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An adaptive machine learning methodology to determine manufacturing process parameters for each part

David Muhr[a], Shailesh Tripathi[a], Herbert Jodlbauer[a]

[a] *University of Applied Sciences Upper Austria, 4400 Steyr, Austria*

Abstract

The identification of appropriate manufacturing process parameters typically relies on rule-based schemes, expertise, and domain knowledge of highly skilled workers. Usually, the parameter settings remain the same for each part in an individual production lot once an acceptable quality is reached. Each part, however, has slightly different properties and part-specific parameter settings have the opportunity to increase quality and reduce scrap. We propose a simple linear regression model to identify process parameters based on experimental data and extend that model with ideas from time series analysis to achieve highly-accurate, part-specific parameter settings in a real-world manufacturing use case. We show the usefulness of exploiting the (autocorrelated) structure of regression residuals to improve the predictive performance of regression models in manufacturing environments.

Keywords:
parameter optimization; process parameters; process optimization; regression analysis; concept drift; adaptation; autocorrelation; machine learning; manufacturing; industry 4.0

1. Introduction

The appropriate adjustment of process parameters in manufacturing processes plays a significant role to ensure the quality of the product and to increase process productivity [12]. Process quality is directly connected to product quality [13, 14] and improvements in manufacturing processes can have an impact on various levels, e.g., efficiency improvements and/or product quality improvements [11]. However, the adjustment of process parameters to meet quality requirements, e.g. dimensions of parts in predefined tolerances, is often a time-consuming and difficult task. Furthermore, if a parameter setting results in a moderate average quality of the parts, it typically remains unchanged for the whole production lot, ignoring that each part has slightly varying properties and its own history in the previous processing steps.

E-mail addresses: david.muhr@fh-steyr.at (David Muhr)., shailesh.tripathi@fh-steyr.at (Shailesh Tripathi)., herbert.jodlbauer@fh-steyr.at (Herbert Jodlbauer).

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Machine learning methods offer the opportunity to generate models based on experimental data, which automatically predict appropriate parameters depending on the state of the produced part and its manufacturing conditions [15]. However, machine learning models are typically based on the assumption that sample points are independently and identically distributed (IID). The design of most learning algorithms also relies on this key assumption. In practice, however, the IID assumptions often do not hold. Sample points can have temporal dependence that possibly affects the learning process [8]. In temporal data, the data distribution might change over time. The phenomenon of distributional changes in data is known as concept drift in the literature [3]. Adaptive machine learning algorithms employ methods to update or retrain models incrementally. Hollis [4] describes the general goal of adaptation as follows:

> "Adaptation is a ubiquitous term, used in the humanities and sciences alike, to refer to the act or process of changing - or, indeed, to the change itself - so as to become better suited to a new situation, or in a new application."

We hypothesize that adaptive machine learning could be a useful strategy to determine appropriate manufacturing process parameters. Specifically, we propose to learn the parameters for an ordinary least squares regression model based on experimental data and incrementally correct the model's prediction based on the observed residual data. We compare this methodology to previous approaches described in the literature on a real-world manufacturing use case.

We show that our approach is able to viably reduce the effects of unobserved influence factors in manufacturing processes. Our adaptive approach to manufacturing process parameter optimization leads to significant improvements in predictive performance over previously described approaches due to better concept drift adaptation.

1.1. Related work

Slight variations of a product's state in the production process can lead to costly and time-consuming rework or even scrap and Wuest et al. [19] suggest an approach based on the recording of an individual product's state along the entire production process. For the injection molding process, there are different approaches to adjust process parameters. A common design method that considers the interaction effects of parameters is the Taguchi method [10, 17]. In additive manufacturing, neural networks are typically used to adjust machine parameters [1, 2], but comparisons show that in some cases linear regression performs similarly [21, 7]. Venkata Rao and Kalyankar [18] present an approach for process parameter optimization in a multi-pass turning operation. They developed a teaching-learning-based optimization algorithm, which outperforms other optimization methods in their multi-objective and single-objective examples. Mia et al. [6] use different evolutionary algorithm approaches to optimize hard-turning process parameters and achieve optimal results with teaching-learning-based optimization. They find that teaching-learning-based optimization leads to better optimization convergence in their multi-objective optimization use case. [22] compare multiple metaheuristic algorithms including the Harris hawks, grasshopper, and multi-verse optimization algorithms for the selection of optimal machining parameters in manufacturing operations. In another publication, Yildiz et al. [23] develop a novel extension of the Harris hawks algorithm specifically for solving design and manufacturing problems. In an approach for estimating control parameters of a plasma nitriding process multiple different methods for generating a regression model are tested in [5]. Their approach includes inverse optimization problems to find good parameter combinations such that desired product qualities can be achieved. In [15], machine learning methods, namely neural networks and linear regression, are applied to generate models based on experimental data, which automatically predict optimal parameters depending on the state of the produced part and its manufacturing conditions. [16] extends the approach described in [15] by introducing symbolic regression because of its higher flexibility in comparison to linear regression and its higher interpretability in comparison to neural networks. The case study in [15] is based on data of 200 produced parts collected in a single experiment, and [16] uses data of more than 500 produced parts over four experiments. We extend the results of [15] and [16] and analyze the process data in a long-term case study that spans four experiments from a real-life industrial environment.

2. Methodology

In this section, we summarize the general procedure to adjust manufacturing process parameters as described in [15], and we extend that procedure with an incremental learning approach for linear regression. The goal of our work is to adaptively determine optimal process parameters for each individual part. To achieve this vision, we introduce an adaptive linear regression model and compare this model to traditional linear regression.

2.1. Product-State View

In a multi-stage manufacturing process, a physical transformation of a product is performed at each step in the process. We analyze a single product that spans multiple process stages. The input for the first stage is the raw material from a supplier and the last step represents the final product.

Variations in material properties and manufacturing conditions (e.g. machine and tool conditions, environmental conditions, the influence of human workers) of each part will be characterized by the individual values of the variables, which describe the life cycle of each part during the manufacturing process. This concept is introduced by Wuest et al. [20] as the product-state based view.

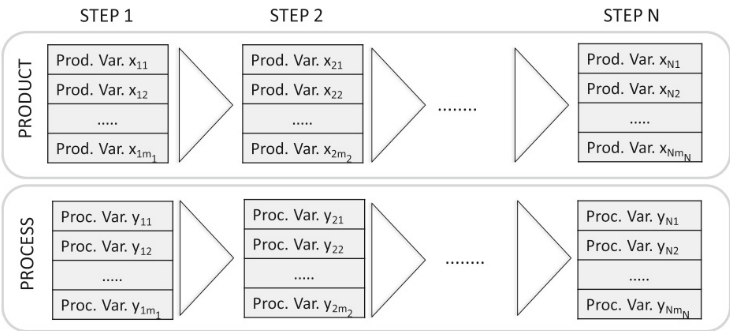


Fig. 1: Product and process variables generated in different manufacturing steps [15].

The data for our use case represents multiple stages in a manufacturing process and each stage consists of a number of measured product and process variables, see figure 1. Some of the process variables are adjustable and we try to predict one of them. Examples of product variables are the dimensions of a part (e.g. diameter, length, and height), or the weight of the part. Process variables describe the condition of the involved machines and the tools with which the part is processed (e.g. temperature, pressure, force, or adjustments of the machine).

It is not obvious, which product and process variables play an important role in parameter setting, so the policy is to record all available data and use feature selection techniques to decide which variables to use.

2.2. General Approach

As described in [15], we apply a two-step approach (see Figure 2) to adaptively set a specific process parameter of interest. First, we learn the parameters of a linear regression model to predict a quality measure of interest $\hat{z}$ given all relevant product and process variables $\mathbf{x}$ and a process parameter y of interest, by a function f.

$$\hat{z} = f(\mathbf{x}, y) \tag{1}$$

This regression function enables us to predict the quality measure z for a specific part based on the data generated for that specific part. Note that we know the optimal value for the quality measure z beforehand, but not the process parameter y necessary to achieve that quality measure.

Therefore, we vary the process parameter y in an experimental setting and measure the corresponding quality measures z to learn the model's parameters.

$$\hat{y} = f^{-1}(\mathbf{x}, z) \tag{2}$$

Then, we calculate the inverse of the function f to estimate the optimal process parameter of interest $\hat{y}$ under consideration of the relevant product and process variables and a fixed target value for the quality measure of interest z. Note, however, that we are only able to address mathematically invertible functions with this approach. The process can be seen in figure 2.

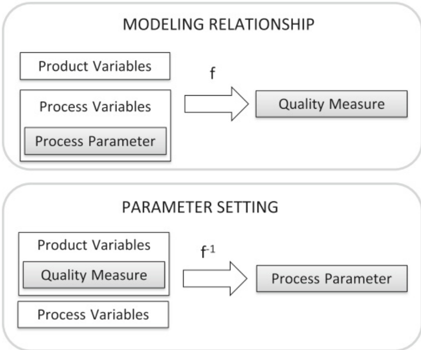


Fig. 2: The general procedure used to optimize manufacturing process parameters [15].

2.3. Variable Selection

When we learn the parameters for a regression model, we first have to answer the question, which variables from the set of the recorded product and process variables of the manufacturing process have the largest influence on the quality measure of interest and should, therefore, be used for modeling.

From a company perspective, a model should achieve accurate predictions and only depend on a few variables that are feasible to measure in-process. However, using too few variables will lead to bias and the inclusion of too many of them is likely to cause overfitting. [15] determined that the optimal number of variables for the given manufacturing use case is smaller than five. Due to the small amount of experimental data and the small number of variables we exhaustively explored all variable combinations in terms of predictive performance.

2.4. Adaptive Regression

Previous investigations of the given industry use case have shown that linear regression is comparable in terms of predictive performance to both neural networks [15] and symbolic regression [16]. Our hypothesis, however, is that manufacturing processes are often temporal in nature and might violate the IID assumptions. Thus, we extend the traditional linear regression approach with an error-correction methodology based on the observed residuals.

In an ordinary least squares linear regression model, the data consists of n observations $\{\mathbf{x}_i, y_i\}_{i=1}^{n}$, where each observation consists of a scalar response y_i and a column vector $\mathbf{x}_i$ of of p variables (regressors) $x_{i,j}$ for $j = 1, \ldots, p$. The response variable y_i is a linear function of the regressors

$$y_i = \beta_1\, x_{i1} + \beta_2\, x_{i2} + \cdots + \beta_p\, x_{ip} + \varepsilon_i \tag{3}$$

where the scalars ϵ_i represent unobserved random errors, which capture all other factors which influence the dependent variable y_i other than the regressors $\mathbf{x}_i$. This model can also be written in matrix notation

$$\mathbf{y} = \mathrm{X}\boldsymbol{\beta} + \boldsymbol{\varepsilon} \tag{4}$$

where $\mathbf{y}$ and $\boldsymbol{\epsilon}$ are $n \times 1$ vectors of the response variable and the errors for the observations, and X is an $n \times p$ matrix of regressors, also sometimes called the design matrix, whose row i is $\mathbf{x}_i^T$ and contains the i-th observations of all the explanatory variables. Fitting a linear model to a given data set requires estimating the regression coefficients $\boldsymbol{\beta}$ such that the error term $\boldsymbol{\varepsilon} = \mathbf{y} - \mathrm{X}\boldsymbol{\beta}$ is minimized. We use the sum of squared errors $||\boldsymbol{\varepsilon}||$ to determine the quality of the fit.

Our adaptive regression approach involves two steps:

1. Learn the parameters $\boldsymbol{\beta}$ based on the ordinary least squares methodology solving the quadratic minimization problem based on experimental data.
2. Correct the model's response based on residual information from past predictions.

In the first step, the *learning step*, we learn the parameters for a traditional linear regression model, as described previously, yielding response variables in the form

$$\hat{y}_i = \sum_{j=0}^{m} \beta_j x_{i,j} \tag{5}$$

In the next step, the *prediction step*, we incorporate m weighted residuals into to model's response to adapt for unobserved (temporal) influence factors

$$\bar{y}_i = \hat{y}_i - \sum_{t=1}^{m} w_t (y_{i-t} - \hat{y}_{i-t}). \tag{6}$$

When there are less than m residuals available for prediction, the residual term is zero and the model represents a traditional linear regression. We further adapt the model to include $\min(m, i-1)$ instead of m residuals, such that adaptation is possible with one or more residuals. We hypothesize that this error correction methodology leads to improved generalization performance due to better adaptation to unobserved temporal influence factors. More specifically, autocorrelation exists in the residuals, and we exploit this property with a moving average error correction methodology. We believe that this combination of time-series analysis and regression analysis has many more applications in non-IID manufacturing environments.

3. Case Study

In this section, we apply the developed adaptive regression approach to a real-world manufacturing process in the metal processing industry, which consists of three production steps. We compare our approach to traditional linear regression in its ability to predict a relevant quality attribute. As described in section 2.2, we will then invert the hybrid regression function to predict the optimal process parameter for each part. Note that we don't have to fully invert our hybrid regression approach. Instead, we can treat the residual correction term as a constant and solve the unique least squares solution for the parameter of interest given a fixed target value for the quality measure.

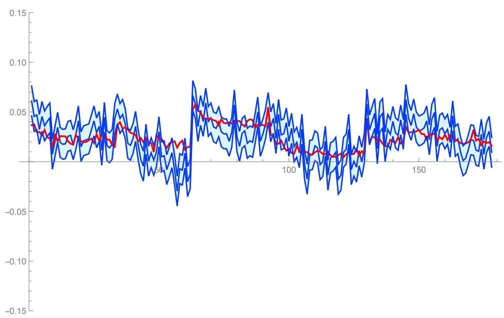
To analyze and compare predictive performance and generalization, we performed four experiments on the same type of part with a variable time delay between experiments ranging from one to three months.

In one experiment, we produce between 100 and 200 parts and record the associated process and quality data. We vary the process parameter to be predicted according to process experts involved in the corresponding production step.

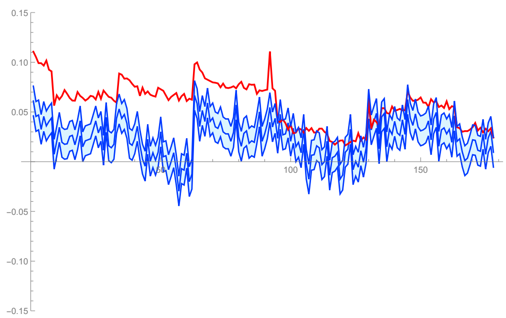
3.1. Results

To evaluate algorithm performance, we calculate the root mean squared error (RMSE) of the predicted quality measure in comparison to the target quality measure. The difference in predictive performance between three, four, and five features was marginal and we thus focused our analyses on three features.

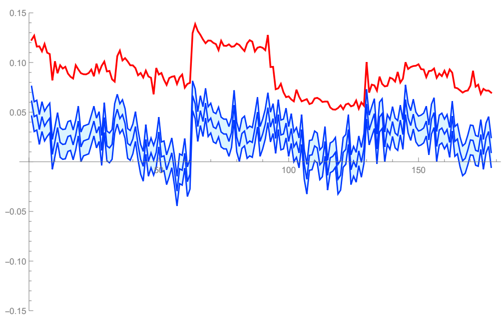
As apparent in figure 3, using a traditional linear regression approach leads to bad generalization performance from one experiment to the other. Our assumption for this behavior is that concept drift is inherent in the observed manufacturing process and thus the data distribution changes over time.



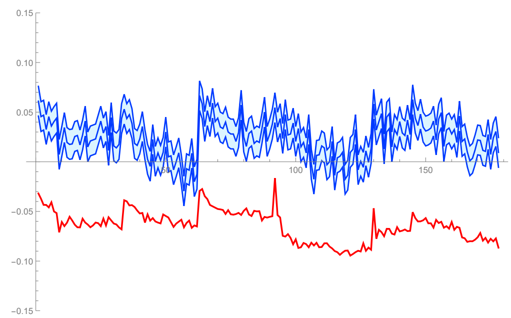
(a) Prediction of Experiment 1



(b) Prediction of Experiment 2



(c) Prediction of Experiment 3

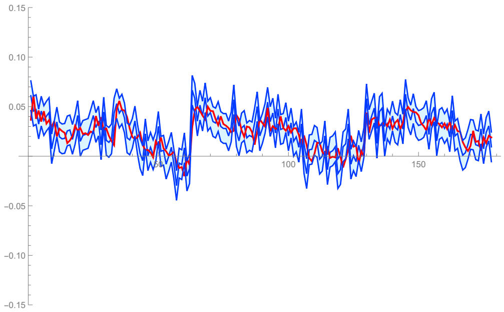


(d) Prediction of Experiment 4

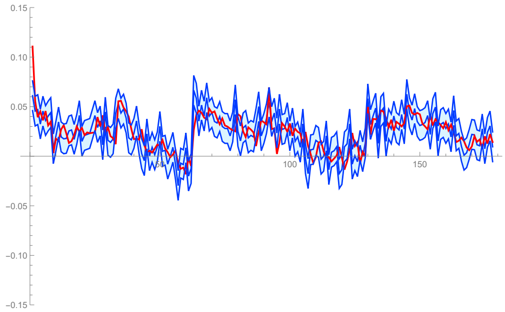
Fig. 3: This figure depicts the results of a traditional linear regression model learned based on the data from the first experiment. The images 3a, 3b, 3c and 3d show the deviation of predictions from different experiments. The center blue line represents the (true) measured quality value and the red line shows the predicted value with the linear regression model. The upper and lower blue lines show the acceptable prediction tolerances.

The RMSE for the simple linear regression model lies around 0.01 when predicting data that belongs to the same experiment as visible in figure 3a. Predicting data from other experiments, that is, data that was generated with a time-delay of multiple months, the RMSE increases to over 0.03 as visible in figures 3b, 3c and 3d. This finding indicates that there are unobserved influence factors between experiments and we cannot reproduce the results of [15] when using a single experiment for training.

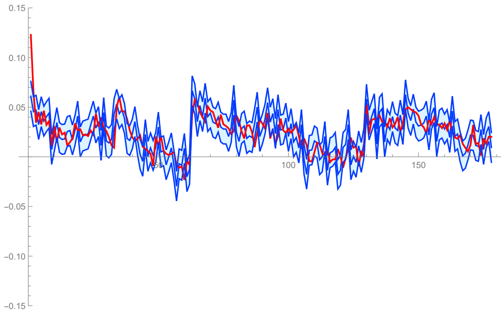
Using a hybrid linear regression approach that factors in the last three residuals, all equally weighted, we can significantly improve the RMSE when generalizing from one experiment to another experiment. We are able to achieve similar predictive performance over all tested experiments between 0.01 and 0.02 RMSE. One aspect of the adaptive approach is that it requires a couple of measured residuals to correct the model's response. We can see this when looking at figure 4. The *x*-Axis shows the parts in order of their processing time and the *y*-Axis shows the predicted



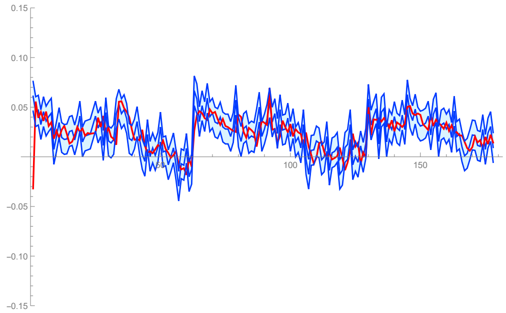
(a) Adaptive Prediction of Experiment 1



(b) Adaptive Prediction of Experiment 2



(c) Adaptive Prediction of Experiment 3



(d) Adaptive Prediction of Experiment 4

Fig. 4: This figure depicts the results of the proposed adaptive linear regression model. Again, the images 4a, 4b, 4c and 4d show the deviation of predictions from different experiments. The center blue line represents the measured quality value and the red line shows the predicted value. The upper and lower blue lines show the acceptable prediction tolerances.

quality value for a specific part in red and the measured (true) values in blue including prediction tolerances. As apparent in 4b, 4c and 4d, the first couple of parts show worse predictions.

4. Conclusions

There are many factors that might change over time in manufacturing processes, for example, the raw materials might have slightly different properties or the tools and machines show different levels of wear and tear. Measuring all of those influence factors might be infeasible in practice and thus requires methods that automatically adapt to unobservable influence factors and concept drift. We propose an adaptive linear regression method to deal with that challenge. The generated adaptive regression model is able to determine accurate estimates for the relevant process parameter for each individual part under various unobservable influence factors.

An adaptive parameter setting, considering the unique history of each part in the manufacturing life cycle, leads to better process and product quality. To set up a real-time process for parameter setting based on machine learning, the relationship between relevant input variables and a certain quality measure has to be modeled and changes in the data distribution over time have to be accounted for.

One limitation of the presented use case is that we only focus on a single quality measure and corresponding process parameter. Typical manufacturing process requirements include multiple, possibly interacting, quality measures, and multiple process parameters and there are many opportunities for future research.

Another interesting topic for further research would be to investigate the proposed residual correction methodology in other (time-dependent) regression problems. Many extensions of our approach combining regression analysis with methods from time series analysis to perform residual error correction are possible for future research. Finally, one could additionally investigate how ensemble techniques and problem simplification techniques, e.g. through a divide and conquer approach [9], could further improve process parameter optimization problems.

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