Digital Twin for CNC Tool Wear Monitoring and Inspection Optimization

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Summary

This project develops a data-driven digital twin for CNC tool-wear monitoring using the publicly available *Multi-Sensor CNC Tool Wear Dataset* from Kaggle. The twin mirrors the physical machine by predicting tool-health status from sensor readings and optimizing inspection decisions with a cost-based risk model. A Random Forest classifier achieves an ROC–AUC of 1.0 for predicting worn versus healthy tools. A cost model is used to select an optimal inspection threshold that balances inspection effort, tool scrap, and the risk of missed failures. A multi-objective Pareto analysis evaluates trade-offs between inspection rate, escape rate, and average cost per part, and a simulation loop reproduces the twin's runtime behaviour and cumulative cost trajectory. Additional advanced analyses include feature-importance and sensor-group interpretation and a cost-sensitivity study of inspection policies. The results show that a risk-aware digital twin can substantially reduce operational cost while preventing escapes of worn tools.

1 Introduction

Digital twins are virtual representations of physical assets or systems that integrate sensor data, predictive models, and decision logic to support monitoring and optimisation. In manufacturing, digital twins enable predictive maintenance, real-time quality assurance, and process optimisation.

Tool wear is a key driver of product quality, machine downtime, and production cost in CNC machining. Excessive wear can lead to dimensional defects, increased scrap, vibration issues, and potentially catastrophic tool failure. The goal of this project is to build a digital twin for CNC tool wear that

- predicts tool health from multi-sensor measurements,
- optimises inspection policies using a cost-based risk framework,
- analyses trade-offs using multi-objective metrics,
- explains which sensors are most influential for wear prediction, and
- simulates runtime twin behaviour and cumulative cost.

The project combines machine learning, cost modelling, multi-objective optimisation, and model interpretability to create a complete digital-twin pipeline suitable for an academic course project.

2 Dataset Description

The study uses the *Multi-Sensor CNC Tool Wear Dataset* published on Kaggle.[1] The data correspond to CNC machining operations with multiple sensors monitoring the cutting process.

Features

The dataset contains multi-modal measurements, including:

- Cutting force features (CF_Feature_1, ..., CF_Feature_5),
- Acoustic emission features (AE_Feature_1, ..., AE_Feature_5),
- Vibration features (Vib_Feature_1, ..., Vib_Feature_5),
- Measured flank wear (VB_mm).

Target Variable

The original target column `Wear_Class` is categorical with three levels:

- `Healthy`,
- `Moderate`,
- `Worn`.

For modelling, the target is binarised as

$$y = \begin{cases} 0, & \text{Healthy}, \\ 1, & \text{Moderate or Worn}. \end{cases}$$

This binary label represents whether the tool is in an unacceptable wear state.

3 Methodology

4 Methodology

The digital twin developed in this study integrates data-driven classification, cost-based decision modelling, and simulation-based evaluation. The overall workflow is summarised in Figure 1.

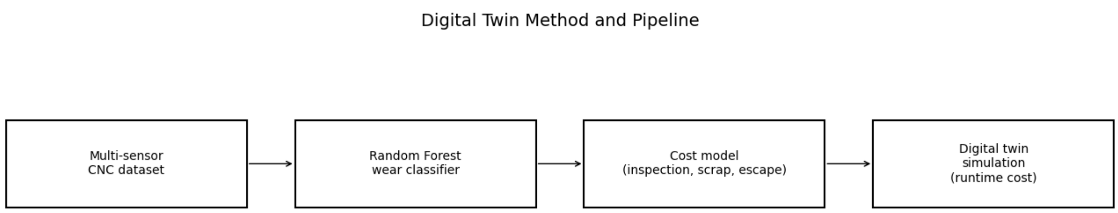

Figure 1: Overall digital twin pipeline showing the flow from multi-sensor CNC data to the Random Forest wear classifier, cost model, optimal inspection policy, and runtime simulation.

[1] `https://www.kaggle.com/datasets/ziya07/multi-sensor-cnc-tool-wear-dataset`

4.1 Predictive Model

The predictive component of the digital twin is a Random Forest classifier. The data are split into training and test sets using an 80/20 stratified split to preserve the class distribution. The model is trained on the training set with class weighting to address any imbalance between healthy and worn tools.

The Random Forest is chosen because it:

- captures nonlinear relationships and interactions between sensor signals,
- is robust to noise and moderate multicollinearity,
- provides stable probability estimates and reasonable interpretability.

The model outputs, for each tool instance, the probability that the tool is in the "not healthy" state.

4.2 Cost-Based Decision Model

The digital twin converts predicted probabilities into actions via a cost-based decision model. Three cost parameters are defined:

Event	Description	Cost (units)
Inspection	Tool is taken out and inspected	$C_{\text{inspect}} = 0.5$
Scrap	Worn tool detected and replaced	$C_{\text{scrap}} = 2.0$
Escape	Worn tool not detected and kept in use	$C_{\text{bad}} = 10.0$

Given a decision threshold $\tau \in [0, 1]$, the inspection policy is:

- if $\hat{p} \geq \tau$, inspect the tool;
- if $\hat{p} < \tau$, continue operation.

For each threshold, the following metrics are computed on the test set:

- inspection rate (fraction of tools inspected),
- scrap rate (fraction of tools that are worn and inspected),
- escape rate (fraction of all tools that are worn and not inspected),
- total cost and average cost per tool.

The *optimal threshold* is chosen as the τ that minimises the average cost per tool.

4.3 Multi-Objective Optimisation

In practice, a manufacturer may care about both the inspection workload and the total cost. To capture these trade-offs, a multi-objective analysis is performed with two objectives to be minimised:

1. inspection rate,
2. average cost per tool.

For a grid of thresholds, the corresponding points in the objective space are computed, and a Pareto frontier is obtained. A similar analysis is conducted for escape rate versus cost, highlighting quality–cost trade-offs.

4.4 Runtime Digital Twin Simulation

To mimic real-time operation, a simulation loop is implemented. At each time step t:

1. the feature vector for the tool at time t is passed to the Random Forest,
2. the predicted probability of being worn is computed,
3. the inspect/continue decision is applied using the chosen threshold,
4. the appropriate cost is incurred and added to the cumulative cost.

The simulation outputs a log containing time step, true label, predicted risk, decision, step cost, and cumulative cost. Plotting cumulative cost versus time step provides a visual trajectory of the digital twin's runtime performance.

4.5 Advanced Analysis: Feature and Sensor-Group Importance

To better understand which signals drive the twin's decisions, feature importance scores from the Random Forest are analysed. The top individual features are identified, and features are also aggregated into sensor groups according to their prefixes: VB, AE, CF, and Vib. This yields group-level importances that quantify the relative contribution of each sensor type to the overall wear prediction.

4.6 Advanced Analysis: Cost-Sensitivity of Inspection Policies

A cost-sensitivity study explores how the optimal inspection threshold changes under different cost assumptions. Four scenarios are considered:

Scenario	C_{inspect}	C_{scrap}	C_{bad}
Base	0.5	2.0	10.0
CheapCheck	0.2	2.0	10.0
CostlyCheck	1.0	2.0	10.0
HighPenalty	0.5	2.0	20.0

For each scenario, the average cost per tool is recomputed across the threshold grid, and the threshold that minimises the cost is recorded.

5 Results

5.1 Model Performance

On the hold-out test set, the Random Forest classifier achieved:

- ROC–AUC of 1.0,
- accuracy of 1.0,
- precision, recall, and F1-score of 1.0 for both classes.

The sensor measurements in this dataset allow near-perfect discrimination between healthy and worn tool states.

5.2 Optimal Threshold, Cost and Trade-Offs

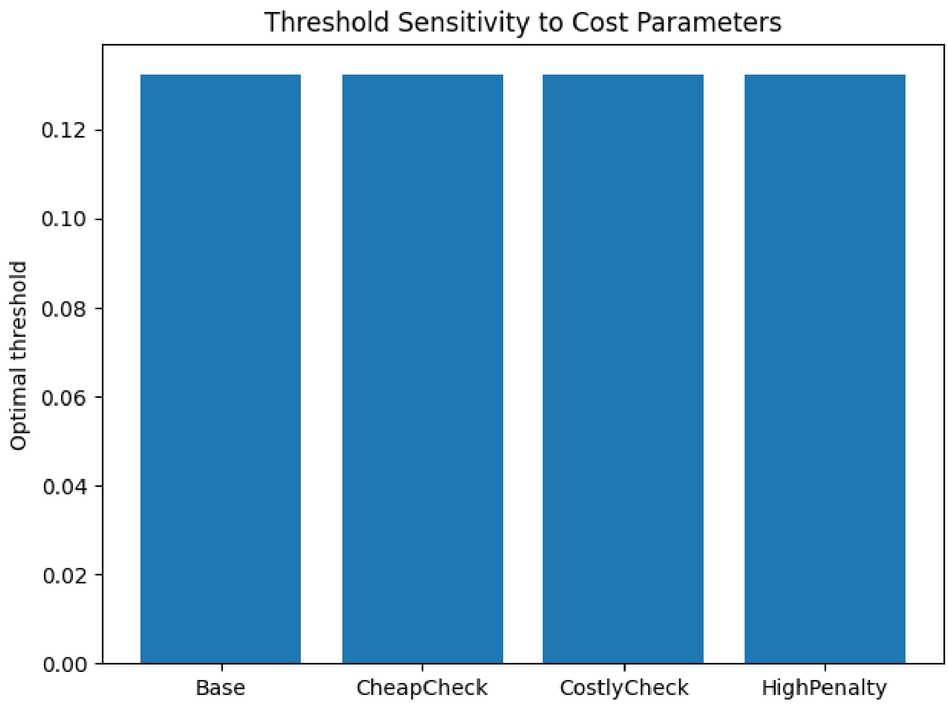

Figure 2: Average cost per tool versus inspection rate for different decision thresholds (blue), with Pareto-efficient points highlighted (orange).

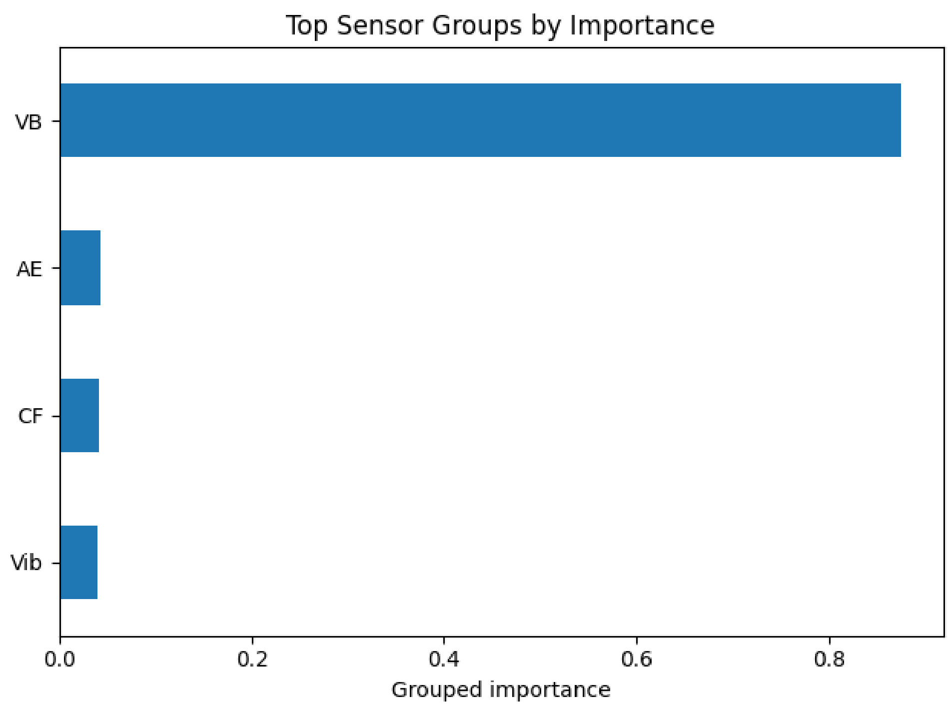

Figure 3: Average cost per tool versus escape rate (fraction of worn tools not inspected).

Sweeping thresholds between 0.01 and 0.99, the cost-minimising threshold was found to be

$$\tau^* = 0.133,$$

with a minimum average cost per tool of approximately 1.775 cost units. The curves in Figures 2 and 3 illustrate how increasing the inspection rate reduces escapes and overall cost, while very high thresholds lower inspection effort but allow more worn tools to slip through.

5.3 Runtime Simulation

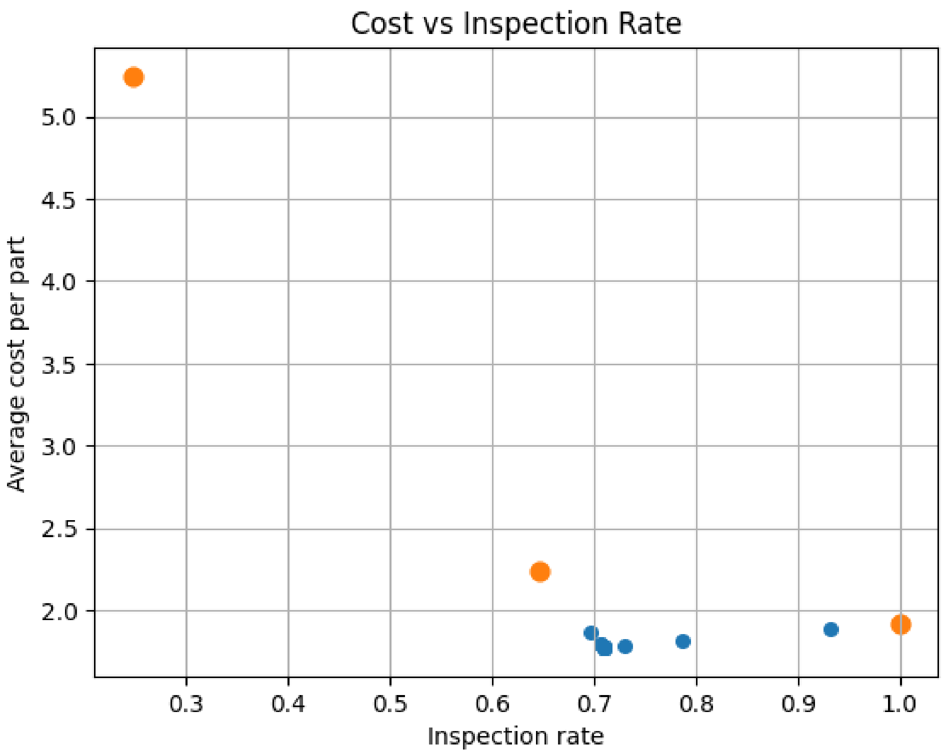

Figure 4: Digital twin runtime cost trajectory: cumulative cost over time steps under the cost-optimal inspection policy.

The cumulative cost trajectory from the simulation (Figure 4) increases approximately linearly over time, with no large spikes. This indicates that the digital twin, using the cost-optimised threshold, effectively prevents expensive escape events while maintaining a manageable inspection rate.

5.4 Feature Importance and Sensor Groups

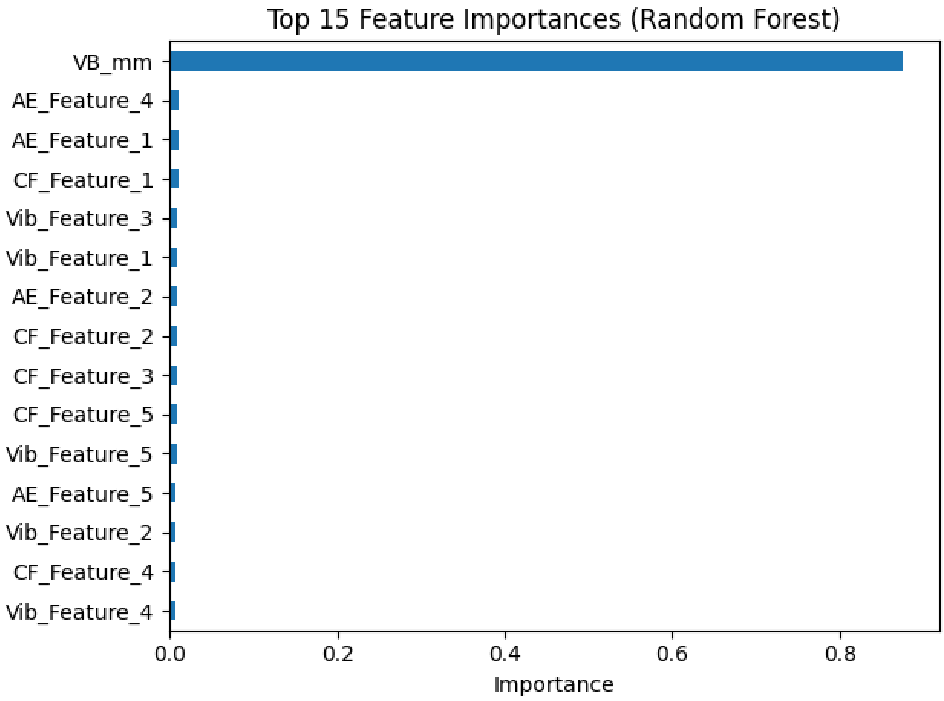

Figure 5: Top fifteen individual features ranked by Random Forest importance.

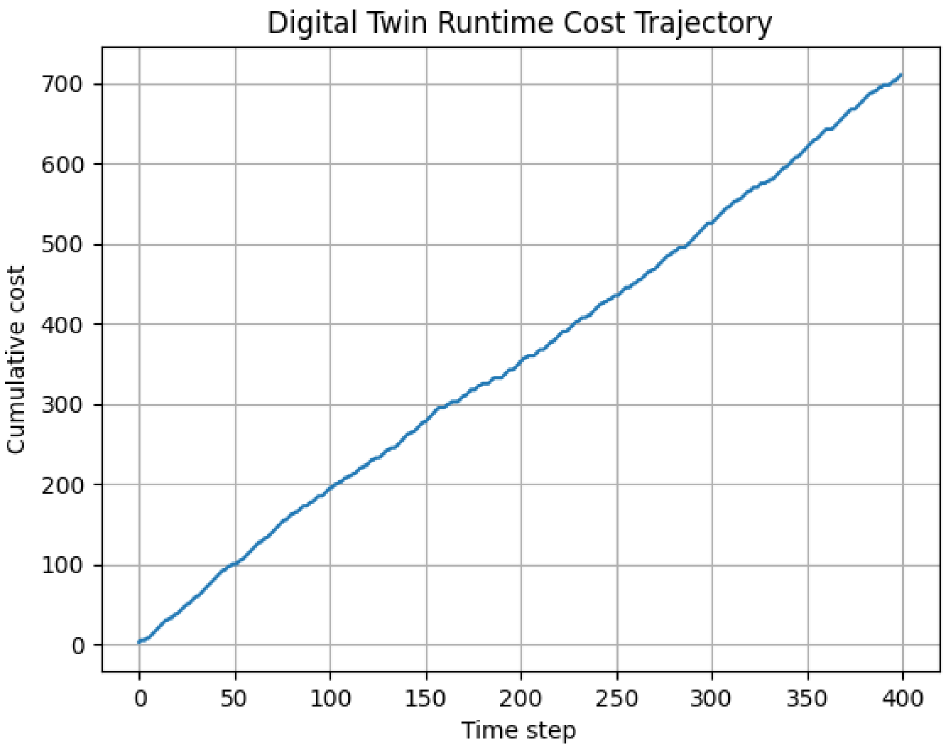

Figure 6: Grouped feature importance aggregated by sensor type (VB, AE, CF, Vib).

The feature-importance analysis (Figure 5) reveals that the measured flank wear, VB_mm, is by far the most influential variable, with an importance weight of about 0.88. Aggregating importance by sensor group (Figure 6) shows that VB accounts for roughly 0.88 of the total importance, whereas acoustic emission (AE), cutting-force (CF), and vibration (Vib) features each contribute around 0.04. Thus, VB_mm dominates the predictive signal, with AE, CF, and vibration sensors providing supporting information.

5.5 Cost-Sensitivity Analysis

Scenario	C_{inspect}	C_{scrap}	C_{bad}	Best threshold
Base	0.5	2.0	10.0	0.1325
CheapCheck	0.2	2.0	10.0	0.1325
CostlyCheck	1.0	2.0	10.0	0.1325
HighPenalty	0.5	2.0	20.0	0.1325

Table 1: Optimal thresholds under different cost scenarios.

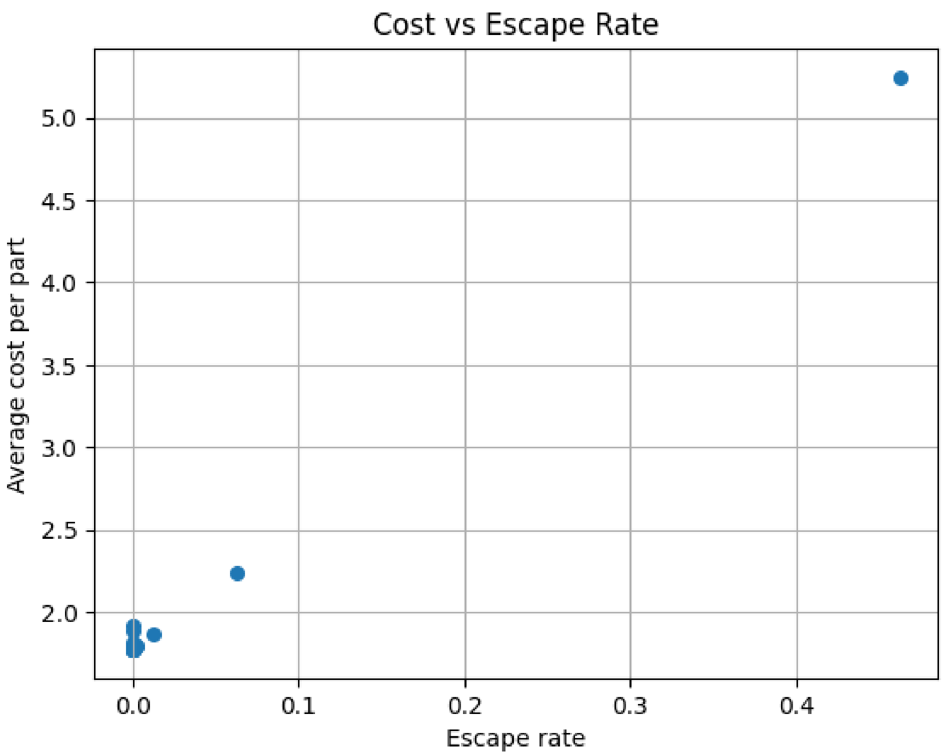

Figure 7: Sensitivity of the optimal threshold to changes in cost parameters.

In all four scenarios the optimal threshold remains essentially unchanged at approximately 0.13 (Table 1 and Figure 7). The minimum average cost per tool changes as the absolute costs change, but the threshold value is robust. This behaviour is consistent with the near-perfect classifier: misclassification probabilities are so small that changing the relative magnitudes of the cost parameters does not significantly shift the cost-minimising decision boundary.

6 Discussion

The results demonstrate that a data-driven digital twin can accurately monitor CNC tool wear and support cost-aware inspection decisions. The cost and trade-off plots visualise the inspection policy design space, while the runtime trajectory shows stable long-run performance. The feature-importance and sensor-group analysis adds interpretability to the twin and highlights which measurements are most crucial for monitoring.

7 Conclusion

This project implemented a complete data-driven digital twin for CNC tool wear monitoring and inspection optimisation using a multi-sensor dataset. The twin combines a high-performing predictive model, a cost-based decision layer, multi-objective analysis, interpretability through feature-importance and sensor-group analysis, and a runtime simulation environment. The approach demonstrates how digital twins can help manufacturers reduce scrap, avoid failures, and optimise preventive maintenance policies.

References

1. Z. Ziya. *Multi-Sensor CNC Tool Wear Dataset*. Kaggle. Available at: `https://www.kaggle.com/datasets/ziya07/multi-sensor-cnc-tool-wear-dataset`.