Proc. of the European Safety and Reliability Conference (ESREL 2026)
Edited by José C. Matos, Paulo B. Lourenço, Michael Beer, Daniel Oliveira,
Edoardo Patelli, Hélder S. Sousa, Rui A. Silva and Monica Santamaria
 Published by Research Publishing, Singapore.
doi: 10.3850/ESREL2026061419_esrel26-p26423-cd

Multivariate Simulation of Manufacturing Processes Based on Fleet Simulation: Case Study in Metal Sawing

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Multivariate simulations have proven valuable in automotive and light electric vehicle (LEV) fleet analysis for reproducing usage patterns and forecasting future developments regarding functional and safety related conditions and failures. Based on these experiences, this paper evaluates how the approach can be adapted to the reliability analysis of manufacturing processes, using metal sawing as a case study. The main challenge is that saw blade wear results from the interaction of multiple variables rather than a single variable. In practice, maintenance decisions are often based on experience or subjective impressions such as increased noise or visible defects. As a consequence, saw blades are sometimes maintained or replaced too early, leaving remaining tool life unused and increasing costs, or too late, leading to quality losses, unplanned downtime, and more expensive refurbishment up to full re-tipping of carbide teeth. A multivariate fleet simulator is applied to generate consistent synthetic datasets from usage and operating data. These data capture the behavior of the sawing process and measurable process parameters, including cutting speed, feed rate and material properties. The method is first illustrated with automotive fleet data and subsequently adapted to the metal sawing process to model operating behavior and load profiles in a data-driven manner. Cutting energy emerges as a practical indicator of saw blade wear. On this basis, reliability analyses can be performed both retrospectively and predictively. The study shows how a proven method from automotive fleet simulation can be adapted to manufacturing processes. This provides a decision basis for data-driven maintenance strategies, timely maintenance, cost reduction and improved efficiency in metal sawing.

Keywords: Reliability Modeling, Multivariate Simulation, Fleet Simulation, Metal Sawing, Multivariate Analysis.

1. Introduction

Manufacturing processes are increasingly affected by high variability in operating conditions, shorter product cycles and rising cost pressure, while expectations regarding product quality and machine availability are increasing. Under these conditions, reliable information about the state and remaining useful life of production tools is essential for effective maintenance planning. However, many industrial environments still rely on fixed maintenance intervals or subjective assessments rather than systematic, data driven evaluations.

Metal sawing provides a representative example of these challenges. The wear of carbide tipped saw blades results from a complex interaction of process parameters such as cutting speed, feed rate, material properties and operational patterns. Blade wear cannot be attributed to a single dominant factor and does not follow a simple monotonic trend. In practice, decisions to replace or refurbish saw blades are often based on indirect indicators such as noise, visual observations or deteriorating cut quality. This leads either to premature replacement with unused remaining tool life or to late intervention associated with quality losses, unplanned downtime and costly retipping.

In parallel, other technical domains have successfully introduced multivariate simulation methodologies to analyze usage dependent degradation. In particular, fleet simulation approaches in the automotive and light electric vehicle sectors have demonstrated the ability to generate consistent synthetic usage data, capture stochastic dependencies between variables and support both retrospective reliability assessments and predictive analyses under realistic operating conditions (Ioannou et al., 2025). These methods integrate operational data directly into the evaluation of system behavior, enabling multivariate assessments of remaining useful life and the identification of usage patterns associated with specific failure mechanisms (Reinecke, 2021).

Building on these developments, this work investigates how the original multivariate fleet simulation concept by Reinecke (2021) based on Monte Carlo simulation can be adapted to manufacturing processes. Metal sawing is used as a case study to demonstrate the applicability of this concept. The objective of this work is to simulate the cutting-energy trajectory for a given process plan based on the corresponding process parameters. Since cutting energy reflects the evolution of cutting forces, it is used as a degradation related target variable to infer blade wear and support maintenance decisions.

The remainder of this paper is structured as follows. Section 2 reviews related work on Monte Carlo based simulation and multivariate degradation modeling. Section 3 outlines the original multivariate fleet simulation concept and its adaptation to manufacturing processes. Section 4 introduces the metal sawing case study and the available data, while Section 5 presents the predictive simulation results. Section 6 concludes the paper and Section 7 provides an outlook on future work.

2. Related Work

The Monte Carlo Method (MCM) is a fundamental technique for the stochastic simulation of complex technical systems and is widely used when system behavior is influenced by uncertainty (Zio, 2013). In essence, MCM relies on repeatedly drawing random samples to approximate the evolution of systems governed by probabilistic processes (Lemieux C., 2009). The method is typically based on pseudo random numbers generated from a uniform $U[0, 1]$ distribution, which are transformed into samples of the required probability distributions. Established algorithms such as inversion based sampling, composition methods and rejection sampling ensure that the generated random numbers exhibit the necessary statistical properties (Zio, 2013; Waldmann and Helm, 2016). Due to its flexibility and general applicability, MCM is employed across numerous scientific and engineering domains, including financial modeling, physical simulations and reliability assessment Lemieux C. (2009); Waldmann and Helm (2016).

In the context of time series generation and condition monitoring, several research contributions have built on MCM. Feijóo et al. (2011) introduced an approach to simulate correlated wind speed profiles using predefined distribution functions tailored to specific locations. An overview of wind speed simulation methodologies is provided in (Feijóo and Villanueva, 2016). Monte Carlo based approaches have also been applied to health monitoring and remaining useful life prediction. Subbiah and Turrin (2015), as well as Turrin et al. (2015), demonstrated how condition monitoring data can be used to derive probabilistic degradation trajectories through data driven MCM techniques. These strategies are conceptually relevant for manufacturing processes, where tool wear or machine condition evolves gradually and must be forecasted under uncertainty.

In addition, Hienzsch (2016) and Hinz et al. (2016) presented two univariate simulation methods for field data originating from the automotive domain. One approach relies on alternating extreme point generation followed by polynomial interpolation, while the other reconstructs signals from frequency and amplitude components obtained through discrete Fourier transformation. Both methods illustrate how stochastic simulation can approximate realistic operational behavior, which is equally valuable for analyzing manufacturing processes.

Building upon these developments, Reinecke (2021) introduced the original multivariate fleet simulation concept, which integrates correlation analysis and classification methods within an MCM based simulation architecture. This enables dependencies among several signals to be modeled, including distinct usage states and transitions between them. Unlike earlier univariate methods, Reinecke's approach allows both product level and fleet level prognostics by capturing how past behavior influences current and future operating conditions. Its ability to represent interacting variables and state dependent dynamics provides a promising foundation for adapting fleet simulation concepts to manufacturing processes, where degradation typically arises from the interplay of multiple process parameters.

3. Methodology

This section provides the methodological foundation of the study. First, the original multivariate fleet simulation concept is introduced. Subsequently, the adaptations required for transferring this concept to manufacturing processes are described.

3.1. *Multivariate Fleet Simulation Concept*

The methodology in this work builds on the original multivariate fleet simulation concept introduced by Reinecke (2021) to analyze automotive field data. The objective of this concept is to generate synthetic time series that reproduce realistic operating behavior while preserving stochastic dependencies between multiple variables.

The simulation framework consists of three main components: data preparation, univariate simulation of stochastically independent variables and multivariate simulation of stochastically dependent variables.

3.1.1. *Data Preparation*

The first step is the preparation of the available signal and sensor data, which are provided as time series. Implausible values and missing data points are corrected to obtain consistent time series.

To represent different operating conditions, discrete usage states are derived from the data. Time series are segmented into intervals of fixed length. For each segment, statistical characteristics including minimum, maximum, range, arithmetic mean, median and standard deviation are calculated. The usage states are then identified using the k-means clustering algorithm based on minimum, maximum and median as clustering features (Hartigan and Wong, 1979).

3.1.2. *Univariate Simulation*

In the original multivariate fleet simulation concept, the univariate simulation generates synthetic time series for variables that are stochastically independent or simulated prior to dependent variables. Each univariate simulation consists of generating a sequence of usage states, sampling characteristic extreme points and level durations for each state and interpolating intermediate values using cubic splines. This produces synthetic time series that reflect the statistical and temporal structure of the original data.

In the manufacturing application considered here, this step is not required because the relevant process variables are predefined by process planning or machine control.

3.1.3. *Multivariate Simulation*

The multivariate simulation is used when stochastic dependencies exist between variables. In these cases, influencing variables are simulated first and passed as input to the multivariate simulator for generating the dependent target variable.

A classification model is trained to assign usage states of the target variable based on the most strongly correlated influencing variables. The model is built using segmented time series and implemented through a decision tree classifier based on the C4.5-Algorithm (Salzberg, 1994). The resulting state assignments guide the simulation of the target variable.

Simulation begins by selecting an initial value from the original data that corresponds to the classified usage state. Subsequent values are generated sequentially, taking into account the empirical distribution of the target variable within the respective usage state. This ensures that the resulting trajectories preserve both characteristic distributions and multivariate dependencies.

3.1.4. *Learning of Dependencies in the Multivariate Simulator*

In the original multivariate fleet simulation concept, the dependencies between influencing variables and a target variable are learned using a nearest neighbor based procedure applied to historical operational data. For each point to be simulated, the multivariate simulator constructs a query vector from the known values of the influencing variables. The Euclidean distances between this query vector and all observations in the normalized feature space of the training dataset are computed, and a set of k nearest neighbors is identified.

Because each neighbor contains an observed value of the target variable, an empirical distribution of the target variable is obtained from these neighbors. To emphasize the influence of observations closer to the query point, inverse distance weighting is applied (Hechenbichler and Schliep, 2004). The resulting weighted empirical distribution is then sampled using the inversion method for discrete random variables.

This mechanism allows the multivariate simulator to generate values that are consistent with the multivariate structure of the historical data while ensuring that simulated outcomes remain within the space of previously observed realizations.

3.2. *Adaptation to Manufacturing Processes*

The original multivariate fleet simulation concept was developed for domains in which long and continuous usage profiles are available, such as automotive and light electric vehicle operation. In these applications, individual time series may contain tens of hours of data and several hundred thousand measurement points. Such extensive datasets allow user behavior to be characterized reliably and enable the extrapolation of future operating patterns. Consequently, the simulation focuses on reproducing realistic usage trajectories within the value range of the historical data.

When transferring this methodology to manufacturing processes, the underlying conditions differ fundamentally. Sawing operations typically produce short time series with 50 to 120 cuts, and many variables represent predefined process settings rather than freely evolving usage behavior. In addition, the degradation related target variable cutting energy may exceed the values observed during the early stage of a blade's lifecycle. Therefore, simulation strategies that split a single time series into training and simulation segments are insufficient because they restrict the simulated cutting energy to the limited value range present in the early part of the data and fail to reproduce the characteristic degradation driven increase.

To address these differences, the simulation concept is adapted to incorporate multiple complete lifetime time series, to treat process parameters as fixed inputs rather than variables to be simulated and to enable the generation of cutting energy trajectories based on a small number of initial measurements combined with predefined process settings. The required modifications to the univariate and multivariate parts of the original multivariate fleet simulation concept are described in the following sections.

3.2.1. *Omission of the Univariate Simulation Step*

In the original multivariate fleet simulation concept, the univariate simulation step is essential for generating synthetic time series of variables that are stochastically independent or simulated prior to dependent variables. This is well suited for vehicle applications, where many operating variables arise from user behavior and are not predetermined.

In manufacturing processes, the situation differs. A large share of relevant variables are predefined through process planning or machine control. In the metal sawing process considered here, cutting speed, feed rate and material properties are externally specified and therefore known before simulation. These variables do not need to be simulated and can be supplied directly to the multivariate simulation as deterministic inputs.

For this reason, the univariate simulation step is omitted in the adapted multivariate simulation. This modification reflects the deterministic character of many manufacturing parameters and reduces model complexity while preserving the capability to represent stochastic dependencies in the multivariate step.

3.2.2. *Modification of the Multivariate Simulation Strategy*

Several adjustments to the multivariate simulation strategy are required when transferring the original multivariate fleet simulation concept to manufacturing processes. In vehicle applications, learning is based on long, densely sampled usage time series that capture a broad range of usage states and transitions. This enables direct learning of stochastic dependencies between influencing variables and a target variable from continuous real-world operation. Simulation is performed by learning from the first part of a time series and simulating the subsequent part.

In manufacturing processes, this assumption is not valid. Metal sawing processes generate comparatively short time series, and the variation between consecutive cuts does not reflect the broad usage variability present in automotive data. Furthermore, many influencing variables correspond to predefined process settings that change according to production planning rather than user behavior. As a result, splitting a single saw blade time series into learning and simulation segments would restrict the simulated cutting energy to the limited value range observed at the beginning of the blade's lifetime and would prevent the reproduction of degradation driven energy increases.

To overcome this limitation, the adapted multivariate simulation uses multiple complete blade run time series for learning instead of segments of individual sequences. Learning across several complete operational runs allows the multivariate simulator to capture how cutting energy responds to variations in workpiece materials, cutting speeds, feed rates and other process settings over the entire blade lifecycle. The learning procedure follows the workflow described in Section 3.1.4, including window based feature extraction, usage state identification and decision tree based state classification. Incorporating multiple heterogeneous lifetime series increases the observable parameter space and enables the learning of degradation relevant dependencies that cannot be inferred from a single short series.

In the predictive application, the multivariate simulator requires an initialization consisting of three consecutive measured cutting energy values. This requirement arises from the simulation procedure, which generates each new cutting energy value from the two preceding time points together with the predefined process parameters for the next cut. In this study, the first three measured values of the current blade are used as initial conditions. Combined with the complete sequence of predefined process parameters representing the upcoming production tasks, these initial values enable the multivariate simulator to generate the cutting energy for all subsequent cuts. In this way, the adapted multivariate simulation reproduces the characteristic progression toward higher energy levels that is typically observed as wear increases.

4. Case Study: Metal Sawing Process

This section applies the proposed methodology to an industrial metal sawing process. The case study illustrates how multivariate relationships are learned from historical process data and how the adapted multivariate simulation is used to predict cutting-energy trajectories under realistic operating conditions.

4.1. *Process Description and Data Basis*

The adapted multivariate simulation is demonstrated using a metal sawing process in which carbide-tipped circular saw blades are operated under varying production conditions. For each cut, the cutting energy is recorded and used as the degradation-related target variable for both learning and predictive simulation.

During production, process and machine settings change in response to workpiece materials, operator decisions and production scheduling. Consequently, the cutting energy evolves as a response to these varying conditions. For each cut, the following process variables were recorded and used as influencing variables in the multivariate simulator: feed rate $[mm/s]$, feed per tooth $[mm/tooth]$, cutting speed $[m/min]$.

These variables were not selected through feature importance or model selection procedures. They are simply the subset of process parameters available consistently across all historical time series, forming a practical and homogeneous basis for learning multivariate relationships.

The full dataset comprises 17 complete lifetime cutting-energy time series, each covering the operational period of a saw blade from the first cut to replacement or refurbishment. 14 time series are used for learning the multivariate dependencies between cutting energy and process parameters. The remaining three time series are held out and used exclusively to evaluate the predictive performance of the adapted multivariate simulation.

Training on multiple heterogeneous blade runs provides sufficient variation in process settings and wear behavior to enable the multivariate simulator to generalize beyond individual production situations and to generate realistic cutting-energy trajectories for unseen sequences.

4.2. *Predictive Simulation of Cutting Energy*

To demonstrate the predictive capability of the adapted methodology, a scenario representative of industrial sawing operations is considered. The predictive simulation begins with the first three measured cutting-energy values, which serve as the initialization required by the simulation procedure. These values are supplied to the multivariate simulator together with the full predefined sequence of process parameters describing the upcoming production tasks. Based on the learned multivariate relationships and the predefined parameter sequence, the multivariate simulator generates the cutting energy for all subsequent cuts. The simulated cutting-energy trajectory represents the expected development under the given operating conditions and enables the planning of blade refurbishment or replacement.

In the present case study, fourteen lifetime series are used for learning the multivariate dependencies, while three unseen time series are reserved for evaluation. For each evaluation run, the simulator is initialized with the first three measured cutting-energy values and the full predefined process parameter sequence. The simulated trajectories are then compared to the corresponding measured data. The results of this comparison and the characteristic patterns observed in the simulated cutting-energy progressions are presented in the following section.

5. Results

This section presents the results obtained from applying the adapted multivariate simulation to the metal sawing case study. Three previously unseen lifetime time series were reserved for evaluation. To maintain clarity and focus, only one representative evaluation run is discussed in detail.

For each evaluation run, the multivariate simulator was initialized using the first three measured cutting-energy values together with the predefined sequence of process parameters describing the subsequent cuts. Based on this initialization, 2000 simulated cutting-energy trajectories were generated using the learned multivariate relationships. All simulated trajectories were compared with the measured cutting-energy progression using the sum of squared errors (SSE), enabling a consistent ranking of the simulation ensemble. The SSE of simulation run j is defined as the sum of squared differences between simulated and measured cutting-energy values over all cuts:

$$SSE_j = \sum_{i=1}^{N} \left(E_{i,j}^{\mathrm{sim}} - E_i^{\mathrm{meas}}\right)^2, \qquad (1)$$

where $E_{i,j}^{\mathrm{sim}}$ denotes the simulated cutting energy of simulation run j at cut i, E_i^{meas} denotes the measured cutting energy at cut i, and N is the total number of compared cuts.

5.1. *Ensemble Variability*

The ensemble of 2000 simulated trajectories exhibits a broad but structured variation in cutting-energy behavior. To illustrate the upper range of deviations within the ensemble, Figure 1 shows the measured cutting-energy progression alongside the ten simulated trajectories with the highest SSE. These trajectories outline the extent to which individual simulations may diverge from the observed behavior and thereby characterize the envelope of possible outcomes produced by the adapted multivariate simulation.

5.2. *Best-Matching Simulation Trajectories*

Figure 2 presents the measured cutting-energy progression together with the ten simulated trajectories with the lowest SSE. These trajectories align closely with the measured data and reproduce its overall evolution with notable accuracy, including global levels and general fluctuation patterns. The narrow spread among the top-ranked simulations highlights the stability of the learned multivariate relationships and demonstrates the

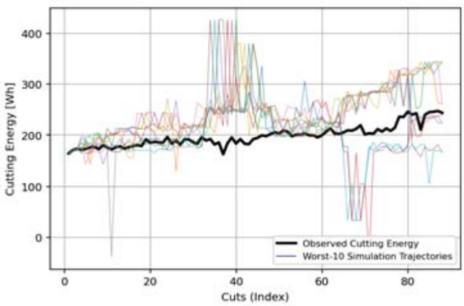

Fig. 1. Ten simulated cutting-energy trajectories with the highest SSE compared to the measured reference.

capability of the adapted multivariate simulation to generate realistic cutting-energy profiles.

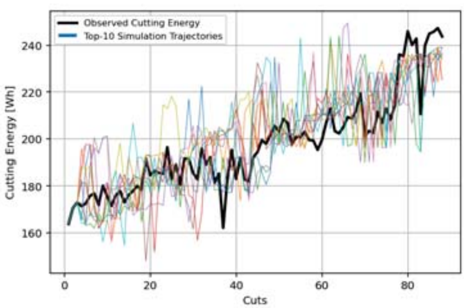

Fig. 2. Ten simulated cutting-energy trajectories with the lowest SSE compared to the measured reference.

5.3. *Representative Ensemble Trend*

While individual simulated trajectories illustrate both accurate and less accurate outcomes, an ensemble-based view provides a more robust picture of the typical behavior produced by the adapted multivariate simulation. Figure 3 shows the measured cutting-energy progression together with a delta-based trimmed-mean curve. This curve is calculated by first computing the incremental changes between consecutive cuts for each simulated trajectory. For each cut, the incremental values are sorted and a trimmed mean is calculated by removing the lower and upper extremes to reduce the influence of outliers. The remaining increments are then averaged and cumulatively summed to obtain a representative cutting-energy trajectory. This results in a smooth and stable representation of the central tendency of the simulation ensemble, offering a consistent basis for comparison with the measured degradation trend.

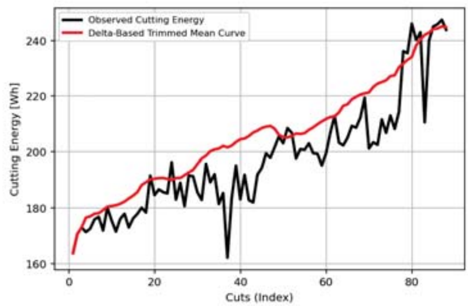

Fig. 3. Delta-based trimmed-mean approximation of the cutting-energy progression, aggregating simulation increments while reducing outlier influence.

6. Summary

The case study demonstrates that the adapted multivariate simulation is capable of generating realistic cutting-energy trajectories for previously unseen operating conditions. Although individual simulated trajectories exhibit varying degrees of deviation, the ensemble characteristics remain stable across 2000 simulation runs. In particular, the delta-based trimmed mean estimator provides a robust aggregate trajectory that closely follows the measured cutting-energy progression, even in the presence of outlier simulations. These results confirm that the adapted multivariate simulation captures the dominant dependencies between process parameters and cutting energy and supports reliable forward simulations based solely on the initial cuts of a new production run.

7. Outlook

The case study demonstrates that the delta-based trimmed mean estimator provides a stable and reasonable approximation of the measured cutting energy, even when the simulation ensemble exhibits substantial variability. Several opportunities exist to further improve the predictive capability of the adapted multivariate simulation.

First, the current multivariate simulator uses only three predefined process parameters: cutting speed, feed rate and feed per tooth. Incorporating additional variables, such as material hardness or the effective cross-sectional area removed per cut, could improve the representation of physical load conditions and further reduce deviations between simulated and measured trajectories.

Second, the learning stage is based on a limited number of lifetime time series. Expanding the dataset with more heterogeneous blade runs would enhance the robustness of the learned operating states and improve generalization across different production environments. With sufficiently diverse data, the simulator may ultimately infer characteristic early life cutting-energy values directly from the process parameters. In this case, explicit measurement based initialization would no longer be required, enabling fully predictive process planning and extending the potential for data driven decision support in tool and production management.

Acknowledgement

This study was conducted as part of the research project ‘Development of a Multivariate Reliability Model for Representing Degradation Behavior, Determining the Remaining Useful Life, and Predicting Failure Events (DEREPRO) of Technically Complex Products Using Multivariate Usage Profiles‘ funded by the Deutsche Forschungsgemeinschaft (DFG, German Research Foundation) - 557903399. This study is also supported by the Federal Ministry for Economic Affairs and Climate Action (BMWK) on the basis of a decision by the German Bundestag with Project-Number KK5066812PK4 (SawMotionAI).

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