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Advisory System for Operators of Complex Industrial Processes Extended by Diagnostic Functions

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Abstract: Operators of industrial processes face the complexity of the process usually. They have to set all appropriate parameters correctly to ensure requested performance and quality of production. This demanding task is additionally complicated by permanent changing of ambient conditions. A probabilistic advisory system was developed as a support tool for operators. The advisory system processes historical data and concentrates the information about process behavior into a mixture of probability density functions. With the help of bayesian statistics, the advisory system compares historical information to the actual working point of the process and generates advisory information on how to change current process settings in order to reach requested performance and quality of production. Large mathematical and computational potential of developed advisory system encouraged an extension of the system by advanced diagnostic functions. The aim of this diagnostics is to recognize sensor and signal malfunctions that cannot be detected by standard diagnostic tools.

Key words: Advisory system, Bayesian statistics, mixture of probability density functions, Kullback-Leibler divergence, diagnostics, rolling mills

INTRODUCTION

Up-to-date control systems of complex industrial processes usually cover all key regulation functions while delegating responsibility to local controllers of particular parts of entire process. Local controllers are coordinated by supervisory functions of the control system while ensuring overall functionality of the process. Big afford of control community was devoted to the development and improvement of automatic control functions and algorithms in last decades. Nevertheless the main responsibility for proper functioning of the whole industrial process often remains to human operator.

The operator has a complex task to adjust all settings and parameters of the process in that way that process produces products with requested quality and with required performance. The control system usually provides the operator with enough information but the operator still needs a long-term experience to fulfill his role successfully. It seems reasonable to provide the operator with a computer based support tool in this situation.

This study describes the development and principles of an advisory system based on bayesian probability theory and the extension of the system by advanced diagnostic functions that help the operator recognize the relevance and reliability of information delivered to operator by the control system.

The probabilistic theoretical background and the resulting advisory system have been developed by several cooperating international teams of people from academia and industry, since, 2000. The development has been supported by several national and international grants. Let us name the first and the last at least; ProDaCTool (Decision Support Tool for Complex Industrial Processes based on Probabilistic Data Clustering, ST-1999-12058) and ProDisMon (Probabilistic Distributed Industrial System Monitor, E!7262). Researcher 1 of this study was a member of team in all of these projects. Final diagnostic extensions of the advisory system is the work of researcher 1 under the support of the University of West Bohemia, Czech Republic. Partial results on these projects were published by Ettler *et al.* (2013, 2015).

In this study, rolling mills and production of steel strips will be mentioned for the purpose of demonstration of a complex industrial process because this domain is native for researcher 1. Therefore, we include a short description of this process here.

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During the rolling of steel strip on a cold reversible rolling mill, the strip is unwound from left coiler in the first pass its thickness is reduced by the force of working rolls and the strip is wound up on the right coiler again. The thickness reduction continues in the second pass and so on. A picture of an example of a reversible cold rolling mill is in Fig. 1. While presents a simplified diagram of the rolling mill. The symbols in Fig. 2 have the following meaning:

- T_1, T_2, ..., input and output strip tensions
- v_1, v_2, ..., input and output speeds of strip
- H_1, H_2, ..., input and output thicknesses
- G, ..., Rolling gap
- F, ..., Rolling force

These symbols will be used later in this study. As mentioned above, the control system controls the industrial process but the operator is responsible for the results of production. Control system covers most automation tasks but settings of some process parameters and top supervisory functions are the domain of operator.

Fig. 1: Example of a reversible cold rolling mill

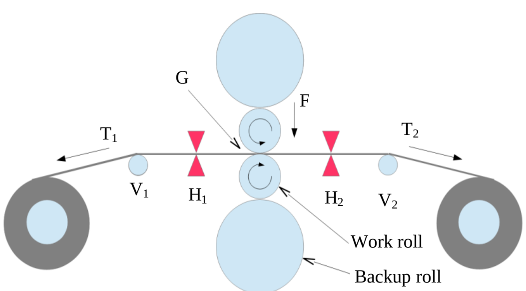

Fig. 2: Simplified diagram of a reversible cold rolling mill with main technological values represented by symbols

Experience with industrial processes shows that the operator's ability to control the process properly is influenced by following factors:

- Older operators with long-term practice are more successful
- Talent has its role
- Operator's character and current psychical status influence the results
- Even an experienced operator reacts to non-standard situations with difficulties
- And many others

This short list denotes that the production results can change substantially with the change of operator person or even with the change of current temper of the operator. This situation evokes an idea to replace the operator by a computer based system that does not suffer from human disabilities. Two main advantages of human operator stay against this idea:

- The ability to utilize conditions that are not covered by input signals
- Intuition

Obviously, the best solution is to combine the advantages of both approaches and support the operator with a computer based advisory system.

Integration of the advisory system into the control of the process is demonstrated by schematic diagram (Fig. 3).

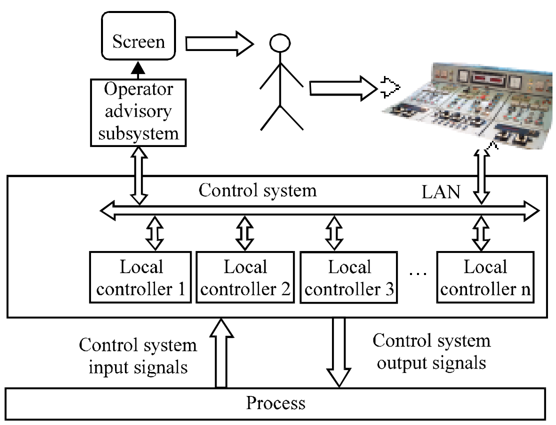

Fig. 3: Integration of advisory subsystem into control system of a process

MATERIALS AND METHODS

Main idea of the advisory system: At the beginning of development of the advisory system, there was an idea to utilize the ability of experienced operators hidden in historical data of the particular industrial process because experienced operators usually reach good results in production quality and performance. If, we are able to extract the historical information on "how to be successful", we will be able to instruct the current operator how to achieve desired results. Historical information about the process can help the operator predict the current behavior.

Up-to-date control systems enable to acquire and store big amount of process data, so, the main prerequisite-sufficient historical data is usually fulfilled. The key problem was how to extract the needed information from the huge amount of data how to express it in a concentrated form and how to make further calculations with this concentrated information.

One of the main participants in the above mentioned research projects, the Department of Adaptive Systems, Institute of Information Theory and Automation, Czech Academy of Sciences has a long-term experience with the probabilistic theory based on bayesian statistics, so, the decision was made to use this theory as the base for the development of the advisory system. At the same time, the software toolbox called mixtools developed in this department was chosen as the main platform for the development.

Mixtures of probability density functions and Bayesian statistics: Based on the probabilistic approach, the industrial process is taken for a stochastic process and data channels are taken for random variables. The behavior of the process can be expressed as a mixture of probability density functions, then. In our case, Gaussian functions are used. The notion mixture means that the probability density function is composed by a combination of several Gaussian functions with different weights and with particular means and standard deviations (Fig. 4).

An example of a mixture of two two-dimensional functions is shown in 0. The mixture consists of two Gaussian functions for two random variables x_1, x_2 defined according to Gut (2009) as follows:

$$f_{X_1, X_2}(x_1, x_2) = \frac{1}{2\pi\sigma_1, \sigma_2\sqrt{1-\rho^2}} e^{\frac{1}{2(1-\rho^2)}\left(\left(\frac{x_1-\mu_1}{\sigma_1}\right)^2 - 2\rho\frac{(x_1-\mu_1)(x_2-\mu_2)}{\sigma_1\sigma_2} + \left(\frac{x_2-\mu_2}{\sigma_2}\right)^2\right)} \quad (1)$$

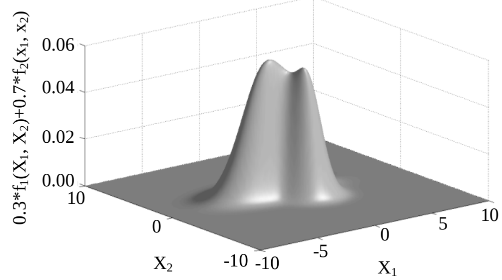

Fig. 4: Example of a mixture defined as weighted sum (weights 0.3 and 0.7) of two bivariate Gaussian functions with $\mu_{11} = 1$, $\mu_{12} = -1$, $\sigma_{11} = 1$, $\sigma_{12} = 1$, $\rho_1 = 0$, $\mu_{21} = -1$, $\mu_{22} = 1$, $\sigma_{21} = 2$, $\sigma_{22} = 1$ and $\rho_2 = 0$

Where:

$\sigma_1, \sigma_1 \in R$	=	Standard deviations
$\mu_1, \mu_2 \in R$	=	Means
$\rho \in R$	=	Correlation coefficient

and following conditions must be met:

$$\sigma_1 > 0 \text{ and } \sigma_2 > 0 \text{ and } |\rho| < 1$$

Mixture m_{X_1, X_2} is then defined as:

$$m_{X_1, X_2}(x_1, x_2) = \sum_{i=1}^{2} a_i . f_i(x_1, x_2) \quad (2)$$

where, a_i is particular weight of component f_i. All details about mixtures of probability density functions can be found by Karny (2006).

As mentioned above, the particular channels of acquired process data can be represented by random variables. The acquired data can then be approximated by a mixture. Transformation of data to a mixture of probability density functions is demonstrated. In the left diagram in clusters of data points are well visible. In the middle diagram, data are presented in the form of histogram where orange shades indicate the regions with highest density of data points. The right diagram is the most interesting where, we can see representation of data points in the form of a mixture of probability density functions. The mixture consists of nine components, small circles are the means and ellipses demote the shape of particular components.

Let us stress the advantage of the mixture representation of data here. Thousands of original data records are replaced by several values of weights, means, correlation factors and standard deviations of particular components. Moreover, calculations and comparisons can be done with mixtures with the help of Mixtools Software toolbox.

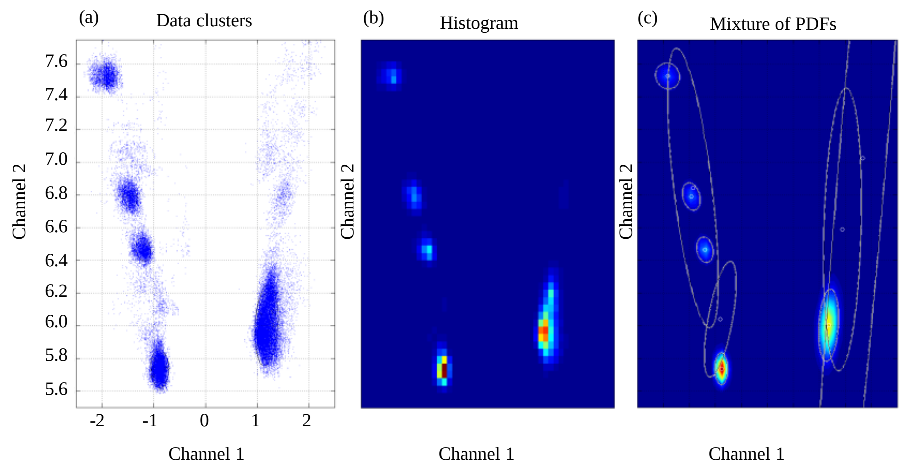

Fig. 5: a-c) Representation of data custers (lest diagram) by distogram (middle diagram) and by mixture of probability density functions (pdfs)

Let us note that the number of dimensions and the number of components is not limited to two generally, so, we can work in multidimensional data space where all main technological values can be involved. Mixtures are the main data objects used in the advisory system as it will be explained in next paragraphs (Fig. 5).

In general, during the process of transformation of data to the form of a mixture of Gaussian functions, the principles of Bayesian statistics are used. The Bayesian statistics differentiates from the classical one, especially in the ability to take into account the prior information. The prior information is very useful in our case. If the mixture is estimated on the base of data records, the prior information speeds up the algorithm substantially and enables to achieve more precise results. There are two possible sources of prior information in our case:

- Historical data
- Expert knowledge

Historical data contain information where particular data channels ranged frequently in the history. Expert knowledge limits the ranges on the base of physical or technological principles.

For the comparison of mixtures, the Kullback-Leibler divergence is used (Kullback and Leibler, 1951). This divergence is not an Euclidean distance of means of particular Gaussian functions only but it takes their shapes into account too. Kullback-Leibler divergence measures loss of information if a probability density function is replaced by another one. At the same time, Kullback-Leibler divergence from mixture m_1 to mixture m_2 is not same as from m_2 to m_1 in general.

RESULTS AND DISCUSSION

Logical structure of the advisory system: On the base of the above described principles, the advisory system was developed with the logical structure presented in 0. Description of data processing and final presentation of results follows (Fig. 6).

Data acquisition: Data are usually acquired from an existing control system.

Data preprocessing: Acquired data are preprocessed with the aim to reach a higher quality of signals which brings more precise results of the advisory system. Methods of signal filtration, reconstruction, etc. are used (Puchr and Herout, 2011).

Archiving of data: Long-term .archiving of acquired and preprocessed data is of great importance because the historical data are the key source of information for the whole advisory system.

Calculation of historical pdf mixture: From historical data, the historical mixture is calculated. Before the calculation, a selection of data is made according to the actual production mode of the industrial process. Another selection criterion is based on the goal we want to instruct the operator to reach (quality of production evaluated by a minimum value of the statistical Coefficient C_p for a given technological value like the output strip thickness H_2 on a rolling mill, e.g).

Calculation of target pdf mixture from actual working point: During the production, the operator selects a

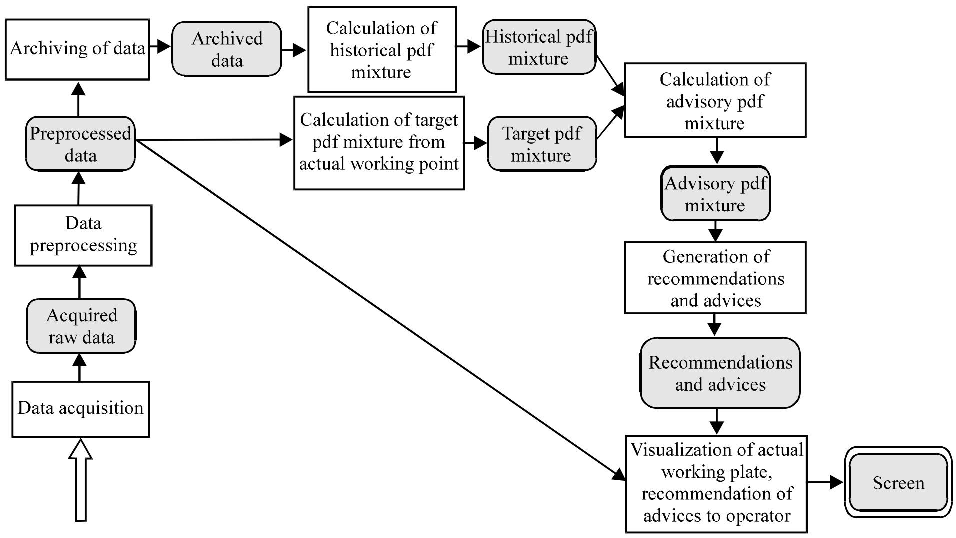

Fig. 6: Logical structure of the advisory system

particular working point of the process by setting some signals to a certain value or by limiting some other signals to an narrower range. These limitations direct the actual working point to a certain region in the whole multidimensional data space and this region can be expressed by probability density function with high density in this region. This function is represented by the target mixture.

Calculation of advisory pdf mixture: The advisory mixture is calculated on the base of historical and target mixtures. In principal, the advisory mixture represents a component of the historical mixture that is the nearest one (meant in the Kullback-Leibler divergence sense) to the actual working point (given by the target mixture). Advisory mixture is a one-component mixture representing a region with high probability that production criterion will be reached if operator keeps the working point in this region.

Generation of recommendations and advices: If the actual working point is not in the region given by the advisory mixture, recommendations are generated that instruct the operator how to move the actual working point to the region with high probability density.

Visualization of actual working point, recommendations and advices: An example of visualization of an advisory system outputs on a rolling mill (Fig. 7).

In the central part of the screen, there is the advisory mixture presented in two dimensions. The mixture is ten-dimensional actually (see left part of the screen with names of signals) but two currently most important signals are selected for visualization only, input and output strip tensions in this example. Cursor shows the actual working point that should be moved to the region with the highest probability density. Recommendation for operator is displayed in the upper part of the screen. Blue rectangle near the recommendation shows in the manner of traffic lights the current status of the process in relation to the optimum given by the advisory system.

Diagnostic functions of the advisory system: After the successful evaluation of the underlying probabilistic theory and the implementation of the advisory system, there was an idea to use the evaluated principles in another area of the support of operators too. There exists a class of diagnostic problems in industrial application where some key signals from sensors are degraded in such a manner that is hard to recognize by standard diagnostic approaches. In this situations, the sensor seems to be functioning properly but its output does not correspond to the measured reality actually. If the operator does not informed about this situation the production continues and this can cause production with degraded quality.

One possibility how to recognize this situation is to use information from other signals coming from the process. And this is the case where the historical mixture can come into account. Historical mixture comprises information about related signals and this information can be exploited for the detection of the sensor malfunction. A procedure was developed for the signalization of this

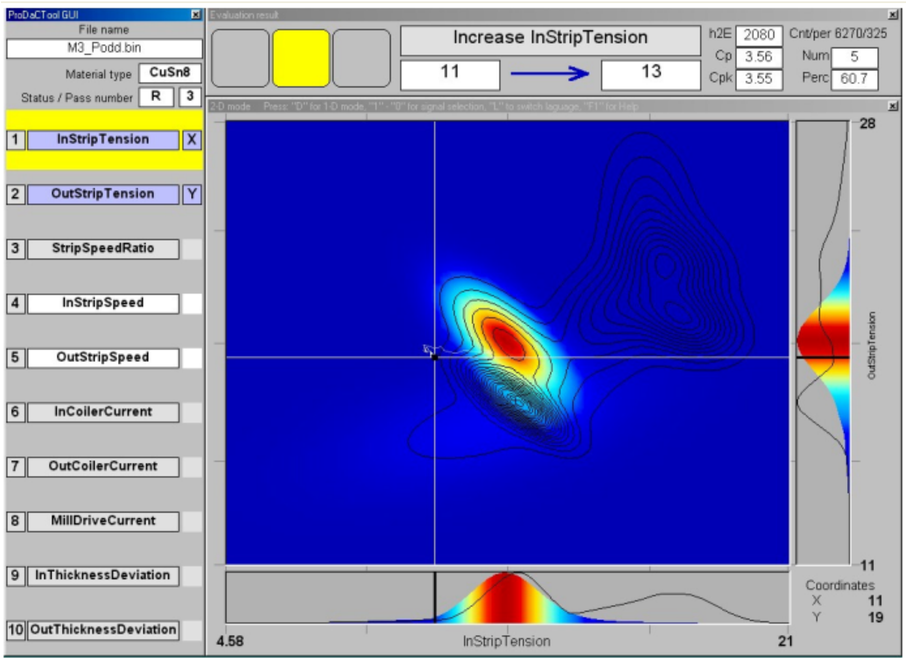

Fig. 7: Example of a screen with advisory system outputs on a rolling mill

problematic situation to the operator. The main principle of this procedure is that a short-time historical mixture is calculated repeatedly online and the result is compared to the long-term historical mixture with the use of Kullback-Leibler divergence. The development of the scalar value of the calculated divergence can be easily monitored then. A big change of this value signals the problematic situation. Operator is informed and can stop the production. For details, Puchr and Herout (2017), we present an illustrative two-dimensional example here.

In this example, two important signals are displayed in plots of mixtures (upper row of plots) while other signals are taken for constants. The mixture is recalculated in a narrow window of samples. New recalculated mixture is compared to the previous one with the use of Kullback-Leibler divergence. In standard situations, the value of divergence changes only slightly. Problematic situation is indicated by a bigger change of divergence value (see lower chart) (Fig. 8).

There exist several approaches to the problem of operator support and the above described solution can be compared with them.

Very often approach is the description of process behavior based on a model. White box model describes the process completely with as little as possible approximation and uncertainty. This strategy is usable for simple processes only. The use of white box model for a complex industrial process is impossible in most cases.

In many cases, the white box model is replaced by grey box model. This approach is characterized by finding of a simplified model of the process controlled by operator. A reasonable amount of approximation is used. Special behavior of the process not supported by the simplified model is covered by a set of parameters and circumferences. For grey box model approach to advisory system, constraints similar to white box model are valid too in the respect of our intention to use the same advisory system for a class of similar processes.

Another approach describes decision problem by a set of criteria and operator is to be advised in making right decisions in a hierarchy of alternatives with the aim to reach as good as possible result according to selected criterion. The methodology is called MCDA-Multiple-Criteria Decision Analysis. This strategy is not suitable for continuous control of process by operator but it can help the operator to decide if the advisory system generates more than one way how to reach requested status of process.

From the point of view of our intention, solution based on black box model (or data-driven solution) is interesting. Principles of process behavior are mined out from historical data. This operation may be automated in principle and thus, may avoid necessity of human professional formulating model of the process. This approach is the base of the above described solution.

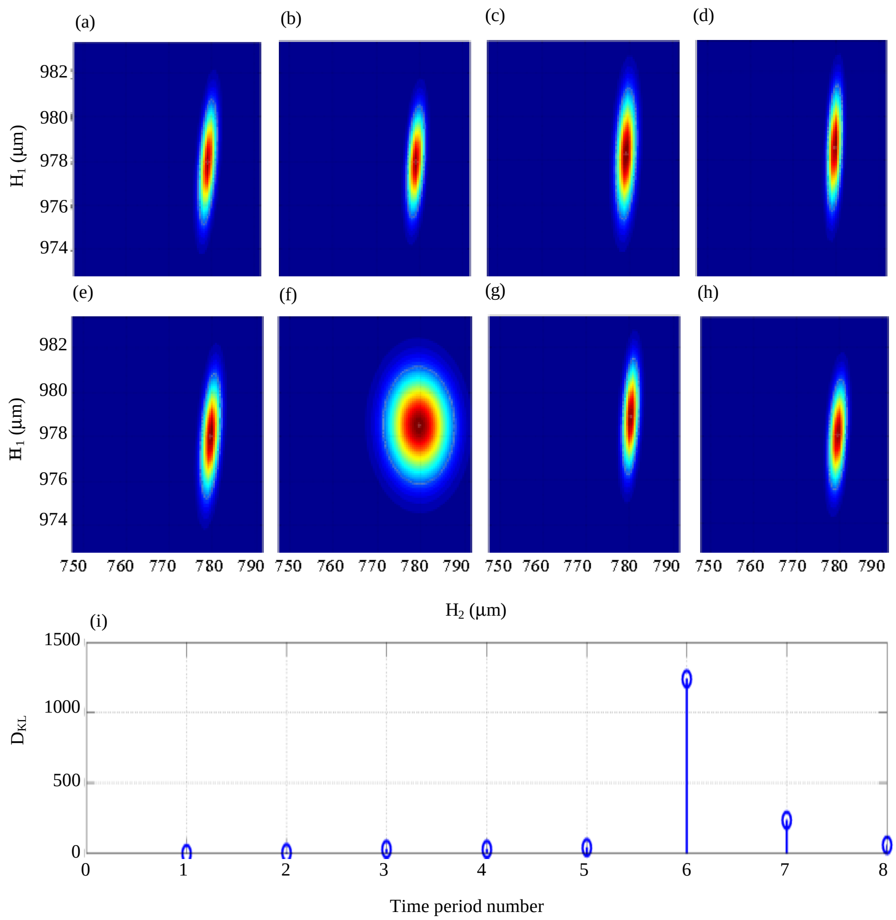

Fig. 8: a-i) Big change in Kullback-Leibler Divergence (D_{KL}) in the bottom chart) indicates problematic situation in the process of metal strip rolling

CONCLUSION

Principles of the probabilistic approach to the investigation of complex industrial processes were evaluated during the development of the advisory system. Big potential of the underlying probabilistic theory and of the software tools developed for the purpose of the advisory system can be utilized in subsequent projects too. An example of this is the extension of the advisory system with the diagnostic functions that were added recently. The advisory system is intended to be incorporated into industrial applications, especially to rolling mill control systems, either as a whole or as a set of sub-functions only.

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