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Application of Time-Series Analysis for Predicting Defects in Continuous Steel Casting Process

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Abstract

The purpose of this paper was testing suitability of the time-series analysis for quality control of the continuous steel casting process in production conditions. The analysis was carried out on industrial data collected in one of Polish steel plants. The production data concerned defective fractions of billets obtained in the process. The procedure of the industrial data preparation is presented. The computations for the time-series analysis were carried out in two ways, both using the authors' own software. The first one, applied to the real numbers type of the data has a wide range of capabilities, including not only prediction of the future values but also detection of important periodicity in data. In the second approach the data were assumed in a binary (categorical) form, i.e. the every heat(melt) was labeled as 'Good' or 'Defective'. The naïve Bayesian classifier was used for predicting the successive values. The most interesting results of the analysis include good prediction accuracies obtained by both methodologies, the crucial influence of the last preceding point on the predicted result for the real data time-series analysis as well as obtaining an information about the type of misclassification for binary data. The possibility of prediction of the future values can be used by engineering or operational staff with an expert knowledge to decrease fraction of defective products by taking appropriate action when the forthcoming period is identified as critical.

Keywords: Application of information technology to the foundry industry, Quality management, Continuous steel casting, Time-series analysis, Naïve Bayesian classifier.

1. Introduction

The time-series analysis is one of the data mining methods, which deals with series of data recorded in a chronological order, usually in regular time intervals or in another sequences. There are two aims of that kind of analysis: the discovery of nature of the given process or phenomenon and the prediction of future values. Time-series prediction can be considered as a particular case of a regression task, where the input and output variables are the same quantity but measured at different time moments.

The time-series analysis has been widely applied in business problems, however, recently multiple examples of their utilization in technology, including manufacturing industry, can be found in the literature (e.g. [1-5]). As indicated in [6], the application of these methods in foundry industry can bring essential benefits. Detection of periodicity in products or materials properties in a foundry can facilitate identification of the abnormalities in the manufacturing processes. Prediction of the process parameters or the product properties can help to prevent unwanted tendencies or can suggest required changes in the process control.

First attempts of application of the time-series analysis to quality control of continuous steel casting process were made by researchers from South Africa [4]. They applied auto regressive methods in modeling specific type of the time-series, with exogenous input (ARX). In their approach the data were divided and used in two models: one describing the effect of casting parameters on thermocouple temperatures and second describing the effect of thermocouple temperatures on defects appearance. The first model was used to control the occurrence of defects and the second one was the defects' predictor.

Industrial data used in the present work were collected in a Polish steel plant equipped in one continuous casting machine producing four strands. Each of them provides a semi-finished product called a billet which is a long square-profiled steel ingot. Defects of billets are formed during the solidification process. Due to the fact, that they can develop both internally and on the product surface, all possible defects can be divided into three types: surface, internal and shape - related.

The production data refers to defective fraction obtained in the process and includes information regarding reason of the rejection. The Pareto chart revealed that billets were classified as defective mostly due to heavy oscillation marks appearing on their surfaces. These symptoms can be easily detected as visible transverse depressions on the billet surface that are deeper than 4 mm. Although some types of defects can be reduced or repaired in the further stages of the manufacturing process, the heavy oscillation marks defect strictly determine the billet as a scrap which cannot be repaired and must be rejected. Therefore, the analysis carried out for this type of defect can bring a crucial information regarding improvement of the manufacturing process.

Present work concerned production of square billets (140, 160, 220 mm) made of a number of different steel grades introducing both reinforcing and special quality steels. The latter included free-cutting, carburizing, structural, bearing, microalloyed, spring as well as hardened and tempered steels. In the process the following parameters were changing: steel grade, billet dimensions, working team and shift IDs, order of the heat in the sequence, exact start-time of the casting process as well as deviations from nominal casting temperature and speed.

2. Research methodology

2.1. Industrial data preparation

The industrial dataset was in an electronic format and included the values of the fraction of defective billets in the heat (calculated by weight). The original data covered only those cases (heats) in which defective products appeared which means that they did not include the heats with zero defective products. All the data were collected in the period of 4 years (from January 2010 till November 2014) and contained almost 600 records. The distribution of defective fractions in those heats in which defective billets were detected, is shown in Fig. 1.

The discontinuity of the measurements in the original data set due to passing over the cases with zero defectives makes a proper time-series analysis impossible. Hence, a supplemented dataset was created by adding records with zero defectives which allowed maintaining the continuity of the observations. The original dataset included days with several values of defective fractions corresponding to several defective heats per day. However, for the time-series analysis only one measurement per day was considered (due to the method's regular time intervals requirement) in two versions defined in the following way:

- first measurement of the day,
- average of the all measurements of the day.

Consequently, the supplemented dataset consisted with days and defective fractions assigned to them.

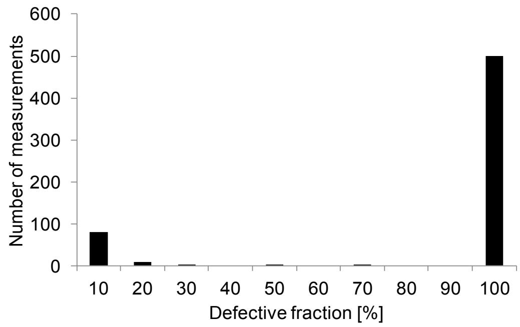


Fig. 1. Distribution of numbers of defective heats; values on horizontal axis denote upper-limits of the intervals

2.2. Time-series analysis

The analysis and prediction of time-series can be done by many different methods. Time-series models have three classical types: Auto Regressive (AR), Integrated) (I) and with Moving Average (MA). The compositions of these three classes make the popular autoregressive with moving average models (ARMA) as well the autoregressive integrated with moving average (ARIMA). An alternative is application for a time-series a generalized regression model.

In the present work the latter approach is applied, described in detail in [6]. The idea is to utilize a multivariate regression model (in the present work it was simple a linear regression) in which the input variables are values of the given quantity recorded in consecutive moments, and the output variable is its value shifted by one or several measurements from the last input point. On the basis of the known values in the time-series data, the records for regression modelling are created, by taking the above mentioned input-output sets, shifted by one point in the series. The composition of the records for regression model is preceded by subtraction of the general trend, the variability amplitude trend as well as the periodical component. The idea of this methodology is to use a regression model for modelling finer changes than those which can be easily described by trends and periodicity.

The above procedure was implemented in a software developed in the Institute of Manufacturing Technologies of Warsaw University of Technology. The program uses MS Excel platform and the VBA as a programming language. The most significant periodical component is always subtracted, irrespective of its statistical significance.

An analysis of the distribution of the defective fraction values revealed that most of the heats were either with zero or 100% defectives. Hence, an alternative approach was to convert the real data to binary ones equating an original value with 1 if defective fraction was greater than 50% or with 0 if it was equal or less than 50%. The resulting quantities of the defective and flawless heats in the binary supplemented dataset are shown in Fig. 2.

In the present work, the time-series analysis for the binary data was carried out using the Naïve Bayesian Classifier (NBC) as a classification model. It is a relatively simple probabilistic method used for classification problems, based on the Bayes' theorem. NBC can be used as a predictor for the binary time-series considering the fact that the variables are categorical. The method utilizes several binary consecutive observations as inputs and gives a forecast of the successive point in the series. Consequently, the prediction is a simple probabilistic classification which assigns the case to one of the two possible classes: 'Good' or 'Defective'.

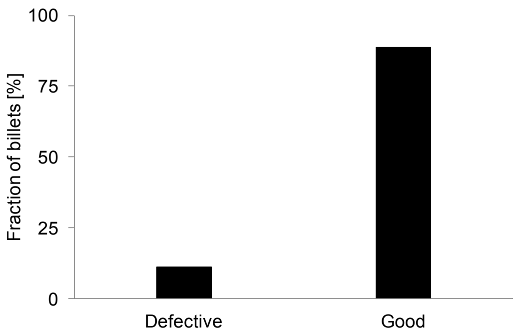


Fig. 2. Fractions of defective and good billets in all real-type data (supplemented set) after converting to binary-type

Both real and binary data analysis were carried out on the supplemented datasets defined in Section 2.1. Computations for the real data were conducted firstly for this same week-days, i.e. dividing the data to 7 subsets corresponding to each day of the week. Secondly, the computations were made for a selected period of 101 consecutive days in years 2010 and 101 days in year 2011, characterized by a large number of non-zero defective fraction observations. Computations for the binary data using NBC were carried out on the same two selected periods of 101 days.

3. Computational results

3.1. Results for real-type data

For all seven data sets referring to week-days the periodicity values varied between 4 to 28 and were significant for both first measurement of the day and average of all measurements of the day subsets. For the data sets referring to selected period of 101 days in 2010 and 2011 the periodicity equals 2 (which shows "up and down" type variations in the data) and is also significant (Tab. 1).

Table 1.
Results for real-type of data obtained with applied software

Variable name			Significant periodicity	Periodicity value	Conventional score values for information content in residual data
Defective fraction First measurement of the day	From 2010 till 2014	Mondays	Yes	19	1
		Tuesdays	Yes	4	1
		Wednesdays	Yes	19	1
		Thursdays	Yes	9	1
		Fridays	Yes	18	1
		Saturdays	Yes	28	1
		Sundays	Yes	4	1
	Selected period of 101 days in 2010		Yes	2	5
	Selected period of 101 days in 2011		Yes	2	5
Defective fraction Average of all measurements of the day	From 2010 till 2014	Mondays	Yes	19	1
		Tuesdays	Yes	4	1
		Wednesdays	Yes	19	1
		Thursdays	Yes	9	1
		Fridays	Yes	18	1
		Saturdays	Yes	28	1
		Sundays	Yes	4	1
	Selected period of 101 days in 2010		Yes	2	5
	Selected period of 101 days in 2011		Yes	2	3

If there is a significant information content in the residual data, the results of modelling of the residual data should be valuable. The software applied provides that kind of information in a verbal form, based on results of two statistical tests: the runs test (also called Wald-Wolfowitz test) and the Durbin-Watson test, both described in [6] and the literature cited there. Like in the previous work [7],these messages were converted to a numerical score scale, as shown in Table 2.

The results presented in Table 1 clearly show that the series of consecutive days are much more informative and easier to interpret comparing to series of week-days with their wide and diversified range of values.

In Fig. 3 an exemplary subset of the real-type data time-series is shown in the form of the average of all measurements of the day in selected period of 101 days in year 2010. It is worth noticing that the defective fraction values were mostly either zero or 100% what prompted the authors to assume the approach based on binary values for further analysis (see Section 3.2.).

Table 2.
Possible messages concerning the residual data information content in time-series analysis, appearing in the applied software

Information displayed by the software used for time-series analysis	Conventional score values for information content in residual data
Residual data are only a noise and do not contain any significant information	1
Residual data are rather a noise and do not contain any significant information	2
Residual data may be not only a noise and may contain significant information	3
Residual data are rather not only a noise and contain significant information	4
Residual data are not only a noise and contain significant information	5

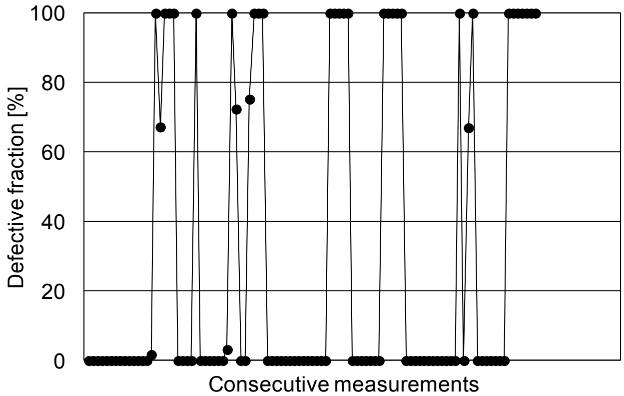
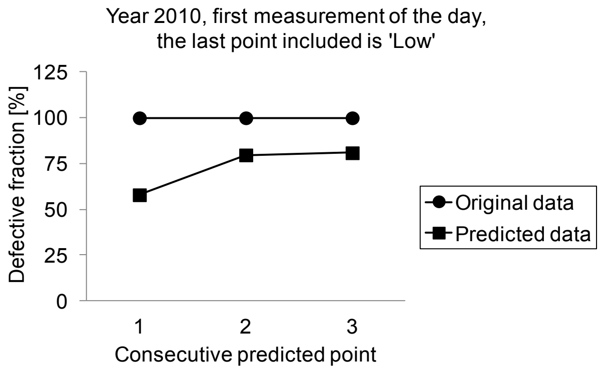


Fig. 3. Exemplary subset of real-type data time series; average of the all measurements of the day in selected period of 101 days in year 2010

Moreover, prediction of future values was carried out for the selected periods of 101 days in years 2010 and 2011. Forecasts have been prepared for 8 subsets dividing data firstly according to year, secondly to the type of information (first measurement of the day or average of the all measurements of the day) and finally to the type of last point included in series. Two cases were taken into account: if the defective fraction was greater or equal 50%, the corresponding point was denoted as ‘High’, otherwise the measurement was classified as ‘Low’. The predictions included three following points ahead of the series (Fig. 4).

The analysis revealed that successive predicted values approach the real values and the best accuracy is achieved for the third consecutive predicted point. Furthermore, when the last input point is indicated as ‘Low’, the model tends to be "cautious" i.e. it underestimates the defective fraction of billets. Otherwise, with ‘High’ point at the end of the series, the model tends to overestimate the predictions. Consequently, the value of the last point included in series has a significant influence on the prediction results.



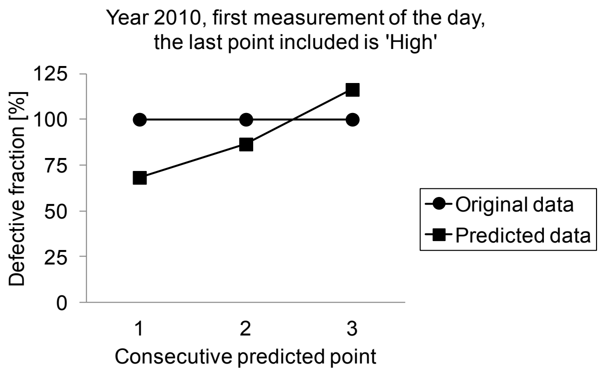


Fig. 4. Comparison of predictions for two subsets of real-type data showing the difference originating from the value of last point included in the series

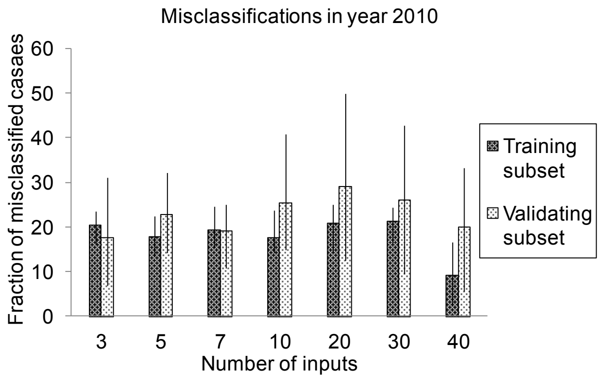
3.2. Results for binary-type data

The computations for the binary-type data were originally planned for selected periods of 101 days in years 2010 and 2011 in two versions: for the first measurements of the day and for the average of all measurements of the day. Each day was classified as ‘Good’ or ‘Defective’ during the categorization process conducted accordingly to guidelines mentioned in Section 2.2. However, two identical subsets were obtained in this way what led to the conclusion that the first recorded measurement of the day had a decisive impact on classifying the day as ‘Good’ or ‘Defective’.

From the two 101 days sets seven subsets for the time-series modelling were obtained. There was always one output but numbers of inputs varied what implied that number of records used in every subset was different. Additionally, 70% of each subset was assumed as training data (T) and 30% as validating data (V). The records in the subsets have been put in a random order nine-fold. As a result there were 10 subsets for each number of inputs (the first one contained records in the original order).Prediction for the investigated point was always made basing on 30 former points in the row.

In Fig. 5 average misclassifications errors for both training and validating data are shown. Vertical lines show ranges between maximum and minimum values of the errors.

(a)



(b)

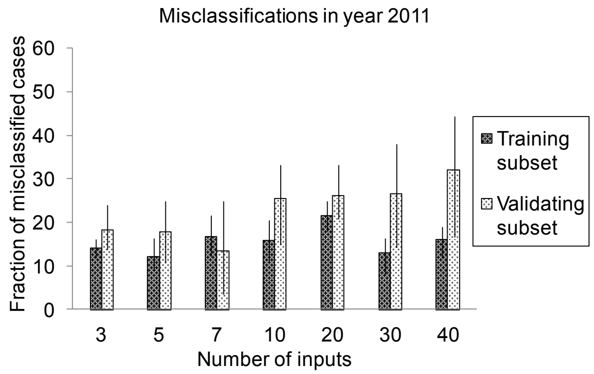


Fig. 5. Comparison of misclassification errors in years 2010 (a) and 2011 (b)

As it could be expected, NBC model tends to misclassify the validating data more often than the training data. The differences between maximum and minimum error values are greater for the validating data as well. An interesting tendency can be noticed: as the number of inputs increases for both training and validating data, the model exhibits worse accuracy of the predictions. This is probably due to the fact that an increase of number of inputs results in a decrease of number of records used for classification. Regarding this fact it is highly likely that if the training data set had been larger, the model would have achieved better results.

Moreover, the type of misclassification has been investigated for subsets with 3, 10 and 40 inputs to check model prediction accuracy for subsets with the maximum, minimum and moderate numbers of inputs assumed. There are four possible situations. First, the model can give correct prediction for a defective result, second, it can be right about good result. In addition, two types of the mistakes are also possible – model can be wrong by giving a false alarm (prediction ‘Defective’ when reality is ‘Good’) or by losing an alarm signal (prediction ‘Good’ when reality is ‘Defective’).

Misclassifications regarding false alarms and lost signals considering training and validating data for 3 inputs’ numbers used in NBC model has been also investigated and provided an information about relations between the type of misclassification and number of inputs. In Fig. 6 average fractions of misclassified cases are denoted with columns and the differences between maximum and minimum values of error are denoted with vertical lines. It is clear that the model tends to lose signals in case of low number of inputs (3) and to give false alarms in case of increased numbers of inputs (10 and 40). These tendencies are similar for both training and validating data.

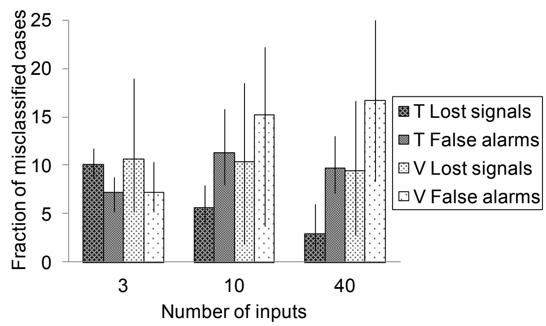


Fig. 6. Misclassifications types for 3 inputs models

The NBC model results have been compared with a blind test which assumed random values of data (‘Good’ or ‘Defective’) with probabilities equal to the fractions of defective and good billets present in all real-type data (see Fig. 2). The results revealed that application of the NBC model can provide a significant improvement of the prediction accuracy compared to the wild guess (see Fig. 7) and therefore it can be considered as a useful tool for operators and quality engineers.

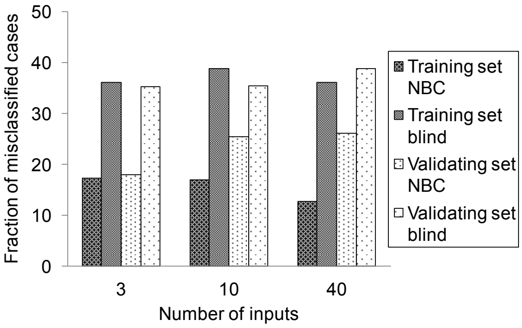


Fig. 7. Misclassifications for 3 inputs' numbers regarding Naïve Bayesian Classifier error and blind test error

4. Summary, conclusions and future work

The main purpose of the present work was to investigate an application of the time-series analysis in production conditions in the aspect of forecasting defective products. The results obtained indicate that the time-series analysis can be a valuable data mining tool for industrial data, recorded both as real and binary-types. Satisfying prediction accuracy implies that some characteristic sequences can be found in the data.

The possibility of prediction of the future values can be used by engineering or operational staff with an expert knowledge to decrease fraction of defective products by taking appropriate action in time intervals which have been identified as 'suspicious' or 'critical' in the forthcoming period.

In spite of the satisfying results obtained in the present study, a future research should also be performed, using more advanced and sophisticated methods of the time-series analysis in order to find most reliable prediction tools for the defect occurrence in the analyzed manufacturing process. However, it should be emphasized that a comprehensive identification of root-causes of the product defects can be made only by implementing models with process parameters as input variables and defect fraction (or just its appearance) as the output. This type of analysis is currently developed and will be presented in another paper.

References

[1] Bisgaard, S. & Kulahci, M. (2008). Quality quandaries: Using a time series model for process adjustment and control. *Quality Engineering*. 20, 134-141. DOI: 10.1080/08982110701771042.

[2] Lin, Z.C. & Chang, D.Y. (2009). A band-type network model for the time-series problem used for IC lead frame dam-bar shearing process. *International Journal of Advanced Manufacturing Technology*. 40(11-12), 1252-1266. DOI: 10.1007/s00170-008-1432-6.

[3] Kapoor, S.G., Terry, R.W. (1983). Time series analysis of tensile strength in a die casting process. In Time Series Analysis: Theory and Practice 4, Proc. 8th International Time Series Meeting and 3rd American Conference, 1983 (pp. 221-228). Cincinnati, OH, USA: North-Holland, Amsterdam.

[4] Camisani-Calzolari, F.R., Craig, I.K. & Pistorius, P.C. (2003). Quality prediction in continuous casting of stainless steel slabs. *Journal of The South African Institute of Mining and Metallurgy*. 103(10), 651-665.

[5] Perzyk, M., Kochański, A., Biernacki, R., Kozłowski, J. & Soroczyński, A. (2011). Applications of data mining to diagnosis and control of manufacturing processes. In Kimito Funatsu and Kiyoshi Hasegawa(Eds.), *Knowledge – Oriented Applications in Data Mining* (pp. 147-166). Rijeka, Croatia: InTech. DOI: 10.5772/13282.

[6] Perzyk, M., Krawiec, K. & Kozłowski, J. (2009). Application of time-series analysis in foundry production. *Archives of Foundry Engineering*. 9(3), 109-114.

[7] Perzyk, M. & Rodziewicz, A. (2012). Application of Time-series Analysis in Control of Chemical Composition of Grey Cast Iron. *Archives of Foundry Engineering*. 12(4), 171-175. DOI: 10.2478/v10266-012-0127-5.