Advanced predictive maintenance models based on Machine Learning for Industry 4.0

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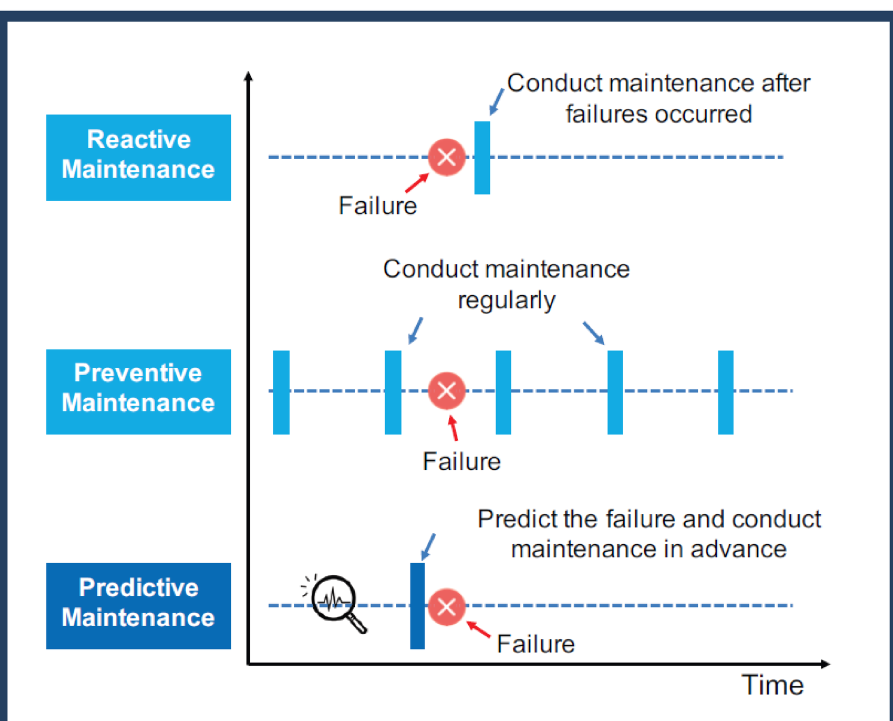
Introduction

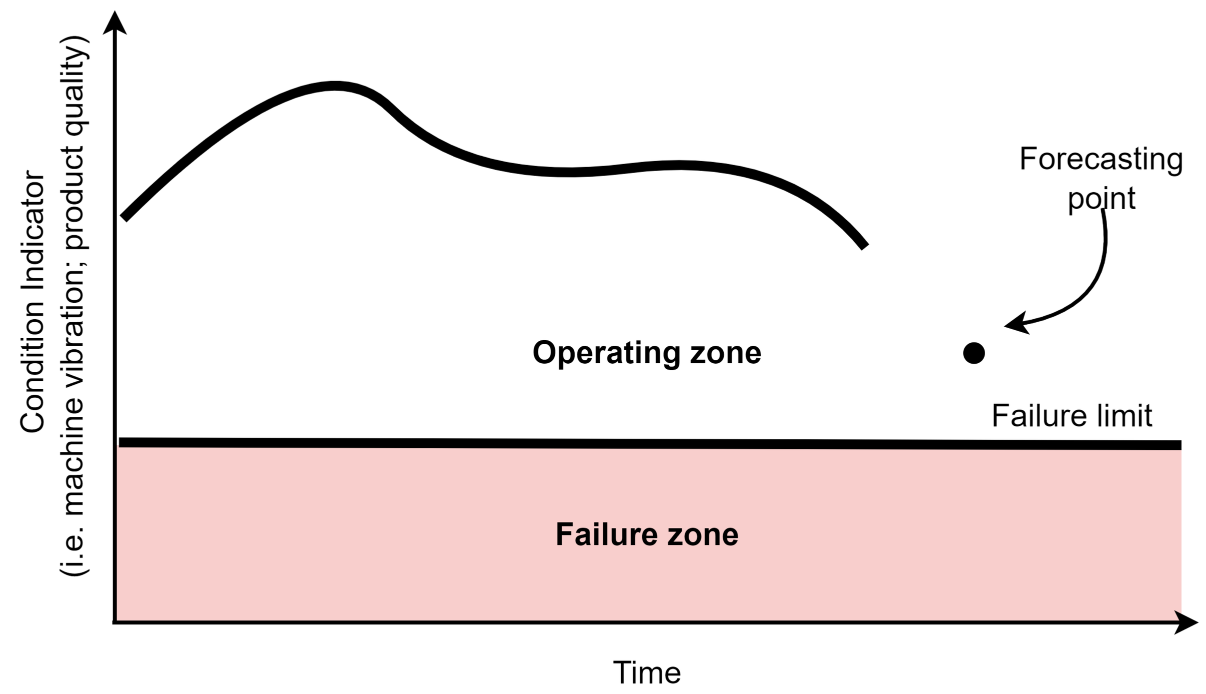
Predictive Maintenance (PdM) is a key technology of Industry 4.0 helping to avoid machine failures and their unexpected costs. The PdM decisions are usually made based on the failure prediction of individual components/machines. In a complex production process containing many components/machines, the failure does not fully reflect the entire process degradation and the quality of output products. For this reason, the main objective of our work is to develop advanced PdM models based on the prediction of product quality. The new PdM models can help to reduce significantly defective products and improve client satisfaction.



The different of maintenance plans [1]

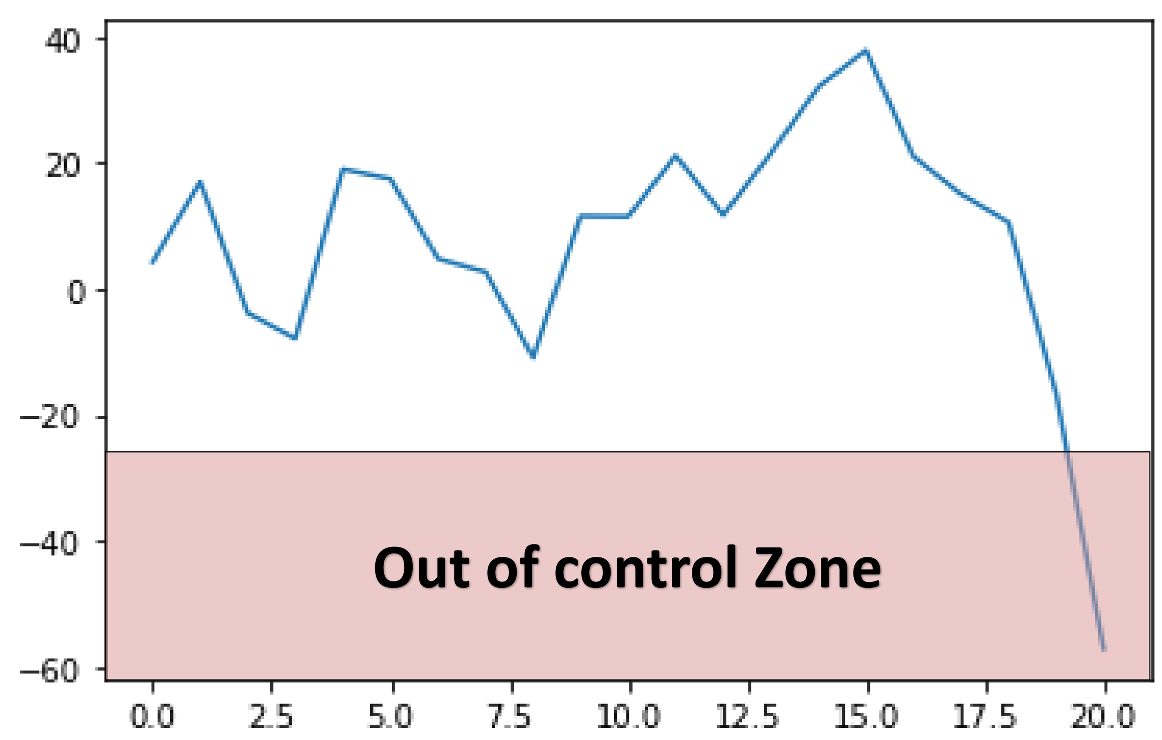
Problem definition

Predictive Maintenance (PdM) aims to predict when the equipment likely fails based on the condition indicator (i.e., the machine vibration or the product quality).



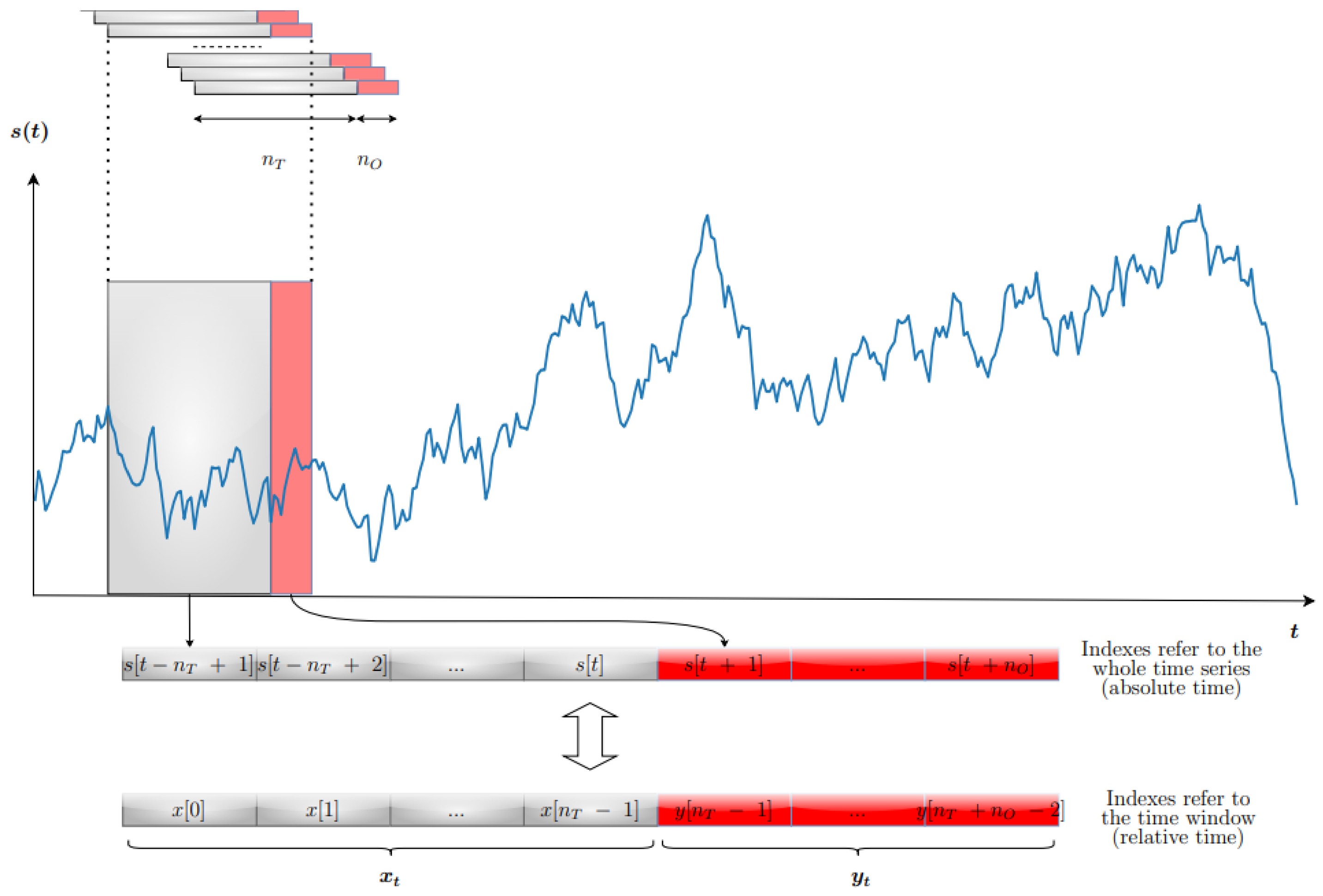
The principle of the PdM method [2]

In manufacturing, product quality can be an indicator representing the system's health.



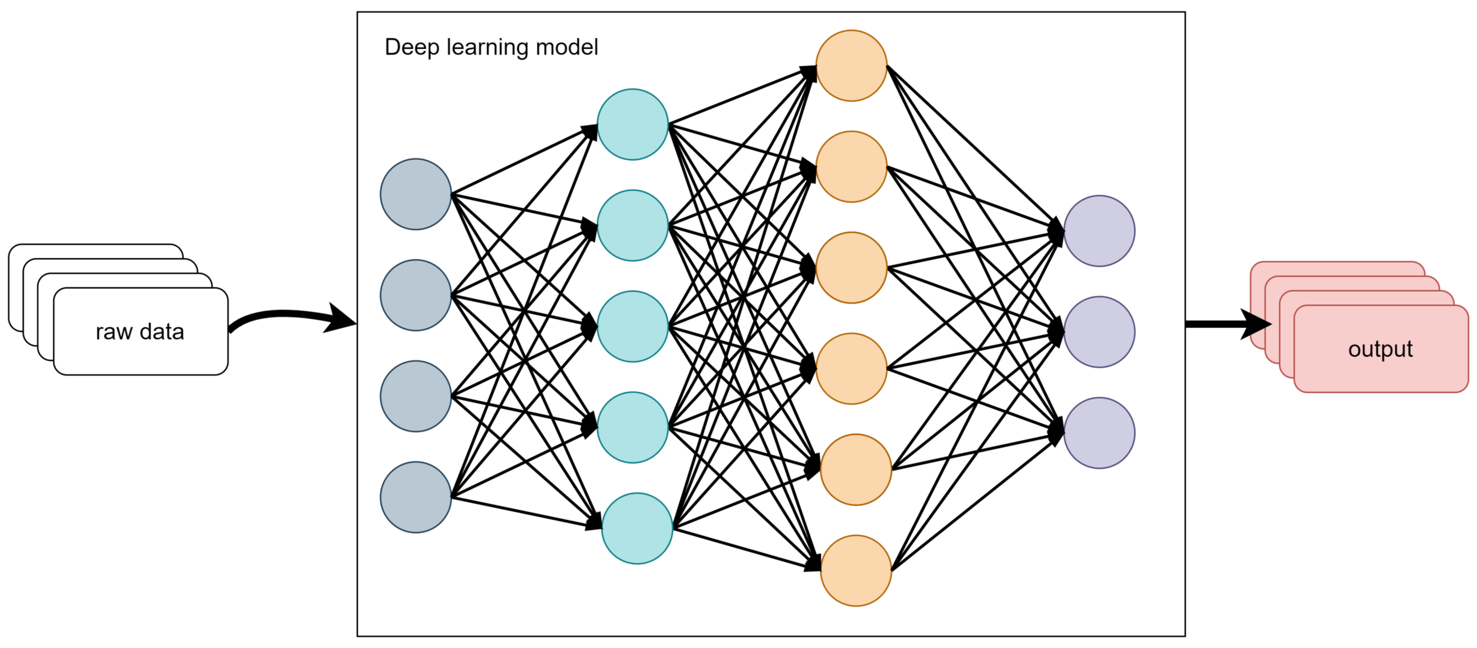
Monitoring quality using cumulative sum chart

Proposed method



A sliding window approach is used to frame the forecasting problem into a supervised machine learning problem based on [3]

Deep Learning (DL) is a machine learning algorithm with the ability to extract feature maps automatically.



Results

This section shows two deep learning model results: Feed-forward neural network and a recurrent neural network (Long Short-Term Memory). The way to experiment to the model is similar to the article [5] on Convolutional neural networks.

Note:

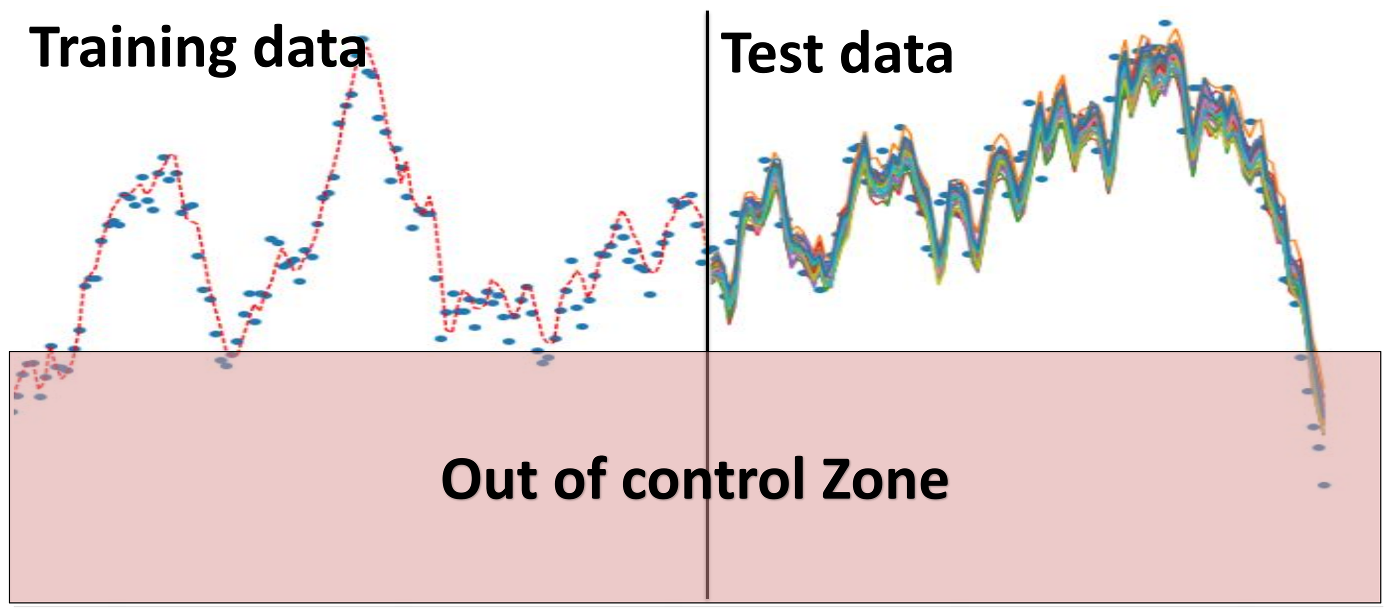
Each model's mean score (± one standard deviation) come from 10 repeated training processes. The fixed model output equals one ($n_O = 1$).

Abbreviations:

FNN, feed-forward neural network;
LSTM, long short-term memory;
RMSE, root mean squared error;
MAE, mean absolute error;
NRMSE%, normalized root mean squared error.

	Hyperparameters	RMSE	MAE	NRMSE%	R2 score
FNN	$n_T = 10$ $L = 1$ $n_{nodes} = 25$ $\lambda = 0.005$ $p_{drop} = 0.1$	37.1 ± 1.91	30.22 ± 1.64	4.12 ± 0.21	0.97 ± 0.00
LSTM	$n_T = 10$ $L = 1$ $n_{nodes} = 50$ $\lambda = 0.01$ $p_{drop} = 0.1$	46.5 ± 9.89	37.74 ± 8.67	5.16 ± 1.09	0.96 ± 0.014

The best configurations of deep learning models are found via grid search for product quality datasets [4]. n_T is the length of model input, L is the number of stacked layers in the network, n_{nodes} is the number of hidden units per layer, λ is the regularization coefficient (L2 regularization) and p_{drop} is the dropout rate.



Visualizing the feed-forward network results.
The blue point is observed data, red-dot-line is training output and the color lines are testing output ten times

Conclusion / Future work

Deep learning is a promising approach for quality prediction.
Different deep learning methods and structures will be developed and tested in the future works.

References

[1] Ran, Yongyi, et al. "A survey of predictive maintenance: Systems, purposes and approaches." arXiv preprint arXiv:1912.07383 (2019).
[2] Ahmad, Rosmaini and Shahrul Kamaruddin (2012). "An overview of time-based and condition-based maintenance in industrial application". In: Computers & industrial engineering 63.1, pp. 135–149.
[3] Gasparin, Alberto, Slobodan Lukovic, and Cesare Alippi. "Deep learning for time series forecasting: The electric load case." CAAI Transactions on Intelligence Technology 7.1 (2022): 1-25.
[4] Kaggle. Production quality: product quality produced by a roasting machine., 2015.
[5] Tuan Le, Hai-Canh Vu, Nassim Boudaoud, Zohra Cherfi-Boulanger, Amelie Ponchet Durupt. "A deep learning approach for Control Chart Patterns (CCPs) prediction". The 32nd European Safety and Reliability Conference (ESREL 2022).

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