Data-Driven Product Quality Monitoring in Quality-Critical Forming Processes

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Introduction and Problem Statement

Use Case: powder metallurgy

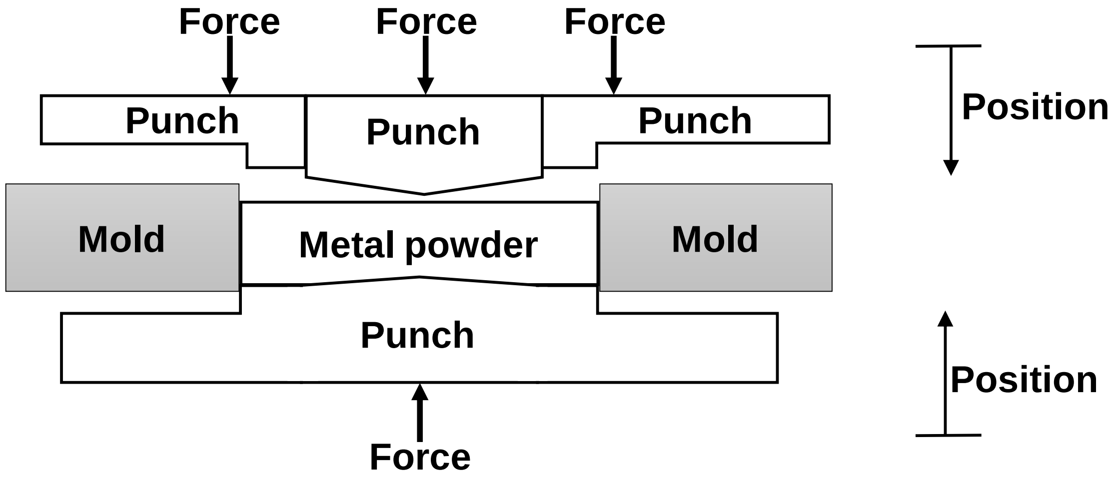


Fig. 1. Principle of a hydraulic metal powder press.

Task: quality monitoring

Classify a workpiece as either good or bad based on process data (punch's position and force).

Requirements:

r1 Nearly unsupervised quality monitoring based on a few data points

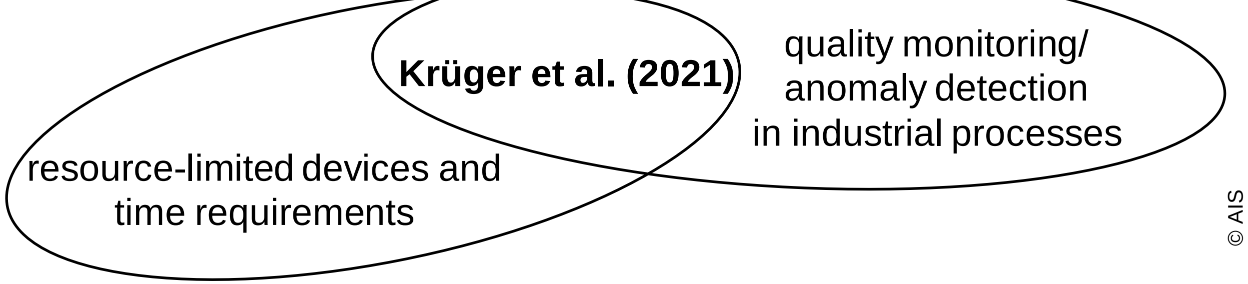
r2 Accuracy close to 100%

Constraints:

c1 Calculation on resource-limited devices with low computational power

c2 Quality assessment in a timely-manner

State of the art:



Nearly Unsupervised Product Quality Monitoring

Approach: supervised learning regression

1) Produce a small set of workpieces (**r1**)
2) Build a regression model
3) Detect abnormal behavior in force-position-diagrams

Limitations of a data-driven approach:

- Single model's prediction can not achieve a claimed 100% accuracy (**r2**)

Counteraction:

- Multiple regression deployment
- Consider model's predictive power
- Cluster good and bad workpieces based on drop in detection rate

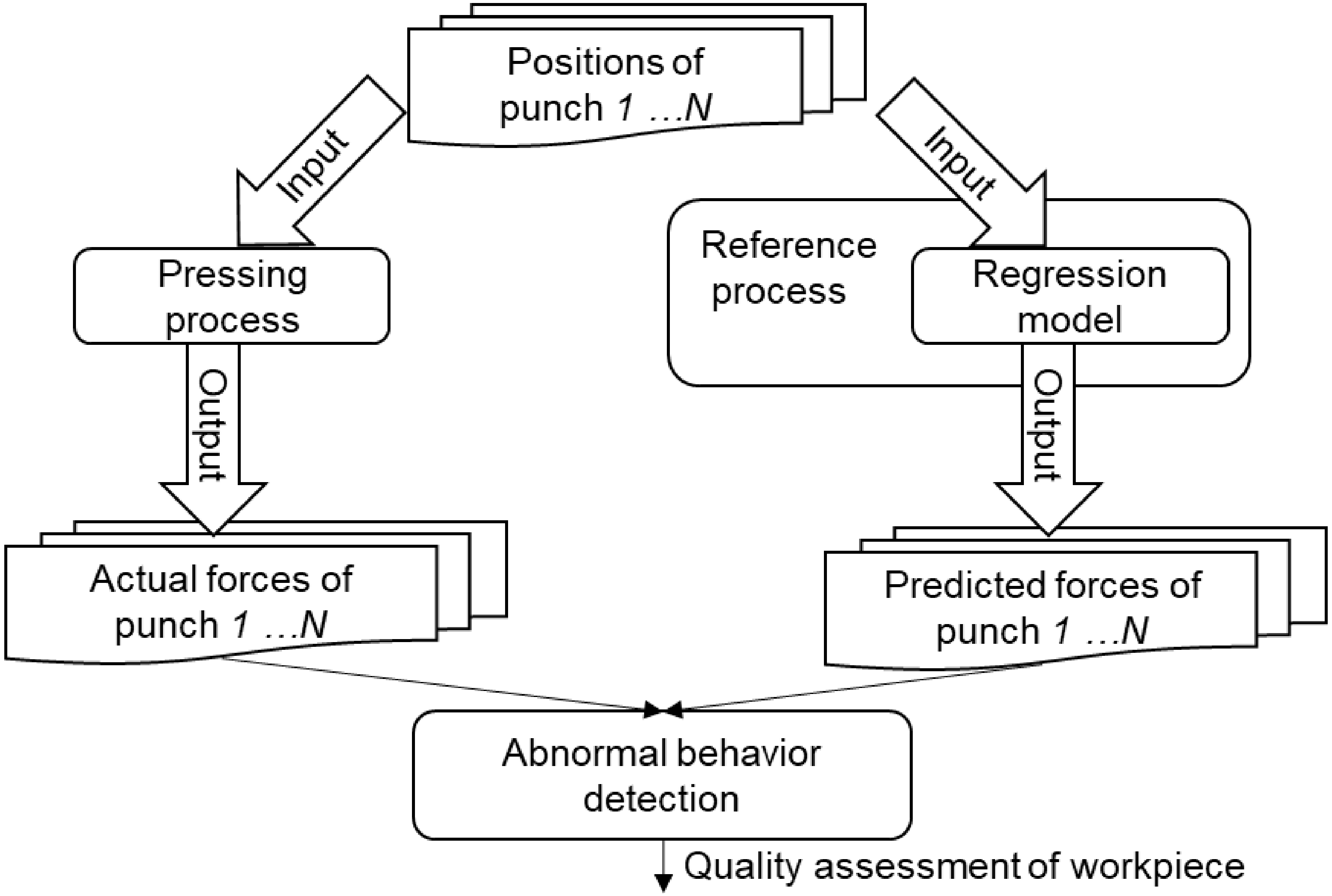


Fig. 2. Product quality monitoring approach based on supervised learning regression.

Model Building

Constraints:

c1 Calculation on resource-limited devices with low computational power
c2 Quality assessment in a timely-manner

Required model properties:

- Non-parametric
- Real multi-input-multi-output characteristic
- Not computational expensive

Model selection:

- *k*-nearest neighbors regression (**KNNR**)
- Random forest regression (**RFR**)

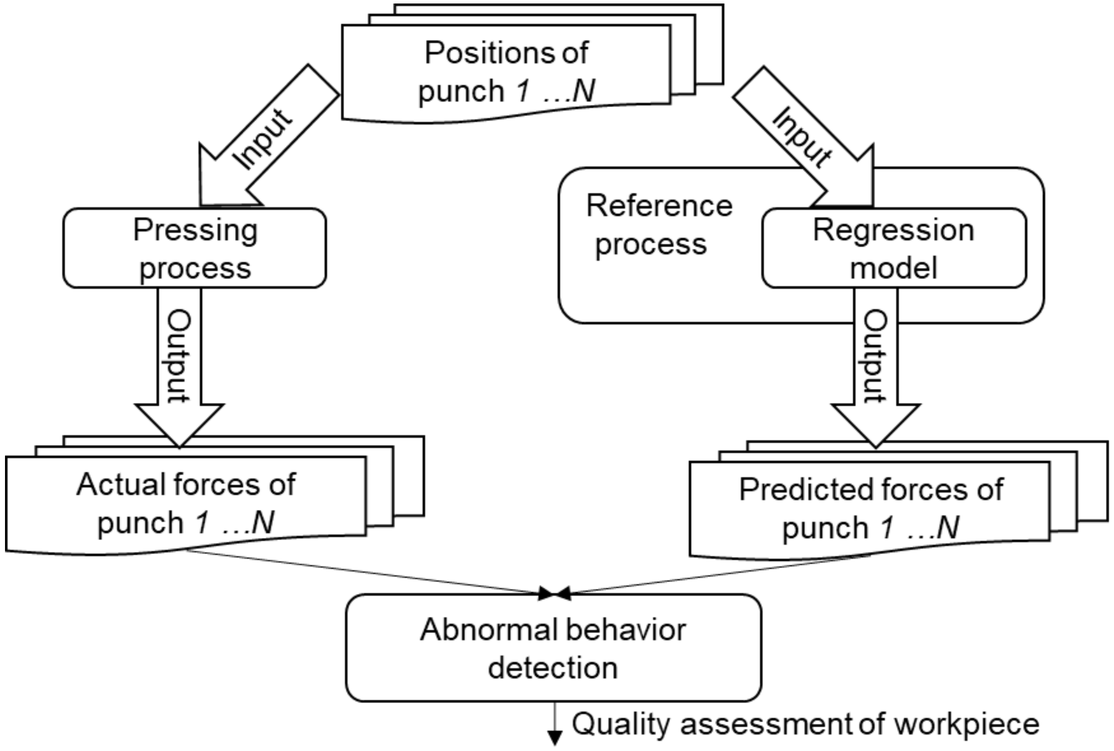


Fig. 2. Product quality monitoring approach based on supervised learning regression.

Abnormal Behavior Detection

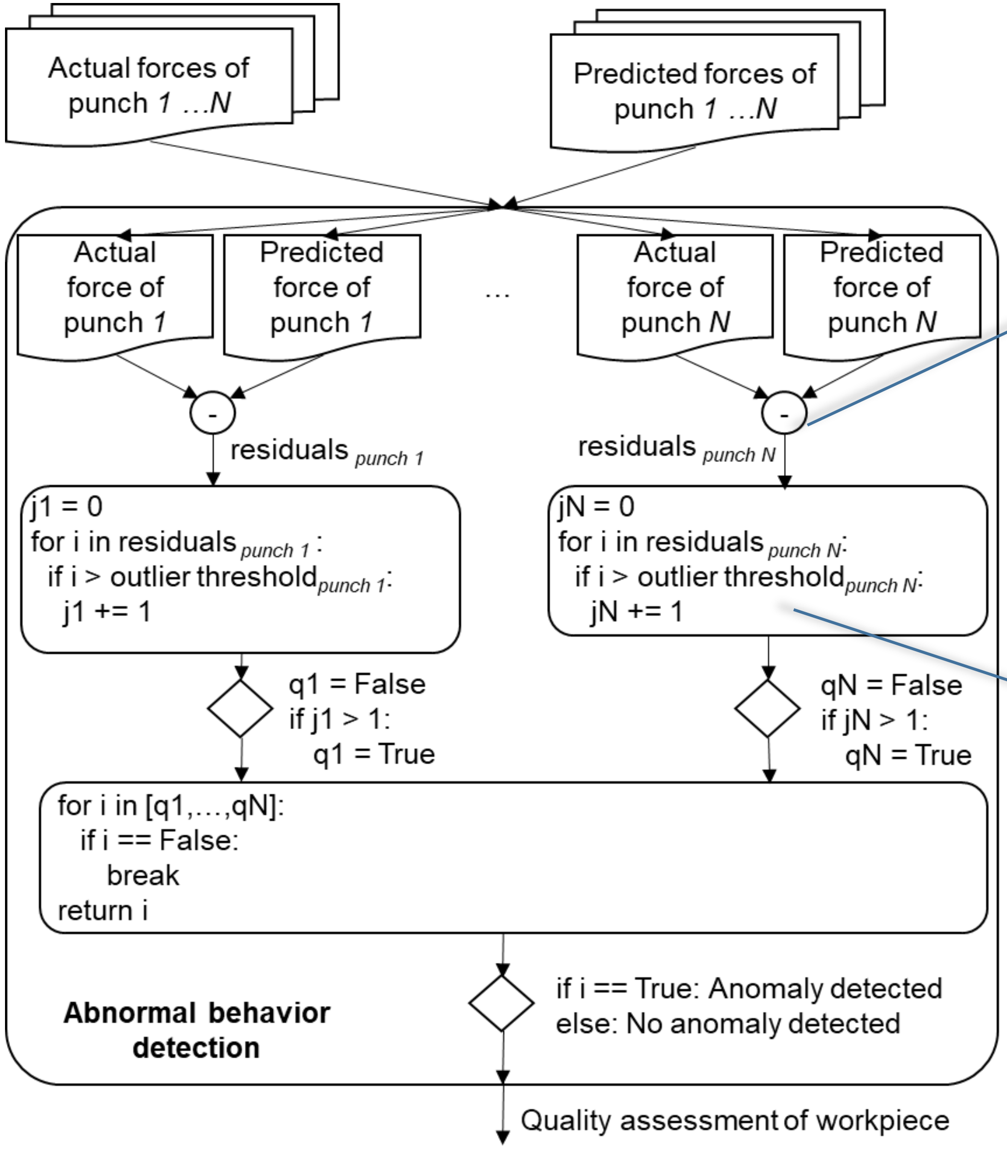


Fig. 3. Abnormal behavior detection based on outlier detection.

Residuals for each punch's time series

$$\text{residuals} = F_{\text{actual}} - F_{\text{predicted}}$$

Adaptive outlier threshold under consideration of model's predictive power

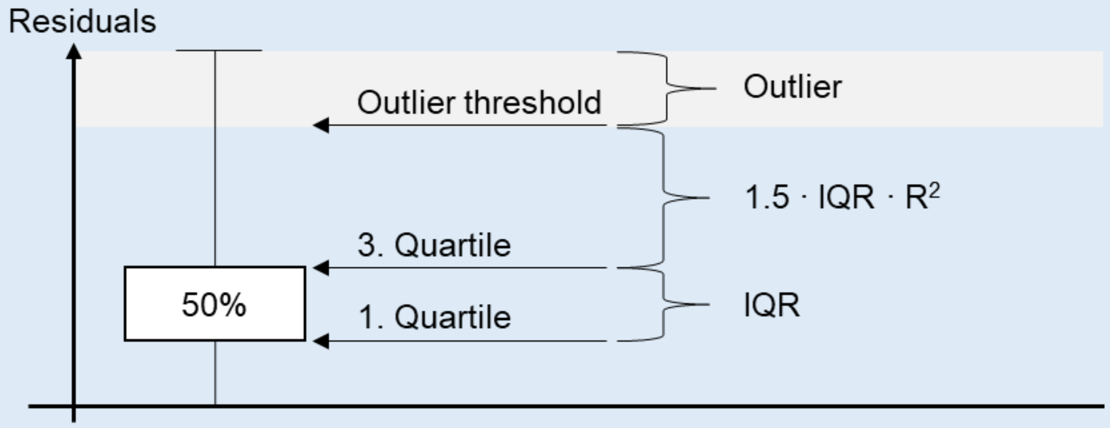


Fig. 4. Boxplot: outlier threshold definition.

Concept for Evaluation

Data set:

- 37 workpieces, 2 good parts, 35 bad parts
- Faulty workpieces with identifier 81, 93
- Hydraulic metal powder press with 9 punches, cycle time of approximately 10 seconds

Model building:

- Select 10 out of 35 good workpieces for model building
- Remaining 27 workpieces for evaluation
- 5-fold-cross-validation for model tuning and model's predictive power assessment
- 10-times regression model deployment and application → $\text{detection rate} = \dfrac{\text{number of anomalies}}{10 - \text{number of training part}}$

Abnormal behavior detection:

Case A: non-observance of model's predictive power → $\text{outlier threshold} = 1.5 \cdot \text{IQR}$

Case B: consideration of model's predictive power → $\text{outlier threshold} = 1.5 \cdot \text{IQR} \cdot \text{R}^2$

Final Results of Anomaly Detection

Case A: non-observance of model's predictive power

Workpiece identifier	93	81	84	98	54	…
Anomalies	10	4	2	2	1	…
Workpiece in training data	0	0	4	4	3	…
Detection rate	**1.0**	**0.4**	**0.3**	**0.3**	**0.2**	**…**

Tab. 1: Anomaly detection using RFR after ten iterations.

Workpiece identifier	93	81	98	56	63	…
Anomalies	10	4	3	2	2	…
Workpiece in training data	0	0	3	4	4	…
Detection rate	**1.0**	**0.4**	**0.4**	**0.3**	**0.3**	**…**

Tab. 2: Anomaly detection using KNNR after ten iterations.

Case B: consideration of model's predictive power

Workpiece identifier	93	81	87	98	54	…
Anomalies	10	10	3	3	2	…
Workpiece in training data	0	0	2	3	4	…
Detection rate	**1.0**	**1.0**	**0.4**	**0.3**	**0.3**	**…**

Tab. 3: Anomaly detection using RFR after ten iterations.

Workpiece identifier	93	81	65	90	95	…
Anomalies	10	9	3	5	3	…
Workpiece in training data	0	0	4	0	4	…
Detection rate	**1.0**	**0.9**	**0.5**	**0.5**	**0.5**	**…**

Tab. 4: Anomaly detection using KNNR after ten iterations.

Confusion Matrix and Key-Performance-Indicator

Comparison of case A and case B for anomaly detection:

		actual		
		positive	negative	sum
predicted case A / case B	positive	1/2	0/0	1/2
	negative	1/0	35/35	36/35
	sum	2/2	35/35	37/37

Tab. 5: Confusion matrix for RFR and KNNR with 0.7 detection rate threshold.

Assessment of case A and case B according to requirement **r2**:

		True-positive rate	True-negative rate	Accuracy
case A	RFR	50.0%	100.0%	97.3%
	KNNR	50.0%	100.0%	97.3%
case B	RFR	100.0%	100.0%	100.0%
	KNNR	100.0%	100.0%	100.0%

Tab. 6: Key-Performance-Indicator of anomaly detection for case A and case B.

Results and Discussion

	KNNR	RFR	Process: upper time limit
Building of ten regression models	60.17 s	425.11 s	350 s + quality inspection time
Cumulated execution time for prediction and abnormal behavior detection	2.35 s	2.38 s	10 s

Tab. 7: Performance measurement on Raspberry Pi 3, Python 3.7, package scikit-learn.

Constraints:

c1 Calculation on resource-limited devices with low computational power ✓

c2 Quality assessment in a timely-manner ✓

Requirements:

r1 Nearly unsupervised quality prediction based on a few data points
→ Transformation to a supervised learning regression task induced by 10 workpieces ✓

r2 Accuracy close to 100%
→ 100% accuracy for RFR and KNNR ✓

Conclusion and Future Work

Conclusion:

Approach for a **quality monitoring system**
for application on **resource-limited devices** to detect anomalies in a **timely-manner** based on a **few sensor data**

Future Work:

- Investigate optimal amount of training data to balance trade-off between model deployment and accuracy
- Examine degree of predictive power to quantify its impact on anomaly detection
- Test quality monitoring system in production under real conditions

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