MERGING OF ADVICES FROM MULTIPLE ADVISORY SYSTEMS
with evaluation on rolling mill data

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Keywords: advisory system, Bayesian decision-making, Bayesian model averaging, multiple-participant decision-making

Abstract: The problem of evaluation of advisory system quality is studied. Specifically, 18 advisory strategies for operators of a cold rolling mill were designed using different modelling assumptions. Since some assumptions may be more appropriate in different working regimes, we also design a new advising strategy based on the on-line merging of advices. In order to measure actual suitability of the advisory systems, we define two measures: operator's performance index and coincidence of the observed operator's actions with the advices. A time-variant model of advisory system suitability is proposed. Merging of the advices is achieved using Bayesian theory of decision-making. Final assessment of the original advisory systems and the new system is performed on data recorded during 6 months of operation of a real rolling mill. This task is complicated by the fact that the operator did not follow any of the recommendations generated by the advisory systems. Validation was thus performed with respect to the proposed measures. It was found that merging of the advising strategies can significantly improve quality of advising. The approach is general enough to be used in many similar problems.

1 INTRODUCTION

Theory and algorithms for design of advisory system based Bayesian decision-making theory have been consistently developed for years (Kárný et al., 2005). The theory was applied primarily to the probabilistic mixtures (Titterington et al., 1985) and the resulting algorithms were implemented in a Matlab toolbox Mixtools (Nedoma et al., 2005) which is also available as a platform-independent library. The first industrial application of the algorithms was designed for the twenty-high cold rolling mill in Kovohutě Rokycany within the international project ProDaC-Tool and was commissioned in autumn 2002 (Quinn et al., 2003), (Ettler et al., 2005a).

Development of the library continued, and within two years, its new version was ready for testing. The new library extended the number of possible settings of the advisory system. Great care was taken to eliminate the need for tuning knobs, and only discrete set of choices (such as class of models describing system behavior) was allowed. Thus, after three years of operation, the use of the original advisory system was suspended, it was replaced by a new experimental version and an experiment was undertaken to test suitability of these choices. To minimize the impact of the experiments on the production, mill operators were not asked to follow recommendations made by the system running in the experimental mode. Thus, we can not evaluate quality of the new systems from behavior of the closed loop, but we have to design evaluation criteria using only the open loop data.

Since only a small number of discrete choices is available, all possible combinations of these choices yield 18 different advisory systems, *advisers*. Each adviser is capable to generate recommendations for operators, *advices*. Thus, rather then simply choosing the best system, we also explore the possibility of merging advices from all the advisers. The merging rule is designed via a proposed model of evolution of advising quality. Relations of this approach to the Bayesian model averaging (Raftery et al., 1997) and multiple participant decision-making (Kárný et al., 2007) is discussed.

2 COLD ROLLING MILL

A reversing cold rolling mill is essentially used to reduce the thickness of a strip of metal. This is done by passing the strip between rolls in alternating direction under high applied pressure and strip tensions. Several basic types of cold rolling mills are distinguished according to the arrangement of working and backup rolls. Data for experiments came from the twenty-high rolling mill mentioned in the Introduction. For this machine the strip thickness is measured by contact meters on both sides of the rolling mill, providing measurements of the input and output thickness and its deviation from the nominal value. A target thickness is defined, and this needs to be achieved with high accuracy depending on the actual nominal thickness and on the type of material. A typical required tolerance in the considered data set was $\pm$ 10μm (microns).

Strip thickness variation h_2 on the output side of the rolling mill is considered as the main system output and the only criterial variable for further considerations. The output is, under normal conditions, securely controlled by the AGC (Automatic Gauge Control) (Ettler and Jirkovský, 1991). The term "normal conditions" is worth a discussion: perfectly working hydraulic roll-positioning system, operating strip thickness measurement together with values of rolling force, strip tensions and speeds and other adjustments from the technologically correct ranges are prerequisites. Nevertheless, performance of the system may not be optimal in all regions within these ranges due to e.g. some hardly observable vibrations, unequal cooling and lubrication conditions, etc. Thus even if the AGC keeps the thickness deviation well in tolerance, its performance can be further improved by tuning of its working conditions. This is a task for an experienced operator. An advisory system was designed to support potentially inexperienced operators (Quinn et al., 2003; Ettler et al., 2005b). Evaluation of quality of advices and their potential improvement is considered next.

The operator directly adjusts variety of variables (*actions*), we consider just three of them: input and output strip tensions and output strip speed. Actual values of these actions form three-dimensional vector, u_t. The operator makes his decision according to his experience, using the provided digital measurements of key internal variables but also his senses (e.g. hearing an unusual noise). On the other hand, the advisory system must depend only on the measured quantities. In the considered experiment, the advisory system operated on ten variables including the three operators actions listed above. The full vector of observed data will be denoted by $d_t = [y_t', u_t']$.

Behavior of the operator and its improvement is difficult to quantify. We define a quantitative criterion, *operator's performance index*, on a batch of 1000 subsequent data records:

$$P = \frac{E(h_2^2)}{E((h_1 - \overline{h_1})^2)}, \tag{1}$$

Here, $E(h_2^2)$ is the expected value of square deviations of output thickness from the desired value, and $E((h_1 - \overline{h_1})^2)$ is the expected value of square deviations of input thickness from the mean value of the batch. The expected values are evaluated empirically with respect to all data in the batch. In effect, (1) measures the ratio of output quality to input quality. An experienced operator is able to adjust conditions for the AGC so that good output quality is achieved even if the input quality is low, yielding small values of P. On the other hand, high values of P indicate worse output quality than optimum when input quality was relatively good, which is a sign of suboptimal settings.

3 ADVISORY SYSTEM DESIGN

An advisory system is a special case of a control system, control actions of which are not implemented automatically, but only displayed to an operator who has the freedom to follow or ignore the advice. However, the advices should be designed in such a way that if followed, the system achieves the optimal performance. Thus, an advisory system can be designed using methodology developed for design of adaptive controllers (Kárný et al., 2005). This methodology is divided in two phases:

off-line phase: a family of parametric models of the system is chosen, and the best model within this family is identified using historical data. Bayesian approach to this step involves the tasks of prior elicitation, parameter estimation, model selection, and model validation. Then, desired behavior of the closed-loop system (i.e. the original system controlled by an ideal controller) is formalized in the form of a *target* model.

on-line phase: the optimal advising strategies are designed such that the closed loop of the controlled system complemented by the advising strategy is the closest to the target behavior. The resulting optimized advising strategy is then presented to the operator in a simplified form. Typically, a small number of low dimensional projections of the probability distribution describing the

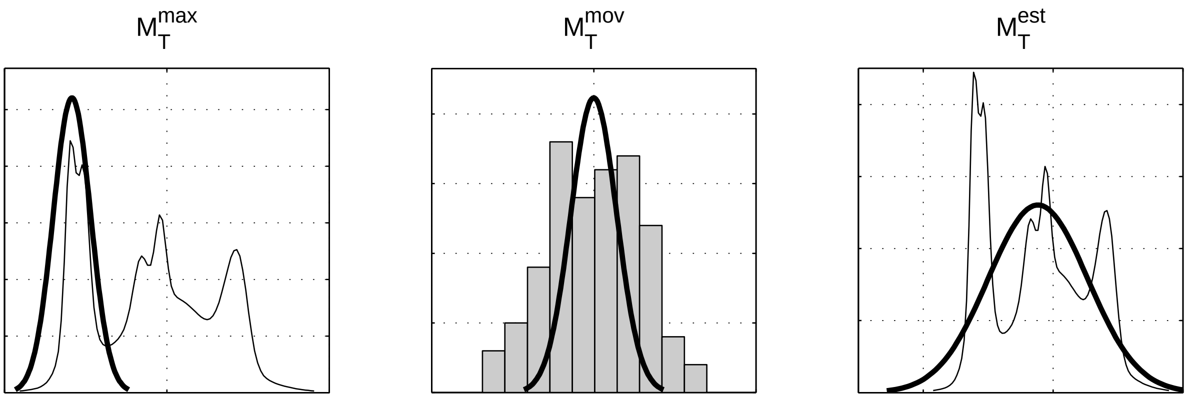

Figure 1: Graphic representation of construction of the target mixture M_T. Shown for a single dimension for the sake of clearness - M_T is depicted by the thick line, M_I or histogram by the thin line. Values of covariance for M_T^{max} and M_T^{mov} are chosen by the user while covariance of M_T^{est} is the result of estimation. Normalization is omitted here.

advising strategy is automatically selected. Specific recommendations such as "Increase the output strip tension to 25 kN" are also provided.

The advising system implemented in Mixtools uses Gaussian mixtures as the main modeling family. Probabilistic mixture is a convex combination of probability densities on the same variables, which are called components. Gaussian mixture is a probabilistic mixture with Gaussian components, i.e.

$$M: \quad f(d_t) = \sum_{i=1}^{c} w_i f(d_t|\mu_i, \Sigma_i). \tag{2}$$

Here, d denotes the modeled data, $f(d|\mu_i, \Sigma_i)$ is the ith Gaussian component with mean value μ_i and variance Σ_i, w_i is the weight of ith component, c denotes number of components. This choice of the model of the system is motivated by universal approximating properties of mixture models (Maz'ya and Schmidt, 2001). All introduced parameters, i.e. w_i, μ_i, Σ_i and c are considered to be unknown for all i.

Under this choice, an advisory system is designed as follows: (i) the unknown parameters are estimated in the off-line phase, yielding a mixture with estimated parameters, M_I, (ii) the target behavior of the closed loop is defined as M_T with specific choice of parameters in (2), and (iii) the part of M_I representing control strategy, is replaced by a parametric model, parameters of which are then optimized to minimize a statistical divergence to the target M_T; the result of this optimization is a new mixture M_A, for details see (Kárný et al., 2005). In each of these steps, it is possible to make several modeling choices, as described now in detail.

3.1 Variants of the System Model

A principal distinction in modeling of the system is the choice of static or dynamic model. The static approach models all observed data as independent realizations from the same density. The dynamic approach models also temporal dependence between subsequent data. This distinction is demonstrated in mixture models as follows:

M_I^{stat}: all observed data, d_t, $t = 1, \ldots, T$, are assumed to be generated from model (2) with time-invariant parameters μ_i, Σ_i, w_i.

M_I^{dyn}: observed data at time t, d_t, are assumed to be generated from model (2) with time-variant mean value, $\mu_i = \theta_i d_{t-1}$, and time-invariant parameters Σ_i, w_i.

3.2 Variants of the Target Mixture

Theoretically, the user can specify an arbitrary mixture model as his desired behavior. In practice however, he is concerned mostly with variables that are critical for the overall performance. If no suitable expert knowledge is available for the remaining non-critical variables, the target model on these must be chosen. Three variants of this choice of M_T were considered for experiments:

M_T^{max}: Means of the non-critical variables in a single-component M_T are given by the maximum marginal probability of M_I in particular axes as depicted in Fig. 1, left. Thus, M_T remains unchanged during on-line operation of the system.

M_T^{mov}: Means of the non-critical variables vary in time according to the outputs of the movingaverage filter processing actual data. Therefore M_T slightly differs for every step of the on-line operation as indicated in Fig. 1, middle.

M_T^{est}**:** A set of historical data from high-quality operating regimes were used to estimate parameters of a single-component mixture. This mixture was used as M_T afterward. During on-line computation M_T is not changed. An example of M_T^{est} is displayed in Fig. 1, right.

3.3 Variants of the Advising Strategy

Since the advising system is not hard-linked with the controlled system, its advices does not have to consider only the directly adjustable parameters. An advice does not have to be a numeric value, but it can suggest the operator to move into another operating mode of the machine, without being explicit about numerical values of adjustable parameters. Thus the freedom in design of an advisory system is with which parameters of the advising strategy are to be optimized. This decision influences the resulting advising strategy and thus the advisory mixture, M_A. Three variants of M_A were considered for experiments:

M_A^{acad}**:** optimization is done only with respect to weights w_i of the advising strategy. In effect, M_A^{acad} is composed of the same components as M_I (i.e all μ_i and Σ_i are the same), however, the component are weighted by different weights w_i.

M_A^{ind}**:** optimization is done with respect to the means μ_i. Weights w_i are assumed to be given by the process. Thus M_A^{ind} differs from M_I in component means and variances but not in their weights.

M_A^{simult}**:** is a combination of both previous approaches, i.e. both the weights and the component parameters are being optimized.

4 MERGING OF ADVICES

The Bayesian theory that was used for design of the advisory system ensures that all nuisance parameters were set (or integrated out). The discrete choices mentioned above are the only degrees of freedom considered in this experiment. All possible combinations of these yield $2 \times 3 \times 3 = 18$ different complete advisory systems, advisers. The task is to assess suitability of these advisers for the production of a real rolling mill. An ideal experiment would be to run a selected task 18 times under the same conditions, each time following different adviser. Since this is practically not feasible, we need to find an alternative evaluation method.

Moreover, each adviser may be more suitable for different operating conditions, and the best advising strategy is then to merge advices of all advisers together. In order to do that, we need to estimate the relation between advices of each adviser and operator's performance index, P_t. Let us consider a measure of coincidence of the current operator's actions with the recommendations of the ith adviser at time t:

$$C_{i,t} = E\left(1 - \frac{\max\left(|u_t - u^{\star}_{i,t}|, u_t\right)}{u_t}\right). \quad (3)$$

Here, u_t denotes the observed actions, $u^{\star}_{i,t}$ recommended actions by the ith adviser, and $|\cdot|$ denotes absolute value. Thus, $C_{i,t} = 1$ when the operator follows recommendation the ith adviser exactly. Furthermore, lets assume that P_t is related to C_i via an unknown function, $P_t = g_i(C_i)$. In order to estimate local approximation of this function, we seek a parametric model of this relation. Since the advisers were designed to improve quality of control, we assume that $g_i()$ is a monotonic function. Application of the Taylor expansion at operating point $\overline{C}_{i,t}$ at time t yields

$$P_t = g_i(\overline{C}_{i,t}) + g_i'(\overline{C}_{i,t})(C_{i,t} - \overline{C}_{i,t}) + e_t, \quad (4)$$

where $g_i'()$ denotes the first derivative of $g_i()$, $\overline{C}_{i,t}$ is the fixed point of expansion, and e_t is an aggregation of higher order term in the expansion. (4) motivates the following parametric model

$$P_t = b_{i,t} + a_{i,t}C_{i,t} + \sigma_{i,t}v_t, \quad (5)$$

where $a_{i,t}$, $b_{i,t}$, and $\sigma_{i,t}$ are unknown time-variant parameters and v_t is a Gaussian distributed disturbance, $v_t \sim \mathcal{N}(0,1)$. (5) constitutes a linear regression, parameters of which can be estimated using recursive least squares. The lack of knowledge about evolution of parameters $a_{i,t}, b_{i,t}, \sigma_{i,t}$ in time motivates the use least squares with forgetting (Kulhavý and Zarrop, 1993), which is appropriate for slowly varying parameters.

We consider an advice to be optimal if it minimizes the operator's performance index in the next step:

$$u^{\text{mer}}_{t+1} = \arg\min_{u_t} E(P_{t+1}|u_{t+1}). \quad (6)$$

The expected value is with respect to all unknown parameters

$$E(P_{t+1}|u_{t+1}) = \sum_{i=1}^{18} \alpha_{i,t} f(P_{t+1}|C_{i,t+1}(u_{t+1})), \quad (7)$$

where $f(P_{t+1}|C_{i,t+1}(u_{t+1}))$ is obtained by integrating (5) over $b_{i,t}, a_{i,t}, \sigma_{i,t}$, and α_i denotes probability that the ith adviser is reliable,

$$\alpha_{i,t} = f(i_t = i|P_t, C_t) \propto f(P_t|C_{i,t}, i). \qquad (8)$$

Here, $\propto$ denotes equality up to a normalizing constant, and $f(P_t|C_{i,t}, i)$ is obtained by integrating (5) over $b_{i,t}, a_{i,t}, \sigma_{i,t}$.

We note the following:

- Evaluation of expectation (7) and its weights (8) is closely related to Bayesian model averaging (Raftery et al., 1997). The only difference of our approach is the recursive evaluation of time-variant weights $\alpha_{i,t}$.
- One possible interpretation of this approach is to consider each adviser as a decision-making unit (DMU) in multiple participant decision-making (Kárný et al., 2007). If the units are not aware of each other presence, they generate individual advices. If they are forced to cooperate in order to maximize common aim—i.e. maximum expected increase in performance (6)—the final advice is a result of negotiation defined via (7)–(8).

5 EXPERIMENTS

The approach was tested on a data set collected during 6 month of production of a cold rolling mill consisting of more than 4,2 million of 10 dimensional data records. The set contains data from a wide range of operating conditions such as different materials or different passes through the mill. The quality of final product was within the required range for great majority of the data, and so was the operator's performance index, see Fig 2. This implies that the AGC low-level controller worked very well, and thus the space for improvement that can be achieved via the use of an advisory system is rather small. Hence, evaluation of the designed advisers is challenging.

Both operator's performance index and coincidence was computed for each model for each of the 4227 data batches. These numbers form irregular clusters, discouraging parametric modeling of the relation. Hence, we propose to split all data records in two sets: (i) high-quality data, $P < \hat{P}$, and (ii) low-quality data, $P \geq \hat{P}$. Here, $\hat{P}$ denotes a chosen threshold of quality which can be chosen e.g. from histogram on Fig 2. For each of the data set, we evaluate median value of coincidence $C_{i,t}$ for all advisers as their representative statistics. These values are displayed for selected advisers in Fig. 3. Interpretation of these results is as follows: advices generated by a

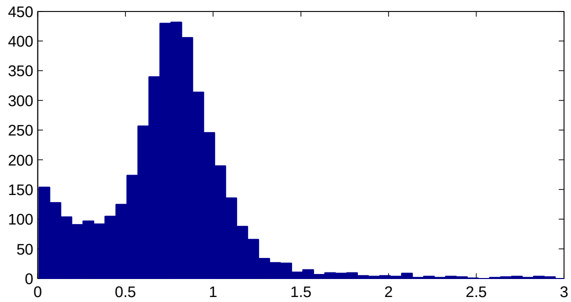

Figure 2: Histogram of operator's performance index for the considered data set. Only the range between 0 to 3 is displayed for clarity. Data records with $P > 3$ are infrequent but considerable.

good advising system should coincide with the operators actions at high-quality data region, but should differ in low-quality data regions, pointing (hopefully) in the direction of improvement. The line in the middle indicates a region where an adviser's coincidence is of the same value for both high-quality and low-quality data. An ideal adviser should be in the right-bottom quadrant of the plot.

Due to the lack of data in low-quality data set, the results are sensitive to the choice of the threshold $\hat{P}$, see results for $\hat{P} = 1.1$ and $\hat{P} = 1.4$ in Fig. 3. This sensitivity leads to a different choice of the best adviser from the original 18, specifically adviser $M_I^{\text{stat}}, M_T^{\text{mov}}, M_A^{\text{ind}}$, denoted by $\square$, and adviser $M_I^{\text{dyn}}, M_T^{\text{max}}, M_A^{\text{simult}}$ denoted by $\diamond$. Notably, however, the merged adviser, denoted by $\circ$, is performing well in both criteria.

This result should be taken only as qualitative for two reasons: (i) sensitivity of the criteria as described above, and (ii) for computational reasons, several approximations were used in evaluation of (6). Namely, integration over all parameters was replaced by conditioning on point estimates, and (7) was minimized only in the direction of its gradient in u_t. Nevertheless, the results indicate that merging of advices yields more robust adviser that any of the original ones.

6 CONCLUSION

A set of advising systems (advisers) was designed using different assumptions. A new adviser was constructed via on-line prediction of suitability of the original advisers for current working conditions and merging their recommendations. Performance of these advisers was assessed on real data. Evaluation of results was complicated by lack of data generated by an incorrectly set machine. Nevertheless, the re-

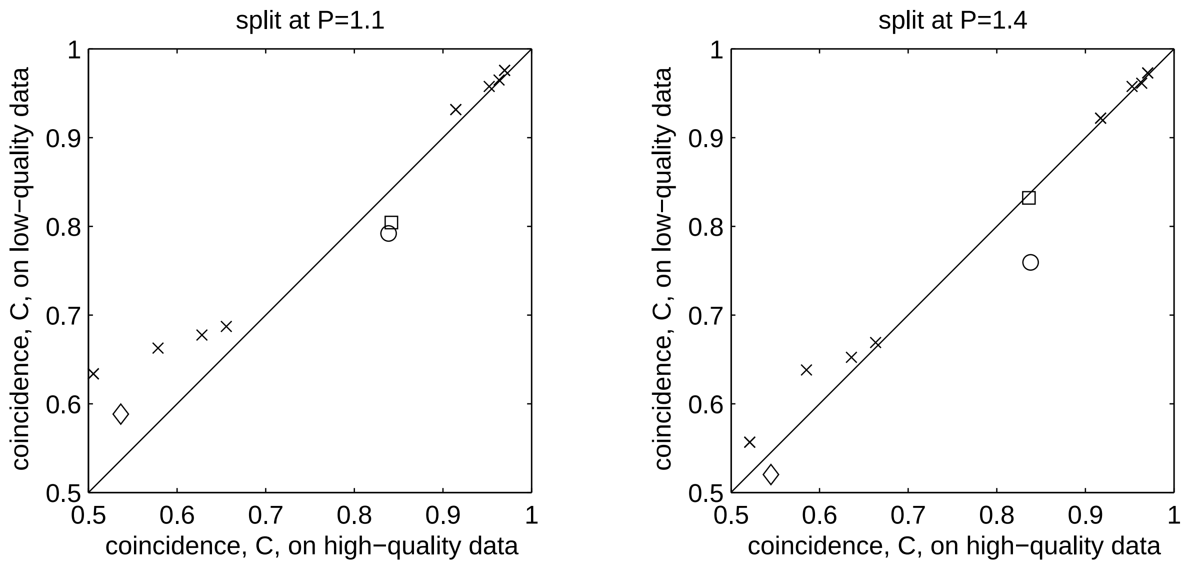

Figure 3: Comparison of coincidence C on high-quality and low-quality data for competing advisers. Two different thresholds between high and low quality were considered: $\hat{P} = 1.1$ (left) and $\hat{P} = 1.4$ (right). Original advisers with $C > 0.5$ are marked by $\times$, $\circ$ are denotes the merging adviser, $\square$ and $\diamond$ denote two remarkable original advisers, $M_I^{\text{stat}}, M_T^{\text{mov}}, M_A^{\text{ind}}$ and $M_I^{\text{dyn}}, M_T^{\text{max}}, M_A^{\text{simult}}$, respectively.

sults clearly show that merging of several advisers has the potential to provide better advices and it is more robust to the chosen evaluation metric.

ACKNOWLEDGMENTS

Support of grants AV ČR 1ET 100 750 401 and MŠMT 1M6798555601 (DAR) is gratefully acknowledged.

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