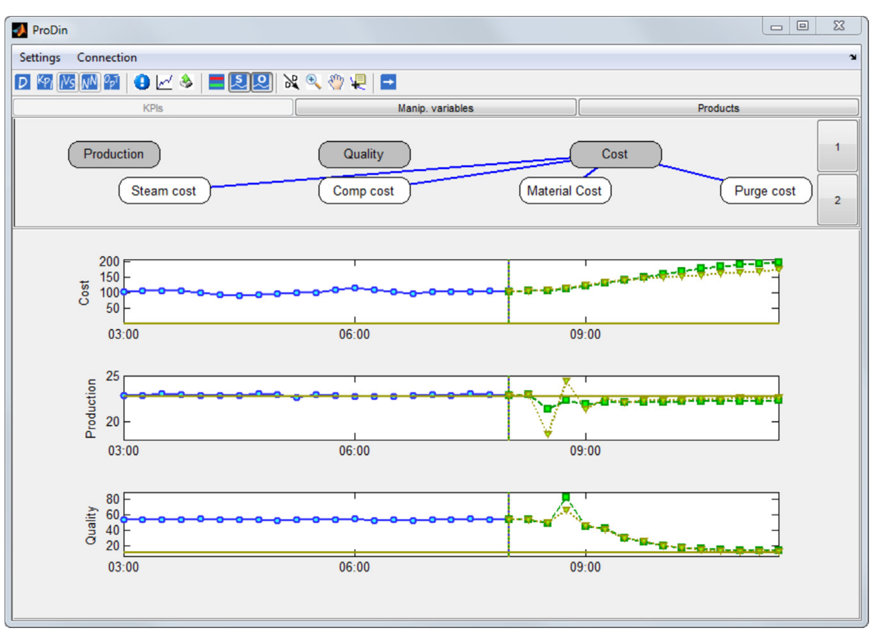

Fig. 11. On-line GUI for efficiency prediction and optimization.

structure, where the regression vector consists of delayed values of the input and output variables, as shown in Eq. (7). The NARX structure is also used in ProOpter. In order to evaluate the long-term prediction of the identified NARX model, it is necessary to transform the model to the NOE structure, where the model's predicted outputs $\hat{K}(t)$ are fed back to the model input. In this way a k-step-ahead prediction $\hat{K}(t+k)$ or simulation response of the system can be obtained.

2.4.2. Optimization module

ProOpter's *Optimization module* offers support for an automatic determination of the optimized production settings. In order for this to be possible, a production model is incorporated into the production control scheme using the model predictive control (MPC) approach [11,21]. This MPC approach is based on the repetitive solution of an optimal control problem, taking the measured system state as the initial state and using the system model to evaluate the effect of possible system-input sequences. A discrete time representation of the system dynamics is used and only the first sample of the calculated optimized input sequence is applied to the system. In the next sample time the calculation is repeated with the newly acquired system state. The optimization is performed over a finite moving horizon, which always starts at the current sampling instant. In each decision step the optimal solution of Eq. (1) is calculated using the following cost function:

$$J(t) = \sum_{j=1}^{H_p} \|\hat{K}(t+j) - K^*(t+j)\|_Q^2 + \sum_{j=1}^{H_c} \|\Delta U(t+j-1)\|_{Q_u}^2 \quad (9)$$

where ΔU marks the change of the manipulative variables ($\Delta U(k+j) = U(t+j) - U(t+j-1)$), the operators $\|\cdot\|_Q$ and $\|\cdot\|_{Q_u}$ represent the weighted Euclidean distances with the weights Q and Q_u. H_p and H_c denotes the prediction and control horizons, respectively.

The user of the *Optimization module* should define the reference values of the KPIs to be optimized. With the GUI we can also set the limits of the manipulative and KPI values and the importance of every KPI. The calculated manipulative values are suggested to the user, who can decide to use them or not. The user also has the possibility to modify the suggested input set and to evaluate a new control scenario with the use of the efficiency-prediction module.

3. Case studies

The performance of the ProOpter was evaluated through a case study on the Tennessee Eastman (TE) benchmark simulation process, where all the steps of a holistic production control are covered.

ProOpter was also validated on two industrial case studies. As the considered production processes were not fully equipped with the IT systems, there were problems with data diversity and with the small amount of data. Despite this, individual modules of ProOpter were successfully applied.

3.1. Case study on the Tennessee Eastman benchmark simulation process

The TE benchmark process was introduced in [7] as a simulation model of a real chemical production process. It consists of five major units: a chemical reactor, a product condenser, a vapour–liquid separator, a product stripper and a recycle compressor. The process products leave the process through an output stream, where they are separated in a downstream refining section. The production process has 41 measured variables and 12 different manipulative variables.

The TE process is a highly unstable system, and is without low-level process control. We used the system that was stabilized with

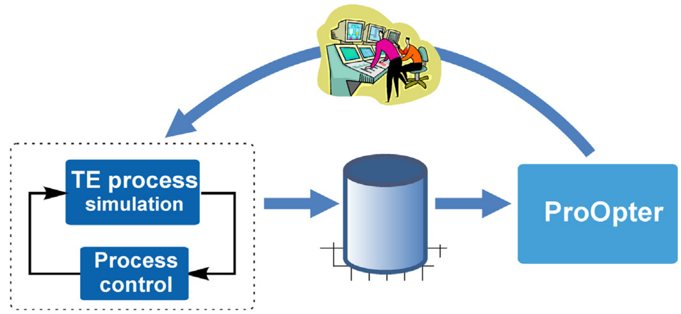

Fig. 12. Production control of TE process using ProOpter.

the low-level control presented in [19], where nine outputs are controlled with cascade loops. In order to realize the HPC concept some changes in low-level control were added, as suggested in [9]. Therefore, ten input variables are available to manipulate the TE process.

The case-study simulation environment is depicted in Fig. 12. The production data of a simulated TE process with low-level control are archived in a production SQL database. ProOpter fetches these data with the use of a B2MML connection in order to analyze the production and to suggest to the production manager how to change the production settings.

3.1.1. Production modelling

From all the available measurements the production performance is monitored through three KPIs: *Costs*, *Production*, and *Quality*. The definition of the *Production* KPI is quite straightforward, as the quantity of product leaving the process is directly measured. An indicator of the process quality is directly derived from the main process objectives. The product *Quality* is viewed as a desired mass ratio between the two final products, G and H. For details about the *Cost* KPI definition, the reader is referred to [7] or [10]. The KPIs constructed for the TE benchmark are depicted in Fig. 13.

Next, the influential variable analysis is performed by considering the available manipulative variables and the defined KPIs. As we can see from Fig. 14 some of them exhibit greater influences. Five manipulative variables are selected (F_p, R_4, R_7, R_9, r_2). A detailed analysis is given by Glavan et al. [9].

Based on the selected input/output variables a neural-network-based model is then identified with the use of ProOpter's modelling module. As is clear from Fig. 15, the resulting neural network gives a satisfactory response to the validation data.

3.1.2. On-line production-efficiency monitoring and optimization

An example of the on-line production-efficiency monitoring and optimization is illustrated in Fig. 16. On the left-hand side of the graph (the line with open circles) we can see the history of the observed KPI variables, where an intermediate vertical line indicates the current time. In this way, a production manager can monitor the current and previous production efficiency in real-time. With a detailed investigation of the variables that contribute to the performance measure as well, an insight into the manipulative values is possible by choosing the drill-down option.

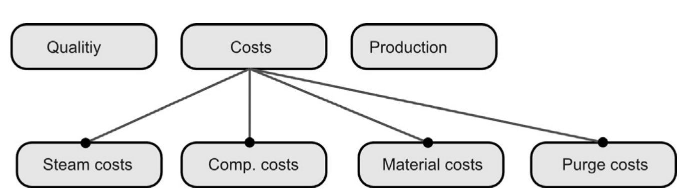

Fig. 13. Aggregated KPIs.

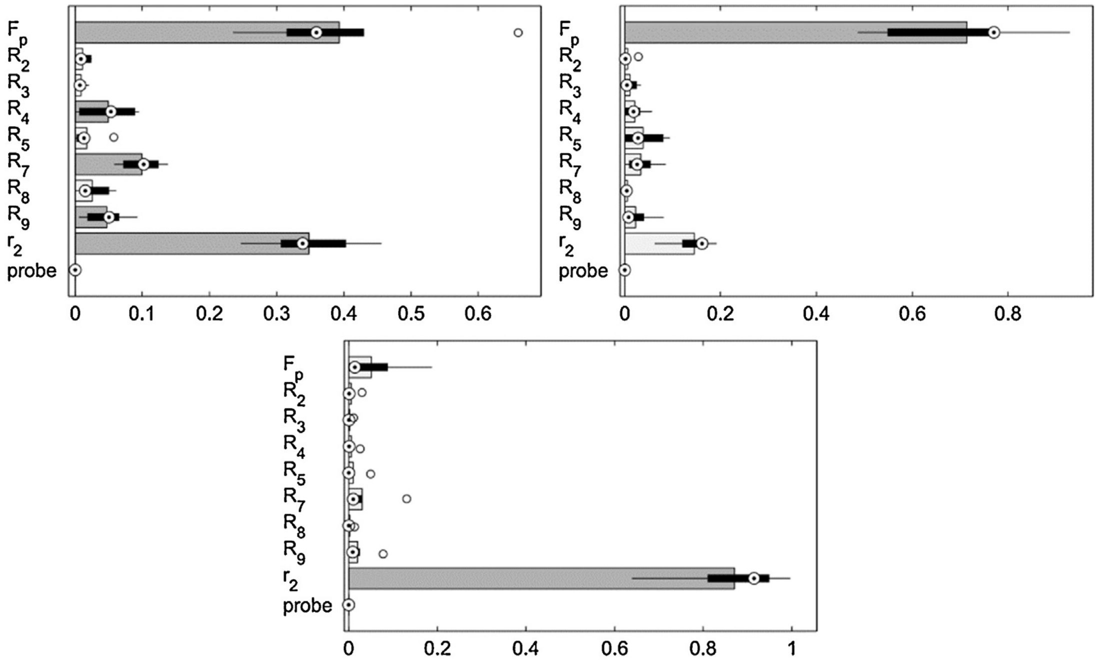

Fig. 14. Selection of influential variables for *Costs* (upper left), *Production* (upper right) and *Quality* (lower).

In order to define the future control scenario, the production manager also has the option to employ the KPI models, using the *KPI prediction* module. Fig. 16 shows a case where the production manager has tested a new control scenario. Based on his/her experiences gained from previous work on an optimization process he/she has manually defined the future manipulative variable values in order to move the process to a new operating mode (increased *Quality* level and maintain *Production* level). With the manual testing of different scenarios and observing the behaviour of the predicted KPI values, he/she has determined the scenario depicted with the line and triangular dots.

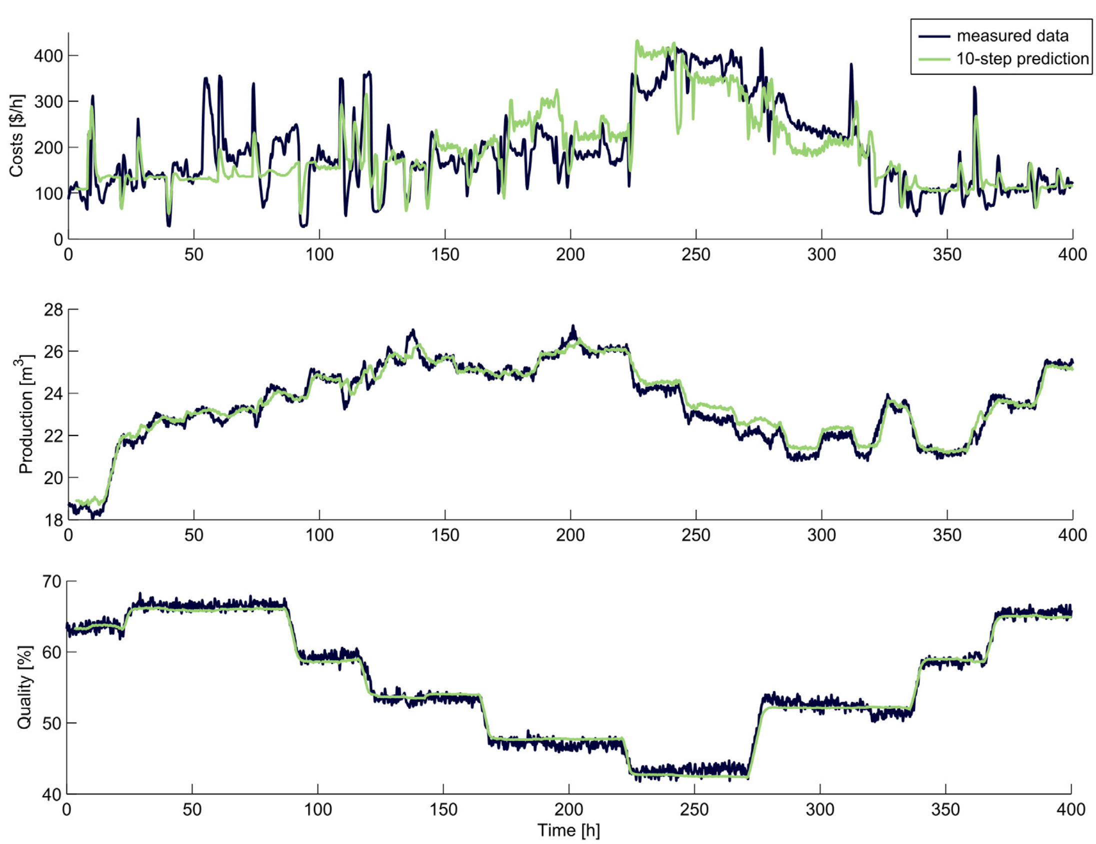

Fig. 15. Model validation on the testing dataset.

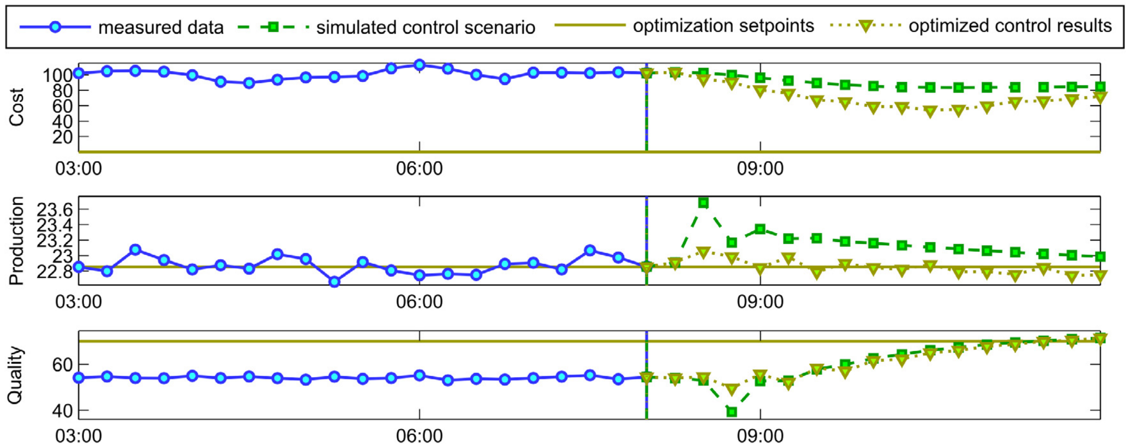

Fig. 16. Efficiency optimization.

The user also has an option to use the *Optimization module*, where the optimized adjustment of the manipulative values is calculated on-line using a model-based predictive control technique. The identified performance model is used to determine more appropriate manipulative variable settings, while the user has to specify the appropriate KPI targets (reference values). In the presented case the user has specified the control objectives and their priorities (i.e., change of *Quality* level and *Costs* minimization objective, while retaining the same *Production* ratio). The line with square dots in Fig. 16 indicates the simulated outcome of this automatically determined control scenario and the solid horizontal lines indicate the KPI's reference values. From these results it can be seen that a higher-quality percentage measure yields lower cost values. This might be rather confusing, but note that the quality indicator cannot be interpreted in a traditional sense, as it is defined as a percentage ratio of the two products leaving the process [19].

After the examination of different control scenarios the production manager has to approve and implement the final settings of the manipulative variables.

3.2. Validation on industrial case studies

Parts of ProOpter were also tested in industrial case studies. Two applications are given in the next subsections.

3.2.1. Case study of batch production

The first industrial case study considers the problem of performance measurement metrics determination and an influential variable analysis in the production of water-based paints and coatings. The production is a typical batch process consisting of a dosing-and-mixing stage, a milling stage, a production stage, and a packing stage. In between the production and packing stages the quality control is performed, where the acceptability of a product for packing is determined. In the case of a negative result, the product can be scrapped, or can go to re-work where the quality is improved. The study was based on actual production data, and therefore ProOpter had to be connected to the existing IT systems.

The performance monitoring in the considered batch production is mainly oriented towards a determination of suitable batch parameter settings. Therefore, batch-related indicators were of primary concern. In cooperation with the production managerial staff the following relevant indicators were identified and formalized with ProOpter's *KPI definition module* (Fig. 17):

- *Product Quality* – calculated per batch as a result of a laboratory analysis. Different products have different measured parameter sets.
- *Raw materials consumption ratio* – ratio of the actual raw-material consumption per work order to the normative consumption.
- *Timeliness* – difference between the actual finish time and the planned finish time.
- *Scrap rate* – ratio of the actual scrap quantity to the planned produced quantity.

Product Quality is the most complex indicator. As the measured parameter sets differ among different products they have to be normalized and aggregated to derive indicator values that are comparable among several batches. For every product (or product family) the relevant set of laboratory-measured quality parameters is identified, and these are normalized and aggregated into a standard valued quality indicator.

The quality indicator is also the most relevant for the production efficiency. Poor-quality products go either to re-work, which decreases productivity, or go to scrap, which is a direct cost. The analysis of influential production variables that determine the quality level is therefore the most important. Unfortunately, the analysis cannot be generalized, but has to be performed for every product family due to various production recipes. An analysis was performed using ProOpter's *IVS module*. The results of the analysis for one of the product families are shown in Fig. 18. The aggregated results of a subset of available variable selection methods are shown as a box plot. In the given case, the maximum *RPM* of the mixer dominates the batch quality,

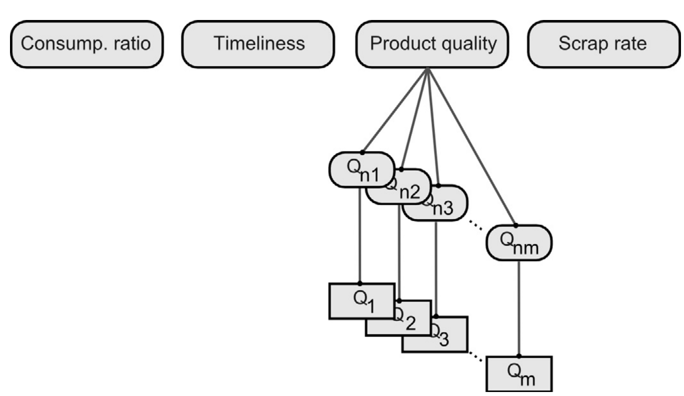

Fig. 17. Aggregated KPIs.

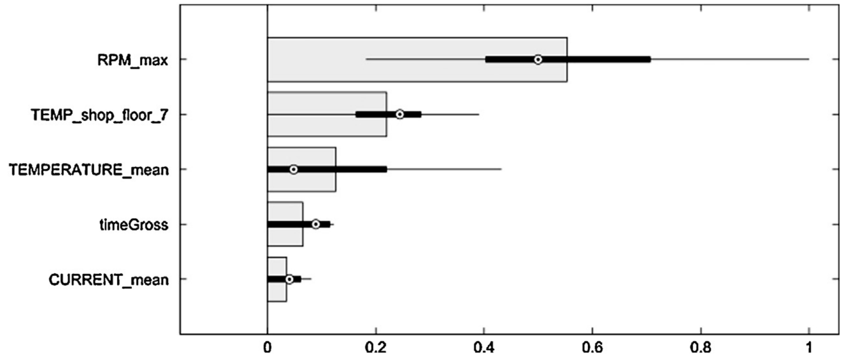

Fig. 18. Selection of *Quality* indicator influential variables for a product family.

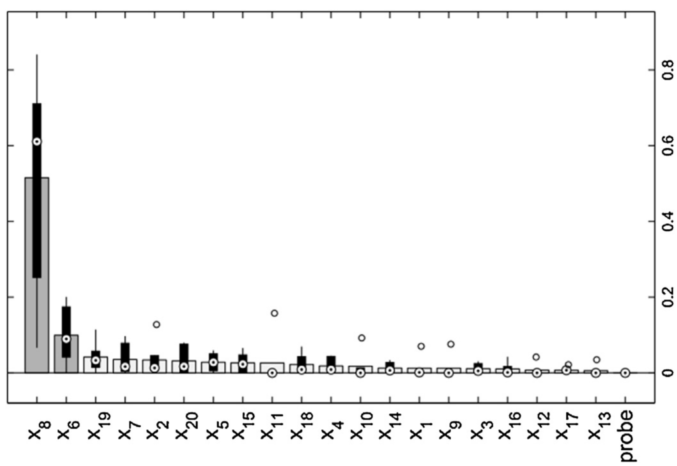

Fig. 19. Selection of influential parameters for final product *Quality*.

and interestingly also the temperature in the production hall appears to be important as well.

Fig. 18 indicates another specific feature of the given production case. Variable selection methods require that measurements on a batch have to be aggregated into a single data point, when considering their influence on the batch quality. For this purpose data-aggregation functions, provided within the *ProOpter Data module*, are used.

3.2.2. *Case study of discrete production*

The second industrial case study considers a moulding process. The process consists of two main phases: moulding and product finalization. With moulding the intermediate product is created and in product finalization the bearing set is mounted into the product. The product quality was estimated using a measure that was used previously in production, i.e., the *Quality* indicator was defined as a force used for mounting the bearing set (Q).

During the moulding phase we can observe a number of different process parameters that describe the internal process state. The observed parameters are defined as characteristic features of the main process variables (e.g., temperatures, pressures, cycle times). With ProOpter's IVS tool we analyzed the historical process data and ranked the influence of the observed parameters. As can be seen in Fig. 19, the influences of the two process parameters (x_8 and x_6) were found to have a major influence on the final product *Quality*.

On the basis of historical process data two separate models were identified. The first model describes the relation between the product *Quality* and the most influential process parameters. The second model is identified in order to describe the relation among the process parameters and the manipulative variables.

The identified models were validated directly on the production process. First, various alternative production process settings were calculated with the use of the models. The calculated settings were then applied to the production process. The final test results are shown in Fig. 20, where it can be seen that the simplified model of the final product quality resulted in a robust model. Such a model can support the tuning phase of

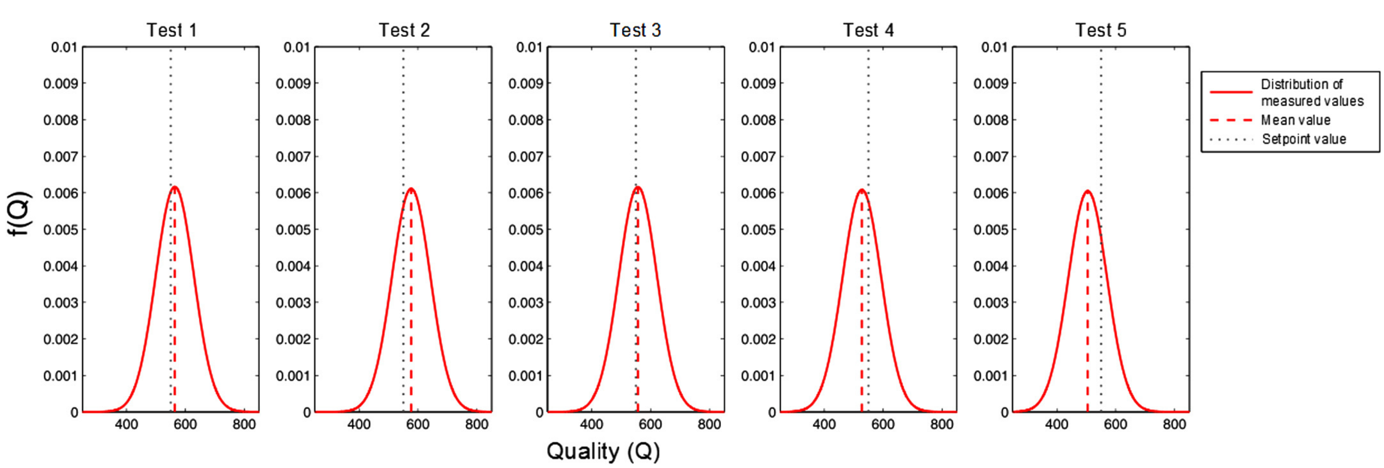

Fig. 20. Validation of the model.

the production process and enables a better understanding of the process.

4. Conclusion

The solutions used so far to control and optimize production are not capable of solving all existing the problems, so some new initiatives (Industry 4.0, Smart manufacturing) addressing this issue have emerged recently. With the advanced platform for production analysis and optimization – ProOpter, presented in this paper, we are following the ideas of these emerging initiatives, concentrating on one of the sub-problems. Namely, ProOpter offers a solution that can upgrade the existing production IT systems using data-analysis and system-modelling techniques. As such, it helps the production manager to analyze and optimize the production process. The ProOpter platform supports the concept of previously introduced holistic production control, where simplified KPI models that are identified from historical data are used as a decision-support tool. The use of the platform can unburden the production manager and help him/her take better decisions in order to improve the production process. With the introduction of the ProOpter platform we can expect savings in various areas of production, with better product quality, efficiency increases, waste reduction, and production cost reduction.

The tool is designed in such a way that enables a connection to the existing production IT systems over the standardized communication channels. Thus it extends their functionality with additional decision-support intelligence. The platform is modularly built using the established industrial standards in order to integrate all the modules.

One of the main advantages of ProOpter is that it enables experimentations with various newly developed methods and algorithms in a real production environment with no influence on the production process.

The platform was successfully validated on a simulated TE production process and partially validated on two industrial applications. The validation showed that such an approach could be useful for the production manager. Industrial case studies pointed out that the current production IT limitations could limit the applicability of such a tool. Nevertheless, it was shown that even a simple analysis of everyday data can open new opportunities for enhanced process understanding and process optimization.

As part of the further work, the platform needs to be upgraded to be fully applicable to all kinds of production processes (e.g., batch, continuous, discrete). For this reasons some additional validation case studies have to be performed on industrial processes. From practical experiences, which we gained from case studies, we can see that an additional simplification and automation of the modules is needed. To handle large databases, additional, efficient IT routines should be utilized for finding the valuable data portions.

We can conclude that the experience with ProOpter and the underlying concept of holistic control obtained so far is positive. This fact additionally explains why the idea of decision-support systems based on black-box models has recently gained a lot of attention. However, we have to be aware of the limitations and possible problems. On one hand, such systems, with a combination of the user's process knowledge, are capable of extracting hidden knowledge from the vast amount of process data. But, on the other hand, they are prone to extrapolate the knowledge included in data outside of the valid limits. Here, ProOpter is no exception. The future development of ProOpter should also focus on an increased awareness of the model's extrapolation limits when future control suggestions are being calculated/offered.

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References

[1] ARC Advisory Group, Enterprise Manufacturing Intelligence – Five Year Market Analysis and Technology Forecast Through 2016, 2011 URL: http://www.arcweb.com/market-studies/pages/enterprise-manufacturing-intelligence.aspx.
[2] M. Brettel, N. Friederichsen, M. Keller, M. Rosenberg, How virtualization, decentralization and network building change the manufacturing landscape: an industry 4.0 perspective, International Journal of Mechanical, Industrial Science and Engineering 8 (1) (2014) 37–44.
[3] A.K. Choudhary, J.A. Harding, M.K. Tiwari, Data mining in manufacturing: a review based on the kind of knowledge, Journal of Intelligent Manufacturing 20 (5) (2009) 501–521. , http://dx.doi.org/10.1007/s10845-008-0145-x.
[4] J. Davis, T. Edgar, J. Porter, J. Bernaden, M. Sarli, Smart manufacturing, manufacturing intelligence and demand-dynamic performance, Computers & Chemical Engineering 47 (20) (2012) 145–156, http://dx.doi.org/10.1016/j.compchemeng.2012.06.037.
[5] Data Mining Group, Predictive Model Markup Language – PMML 4.2.1, 2014 URL: http://www.dmg.org/v4-2-1/.
[6] D. Dovžan, V. Logar, I. Škrjanc, Implementation of an evolving fuzzy model (eFuMo) in a monitoring system for a waste-water treatment process, IEEE Transactions on Fuzzy Systems (2014), http://dx.doi.org/10.1109/TFUZZ.2014.2379252.
[7] J. Downs, E. Vogel, A plant-wide industrial process control problem, Computers & Chemical Engineering 17 (3) (1993) 245–255, http://dx.doi.org/10.1016/0098-1354(93)80018-I.
[8] P. Folan, J. Browne, A review of performance measurement: towards performance management, Computers in Industry 56 (7) (2005) 663–680, http://dx.doi.org/10.1016/j.compind.2005.03.001.
[9] M. Glavan, D. Gradišar, M. Atanasijević-Kunc, S. Strmčnik, G. Mušič, Input variable selection for model-based production control and optimisation, International Journal of Advanced Manufacturing Technology 68 (9–12) (2013) 2743–2759, http://dx.doi.org/10.1007/s00170-013-4840-1.
[10] M. Glavan, D. Gradišar, S. Strmčnik, G. Mušič, Production modelling for holistic production control, Simulation Modelling Practice and Theory 30 (2013) 1–20, http://dx.doi.org/10.1016/j.simpat.2012.07.010.
[11] L. Grüne, J. Pannek, Nonlinear Model Predictive Control: Theory and Algorithms, Communications and Control Engineering, 1st ed., Springer, 2011, http://dx.doi.org/10.1007/978-0-85729-501-9.
[12] I. Guyon, A. Elisseeff, An introduction to variable and feature selection, Journal of Machine Learning Research 3 (2003) 1157–1182.
[13] N.K. Hastilow, R.I. Young, Understanding 'manufacturing intelligence': a precursor to interoperable manufacturing systems, Enterprise Interoperability, Proceedings of the I-ESA Conferences 5 (2012) 49–57, http://dx.doi.org/10.1007/978-1-4471-2819-9_5.
[14] M. Holweg, The genealogy of lean production, Journal of Operations Management 25 (2) (2007) 420–437. , http://dx.doi.org/10.1016/j.jom.2006.04.001.
[15] Industrie 4.0 WG, Recommendations for Implementing the Strategic Initiative INDUSTRIE 4.0, Final Report, Industrie 4.0 Working Group, 2013.
[16] International Electrical Commission, IEC 62264, Enterprise-Control System Integration, 2009.
[17] International Organization for Standardization, Automation Systems and Integration – Key Performance Indicators (KPIs) for Manufacturing Operations Management – Part 2: Definitions and Descriptions. International Standard ISO 22400-2, 2014.
[18] G. Köksal, I. Batmaz, M.C. Testik, A review of data mining applications for quality improvement in manufacturing industry, Expert Systems with Applications 38 (10) (2011) 13448–13467, http://dx.doi.org/10.1016/j.eswa.2011.04.063.
[19] T. Larsson, K. Hestetun, E. Hovland, S. Skogestad, Self-optimizing control of a large-scale plant: the Tennessee Eastman process, Industrial and Engineering Chemistry Research 40 (22) (2001) 4889–4901, http://dx.doi.org/10.1021/ie000586y.
[20] L. Ljung, System Identification: Theory for the User, 2nd ed., Prentice Hall, Upper Saddle River, NJ, 1999.
[21] J. Maciejowski, Predictive Control with Constraints, Prentice-Hall, 2002.
[22] G. Mušič, M. Glavan, D. Gradišar, S. Strmčnik, ProOpter, production dynamics analysis and optimization tool, in: The 26th European Modeling & Simulation Symposium, September 2014, Bordeaux, France, 2014.
[23] R. Pearson, Nonlinear empirical modeling techniques, Computers & Chemical Engineering 30 (10-12) (2006) 1514–1528.
[24] SMLC, Implementing 21st Century Smart Manufacturing, Workshop Report, Smart Manufacturing Leadership Coalition and U.S. DOE, 2011.
[25] TechNavio, Global Enterprise Manufacturing Intelligence Market 2012–2016, 2013 URL: http://www.technavio.com/report/global-enterprise-manufacturing-intelligence-market-2012-2016.

[26] The Organization for Production Technology, Business to Manufacturing Markup Language (B2MML) – Production Performance Schema Documentation. WBF – Technical Report, 2012.
[27] The OpenMath Society, The OpenMath Standard 2.0, 2014.
[28] S. Zorzut, D. Gradišar, V. Jovan, G. Mušič, Use of a procedural model in the design of production control for a polymerization plant, International Journal of Advanced Manufacturing Technology 44 (11–12) (2009) 1051–1062, http://dx.doi.org/10.1007/s00170-008-1915-5.

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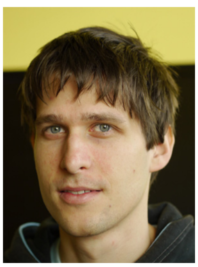

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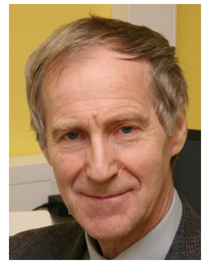

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