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ADVANCED METHODS OF FOUNDRY PROCESSES CONTROL

ZAAWANSOWANE METODY STEROWANIA PROCESAMI ODLEWNICZYMI

The paper discusses two main approaches utilized in contemporary industry to control of discrete and continuous manufacturing processes: Statistical Process Control and Engineering Process Control as well as applications of learning systems and time-series analysis in the control systems. The use of time-series techniques for anticipated control of selected foundry processes is presented and positively evaluated using industry data obtained from the green molding sand processing.
Keywords: foundry production, process control, learning systems, time-series

W artykule omówiono dwa podejścia stosowane we współczesnym przemyśle do sterowania dyskretnymi i ciągłymi procesami wytwarzania: Statystyczne Sterowanie Procesem oraz sterowanie techniczne (ang. Engineering Process Control), a także zastosowania systemów uczących się i analizy szeregów czasowych w systemach sterowania. Zaprezentowano i poddano pozytywnej ocenie wykorzystanie technik szeregów czasowych w antycypacyjnym sterowaniu wybranymi procesami odlewniczymi, z użyciem danych przemysłowych uzyskanych z procesu przerobu wilgotnych mas formierskich.

1. Introduction

Foundry technology is recognized as one of the most complex technologies in manufacturing industry. It includes a large number of highly diversified processes, related to preparation and processing of alloys and non-metallic materials and making of the shaped final products, i.e. castings as well as expendable molds and patterns. In contemporary foundry industry high production volumes and production rates, combined with increasing quality requirements, make a proper control of production processes one of the key issues in a foundry operation.

There are two main approaches to control of manufacturing processes: Statistical Process Control (SPC) and Engineering Process Control (EPC). SPC techniques are applied to monitor the processes, whereas EPC techniques are used to regulate them. Originally, SPC was first applied in the parts industry, where discrete processes are typical, whereas EPC comes form the process industry, where continuous processes dominate. Both control strategies are aimed at reduction of process variability, however, they seek to accomplish this objective in different ways [1]. SPC assumes that the process output can be described by statistically independent observations fluctuating around a constant mean and is intended to detect signals which represent the special (assignable) causes of external disturbances increasing the process variation. EPC counteracts the process disturbances by making adjustments to process variables in order to keep the output quality parameter on target. These disturbances are usually not a white noise but exhibit a dependence on past values, i.e. they are auto-correlated. Hence, it is possible to anticipate the process behavior based on past observations and to control the process and its outputs by adjusting the input variables [2].

To identify and understand the cause of process changes, a unified control framework should be applied to regulate a process using feedback control and using the diagnostic capability of SPC to detect unexpected disturbances to the process. However, it should be noticed that application of EPC integrated with SPC can cause some problems as the EPC feedback compensation mechanism affects the out-of-control detection by SPC and degrades the output quality once suddenly assignable causes are removed [3].

In the foundry industry a large variety of processes can be observed. An example of a continuous process is the molding sand processing, whereas molding itself is a discreet process. The two approaches to the process control, i.e. SPC and EPC are widely utilized.

The most commonly used type of EPC in manufacturing industry is probably the feedback control. It uses deviations of the output from the target to calculate the amount of adjustment. EPC requires a process model in a form of input-output relationship which, for the feedback control, can utilize the time-series analysis tools (see, e.g. [2]). Application of the time-series models to control of foundry processes is the main subject of the present study.

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2. Assessment of time-series capabilities to anticipated control of foundry processes

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 main purposes of that kind of analysis: the discovery of the nature of a given process and prediction of the future values. The time-series prediction can be considered as a particular case of the regression task, where the input and output variables are the same quantity but measured at different time moments.

As indicated earlier, the time-series analysis can be a useful tool in the feedback control of manufacturing processes, providing they are able to anticipate the process behavior based on past observations. In the present study, the time-series predictive capabilities are evaluated, based on real data acquired from green sand processing.

2.1. Methodology

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 those three classes make the popular autoregressive with moving average models (ARMA) as well the autoregressive integrated with moving average (ARIMA). An alternative is an application a generalized regression model, described in detail in [5]. The idea is to utilize a multivariate regression model in which the input variables are values of the given quantity recorded in several consecutive moments, and the output variable is its next value (i.e. shifted by one measurement from the last input point). The regression model is built for the residual data, i.e. obtained by subtraction the following components from the original data: the mean's trend, the variability amplitude trend and the periodical component. The idea of this methodology is to use a regression model for modeling finer changes than those which can be easily described by trends and periodicity.

In the present work three types of the multivariate regression models were considered: a linear regression (LR), regression tree (RT) and artificial neural network (ANN), as proposed in [5]. For the RT modeling the well known C&RT algorithm was used, assuming the minimum number of records in a node equal 2 and the 10-fold cross-validation procedure for finding optimum trees. For the neural models the MLP-type networks with one hidden layer including 3 to 5 neurons, were built. The test subsets, used for checking the stopping criterion, contained 20% of all data records. All the computations for RTs and ANNs were done using Statistica v8 software. For all types of the regression modeling, 5 consecutive points were taken as the input variables.

The methodologies used in the mean's trend, variability amplitude trend and periodicity computations as well as for the estimation of information content in residual data were similar to those applied in the previous works [4, 6]. These computations were made using the authors' own software having a wide range of capabilities.

The prediction capabilities of the regression models were also compared to simple predictions based on the trends and periodicity only, i.e. assuming zero values for new points in the residual data.

The green sand data were collected in a large iron foundry during the period of 14 months of normal production. The original foundry database of over 1960 records included the following properties of the molding sand: four green sand properties measured at the outlet of the muller: moisture contents, permeability, compression strength, compactibility as well as temperature of the used sand. For the purposes of the time-series analysis two types of records were extracted from the original foundry database:

Data type 1: two series of 100 consecutive measurements taken form the original data, one from the beginning and one from the middle of the whole period.

Data type 2: four quantities characterizing a working day: the first measurement of a day, average of the first 3 measurements of a day, average of a whole day and average of the last 3 measurements of a day. Each of the four data sets of this type included 85 records, corresponding to 17 full sequences of 5 working days from Monday to Friday which could be found in the original data.

Altogether, 30 data sets have been prepared for the analysis. In each of the sets the first portions of records were used for finding the trends and periodicity as well as for building the residual data models (further referred to as 'training' data) and the last 5 records were used for evaluation of the time-series predictive capabilities (further referred to as 'new' data). These were evaluated on the basis of relative prediction errors, defined as a ratio of absolute difference between predicted and observed values to the whole observed variability range of the variable, averaged over 5 new points.

2.2. Results

In Fig. 1 an example of the main components of the time-series analysis and the predictions made for this same case are shown. In Fig. 2 some representative examples of prediction accuracies are presented.

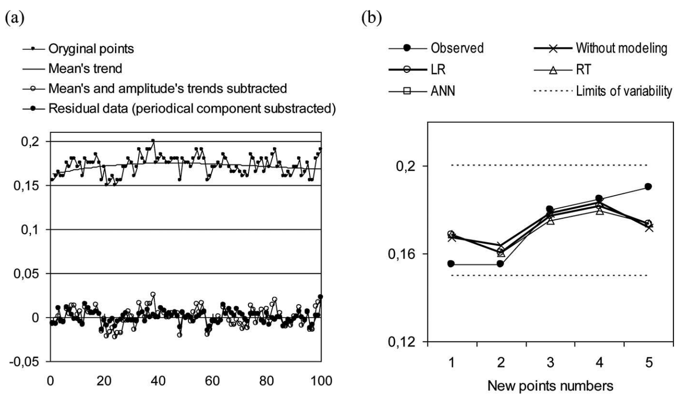

Fig. 1. Main components and predictions of the time-series analysis for green sand compression strength data type 1; 3^{rd} degree polynomial was used as the mean's trend

The general observation is that the relative errors vary between 10% and 20% in most cases and of the total 50 prediction series made in this study, only 3 of them exceed 30% (all obtained from one type of model – regression tree). For the industrial process it means that, with a great confidence, the operators would be able to predict the next value of a given sand property with the accuracy of 1/5 of its whole range. This would enable them to adjust the current amounts of the additives with a much greater accuracy than if they rely only on the current measurements. These results are even better than those obtained previously for the melting process of the grey cast iron [6], where the alloy's chemical composition predictions have reached the accuracy of about 1/3 of the appropriate ranges of chemical components.

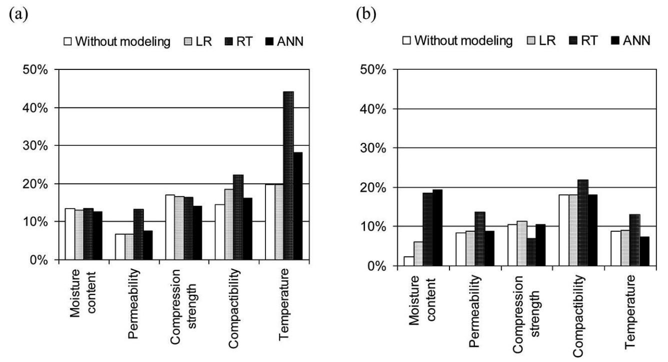

Fig. 2. Exemplary prediction errors (averaged over 5 new data points), obtained assuming the 3rd degree polynomial as the mean's trend function: (a) data type 1 (first 100 measurements), (b) data type 2 (averages of a day)

Another important observation is that the advanced regression models have appeared to be worse compared to the multivariate linear regression. The best results were obtained without modeling of residual data, i.e. based on trends and periodicity only. This could possibly be a result of low amounts of the information content in the residual data. In Fig. 3 the ratios of prediction errors obtained with regression modeling of residual data to those obtained form trends and periodicity only are plotted as a function of the information content in the residual data. For the data type 1 the positive results of application of residual data modeling were achieved for large information contents, particularly the linear regression. For the data type 2 this observation is not so clear, however, the best result was also obtained for a high information content. Similar results were found for the grey iron melting process [6].

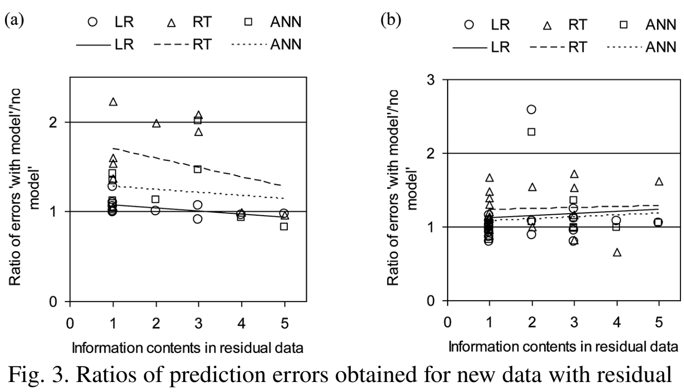

Fig. 3. Ratios of prediction errors obtained for new data with residual data regression modeling to those obtained from trends and periodicity only, in a function of the information content in the residual data; (a) for type 1 data sets, (b) for type 2 data sets

In the present study, an influence of the form of mean's trend line function was also examined. The tests were made for the both data types (1 and 2) with extreme values of prediction errors (averaged over all models), obtained previously. For all the data sets the best performance was achieved with the 3^{rd} degree polynomial assumed as the trend function. This result can be possibly attributed to the fact that a less 'flexible' trend function generally increases the variability of the residual data. This reduces the role of the predictions based on the trends and periodicity and increases the expectations of the residual data modeling. It is worth noticing that for a single point extrapolation (one point forward predictions) there is a very little threat to obtain a significant divergence between the real trend in data and the trend approximated by 3^{rd} degree polynomial function. The application of linear trend significantly reduced prediction errors only for two advanced models using learning systems (RTs and ANNs) and only in the cases where these errors were high compared to the simple methods.

3. Summary and conclusions

Contemporary foundry industry requires advanced control methods, aimed at stabilization of the manufacturing processes and including fault prevention and diagnosis for the processes and the products. The two main approaches to process control, Statistical Process Control and Engineering Process Control, are useful in control of foundry processes, characterized by especially large diversity of technologies, materials and production problems.

The paper presents methodology and results of the assessment of predictive capabilities of the time-series analysis, based on green molding sand processing data collected in a large iron foundry. The main finding, also supported by some previous works, is that the time-series analysis can be a valuable tool for the anticipated control of important foundry processes. In particular, the authors' approach based on the mean's trend, amplitude trend and periodicity component, possibly combined with multivariate regression modeling of the residual data, appeared to be very satisfactory in accurate predictions of the expected values of process or product characteristics. However, the modeling of residual data must be done with care and should be limited to the cases, in which the information content in these data is definitely significant.

A further work is desirable, aimed at developing practical control procedures for typical foundry processes. They should include various problems, such as detection of disturbances in auto-correlated processes, the actions that should be taken when a process disturbance is identified and analysis of process changes due to corrections made according to the time-series analysis predictions.

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