DETECTION OF THE NEED FOR A MODEL UPDATE IN STEEL MANUFACTURING

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Keywords: Adaptive model update, similar past cases, error in neighborhood, process data.

Abstract: When new data are obtained or simply when time goes by, the prediction accuracy of models in use may decrease. However, the question is when prediction accuracy has dropped to a level where the model can be considered out of date and in need of updating. This article describes a method that was developed for detecting the need for a model update. The method is applied in the steel industry, and the model whose need of updating is under study is a regression model developed to model the yield strength of steel plates. It is used to plan process settings in steel plate product manufacturing. To decide on the need for updating, information from similar past cases was utilized by introducing a limit called an exception limit. The limit was used to indicate when a new observation was from an area of the model input space where the prediction errors of the model have been too high. Moreover, an additional limit was formed to indicate when too many exceedings of the exception limit have occurred within a certain time scale. These two limits were then used to decide when to update the model.

1 INTRODUCTION

At the Ruukki's steel works in Raahe, Finland, liquid steel is cast into steel slabs that are then rolled into steel plates. Many different variables and mechanisms affect the mechanical properties of the final steel plates. The desired specifications of the mechanical properties of the plates vary, and to fulfill the specifications, different treatments are required. Some of these treatments are complicated and expensive, so it is possible to optimize the process by predicting the mechanical properties beforehand on the basis of planned production settings (Khattree and Rao, 2003).

Regression models have been developed for Ruukki to help development engineers control mechanical properties such as yield strength, tensile strength, and elongation of the metal plates (Juutilainen and Röning, 2006). However, acquirement of new data and the passing of time decrease the reliability of the models, which can bring economical losses to the plant. For example, when mechanical properties required by the customer are not satisfied in qualification tests, the testing lot in question need to be reproduced. If also retesting gives unsatisfactory result the whole order has to be produced again. Because of the volumes produced in a steel mill, this can cause huge losses. Thus, updating of the models emerges as an important step in improving modelling in the long run. This study concerns the need to update the regression model developed to model the yield strength of steel plates.

In practice, because the model is used in advance to plan process settings and since the employees know well how to produce common steel plate products, modelling of rare and new events becomes the most important aspect. However, to make new or rarely manufactured products, a reliable model is needed. Thus, when comparing the improvement in the model's performance, rare events are emphasized.

In this study, model adaptation is approached by searching for the exact time when the performance of the model has decreased too much. In practice, model adaptation means retraining the model at optimally selected intervals. However, because the system has to adapt quickly to a new situation in order to

Koskimäki (née Junno) H., Juutilainen I., Laurinen P. and Röning J. (2007).
DETECTION OF THE NEED FOR A MODEL UPDATE IN STEEL MANUFACTURING.
In *Proceedings of the Fourth International Conference on Informatics in Control, Automation and Robotics*, pages 55-59
DOI: 10.5220/0001639500550059

avoid losses to the plant, periodic retraining, used in many methods ((Haykin, 1999), (Yang et al., 2004)), is not considered the best approach. Moreover, there are also disadvantages if retraining is done unnecessarily. For example, extra work is needed to take a new model into use in the actual application environment. In the worst case, this can result in coding errors that affect the actual accuracy of the model.

Some other studies, for example (Gabrys et al., 2005), have considered model adaptation as the model's ability to learn behavior in areas from which information has not been acquired. In this study, adaptation of the model is considered to be the ability to react to time-dependent changes in the modelled causality. In spite of extensive literature searches, studies that would be comparable with the approach used in this article were not found. Thus, it can be assumed that the approach is new, at least in an actual industrial application.

2 DATA SET AND REGRESSION MODEL

The data for this study were collected from the Ruukki's steel works production database between July 2001 and April 2006. The whole data set consisted of approximately 250,000 observations. Information was gathered from element concentrations of actual ladle analyses, normalization indicators, rolling variables, steel plate thicknesses, and other process-related variables (Juutilainen et al., 2003). The observations were gathered during actual product manufacturing. The volumes of the products varied, but if there were more than 500 observations from one product, the product was considered a common product. Products with less than 50 observations were categorized as rare products.

The response variable used in the regression modelling was the Box-Cox-transformed yield strength of the steel plates. The Box-Cox transformation was selected to produce a Gaussian-distributed error term. The studied regression model was a link-linear model $y_i = \mu_i + \varepsilon_i$, where $\mu_i = f(x_i\beta)$ and ε_i are independently distributed Gaussian errors. The length of the parameter vector β was 130. In addition to 30 original input variables, the input vector x_i included 100 carefully chosen non-linear transformations of original input variables; for example, many of these transformations were products of two or three original inputs. The results are presented in the original (non-transformed) scale of the response variable.

3 NEIGHBORHOOD AND *APEN*

In this study the need for a model update was approached using information from previous cases, namely the average prediction errors of similar past cases. Thus, for every new observation, a neighborhood containing similar past cases was formed and an average prediction error inside the neighborhood was calculated.

The neighborhoods were defined using a Euclidian distance measure and the distance calculation was done only for previous observations to resemble the actual operating environment. The input variables were weighted using gradient-based scaling, so the weighting was relative to the importance of the variables in regression model (Juutilainen and Röning, ress). A numerical value of 3.5 was considered for the maximum distance inside which the neighboring observations were selected. The value was selected using prior knowledge of the input variable values. Thus, a significant difference in certain variable values with the defined weighting resulted in Euclidean distances of over 3.5. In addition to this, the maximum count of the selected neighbors was restricted to 500.

After the neighborhood for a new observation was defined, the average prediction error of the neighborhood (= $APEN$) was calculated as the distance-weighted mean of the prediction errors of observations belonging to the neighborhood:

$$APEN = \frac{\sum_{i=1}^{n}[(1-\frac{d_i}{max(d)})\cdot\widehat{\varepsilon}_i]}{\sum_{i=1}^{n}(1-\frac{d_i}{max(d)})}, \tag{1}$$

where

n	=	number of observations in a neighborhood,
$\varepsilon(i)$	=	the prediction error of ith observation of the neighborhood,
d_i	=	the Euclidian distance from the new observation to ith observation of the neighborhood,
$max(d)$	=	the maximum allowed Euclidian distance between the new observation and the previous observations in the neighborhood (= 3.5).

4 STUDY

The method used to observe the need for a model update was to determine when the model's average prediction error in the neighborhood of a new observation ($APEN$) differed from zero too much compared with the amount of similar past cases. When there are plenty of accurately predicted similar past cases, the $APEN$ is always near zero. When the amount of similar past cases decreases, the sensitivity of the $APEN$ (in relation to measurement variation) increases, also in situations when the actual model would be accurate. In other words, the relationship between the sensitivity of the $APEN$ and the number of neighbors is negatively correlated. The actual updating is also time-dependent, which means the model is updated when too many observations have an $APEN$ value that differs significantly from zero within a certain time interval.

A limit, called the exception limit, was introduced to detect the need to update the model. The limit defines how high the absolute value of the average prediction error of a neighborhood ($= |APEN|$) has to be in relation to the size of the neighborhood before it can be considered an exception. This design was introduced to avoid possible sensitivity issues of the $APEN$. In practice, if the size of the neighborhood was 500 (the area is well known), prediction errors higher than 8 were defined as exceptions, while with a neighborhood whose size was 5, the error had to be over 50. The values of the prediction errors used were decided by relating them to the average predicted deviation, $\bar{\hat{\sigma}}_i$ (≈ 14.4). The predicted deviations were acquired by using a regression model (Juutilainen and Röning, 2006). The limit is shown in Figure 1.

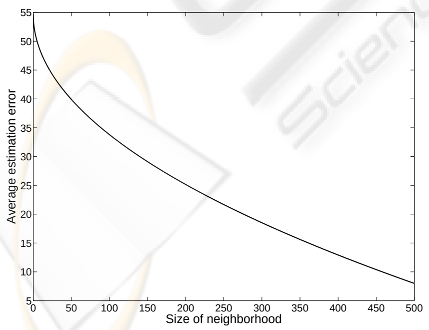


Figure 1: Exception limit.

A second limit, the update limit, was defined as being exceeded if 10 percent of the average prediction errors of the neighborhoods within a certain time interval exceeded the exception limit. The chosen interval was 1000 observations, which represents measurements from approximately one week of production. Thus, the model was retrained every time 100 of the preceding 1000 observations exceeded the exception limit.

The study was started by training the parameters of the regression model using the first 50,000 observations (approximately one year). After that the trained model was used to give the $APEN$s of new observations. The point where the update limit was exceeded the first time was located and the parameters of the model were updated using all the data acquired by then. The study was carried on by studying the reliability of the model after each update and repeating the steps iteratively until the whole data set was passed.

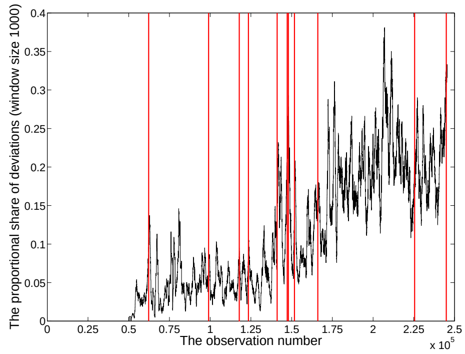
5 RESULTS

First the reliability of the model with and without updating was studied. Figure 2 shows the average prediction errors of the respective neighborhoods. Figure 2(a) shows the model's performance without updating. The straight line in the beginning represents the training data and the rest of the curve shows the proportional share of the exceedings of the exception limit, in other words, the percentage of $APEN$s that exceeded the exception limit. For example, it can be seen that at the end of the curve the $APEN$ of every fourth new observation per week has exceeded the exception limit. The vertical lines mark the points of iteration where the update limit has been exceeded. On the other hand, Figure 2(b) presents the reliability of the model when the parameters are re-estimated at times indicated by the vertical lines. The curve represents the error rate of the re-trained model.

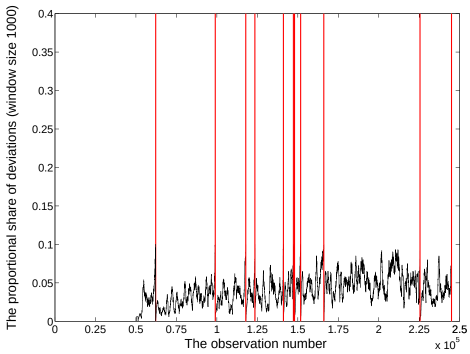
The positive effect of the updates on the average prediction errors of the neighborhoods can be clearly seen from Figure 2. Therefore, it is evident that the model's performance increases when the developed updating strategy is applied.

Although the reliability information of the model is very useful, the effect of the update on the actual prediction error was considered more important. Two different goodness criteria were used to compare the actual prediction errors of the updated models. Both criteria emphasize rare events, because that is the case when the model is needed the most. Both of them show the weighted average of the absolute prediction errors, with different weighting schemes.

In the first goodness criterion the idea is to emphasize all the products by approximately an equal amount. This means that in the calculation of the average prediction error, the weights of observations



(a) Without update.



(b) With update.

Figure 2: Reliability of the model.

belonging to products having more than 50 observations are decreased. The results of the goodness criterion are shown in Table 1. The step size indicates the length of the iteration step (comparable with the space between the vertical lines in Figure 2). The results are averages of the absolute prediction errors of the observations between each iteration step. Thus, the size of the data set used to calculate the average is the same as the step size. In addition to this, to compare the results, the prediction error averages are presented in three different cases: predicted with a newly updated model, with a model updated in the previous iteration step, and with a model that was not updated at all. The results show that, although the differences between the new model and the model from the previous iteration step are not big, the update improves the prediction in each of the steps. The benefit of the model update is obvious when the results of the updated model and the model without an update are compared.

The second goodness criterion was formed to take only rare events into account. Thus, only the cases

Table 1: Means of absolute prediction errors with the first goodness criterion.

Step size	With new model	With previous model	Without update
12228	-	-	-
36812	11.59	11.74	11.74
18826	10.47	11.00	10.69
5623	10.93	11.08	11.25
17636	12.48	12.57	12.97
6165	11.48	12.38	13.31
699	29.92	30.20	41.00
3765	11.79	12.21	13.96
14317	12.35	12.42	13.53
59432	12.22	12.39	12.87
19455	12.72	13.46	14.81
507	11.46	11.68	15.22
mean	**12.07**	**12.32**	**12.79**

where the neighborhood size is smaller than 50 are considered. The absolute prediction errors of these rare observations affect the average equal amount. The update proves its functionality in this scheme, also. The prediction errors are notably smaller when the model is updated (see Table 2).

Table 2: Means of absolute prediction errors with the second goodness criterion.

Step size	With new model	With previous model	Without update
12228	-	-	-
36812	14.41	14.63	14.63
18826	13.14	14.12	13.99
5623	12.94	13.11	13.10
17636	16.48	16.60	18.22
6165	12.60	13.90	14.71
699	84.86	85.86	115.44
3765	13.88	17.08	21.28
14317	16.23	16.21	22.09
59432	15.42	15.54	17.90
19455	26.42	27.88	43.87
507	15.99	15.18	16.04
mean	**15.67**	**16.04**	**18.10**

With this data set, determination of the need for a model update and the actual update process proved their efficiency. The number of iteration steps seems to be quite large, but like in Figure 2, the iteration steps get longer when more data is used to train the model. Thus, the amount of updates decreases as time goes on. However, the developed approach can also adapt to changes rapidly, when needed, as when new products are introduced or the production method of an existing product is changed. Finally, the benefits of this more intelligent updating procedure are obvious in comparison with a dummy periodic update procedure (when the model is updated at one-year intervals, for example, the prediction error means of the whole data sets are 12.24 using criterion 1 and 16.34 using criterion 2, notably worse than the results achieved with our method, 12.07 and 15.67). The periodic procedure could not react to changes quickly or accurately enough, and in some cases it would react unnecessarily.

6 CONCLUSIONS

This paper described the development of a method for detecting the need for a model update in the steel industry. The prediction accuracy of regression models may decrease in the long run, and a model update at periodic intervals may not react to changes rapidly and accurately enough. Thus, there was a need for a reliable method for determining suitable times to update the model. Two limits were used to detect these update times, and the results appear promising. In addition, it is possible to rework the actual values of the limits to optimize the updating steps and improve the results before implementing the method in an actual application environment. Although the procedure was tested using a single data set, the extensiveness of the data set clearly proves the usability of the procedure. Nevertheless, the procedure will be validated when it is adapted also to regression models developed to model the tensile strength and elongation of metal plates.

In this study the model update was performed by using all the previously gathered data to define the regression model parameters. However, in the future the amount of data will increase, making it hard to use all the gathered data in an update. Thus, new methods for intelligent data selection are needed to form suitable training data. In addition, the model update could be developed into a direction where the input variables of the regression model can also be changed during the update.

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