ProOpter, production dynamics analysis and optimization tool

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ABSTRACT
The paper deals with analysis and optimization of production performance dynamics expressed by key performance indicators (KPI). The architecture of a supporting software tool that integrates into production information systems is presented. The tool is able to support efficiency indicators composition, determination of performance influential variables and building of prediction model that enables a short-term prediction of the expected performance. The model can be used within predictive control algorithms, composing a production management decision support, which assists production operators at on-line production management. The tool is built modularly and employs industrial standards that facilitate the tool integration into production information systems of different vendors. The functionality of the tool is demonstrated by simulation benchmark as well as by real industrial production data.

Keywords: Production control, production efficiency, key performance indicators, modelling, simulation, optimization

1. INTRODUCTION

Manufacturing companies are faced with several challenges in their struggle to gain a competitive advantage. Among others, energy and resource efficiency are becoming increasingly decisive factors for competitiveness, companies are forced to shorten innovation cycles, and markets are becoming more volatile.

These challenges can be addressed by the extensive use of contemporary information technology within all organization levels of a company. A careful orchestration of the related information system improvements throughout the company has to be maintained in order to avoid bottlenecks on the one hand, and oversized capacity on the other. In any case, production itself is a base of any manufacturing company operation. Effective production management is one of the fundamental operational activities that has to be carefully designed and integrated into the overall management structure in order to meet the given requirements.

A number of initiatives emerged with a goal to establish a continual production efficiency improvement framework by the use of the latest technological advancements. In Europe, the German Industry 4.0 initiative (Industrie 4.0 2013) is perhaps the most known. It proposes to employ the Internet of Things paradigm on the factory floor and derive intelligent, intercommunicating autonomously operating production units, co called cyber-physical systems. This should result in flexible and efficient Smart Factory, with consideration of ergonomics and customer needs, and integration of supply-chain partners along the value chain (Brettel et al. 2014).

A similar North American initiative is Smart Manufacturing Leadership Coalition (SMLC 2011), 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 (Davis et al. 2012).

In terms of organizational advancements Japanese manufacturing has long tradition dating back in 1980's with Just-in-time manufacturing and lean production (Holweg 2007). Recently, also other Asian manufacturers are forced to adopt these advancements as they are faced with rising consumer sophistication that makes traditional low cost mass production strategies inadequate.

While these initiatives improve the organization of the production process and establish a decision-support framework with improved insight into the current state of production and its current performance, an obvious further advancement is to employ sophisticated data analysis and system modelling methods in order to predict the effect of production control measures on the future performance. This way a decision-making process at the production control level would be substantially improved by the possibility of beforehand evaluation of the various decisions.

To this end a holistic production control concept is proposed in Zorzut et al. (2009) and further elaborated in Glavan et al. (2013a) and Glavan et al. (2013b). The proposed modelling approach uses historical production performance data jointly with history of most influential decision variables to derive a black-box model by contemporary soft computing techniques, e.g. neural networks. Several additional steps are provided, such as data preparation, influential variable selection, etc. (Glavan et al. 2013a).

This paper describes the design and prototype implementation of a software tool that supports the application of modelling methodology in the context of production performance prediction and optimization. This is one of the fields where information technology has an immediate and considerable impact on the efficiency and quality of production control and related manufacturing processes. The tool modular architecture is described and the used industrial standards are presented, which facilitate the tool integration into production information systems of different vendors. The functionality of the tool is demonstrated through a selection of results from case studies, which include simulation benchmark as well as historical data from the actual industrial production.

2. HOLISTIC PRODUCTION CONTROL

The presented tool is based on the holistic production control concept, which attempts to bring classical feedback control approach, extensively used on the factory floor, also to the higher production control levels.

The concept of holistic production control can be best explained by the scheme depicted in Figure 1. The process we would like to control is indicated by the block *Production process*. Note that this block also covers the low-level process control. Different inputs (u) are available to manipulate the production process. These inputs are mostly the reference values for the process control loops and/or other manipulating variables not used within the stabilisation loops. On the other hand, there are many measurable disturbances (d) and outputs (y), which are used to calculate on-line the key performance indicators (K) – *KPI calculation* block. The key performance indicators (KPIs) are the production variables that are used by production manager to determine the appropriate input values (u) in order to optimise the production process. The demands from the business control level are given as reference KPIs (K^*). The attempt of the concept described here is to help the production manager with the decision-making process, which would close the loop through the introduction of the *Production controller & Optimiser*.

One of the possible solutions with this approach is to apply model-based control concept on the production management level. To enable this, an appropriate model describing the behaviour of the process projected on KPIs is required (the *KPI model* M). The model can be updated online and can provide the controller with the predicted outputs $K|M$. The model can also consider the measurable disturbances (d). Based on current values K, the predicted outputs $K|M$ and the reference values K^* (i.e., the planned business goals) the *Production controller & Optimiser* determines the appropriate input values $\hat{u}$ and in this way supports (or substitutes) the production manager (Eq. (1)).

$$\widehat{u} = \arg\min_{u \in R} C(K, K^*, K|M) \tag{1}$$

This concept has been introduced in Zorzut et al. (2009), and further elaborated and extended in Glavan et al. (2013a) and Glavan et al. (2013b).

How to derive an appropriate KPI model represents the main challenge of the HPC approach.

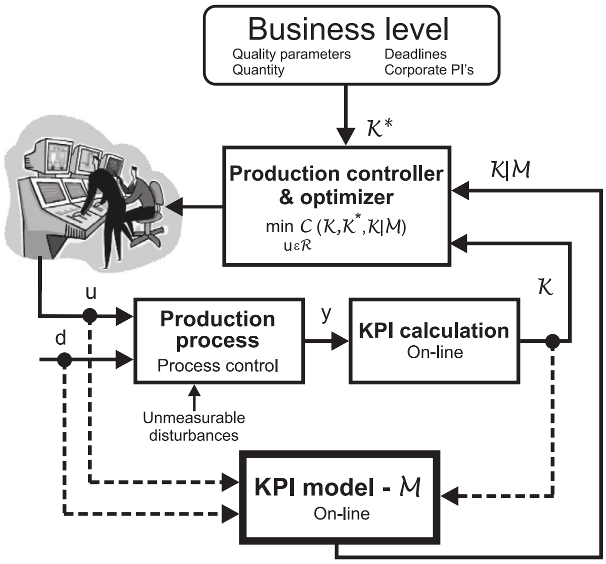

Figure 1: Holistic production control

2.1. Production modelling for holistic production control

Modern manufacturing systems are in many cases and for various reasons too complex to be accurately described analytically from first principles. Instead, one 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 that the model is easy to adapt online as well. Therefore, the main objective is the development of the concept of identifying a relatively simple input–output model of the production.

The main steps of the production modelling are shown in Figure 2. More detailed discussion about each of these steps and a short overview of the potential methodologies are given in the following subsections.

Data preprocessing

Special attention is needed when data from a historical production database are used. From the vast amount of data, the informative portions need 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 need to be properly substituted, and to cover all the process operating conditions an uneven data distribution is needed.

Data-cleaning procedures can be applied to detect and remove any outliers present in the data. As pointed out in Pearson (2006), 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.

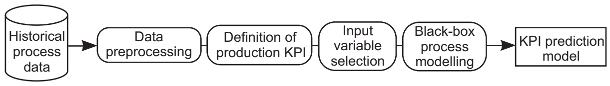

Figure 2: Holistic production control design steps

Definition of production performance indicators – KPIs

The research field of performance measurement systems (PMSs) is becoming increasingly important for industry and academics (Neely et al. 1995). Performance indicators (PIs) are commonly used by organisations to evaluate their overall economic success and many recommendations have been presented on how to specify such indicators (Folan and Browne 2005). These indicators should cover the relevant business aspects of the specific process, where the status of the process should be evaluated with relatively short-term indicators, since longer-scale business estimations (e.g., an annual profit report) are useless for quick process adjustments (Gerry and Buckbee 2005).

The production objectives are usually aggregated in key production performance indicators (KPIs). The selection of these KPIs should be performed manually, with extensive consideration of the production expert's knowledge of the process.

Input variables selection

To simplify the model and to enhance model's accuracy only the most relevant manipulative variables need to be identified. On the basis of the historical process data, an extensive analysis is needed to evaluate which inputs have the most significant impact on the selected KPIs.

Variable selection is already a widely applied methodology in the field of data mining. But, as noted by some authors, like Smits et al. (2006), in modelling projects it is mostly assumed that true inputs are a-priori known or all the available inputs are used in a model. To avoid the so-called curse-of-dimensionality, which essentially limits the robustness of a data-based model, only the most relevant inputs need to be selected. This represents an especially important step for HPC design, as in real-world production processes many potential variables are available. Furthermore, as aggregated KPIs are connected with many process variables it is often found that some a-priori excluded inputs are later identified as significant, and vice versa.

In the literature, three major principles for variable selection are used (Guyon and Elisseeff 2003):

- feature construction,
- variable ranking,
- variable subset selection.

For detailed discussion and evaluation of the related methods, see Glavan et al. (2013b).

As we are dealing with dynamical systems, the current values of production performance indicators are not dependent 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.

Black-box process modelling

The HPC efficiency is closely related to the production model, which should describe the main features of the production process with an acceptable level of approximation. The production process is typically a highly complex process, with nonlinear relationships among the vast quantity of process variables. Since our model should be simple enough and the development time needs to be short, black-box modelling techniques are preferred. Furthermore, the production model should be extracted mainly from the historical process data, since extensive experimentation on the real process is often too expensive or restricted. If the process characteristics were to change during the use of the production model, new process data should be analysed and a better model extracted. The cyclical generation and validation of new models will enable a rather conservative adaptation of the model-in-use to long-term changes in the production.

The main idea of the parametric black-box modelling techniques is to trim some universal input–output functions, with a fixed number of parameters, to represent the true process dynamics (2).

$$y(t) = g(\varphi(t), \vartheta) + e(t) \tag{2}$$

The goal is to minimise the mismatch $e(t)$ between the true process response $y(t)$ and the model prediction $g(\cdot)$, where the trimming is performed solely on the basis of the process input–output data pairs $Z^N = \{u(t), y(t)\}_{t=1}^N$

Black-box models can be seen as the connection of two mappings (Sjöberg et al. 1995). The first mapping constructs the regression vector $\varphi(t)$ from past inputs and outputs, which enables a representation of the dynamical model behaviour. Another mapping predicts the future behaviour of the system $\hat{y}(t)$, with the nonlinear mapping from the regressor space to the system output. This nonlinear mapping is found within a family of functions (3), parameterised by the parameter vector (ϑ), where g_k refers to the basis function, usually derived from a single, mother basis function.

$$\begin{aligned} \hat{y}(t) &= g(\varphi(t), \vartheta) = \textstyle\sum_{k=1}^{N} \alpha_k g_k(\varphi(t), \beta_k, \gamma_k) \\ \vartheta &= [\alpha_1 \ldots \alpha_n, \beta_1 \ldots \beta_n, \gamma_1 \ldots \gamma_n]^T \end{aligned} \tag{3}$$

From such a flexible structure, popular nonlinear mappings can be derived, like Neural Networks, Wavelets, Kernel Estimators, Nearest Neighbors, B-splines, Fuzzy models, etc. (Ljung 1999).

2.2. Optimization and holistic production control

Optimization is a vital component of holistic production control concept. Once a production performance dynamic model is derived, a natural way of incorporating the model in a production control scheme is to apply the model predictive control (MPC) approach (Maciejowski 2002, Grüne and Pannek 2011).

The MPC approach is based on repetitive solution of an optimal control problem, taking measured system state as the initial state and using system model to evaluate the effect of possible system input sequences. A discrete time representation of system dynamics is used and only the first sample of the calculated optimal 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. Depending on the method, prediction and control horizons can be of different lengths. The approach can be applied to feedback control of nonlinear systems, the method is then denoted NMPC.

For simplicity, we assume prediction and control horizon of length N. The determination of the optimal production manipulative values $\hat{u}$ can therefore be formulated as an optimal control problem

$$\begin{aligned} &\text{minimize} \quad J_N(x_0, u(\cdot)) := \sum_{k=0}^{N-1} l(x_u(k, x_0), u(k)) \\ &\text{with respect to} \quad u(\cdot) \in \mathbb{U}^N(x_0) \\ &\text{subject to} \quad x_u(0, x_0) = x_0, \\ &x_u(k+1, x_0) = f(x_u(k, x_0), u(k)) \end{aligned} \tag{4}$$

Here $x_0 = x(n) \in X$ is the current state of the system at the sampling instant $n = 0, 1, 2 \ldots$, $u(\cdot) \in \mathbb{U}^N(x_0)$ is a control sequence where $\mathbb{U}^N(x_0) \subseteq U^N$ is a set of admissible control sequences over which we optimize, $l(x, u)$ is a distance (deviation) measure, $J(x, u)$ the cost function, and $f(x, u)$ is the nonlinear state transition map representing discrete time dynamics.

When the solution is obtained, $\hat{u} = u(0)$ is chosen. For a non-constant reference and in the presence of terminal constraints the formulation is slightly modified, but the general idea remains the same.

In any case, the NMPC problem can be reformulated to match the standard problem in nonlinear optimization (NLP) (Grüne and Pannek 2011)

$$\begin{aligned} &\text{minimize} \quad F(z) \\ &\text{with respect to} \quad z \in \mathbb{R}^{n_z} \\ &\text{subject to} \quad G(z) = 0 \quad \text{and} \quad \mathrm{H(z)} \geq 0 \end{aligned} \tag{5}$$

with maps $F : \mathbb{R}^{n_z} \rightarrow \mathbb{R}$, $G : \mathbb{R}^{n_z} \rightarrow \mathbb{R}^{r_g}$ and $H : \mathbb{R}^{n_z} \rightarrow \mathbb{R}^{r_h}$. Here r_g and r_h denote the resulting number of equality and inequality constraints, respectively.

This reformulation, called discretization, can be done in different ways. Among them, the so-called recursive discretization recursively computes $x_u(k, x_0)$ from the open-loop system dynamics outside of the optimization problem, thus maintaining low dimension of the optimization variable z and the number of constraints $p = r_g + r_h$. The optimization variable z reduces to $z := (u(0)^T, \ldots, u(N-1)^T)$.

Utilizing this form, common solution methods for NLP problems can be applied, such as Sequential Quadratic Programming (SQP) or Interior Point Methods (IPM).

The recursive discretization is optimal regarding the number of optimization variables and constraints. Still, the method has some drawbacks compared to the full discretization. In particular, it is difficult to use the information on current control sequence solution in search for good initial guess in the next step, and the solution $x_u(k, x_0)$ may depend very sensitively on the control sequence $u(\cdot)$, in particular when N is large (Grüne and Pannek 2011).

The advantage of the method is that it separates the NLP solver from the solver of the dynamics. This is particularly well suited to models derived by soft-computing techniques, because an arbitrary numeric implementation of the model can be used. In the case of HPC, this enables to use the above mentioned black-box models in the form of nonlinear mappings in a straightforward way.

2.3. Software support

To assist the modeller in deriving production performance model for the HPC, and facilitate the application of the NMPC methods within HPC, a user-friendly software tool is needed. Using such a support tool, the system integrator and the production manager would have the possibility to identify a production model based on the historical operational data of the process, and integrate it in a model-based HPC solution.

The main purpose of the developed tool is to facilitate implementation of performance indicators, analyze the main performance influences, automate the model-development procedure and to support the manipulation and maintenance of already existing models, as well as their use in production optimization. As the potential users of such a tool are non-modelling experts (e.g., production managers), the program tends to simplify the model identification and control optimization procedures, where the user would not need to understand a detailed identification and control theory.

3. PROOPTER - PRODUCTION DYNAMICS ANALYZER AND OPTIMIZER

ProOpter extends the functionality of classical Manufacturing Execution Systems (MES) with embedded intelligence. It enables the analysis of production dynamics using complex analytical functions and application of advanced production control concepts that are based on embedded models. The Production dynamics analyser and optimizer represents an upgrade of classical MES systems, and thus increases the functionality and efficiency of production information systems.

3.1. Architecture

ProOpter enables the analysis of the production dynamics using advanced methods like data mining, data reduction, determination of relevant manipulated variables and production performance indicators model identification, as described in Section 2. The obtained models enable a short-term prediction of production dynamics, which is the basis for production optimization. The general architecture is shown in Figure 3.

ProOpter is composed of several modules, where some of them are used on-line, and others off-line. Connectivity with classical MES systems is enabled by standard IT interfaces, described in the following subsections.

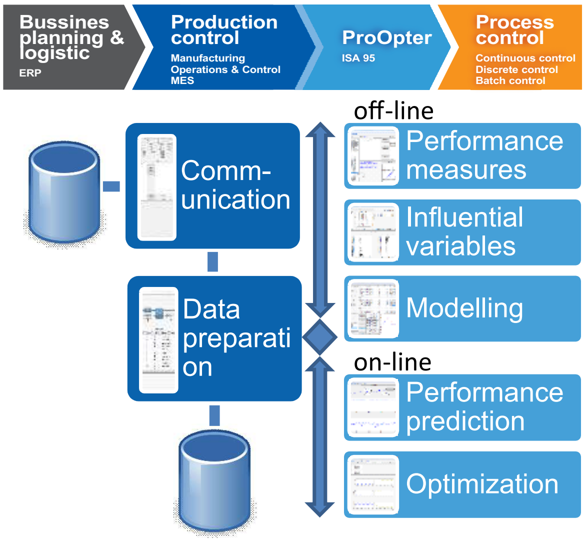

Figure 3: ProOpter architecture

3.2. ProOpter workflow

ProOpter workflow is depicted in Figure 4. The main ProOpter output is a set of manipulative variable values that should bring the manufacturing process close to the optimal operating mode.

The performance of the process is estimated through a set of KPI values. The indicators are calculated from the data acquired by the production management information system (MES) and stored in the production database. Various data irregularities typically appear in a real production environment, therefore the data is preprocessed and cleaned. During ProOpter development, a particular attention has been devoted to simplification of the KPI definition, and a corresponding data viewer and KPI formula editor have been implemented. When using on-line, the performance monitoring module supports various views with adjustable level of aggregation. Complex KPIs can be monitored and can also be drilled down to monitor their components.

The detemination of the most influential variables is one of the key steps in deriving applicable performance dynamic model. To support this a set of standard input variable selection (IVS) methods can be called from ProOpter IVS module. A user interface has been designed, which enables an aggregate representation and evaluation of results obtained by various methods. Due to predominantly nonlinear relations within the production process the IVS analysis results are typically non-uniform, and final decision on the set of variables that will be used in model identification has to be performed by the modeller. The developed user interface assist the modeller by providing graphical representation of the variable impact in various configurations.

A separate module has been developed for model identification support. The modeller can choose the data segments used for model identification and model validation, and adjust various identification parameters. Two soft computing methods are currently supported: neural-network based identification and fuzzy model identification.

The on-line operation of ProOpter provides the insight into production performance as described above, as well as supports the production manager in determining the optimal production settings. The nonlinear model predictive control described in Section 2 is applied here with an important distinction comparing to the classical MPC applications on the process level: the calculated inputs are not automatically applied to the production process, the decision on the application of the calculated manipulative values to the process is left to the production operator instead.

Some of the described ProOpter features are further illustrated by case studies in Section 4.

3.3. Data integration and communication standards

ProOpter was designed as an add-on to existing production management information systems. 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.

One of the main requirements for such an add-on is to support established industrial standards to be able to connect and integrate into existing information-communication infrastructure.

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

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

IEC/ISO 62264 (ANSI/ISA 95) standard defines models and terminology that are used for marking information, which has to be exchanged between business level and production control level. The information is structured by UML models and is a basis of production control integration into overall business information systems. The standard is used by IT developers as a guideline for specifying user requirements and as a basis of systems and databases development. The standard can be used in any type of production: continuous, batch or discrete.

Within the ProOpter tool the standard was used for designing internal communication messages. The messages were designed based on XML implementation of the standard that was developed by WBF (The Organization for Production Technology). Each data model of the standard has an XML equivalent within the B2MML (Business to Manufacturing Markup Language), and the model structure is defined by XML schemes (XSD).

Among the standard data models ProOpter tool uses the model that is intended for production response reporting (Production Performance).

Open Math is a standard for representation of mathematical objects that has been developed by OpenMath

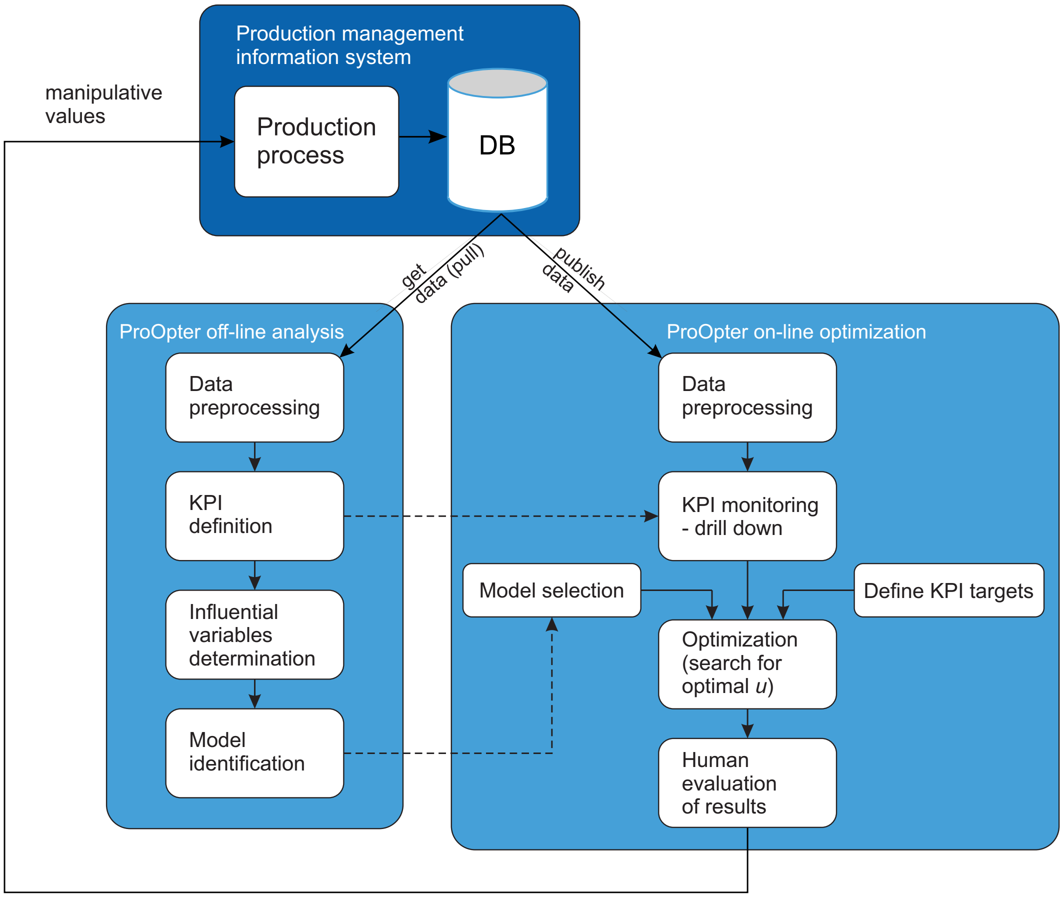

Figure 4: ProOpter workflow

Society. Two equation representations are supported, XML and binary format. The standard is based on the use of extendable content dictionaries, which structurally document mathematical definitions and unambiguously define mathematical symbols. Their openness enables definition of new functions and symbols. Custom content dictionaries can be added to common OpenMath repository and used by all interested parties. The standard does not require that all of the newly developed content dictionaries are public, but have to be accessible to all users of the particular concept.

By using OpenMath the KPIs can be described in a standard way that is recognised by various ProOpter modules, and can be exported to other tools.

PMML is used for transfer of identified KPI performance models among the ProOpter modules. PMML (Predictive Model Markup Language) is a standardized XML scheme for model representation in the area of predictive analytics and data mining. The PMML standard has evolved during the years and the recent version includes a rich set of model types and is supported by large number of statistical software tools.

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

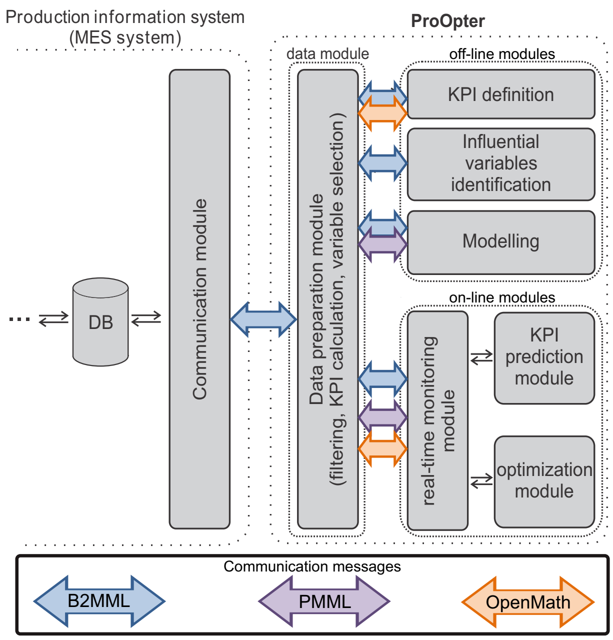

Figure 5: ProOpter standard messages

3.4. Communication

The use of unified communication protocols within production information system is of significant importance.

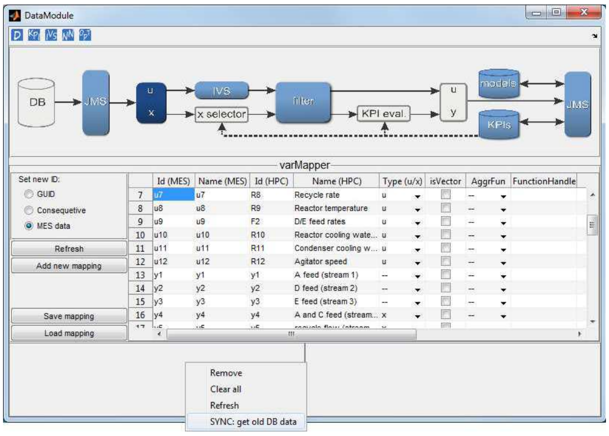

Figure 6: ProOpter data module

Use of communication standards guarantees the long term stability of developed applications as well as easier integration with the existing information infrastructure. In compliance with IEC 62264 two standard ways of data transmission are used within ProOpter:

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

The use of MOM (Message Oriented Middleware) systems is best suited for such an asynchronous XML message exchange among several clients. It supports both point-to-point and publish-subscribe communication principles. MOM enables distributed communication among loosely coupled clients, meaning that 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, MOM communication was implemented by JMS (Java Message Service) specification (Figure 6). Even if JMS originates from Java environment it is general and extensible enough to be useful also for clients that are designed within other development environments and platforms.

4. CASE STUDIES

The performance of the tool was tested through a set of production monitoring and control case studies of various production types. The continuous production was covered by a simulation benchmark, while in discrete and batch production the tool was tested on a real production data.

4.1. Batch production

Actual batch production data were considered in connection to performance measurement and influential variable analysis in water based paints and coatings production. The production is a typical batch process consisting of dosing and mixing stage, milling stage, production stage, and packing stage. In between production and packing stages the quality control is performed, where the acceptability of product for packing is determined. In the case of negative result, the product can be scrapped, or can go to re-work where the quality is improved.

Performance indicators

The performance monitoring in the considered batch production was mainly oriented toward determination of suitable batch parameter settings. Therefore batch related indicators were of primary concern. In cooperation with production managerial staff the following relevant indicators were identified:

- Quality - calculated per batch as a result of 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 - ration of the actual scrap quantity to the planned produced quantity.

Among the chosen indicators, Quality is the most complex and needs additional explanation. 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. This is illustrated in Figure 7. For every product (or product family) the relevant set of laboratory measured quality parameters is identified, and these are normalized and agregated into a standard valued quality indicator (common estimate in Figure 7).

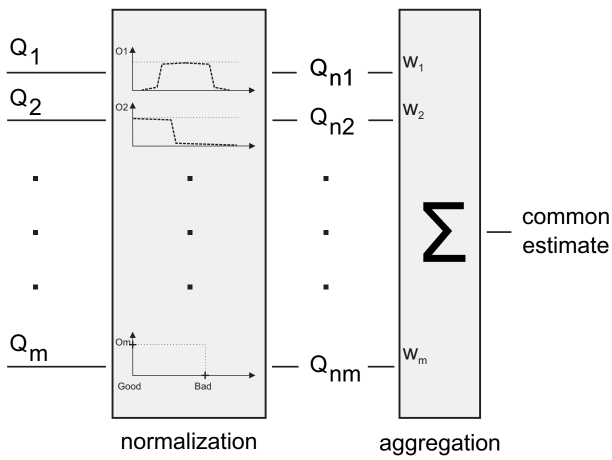

Figure 7: Aggregated KPI composition

The normalization and aggregation is supported by ProOpter KPI definition module. Two of the normalization screens are shown in Figures 8 and 9. For every measurement, the user can chose one of the predefined normalization types and then adjust the relevant parameters. Finally, the normalized measurements are aggregated into a KPI.

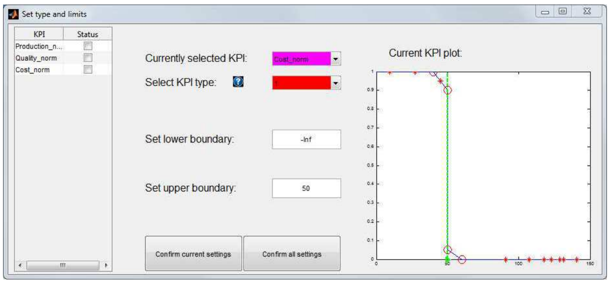

Figure 8: ProOpter normalization

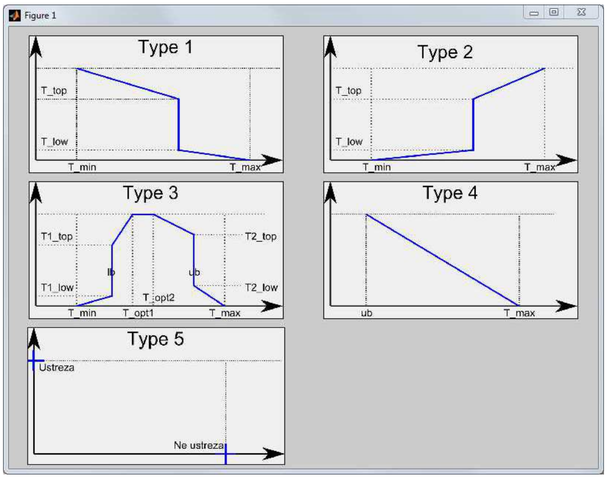

Figure 9: Predefined normalization types

Influential variables

In the considered case of coatings production the quality indicator is most relevant for the production efficiency. Bad 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 can not be generalized but has to be performed for every product family due to various production recipes.

The ProOpter tool supports the analysis by embedding several standard and advanced variable selection methods that are used in data mining: Linear Correlation, Partial correlation (with forward selection approach), PLS (variable importance in projection – PLS VIP), Non-Negative Garrote, LASSO, DMS search (pareto search of minimum error of linear model as objective function), and others. The problem of variable selection is elaborated in detail in (Glavan et al. 2013b).

The results for one of the product families are shown in figure 10. The aggregated results of a subset of available variable selection methods are shown as a box plot. In the given case, Max. RPMs of the mixer dominate the batch quality, and interestingly also the temperature in the production hall points out to be important as well.

Figure 10 points out another specific of the given production case. As several production variables are continuously sampled we typically have a range of corresponding variable values for a batch. Most of the used variable selec-

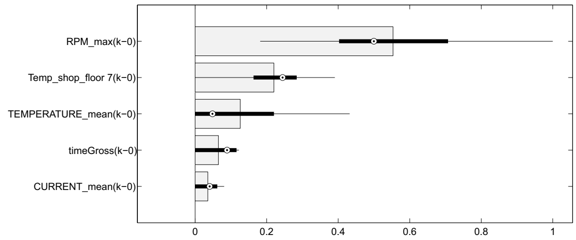

Figure 10: Selection of Quality indicator influental variables for a product family

tion methods require for such values to be aggregated into a single data point when considering the variable influence to the batch quality. For this purpose a set of standard data aggregation functions are provided within the ProOpter Data module, e.g. average, min, max.

4.2. Tennessee Eastman benchmark

The Tennessee Eastman (TE) benchmark process was introduced by Downs and Vogel (1993) as a model of a real chemical production process. The model represents a test problem for researchers to experiment with different control-related solutions. The process consists of five major units: a chemical reactor, a product condenser, a vapour–liquid separator, a product stripper and a recycle compressor. Four reactants (A, C, D, E) and an inert component (B) are entering the process, where four exothermic, irreversible reactions result in two products (G, H) and one byproduct (F). The process products leave the process through an output stream, and are later separated in a downstream refining section. The production process has 41 measured variables (y) and 12 different manipulative variables (u).

A specific combination of the production rate and/or the product mix are usually demanded by the market or some capacity limitations. Therefore, six typical operational modes are defined in the benchmark proposal. The model also provides 20 different process disturbances, which imitate the disturbances typical of real TE production.

As the research literature provides several results on the control of TE process by various methods, the proces was used as a primary test bench for verifying the operation of the various ProOpter modules and validation of the obtained results.

Production modelling

The historical data records needed for production performance evaluation and modelling were generated by simulation. To make the problem more realistic the process measurements have some intensionally added noise, typical for the specific measurement.

Production performance is monitored through three KPIs: Costs, Production, and Quality. The definition of Production KPI is quite straightforward, as the quantity of product leaving the process is directly measured. Directly from the process objectives an indicator for the process

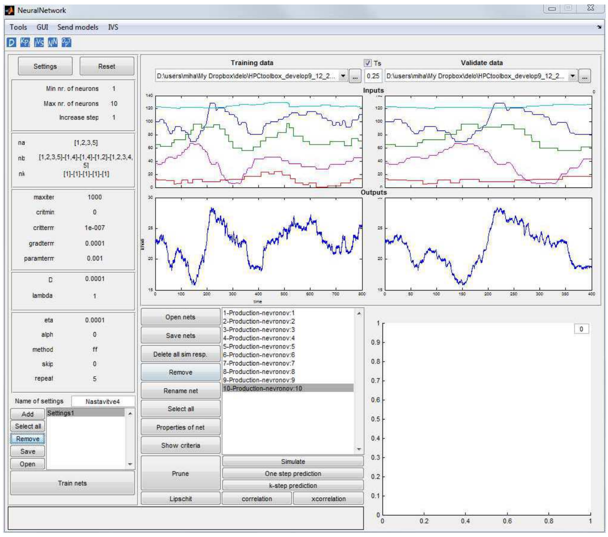

Figure 11: Modelling with ProOpter

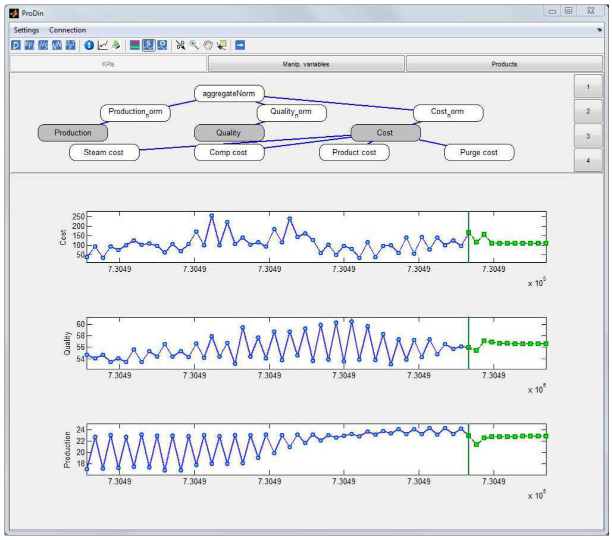

Figure 12: Efficiency monitoring and prediction

quality is also derived, since the product quality can be viewed as a desired mass ratio between the two final products, G and H. For details on the Cost KPI definition, the reader is referred to (Downs and Vogel 1993) or (Glavan et al. 2013a).

Next, the influential variable analysis is performed considering available manipulative variables and the defined KPIs. As described in Glavan et al. (2013b), five manipulative variables are selected, and then a neural-network based model is identified that enables to calculate a short-term prediction of the defined KPIs, provided chosen manipulative values are specified. The modelling is supported by the ProOpter modelling module, shown in Figure 11.

On-line production efficiency monitoring and optimization

The use of the derived performance models for real-time monitoring and performance prediction is illustrated in Figure 12. Observation variables can be chosen in the upper part of the window, while the chosen variable history can be seen in the lower part. The right sections of the plots indicate the estimated future KPI evolution based on the identified performance model and the manipulative values. A detailed investigation of the variables that contribute to the performance measure as well the insight into the manipulative values is possible by choosing the *drill-down* option.

Additional optimization module supports the adjustment of the manipulative values in a model based predictive control manner. The identified performance model is used to determine optimal manipulative variable settings, while the user has to specify appropriate KPI targets. E.g., Figure 13 illustrates how Production and Quality can be maintained at certain levels while the production Cost is minimized.

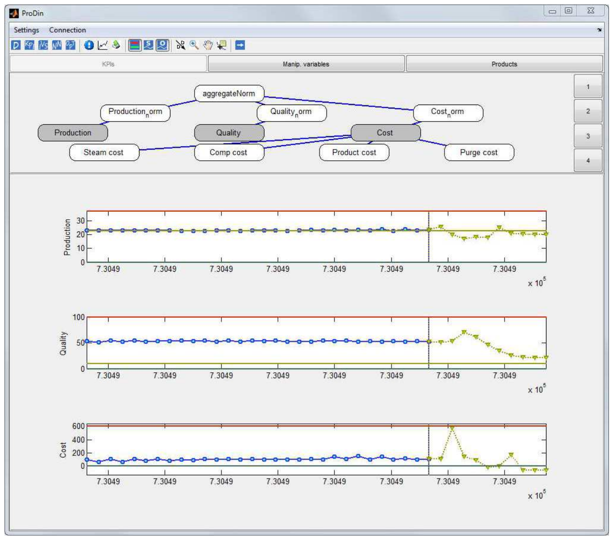

Figure 13: Efficiency optimization

6. CONCLUSIONS

Production information systems currently used in production companies are very efficient in data collection and data presentation, but are quite limited in the support of decision making and production optimization. The ProOpter - Production dynamics analyser and optimizer enables effective control of various types of manufacturing processes. Its main advantage is in use of simplified dynamic KPI models that are identified from historical data.

ProOpter will unburden the production manager and help him take better decisions in order to improve the production process. With the introduction of Production dynamics analyser and optimizer we can expect savings in various segments in the production through better product quality, increasing the efficiency, reduction of waste, and production cost reduction.

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