12th CIRP Conference on
Photonic Technologies [LANE 2022]

Industrial Paper

# Machine Learning used for Insitu Process Control

Thomas Gruenberger[a]

[a]nLIGHT GmbH, Dresdnerstrasse 81-85, Vienna, 1200, Austria

**Abstract**

Artificial intelligence, big data, data analytics and deep strategies are actual hype topics. Edge/cloud platforms and data centers on premise enable analysis of high amount of labelled data in safe environments according e.g. ISO27000. Digital ecosystems are on the way giving added value and new business models.
Machine learning and data analytics methods as part of Artificial intelligence enables the user to analyze multidimensional data in the field of process monitoring of thermal joining processes.
Feature engineering based on physics and domain knowledge enables models fulfilling requirements of trustworthy AI (IBM, 2022).
The paper presents examples of applying machine learning to insitu process monitoring data of laser processes and additive manufacturing.



*Keywords: "process monitoring; feature engineering; machine learning; data analytics"*

## 1. Introduction

### 1.1. Machine learning, data analytics

Insitu process monitoring systems are widely used in laser materials processing and additive manufacturing (McCann, et al., 2021). A high amount of raw data is available to analyze these processes. To extract information from this data machine learning or data analytics methods can be used.

Machine learning (Alypaydin, 2020) can be grouped into supervised and unsupervised methods and reinforcement learning techniques (see Fig. 1). Supervised learning enables modelling predictors to targets based on presenting input/output pairs and can be used for classification tasks (e.g. part OK or NOK) or regression tasks (e.g. determination of part properties like density). Unsupervised learning enables finding clusters by presenting only input values, which can be used to identify e.g. irregularities or different process parameters or machine status in the data. Reinforcement learning can be used to train e.g. robot trajectories and is not covered in this paper.


Fig. 1. Different machine learning techniques and their application

Data analytics methods can be grouped in descriptive, predictive and descriptive analytics. Descriptive analytics explains relationships and correlations, predictive analytics can predict future values based on existing predictors (e.g. predictive maintenance tasks), prescriptive analytics will explain the root cause and offer decisions to avoid situations (expert systems). All these techniques can be seen as part of Artificial Intelligence. A description of methods can be found e.g. in Hill (2021).

### *1.2. Data processing*

Typically different sensor systems are used to monitor laser processes, additionally machine sensor data, process parameters and geometry data has to be used for machine learning. After data acquisition plausibility checks has to be performed and data has to be registered in time and space to enable multi sensor data fusion. For modelling tasks the raw data has to be aggregated into features. Appropriate tools for feature engineering are available, many of these techniques are based on mathematics and not on physics and domain knowledge. Accepted models in industry must be transparent and explainable (as part of trustworthy AI), therefore explainable features must be used as input to the models. Therefore the process of feature engineering has to be rethought. Data storage and training can be done at data centers on premise or in edge/cloud based big data solutions, IT security can be established based on standards e.g. ISO27000.

Machine learning based on insitu monitoring data especially in the field of additive manufacturing can be found in Scime et al (2021) and Mi (2021), a method for a predictive approach can be found in Merschroth (2019).

## 2. Examples

### *2.1. Example supervised learning, microstructural welding*

As a first example a supervised approach of modelling OK NOK decisions is presented. Based on measurement data from microstructural welding and labelled OK NOK data models are trained based on logistic regression, random forest and artificial neural networks (Du, et al., 2019). The measurements consist of diode based process monitoring signals in the area of laser back reflection and in the NIR area. Features are extracted for form of the cross sections and process stability for each diode signal yielding in 4 predictors. Plotting the OK (green) and NOK (red) information over 2 of these predictors (Mean sensor 1 and Mean sensor 2 in Fig. 2 (a)) shows, that not all regions OK and NOK can be separated. Fig. 2 (b) show the results using classic logistic regression mapping the 4 predictors to OK (blue) and NOK (yellow), the corresponding confusion matrix shows Fig. 3 (a).

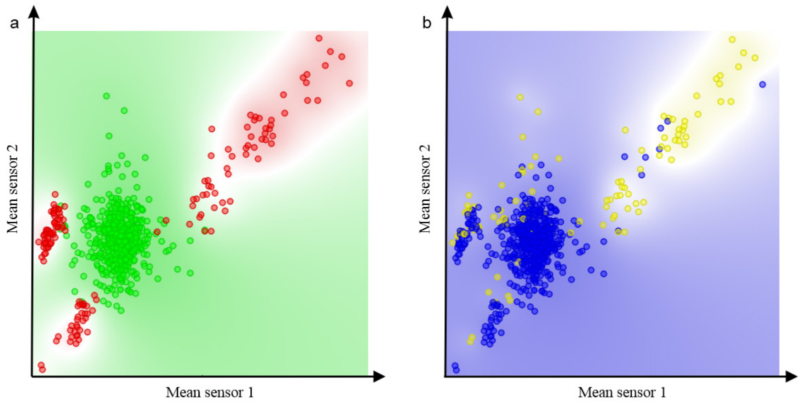


Fig. 2. 2dimensional representation of 4 dimensional predictor space. (a) labelled OK (green) NOK (red) distribution; (b) result logistic regression OK (blue) NOK (yellow)

a) Logistic regression

| Target \ Predicted | 0 | 1 | Σ |
|---|---|---|---|
| 0 | 72 | 82 | 154 |
| 1 | 32 | 524 | 556 |
| Σ | 104 | 606 | 710 |

b) Random forest

| Target \ Predicted | 0 | 1 | Σ |
|---|---|---|---|
| 0 | 154 | 0 | 154 |
| 1 | 1 | 555 | 556 |
| Σ | 155 | 555 | 710 |

c) Artificial neural network

| Target \ Predicted | 0 | 1 | Σ |
|---|---|---|---|
| 0 | 154 | 0 | 154 |
| 1 | 0 | 556 | 556 |
| Σ | 154 | 556 | 710 |

Fig. 3. Confusion matrix for prediction OK NOK. (a) logistic regression; (b) random forest; (c) artificial neural network

The results for logistic regression of false positive and false negative are quite bad (Fig. 3 (a)), a random forest model or a feedforward neural network with 5 input and 10 hidden neurons can solve the task quite good (Fig. 3 (b) and (c) respectively) for all 710 welded and labelled seams.

*2.2. Example unsupervised learning, coil welding machines*

Coil welding machines have high quality needs to the welded seems due to the fact of possible plant downtime. After process changes the quality of the seems decreased, and unsupervised machine learning was used to analyze the problem. Measurement values from diode based monitoring systems including process parameters and geometry parameters of the welded metal sheets setup the data base. The features corresponding to energy input and process stability are calculated from the diode based and 3D camera based measurement values. No information like OK or NOK was available, so an unsupervised approach was used to analyze the data. K-means found 2 clusters in the data (Fig. 4 (a)). Correlating the clusters with the process parameters gives the focal position as the main influencing variable (as can be found in Fig. 4 (b)). After discussion with the end user the change in focal position was identified as real source for the lowered welding quality, so these parameter settings has to be avoided in future.

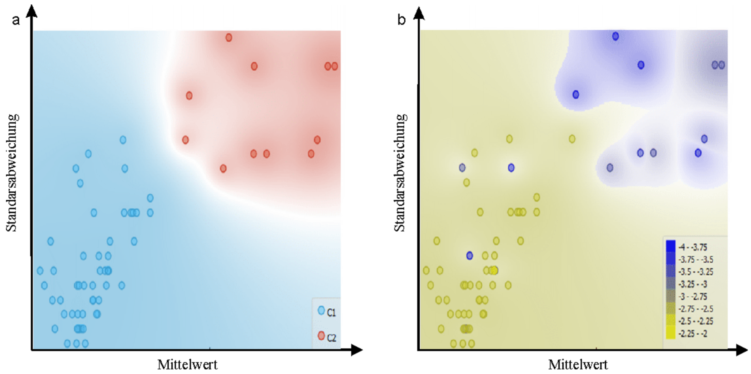


Fig. 4. 2dim presentation of the feature space. (a) 2 found clusters by k-means; (b) focal position in false color from -2 (yellow) to -4 (blue)

## 3. Summary and Outlook

Machine learning based on features calculated from measurement values of insitu process monitoring systems combined with process, part geometry and machine parameters enables new analysis possibilities.

It was shown that e.g. supervised learning techniques like feedforward neural networks with multidimensional predictor space can increase the quality of prediction OK NOK. Additionally unsupervised learning can be used to identify clusters and outliers to assist process optimization. So faster time to market and higher quality can be achieved using machine learning.

The shown analysis tools are available on premise actual development bring the technology to edge/cloud based systems.

Predictive analytics will give additional added value in e.g. avoiding plant downtime by improved planning of predictive maintenance.

More effort has to be invested in feature engineering, explainable features based on physics and domain knowledge are necessary to obtain explainable and transparent models (trustworthy AI). Features e.g. corresponding with process stability were shown and identified as proper ones. More sophisticated features are already available to analyze different frequency areas.

Data analytics in digital ecosystems over complete process chains will enable new deeper insight in production processes and feedback from real parts to e.g. production processes of tools producing them.

If enough labelled data is available, expert systems and prescriptive data analytics will be possible to train, concepts like open data to share data to enable this exponential growth of knowledge should be enabled.

## References

Alypaydin, E. Introduction to Machine Learning, fourth edition (Adaptive Computation and Machine Learning series), MIT press, 2020

Du, K., Swamy, M. Neural Networks and Statistical Learning, Springer, 2019

IBM, https://www.ibm.com/watson/trustworthy-ai, 2022

McCann, R., Obeidi, M., Hughes, C.et al, In-situ sensing, process monitoring and machine control in Laser Powder Bed Fusion: A review, Additive Manufacturing 45, 2021

Merschroth, H. et al, Predicting and controlling the thermal part history in powder bed fusion using neutral networks, SFFS Austin Texas, 2019

Mi, Jiquian, Li, Hui, et al, In-situ monitoring laser based directed energy deposition process with deep convolutional neural network, Springer, 2021

L. Scime, J. Beuth, Using machine learning to identify in-situ melt pool signatures indicative of flaw formation in a laser powder bed fusion additive manufacturing process, Science direct, 2018

Richard Hill, Stuart Berry, Guide to Industrial Analytics: Solving Data Science Problems for Manufacturing and the Internet of Things, Springer, 2021