

Article

A Contextual Model for the Industrial Machine Failure Prediction

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Abstract

Failure prediction of industrial machinery remains a concern for numerous researchers and practitioners. In this research, the improvement of failure predictions was highlighted by including contextual factors due to the fact that machine operation is a socio-technical process influenced not only by historical data but also by machine operating conditions, maintenance policies, and environmental conditions, etc. The paper proposes a contextual framework for the prediction of failure, which involves the application of various quantitative and qualitative methods, such as statistical analysis, time-series, machine learning algorithms, interviews, and survey questionnaires. The results of the application of the model indicate that it is possible to obtain quantitative estimates of the time between failures (TBF) and the downtime (DT) by applying the aggregated expert assessments of contextual factors. The key findings of the research indicate that the development of TBF and DT prediction models, in a contextual sense, represents an important segment for the further planning of maintenance of machine systems.

Keywords: predictive maintenance; unplanned downtime; failure time analysis; machine learning

1. Introduction

The operation of industrial machines is the subject of numerous research studies, especially in terms of failure prediction, reliability calculations, and behavior patterns of unplanned failures. The prediction of failures is very important for planning the stock of spare parts, planning the duration of the production cycle (especially in situations where the delivery of finished parts to the customer is planned), cost planning, and general planning of all production resources, as well as the performance of immediate production functions.

The growing complexity of industrial systems, combined with increasing demands for reliability and cost efficiency, creates a need for more comprehensive approaches to downtime prediction. While existing predictive models provide valuable analytical capabilities, their practical applicability is often constrained by limited interpretability and insufficient integration with real operational conditions.

A key motivation for this research lies in bridging the gap between analytical model outputs and their practical use in maintenance planning. In many real-world scenarios, predictive models do not achieve satisfactory performance due to data limitations, system variability, or the presence of rare failure events.

Furthermore, existing methodologies predominantly focus on improving model accuracy, while relatively little attention has been devoted to the systematic integration of



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human and organizational factors. This represents a significant limitation, given that maintenance decisions are inherently socio-technical processes influenced not only by historical data but also by operating conditions, maintenance policies, environmental conditions, etc.

The objective of this research is therefore to develop a methodological framework that enables the integration of data-driven predictions, expert judgment, and contextual factors into a unified approach for failures and their downtime forecasting. The proposed framework aims to support decision-making under uncertainty by providing a structured mechanism for combining different sources of information, particularly in cases where predictive models alone do not yield reliable results.

In the professional literature, numerous predictive models have been developed for the analysis of stoppage or failure of individual machine components in the production process, specific to the industry in which the machine operates (railway, aviation, process industry). Classic, i.e., traditional approaches to the analysis of unplanned stoppages can be found in the works of Mobley [1], Windmark et al. [2], Alvarado et al. [3], Nallaperuma et al. [4], Hubicki et al. [5], Igbokwe and Godwin [6], Tsarouhas and Arvanitoyannis [7], Alsyouf [8], Pires et al. [9], in which the application of statistical methods, frequency analysis, and reliability models is presented in order to understand stoppages. As part of these studies, stoppages are most often analyzed on the basis of historical data, with the aim of identifying patterns and dominant causes. The analyses included the frequency of stoppages and downtime, the distribution of failures within production cycles, as well as the categorization of events related to process incidents and tool changes [1–4]. A special focus was placed on the identification of the dominant sources of losses and the classification of the types of stoppages in order to improve the evaluation of production data and the optimization of the maintenance process [3,4]. It has also been shown that a small number of key types of stoppages can have a dominant impact on the overall performance of the system, whereby the control of the most significant causes enables a significant improvement in work efficiency [4]. A significant part of the research is focused on the analysis of the impact of micro-stoppages and short-term operational stoppages on the overall efficiency of the system, most often expressed through the OEE indicator [5,6,8]. The results of conducted studies indicate that micro-stoppages, despite their short duration and difficulty in recording, represent a significant cumulative source of production losses [5,8]. Analyses carried out in different industrial environments have shown that short-term stoppages can have a dominant share in the total downtime, while at the same time, there are significant challenges in their precise diagnosis and identification of causes [5,8]. In addition, special importance is attached to the evaluation of maintenance performance and the continuous improvement of production processes through the application of indicators of overall equipment efficiency and failure analysis [6]. Approaches based on reliability analysis and maintenance optimization have been further developed through the application of theoretical distributions, failure rate models, and preventive maintenance strategies [7,9]. Previous research has included the analysis of time between failures (TBF), time to repair (TTR), equipment availability, and dominant failure modes in order to evaluate existing maintenance policies and improve system efficiency [7]. At the same time, some authors propose the integration of preventive maintenance activities into existing periods of downtime, whereby stoppages are viewed as potential opportunities for implementing preventive activities and optimizing the production schedule [9]. Such approaches indicate that effective maintenance planning can significantly reduce additional stoppages and enable better utilization of existing operational stoppages.

The development of predictive maintenance systems is increasingly moving from descriptive stoppage analysis to approaches based on system condition monitoring and sensor diagnostics. Modern approaches based on continuous system monitoring, signal

processing, and fault detection and diagnosis (FDD) methods enable the identification of degradation patterns, abnormal operating conditions, and potential failures before critical failures occur [10,11]. The application of machine learning methods and artificial neural networks included component state classification, tool wear analysis, bearing failure diagnostics, and assessment of the degree of system degradation based on multisensor operational data [11]. Recent developments in system status monitoring increasingly rely on advanced sensor and signal analysis methods. Widely accepted approaches include vibration monitoring, infrared thermography, stator current analysis, and stray magnetic flux monitoring. Infrared thermography enables non-contact recognition of abnormal temperature patterns and early detection of faults in industrial plants, while electromagnetic monitoring methods, such as loose-flux analysis, support the diagnosis of faults in rotating electrical machines. These approaches are increasingly combined with machine learning algorithms in order to improve fault diagnostics and predictive maintenance capabilities in industrial environments [12–14]. Subsequent development in the field of diagnostics and prognostics is additionally directed towards the development of models capable of interpreting multisensory data and supporting decisions based on condition-based maintenance in various mechanical systems [15].

Modern approaches in the field of predictive maintenance indicate that the integration of artificial intelligence and machine learning methods significantly improves stoppage analysis, identification of failure patterns, and maintenance planning. Systematic reviews of the literature [16,17] indicate that machine learning (ML) and deep learning (DL) methods are intensively applied in industries such as manufacturing, energy, transport, and healthcare, where CNN, LSTM, GRU, Random Forest, and XGBoost models are most often used. The authors conclude that combining sensor data and advanced algorithms improves the accuracy of detection and estimation of the remaining useful life of equipment. The importance of data-driven approaches is particularly emphasized, in which the combination of multi-sensor operational data and advanced algorithms enables the improvement of diagnostic accuracy and predictive performance of the system [18–21]. Machine and deep learning methods have been applied in various industrial environments, including metalworking, automotive, mining, and semiconductor industries [18–20,22,23]. In industrial applications, studies on predictive maintenance and production downtime forecasting underscore the role of advanced deep learning models (e.g., LSTM), but also the need for explainability and integration with human factors [24,25]. Special focus is placed on the analysis of large datasets, component condition classification, tool wear assessment, bearing failure, and equipment remaining useful life (RUL) prediction based on historical and operational data [18,20]. The importance of interpretability of models, integration of IoT sensors, and the adaptability of algorithms to different structures of input data in complex industrial conditions is particularly emphasized [18,19]. The development of data-driven predictive maintenance systems is increasingly based on multisensor data, signal processing, and advanced time-series analysis methods [22,23]. In doing so, special importance is attached to data preparation, sensor selection, characteristic engineering, data scaling and normalization, as well as the application of time, frequency, and time-frequency domain analysis of vibration signals [22]. At the same time, it was shown that the effectiveness of the predictive maintenance system strongly depends on the quality of the data, the choice of input parameters, and the ability of the model to include the variability of real working conditions and rare failures [21,23]. In the field of time series, classical statistical models such as ARIMA and SARIMAX, as well as recurrent neural networks and deep learning architectures, are applied [26–28]. Although some models achieve satisfactory results in short-term predictions, numerous studies indicate that the predictive power of the model decreases with the extension of the prediction horizon and the increase in the complexity

of failure patterns [28,29]. An additional challenge is the limited generalizability of the model, given that a large number of approaches have been validated on publicly available or synthetic datasets, while the application in real industrial conditions has been much less frequently analyzed [16,28]. Therefore, the authors [27,30] point out that there is a need to integrate predictive models with operational context, risk assessment, and characteristics of real industrial systems.

Despite significant progress in the field of machine learning-based predictive maintenance and diagnostics, several important limitations remain insufficiently addressed in industrial applications. One of the main challenges is related to data quality, feature selection, and class imbalance, given that failure events are typically rare compared to normal operating conditions [31,32]. As a consequence, predictive models can achieve high sensitivity but at the same time generate an increased number of false-positive alarms, which can reduce operator confidence and limit the practical application of the system [32]. Another significant limitation concerns the generalizability of predictive models. Numerous studies have been validated using synthetic or publicly available datasets, while a significantly smaller number of studies have examined model performance in real industrial conditions characterized by stochastic disturbances, heterogeneous failure patterns, and variable operating modes [16,28]. Previous research also indicates that increasing model complexity does not necessarily lead to improved predictive performance, especially in situations involving limited, noisy, or non-uniform industrial data [28]. Approaches based on time-series forecasting face additional challenges associated with the extension of the prediction horizon and operational uncertainty. Although statistical prediction models and recurrent neural network architectures often achieve satisfactory short-term prediction accuracy, their performance tends to degrade with increasing prediction horizons, especially in systems characterized by highly dynamic and heterogeneous failure behavior [26–29]. In addition, the issues of interpretability and trust in models represent an important obstacle to the implementation of predictive maintenance. Black-box machine learning models often provide limited insight into the underlying operational causes of failures, while standard explainability techniques are often insufficient for complex time-dependent industrial processes [33]. Previous research further emphasizes that system acceptance and its practical usability strongly depend on organizational conditions, maintenance flows, operator behavior, and the integration of decision support systems [34].

In addition to technical and algorithmic limitations, new literature increasingly emphasizes the importance of human and contextual factors in predictive maintenance systems. Maintenance performance and failure occurrence are strongly conditioned by operating conditions, organizational practices, operator behavior, maintenance quality, and decision-making processes within industrial environments [34–37]. Analyses in publications [35,37] show that the probability of human error, maintenance organization, and operational variability can significantly affect equipment reliability, maintenance costs, and overall system performance. Particular importance is attached to the impact of stochastic disturbances and variations in operator actions, which can significantly increase production losses and reduce process efficiency, even in systems equipped with advanced technologies for monitoring and diagnostics [36]. At the same time, the literature emphasized that the practical implementation and acceptance of predictive maintenance systems do not depend solely on algorithmic performance but also on the integration of decision support systems, the organization of maintenance flows, and contextual operational knowledge [34]. In complex industrial environments, decisions related to maintenance are often conditioned by incomplete information, uncertain operating conditions, and expert interpretation of system behavior. These findings indicate that predictive maintenance cannot be completely reduced to sensor signals and machine-learning model outputs. Instead, effective maintenance

nance decision-making increasingly requires the integration of operational context, expert knowledge, and probabilistic judgment under uncertain industrial environments.

Table 1 presents an overview of relevant research in the areas of stoppage analysis, predictive maintenance, and failure diagnostics, with special reference to the used methodologies, key contributions, and identified limitations of existing approaches.

Table 1. Comparative overview of previous research and identified limitations.

	Area/Industry	Approach/Methodology	Key Contribution	Identified Limitations
[1–4]	Industrial production systems	Statistical analysis, stoppage analysis, historical data	Identification of stoppage patterns, dominant causes, and classification of failures	Reliance on historical data and descriptive analysis
[5,6,8]	Production and process systems	OEE analysis, micro-stoppage analysis	Quantification of losses caused by short-term stoppages	Difficult diagnosis and registration of micro-stops
[7,9]	System maintenance and reliability	Reliability models, TBF/TTR analysis, preventive maintenance	Evaluation of maintenance policies and optimization of maintenance schedules	Limited adaptability to dynamic operating conditions
[10–15]	Condition monitoring and diagnostics	FDD methods, signal analysis, multisensor data	Early detection of degradation and support for condition-based maintenance approaches	Dependence on signal quality and sensor selection
[16,17]	Reviews of literature from the field of predictive maintenance	ML/DL systematic reviews	Identification of dominant AI approaches in predictive maintenance	Limited generalization of the model
[18–21,24,25]	Industrial AI and predictive maintenance	ML/DL models, SHAP, IoT integration	Improving diagnostics, interpretability, and RUL assessment	Dependence on data quality and interpretability
[22,23,30]	Mining and manufacturing industry	Data-driven approaches, vibration signal analysis	Development of multisensor systems and feature engineering approaches	Sensitivity to the choice of input parameters and real working conditions
[26–29]	Time series prediction	ARIMA, SARIMAX, RNN, LSTM	Prediction of failures and degradation trends	Decreased accuracy at longer prediction horizons
[28,31,32]	Predictive maintenance systems	ML classification and anomaly detection	High sensitivity of the model for rare failures	Class imbalance and false positive alarms
[33,34]	DSS and model interpretability	Explainable AI, DSS integration	Analysis of confidence in models and decision support	Insufficient interpretability of black-box models

Table 1. Cont.

	Area/Industry	Approach/Methodology	Key Contribution	Identified Limitations
[34–37]	Human and organizational factors	Analysis of human error and operational context	The influence of the operator and the maintenance organization on the performance of the system	Complexity of modeling contextual factors

2. Methodology

Figure 1 shows a general hybrid framework for failure forecasting that combines data-driven predictive models, expert judgment, and contextual factors. Historical data (e.g., times between failures—TBF and downtime—DT, as well as maintenance records) form the starting point, on the basis of which statistical and machine learning models (time series, regression, survival, and ML models) are developed that generate point forecasts and forecast intervals (PI). The resulting forecasts are then subjected to validation (e.g., via walk-forward backtesting or cross-validation) using standard error metrics (MAE, RMSE) and calibration/interval coverage criteria.

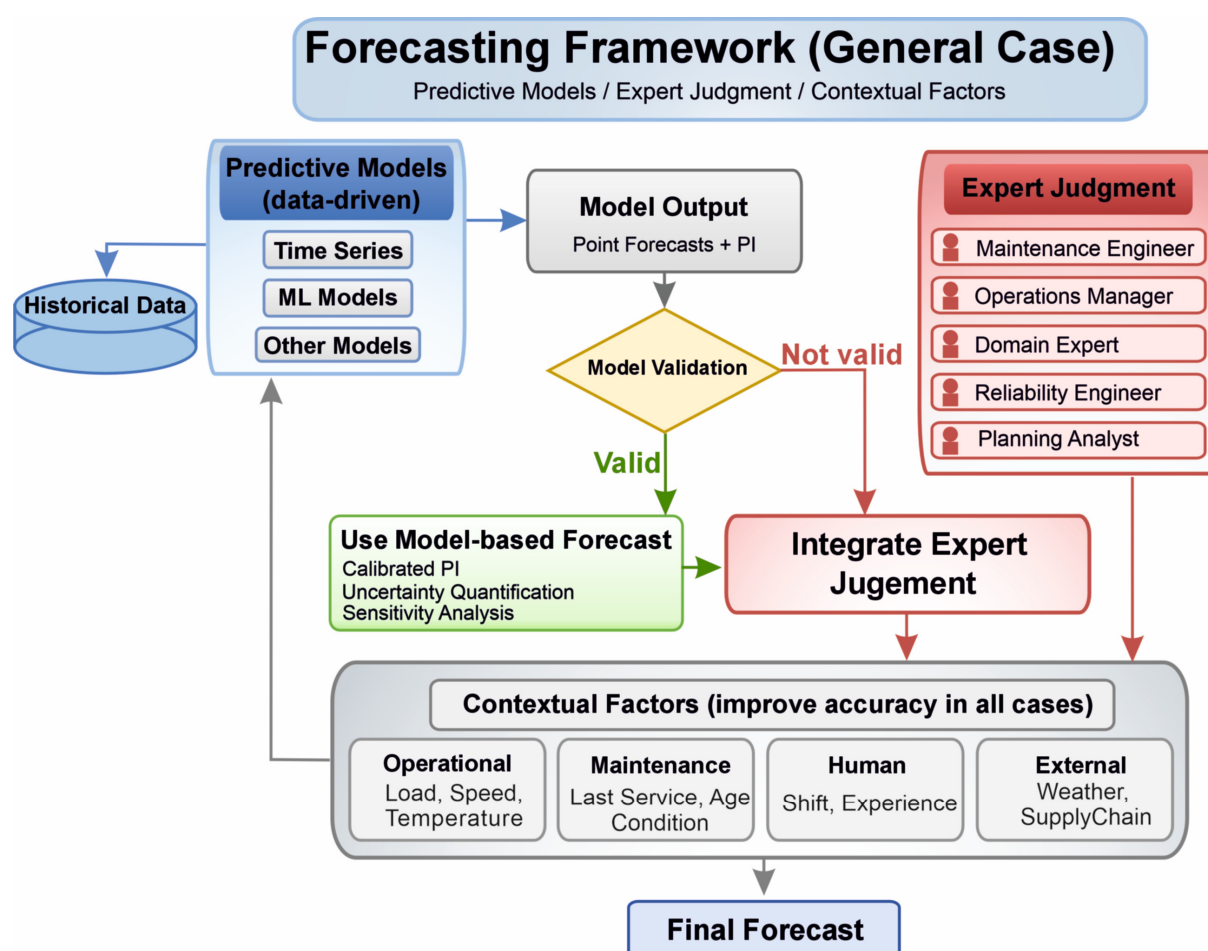


Figure 1. Contextual model for predicting TBF and DT.

The application of the proposed framework begins with the collection, classification, and preprocessing of chronological operational and maintenance records required for the extraction and analysis of TBF and DT parameters.

In the process of data collection, it is necessary to record the start of machine operation, duration of operation, time of failure occurrence, downtime, and cause of failure. The methodology requires chronological operational and maintenance records that enable the identification of operating intervals, failure events, and failure occurrence patterns over time.

Based on the data collected in this way, it is possible to calculate the time between failures (TBF) for various causes of failures, which, together with the already recorded downtime, enables the implementation of statistical analysis, probabilistic modeling, prediction of time series, and contextual interpretation of maintenance events.

In addition, the different categories of failures do not have the same analytical significance within predictive maintenance. Certain failures are directly related to the degradation or failure of system components, such as broken teeth, engine failure, and similar mechanical or technical disturbances, which makes their frequency and occurrence patterns meaningful for statistical analysis and modeling.

On the other hand, certain events are the result of external or hard-to-predict factors, such as extreme weather conditions, organizational disruptions, or certain human factor influences. Such events are not directly related to the technical condition and degradation of the observed system components, which is why they are not analyzed within the framework of predictive maintenance in the same way as failures of mechanical and technical equipment elements. The bottom line is that, within the proposed methodology, it is necessary to classify and select relevant types of failures before conducting analysis and developing predictive models.

The structure of the dataset, with a description of elements, is shown in Table 2.

Table 2. Structure of the dataset.

Element	Description
start_date	Beginning of the observed interval
end_date	End of the observed interval
rad_nerad	Operational state of the system
0	Normal machine operation
1	Failure/stoppage
DTF_min	Downtime expressed in minutes
TBF_min	Time between two consecutive failure events expressed in minutes
failure cause	Cause of stoppage/component failure

After the collection and preprocessing of operational and maintenance data, the next phase of the proposed methodology involves expert evaluation and contextual interpretation of factors influencing failure occurrence and failure behavior.

The implementation of the expert evaluation procedure within the proposed model begins with the selection of the expert group. It is preferable that the experts are from the industrial system in which the methodology is applied and that they have operational experience in working with the observed machine, the maintenance process, and the production environment. The expert team should include representatives of maintenance, planning, supervision, and operational management, in order to include technical, organizational, and operational aspects of system operation.

The next step refers to the definition of contextual factors relevant to the selected type of failure. A brainstorming method is applied to obtain an initial list of influential

contextual factors from experts that may influence the occurrence of the observed failure and associated downtime. The set of relevant contextual factors differs depending on the characteristics of the industrial system and the observed type of failure. The choice of factors can be influenced by the type of machine, the type of production (individual, serial or mass production), working conditions (outdoor work, underground work, work at height or depth), the number of shifts in which the machine operates, the degree of automation of the system, the organization of planned preventive maintenance and the previous history of breakdowns and failures. In addition to the technical characteristics of the system, organizational and operational factors can also have a significant impact, including the availability of spare parts, system load, operating modes, operator experience, and operating conditions. Therefore, the definition of contextual factors must be adapted to the specific industrial system and the chosen type of failure that is the subject of the analysis.

After defining the relevant contextual factors, the expert team evaluates their influence on the expected TBF and DT values for the observed type of failure. The impact is expressed by multiplicative coefficients with which experts assess whether a certain factor contributes to an increase or decrease in TBF and DT values. Estimates are formed through relative deviations (e.g., $\pm 5\%$, $\pm 10\%$) in accordance with the estimated intensity of the factor's influence. At the end of this step, an aggregated expert estimate is determined for each contextual factor in the form of a mean value and standard deviation ($AVG \pm STD$).

Subsequently, the expert team determines the weighting coefficients of the identified contextual factors using the interview method, thus defining their relative importance within the prediction of TBF and DT parameters. As in the previous step, the assessment is carried out expertly, with each expert assigning weight coefficients to individual factors in accordance with the estimated intensity of their influence. At the end of this step, an aggregated weighted rating is determined in the form of the mean value of expert ratings, after which the coefficients are normalized so that their sum for TBF and DT, in particular, is 1, which enables the proportional inclusion of all contextual factors in the aggregated rating.

The final step is the multiplication of the aggregated expert ratings of the contextual factors by their respective weight coefficients and the probabilistic ratings obtained from historical data, after which the weighted impacts thus obtained are added up. In this way, contextually adjusted evaluations of the probability of failure occurrence, the expected number of events, and the total downtime in defined time horizons are obtained.

In case the validation shows satisfactory performance (the model is valid), the data-based forecast is used as the primary output, with mandatory uncertainty quantification across the forecast intervals. If the performance is not satisfactory (the model is not valid), the framework envisages a transition to a structured expert assessment (interviews, surveys, Delphi or voting), whereby the expert knowledge is formalized as a risk assessment and/or a distribution/interval for TBF and DT in defined horizons (1/7/30 days). In both cases, contextual factors (operating conditions, maintenance policy, human factor, external influences, etc.) remain an integral part of the process, as they allow forecast correction and better interpretation of results in real working conditions.

The final step is the integration of forecasts into a hybrid output, where model estimation and expert estimation are combined with weights that depend on model reliability (e.g., calibration and test-sample errors). The final output is a risk-driven forecast: the probability of failure in a given horizon, the expected frequency of events, and the expected downtime, along with the associated uncertainty. Such an output directly supports maintenance planning and risk assessment (procurement of spare parts, resource allocation, preventive activities), with a feedback loop that updates the framework with new data and periodic review of expert assessments.

3. Experimental Study

In this research, failures of a construction machine were analyzed. During a six-month continuous monitoring period, a total of 5345 unplanned failures were recorded, occurring across different components and caused by various factors (the observed machine operated in three shifts, in an open area). For the application of the hybrid framework, only failures caused by bucket tooth breakage on the excavator were selected, with a total of 78 such events identified. For this specific type of failure, a statistical analysis was conducted, along with the application of machine learning algorithms, in order to identify linear and nonlinear trends in the times between failures as well as in their duration.

Table 3 provides an overview of descriptive statistics, time-series forecasting results based on exponential smoothing (including parameter sensitivity analysis), linear regression outputs, and machine learning model performance, evaluated using standard error and goodness-of-fit metrics.

The results presented in Table 3 indicate that linear models do not exhibit satisfactory predictive performance, while nonlinear approaches show comparatively better performance; therefore, the analysis is further extended to explore more advanced modeling techniques and alternative approaches for improving prediction accuracy.

Lag-based forecast tables and a walk-forward test are also provided in the paper's Appendix A. Walk-forward evaluation for lag-based models (at least 80/20 by time) and the following day, seven days, and 30 days for FBT and DT. The best result was Random Forest(lag) with $R^2(\text{TBF}) = 0.092$, RMSE of 5525.6 min, and MAE of 454.9 min, which do not indicate good predictive indicators.

Furthermore, probabilistic modeling of the time between failure (TBF) and downtime (DT) with parametric distributions was conducted as an alternative to point forecasts, which showed poor predictive power. The parameters of the lognormal distribution for TBF and the gamma distribution for DT were estimated on the training sample, and then the 80% forecast interval (PI80) was derived. The results in Table 4 show that the achieved test coverage of PI80 is close to the nominal value (0.8125), which indicates an indicative (approximate) interval calibration. However, given the small test sample and the possibility of deviation of the actual process from the assumed distributions, the obtained intervals should be interpreted as indicative, intended for risk assessment and planning, and not as a precise determination of the time of the next breakage.

At the same time, point tests (BestByMAE) were performed on the test sample. MAE rankings show that more complex models do not consistently improve over simple baseline approaches, confirming that without additional contextual covariates, point prediction remains unreliable.

Based on the estimated distributions, a probabilistic risk assessment was performed in defined horizons (1/7/30 days) in Table 5, through the probability that the next breakage will occur within each horizon, as well as through the expected number of events and the total expected downtime in the observed period. This display is operationally relevant for planning spare parts and organizing interventions because, instead of a point value, it provides a quantified risk level and expected system load.

Due to the absence of sufficiently stable predictive indicators, which is a common situation in practice when stochastic events exhibit high variability, expert evaluations (chief maintenance engineer, shift chief, unit chief, operational planning, technologist/process engineer) were incorporated into the proposed framework. In Table 6, expert assessments of the influence of contextual factors on the prediction of TBF and DT are presented, and in Table 7, the weighting coefficients of the influence of individual influential factors are provided.

Table 3. Comparative overview of the performance of methods for estimating time between failure (TBF) and downtime (DT).

Metric	TBF (min)		Downtime (min)	
Mean	4471.154		66.34615	
Min	0		10	
Max	29,030		250	
Std Dev	5342.13		50.10676	
Coeff. of Variation	1.194799		0.755232	
SES Metric			Value	
Forecast TBF (min)			7430.163	
Forecast DT (min)			72.62401	
RMSE TBF (min)			4902.911	
RMSE DT (min)			47.1337	
Alpha TBF			0.108605	
Alpha DT			0.133692	
Series			Alpha	
Time Between Failures			0.108605	
Downtime Duration			0.133692	
Alpha	Forecast_TBF	RMSE_TBF	Forecast_DD	RMSE_DD
0.05	6745.374	5060.852	80.85248	48.06865
0.1	7433.917	4903.725	78.07128	47.22718
0.2	6947.148	5002.574	62.13612	47.34512
0.3	6411.864	5182.689	51.58586	48.12286
0.5	5655.2	5607.675	45.43528	50.50866
0.7	4831.653	6106.487	46.68446	53.7056
0.9	3886.576	6731.924	48.95117	57.78087
LP Metric			Value	
Forecast TBF (min)			9177.018	
Forecast Downtime (min)			102.992	
RMSE TBF (min)			4619.904	
RMSE Downtime (min)			45.54537	
R2 TBF			0.252111	
R2 Downtime			0.17378	
ML Model	MSE_TBF	R2_TBF	MSE_DD	R2_DD
Random Forest	6,620,154	0.768026	462.9093	0.815625
SVR	28,551,201	−0.00045	660.2456	0.737026
Decision Tree	3,284,253	0.884918	155.4487	0.938085
KNN	13,595,514	0.523606	1166.774	0.535277
XGBoost	3,378,709	0.881608	159.8278	0.936341

Table 4. Parametric forecast intervals (PI80) and coverage on the test sample.

Series	Dist	Median	PI80_Low	PI80_High	PI80_Coverage_Test
TBF	Lognormal	1585.543	233.2734	10,776.83	0.8125
DT	Gamma	52.37576	18.19511	115.2983	0.8125

Table 5. Probabilistic risk assessment (breakage in the horizon) and expected number of breakages and total downtime.

Horizon	h (min)	P (Breakage in the Horizon)	Expected Number of Breakages in the Period	Expected Total Downtime (min)
1 day	1440	0.397 (39.7%)	0.227	15.0
7 days	10,080	0.854 (85.4%)	1.586	105.2
30 days	43,200	0.979 (97.9%)	6.796	450.9

Table 6. Expert evaluation of contextual factors.

Factors	Expert 1		Expert 2		Expert 3		Expert 4		Expert 5		TBF	DT
	TBF	DT	TBF	DT	TBF	DT	TBF	DT	TBF	DT		
Maintenance	0.92	0.95	0.9	1.05	0.94	0.98	0.88	1.1	0.93	1	0.91 ± 0.02	1.02 ± 0.06
Operational Condition	0.93	1.08	0.95	1.08	0.9	1.12	0.92	1.05	0.96	1.03	0.93 ± 0.02	1.07 ± 0.03
Human factor	0.99	1.02	0.97	1.05	1.01	1	0.96	1.08	0.98	1.02	0.98 ± 0.02	1.03 ± 0.03
Technical factor	1.04	1.15	1.06	1.12	1.02	1.18	1.08	1.1	1.05	1.14	1.05 ± 0.02	1.14 ± 0.03
External factor	0.91	1.2	0.88	1.25	0.93	1.15	0.9	1.22	0.86	1.28	0.9 ± 0.03	1.22 ± 0.05

Table 7. Weight coefficients for contextual factors.

Factors	TBF	DT
Maintenance	0.2	0.3
Operational Condition	0.3	0.1
Human factor	0.2	0.3
Technical factor	0.2	0.2
External factor	0.1	0.1

Figure 2 presents the contextual TBF and DT prediction model for the specific case of the observed machine.

The aggregated assessment was obtained in three steps: the derived probabilistic risk assessment from historical data was cross-referenced with the consensus of five experts (chief maintenance engineer, shift chief, unit chief, operational planning, and technologist/process engineer), whereby greater weight was assigned to expert assessments due to the limited predictive stability of the prediction models under conditions of high stochastic variability. In this aggregation, a pre-defined weight $\lambda = 0.3$ for data-based assessment and $1 - \lambda = 0.7$ for expert assessment, because the prediction models (SES, LR, and ML) in validation showed weak predictive power and inconsistent improvement compared to simple baseline approaches, so it was justified that expert knowledge has a dominant role in the assessment. The final result was corrected by contextual factors (operating conditions, maintenance, human and external factors) through appropriate weighting

coefficients, which brought the frequency and duration of downtime into line with real working conditions.

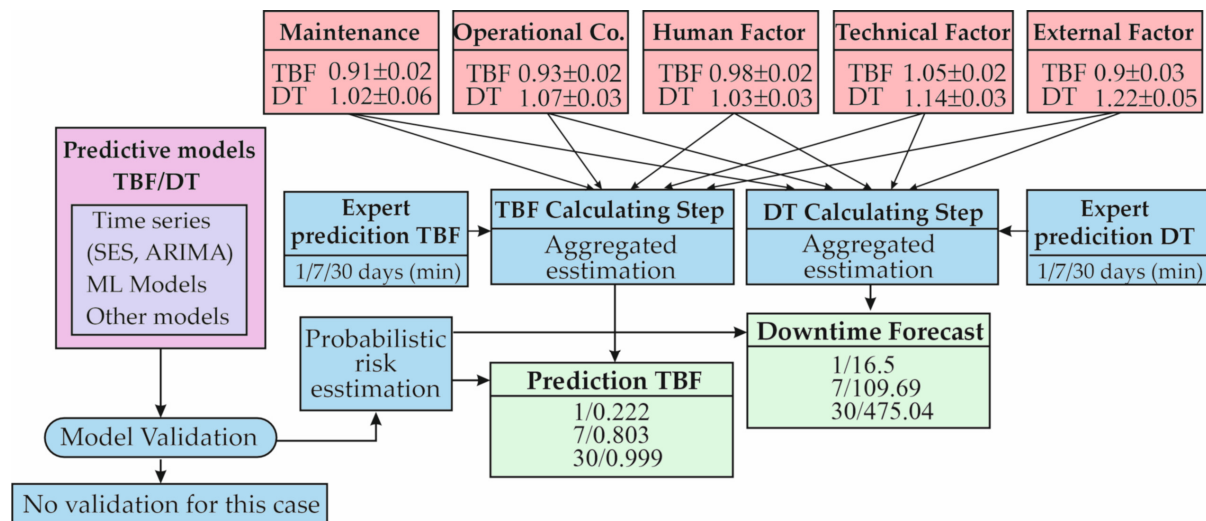


Figure 2. Contextual model for TBF I DT forecast.

The final forecast presented in Table 8 indicates that in the next 1 day the risk of breakage is 22.0%, 0.2 expected breakage events and a total of 16.8 min of downtime are expected; in the next 7 days, the risk of breakage is 80.3%, 1.6 breakages and a total of 109.7 min of downtime are expected; in the next 30 days, the risk of breakage is 99.9%, 7.0 breakages and a total of 475.0 min of downtime are expected.

Table 8. Aggregated ratings.

Horizon	Rd	Nd	Re	Ne	R Final	N Final	DT Final (min)	D Final (min)
1 day	0.397	0.227	0.215	0.242	0.220	0.248	67.48	16.75
7 days	0.854	1.586	0.786	1.540	0.803	1.624	67.56	109.69
30 days	0.979	6.796	0.999	6.700	0.999	7.031	67.56	475.04

Where are: Rd—The probability that a breakage occurs in a given horizon (from a probabilistic model). Nd—Expected number of breakages from the data. Re—Breakage probability derived from expert frequency estimation. Ne—Expected number of breakages according to experts. R final—Aggregated (final) probability of a breakage occurring at a given horizon. N final—Aggregated expected number of breakages. DT final (min)—Final expected duration of one breakage (in minutes). D final (min)—Final total expected downtime in the period.

The contextual model was additionally tested by retrospective validation on historical events, applying the approach of backtesting on unseen historical events. As part of the validation procedure, the analysis was performed on all available cross-sections of the time series, where the events following each cross-section were used to compare the forecasted and the actual registered values of the failure.

Within the validation procedure, a comparison of the percentage deviations of the predicted time between failures (TBF) and downtime duration (DT) values obtained using the probabilistic and contextual models was performed with respect to the actually recorded values of the subsequent event, where the analysis was conducted over all possible time series cut points. The resulting comparative error metrics are summarized in Appendix A, Table A1.

After that, an additional comparative analysis was conducted, which, in addition to probabilistic and contextual models, also included machine learning models in order to assess their accuracy in forecasting the next event. The frequency with which each approach achieved the lowest prediction error across validation cuts is presented

in Appendix A, Table A2. Key excerpts of the Python code used in the analyses are provided in Appendix A. The analyses were performed using Python 3.12.3 (Python Software Foundation, Wilmington, DE, USA).

The obtained results indicate that the contextual model achieves the greatest contribution in the estimation of the downtime (DT), especially in the conditions of a limited historical sample, whereby in approximately 69% of the analyzed sections it achieved a smaller deviation from the base probabilistic model (Appendix A, Table A3). On the other hand, when estimating the time between failures (TBF), the contextual model achieved smaller deviations in approximately 24% of the sections (Appendix A, Table A3), which confirms that the occurrence of the next failure retains a dominantly stochastic character. The validation results (Appendix A, Table A1) also show that the machine learning models achieve the highest forecast accuracy when more historical data is available, with the average DT size forecast error reduced from approximately 43% for the probabilistic and contextual model to approximately 23% for the best ML model. In this way, the proposed framework enables the complementary application of probabilistic analysis, contextual expert knowledge, and a data-driven approach in forecasting and interpretation of failures of industrial systems.

4. Conclusions

In this research, an analysis of the prediction of unplanned failures of a construction machine was conducted, with a special focus on tooth breakage on the excavator bucket. Standard statistical models of time series, linear regression, and various machine learning models were applied, with validation through a walk-forward approach and testing on a separate sample. However, the results showed that none of the applied models provided stable and reliable predictive performance, especially in terms of generalization and the accuracy of point forecasts. The high variability of the data and the limited number of events pointed to the inherent limitations of a purely data-driven approach in such conditions.

For this reason, a contextual model was developed that combines a probabilistic assessment of the probability of the occurrence of a failure based on historical data, a structured expert assessment, and correction through contextual factors. Aggregation was carried out by weighting data-driven and expert components, with additional adjustment through weighting coefficients that reflect operational, technical, and external working conditions. In this way, a unified assessment of the probability of breakage, the expected number of events, and the total downtime in the observed time horizons was obtained.

The obtained results represent a quantified assessment of time between failures (TBF) and downtime (DT), and a practically applicable tool for planning maintenance, organizing resources, and reducing operational losses under conditions of high stochastic uncertainty.

The advantages of the proposed contextual model are reflected in the possibility of including the operational context, expert knowledge, and real conditions of exploitation in the process of predicting failures and stoppages. Unlike classical statistical and data-driven approaches that predominantly rely on historical data and stable statistical patterns, the proposed model allows correction of estimates in conditions of high stochastic variability, a limited number of failure events, and changing working conditions. An additional advantage of the approach is that the proposed contextual model is not limited exclusively to TBF and DT parameters, but can also be applied to other types of operational and sensor signals relevant to system condition monitoring and predictive maintenance. The proposed approach is applicable in various industrial systems where the number of registered failures is small, data is discontinuous or highly variable, and decisions must be made despite limited information.

Despite the practical applicability of the proposed framework, several limitations of the method should be considered. The reliability of the methodology strongly depends on the quality, continuity, and representativeness of operational and maintenance records. In industrial systems, downtime events are often heterogeneous and conditioned by various technical, operational, and external factors, which is why a careful classification and selection of relevant types of failures is necessary before conducting the analysis. In addition, the small number of characteristic failure events and limited historical datasets can reduce the statistical stability of predictive models and probabilistic estimates.

A significant limitation of the proposed model also refers to the expert component of the methodology. Contextual factors, correction coefficients, and weighting structures are determined by expert judgment and therefore partly depend on operational experience, heuristic knowledge, and subjective interpretation of system behavior. For this reason, the proposed framework requires careful selection of experts, as well as periodic reevaluation of contextual factors and weighting coefficients in accordance with changes in working conditions and maintenance practices.

Further research can be directed towards improving knowledge about contextual models through the development and implementation of knowledge-based group decision support systems that would support expert evaluation of contextual influential factors, as well as the systematization of experiences, heuristic knowledge, and operational rules from different industrial systems. The acquisition of expert knowledge and its structured storage in knowledge bases within expert systems and other knowledge-based systems can be of particular importance, which would enable the formation of a broader set of contextual rules, patterns, and experiences associated with different types of failures and operational conditions.

Additional improvement is possible through the integration of artificial intelligence methods for automated analysis and updating of contextual factors, as well as through the development of intelligent systems capable of adaptive learning based on new operational data and previous failure events. Case-based information systems have a special potential that enables the storage and reuse of knowledge about previously analyzed sets of contextual factors, failure scenarios, and expert assessments, which would enable more efficient recognition of similar situations and improvement of the decision-making process within predictive maintenance.

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Appendix A

This appendix presents generalized validation matrices together with abbreviated Python code segments used to generate the key validation results reported in the manuscript.

Table A1. Comparative validation results of probabilistic, contextual, and machine learning approaches.

Validation Criterion	Probabilistic Model	Contextual Model	Best ML Model
Number of analyzed cuts for TBF	67	67	67
Mean TBF error (%)	132.21	128.77	124.94
Median TBF error (%)	79.42	79.83	27.83
Number of analyzed cuts for DT	68	68	68
Mean DT error (%)	43.07	43.41	22.80
Median DT error (%)	37.13	33.87	9.94

Abbreviated Python code used to generate Table A1 is provided below.

```
def comparison_metric(model_name, tbf_col, dt_col):
    valid_tbf = validation_results.dropna(
        subset=[tbf_col]
    )
    valid_dt = validation_results.dropna(
        subset=[dt_col]
    )
    return pd.DataFrame({
        'Metric': [...],
        'Value': [
            len(valid_tbf),
            valid_tbf[tbf_col].mean(),
            valid_tbf[tbf_col].median(),
            len(valid_dt),
            valid_dt[dt_col].mean(),
            valid_dt[dt_col].median()
        ]
    })
summary_error_comparison = pd.concat([
    comparison_metric(...),
    comparison_metric(...),
    comparison_metric(...)
])
```

Table A2. Frequency of best-performing model across validation cuts.

Method	Best TBF Count	Best TBF (%)	Best DT Count	Best DT (%)
Best ML model	51	75.00	54	79.41
Contextual model	14	20.59	3	4.41
Probabilistic model	3	4.41	11	16.18

Abbreviated Python code used to generate Table A2 is provided below.

```

best_method_rows = []
for _, row in validation_results.iterrows():
    tbf_errors = {
        'Probabilistic': row['Prob_TBF_error_%'],
        'Contextual': row['Context_TBF_error_%'],
        'Best ML model': row['Best_ML_TBF_error_%']
    }
    dt_errors = {
        'Probabilistic': row['Prob_DT_error_%'],
        'Contextual': row['Context_DT_error_%'],
        'Best ML model': row['Best_ML_DT_error_%']
    }
    best_method_rows.append({
        'Best_TBF_method': min(tbf_errors, key=tbf_errors.get),
        'Best_DT_method': min(dt_errors, key=dt_errors.get)
    })
best_method_df = pd.DataFrame(best_method_rows)
best_tbf_counts = best_method_df['Best_TBF_method'].value_counts()
best_dt_counts = best_method_df['Best_DT_method'].value_counts()
best_method_counts = pd.DataFrame({
    'Best_TBF_count': best_tbf_counts,
    'Best_DT_count': best_dt_counts
}).fillna(0)
best_method_counts['Best_TBF_percentage'] = (
    best_method_counts['Best_TBF_count'] /
    len(validation_results) * 100
)
best_method_counts['Best_DT_percentage'] = (
    best_method_counts['Best_DT_count'] /
    len(validation_results) * 100
)

```

Table A3. Comparison of contextual and probabilistic models across validation cuts.

Criterion	Value
Number of TBF cuts where the contextual model outperformed the probabilistic model	16
Percentage of TBF cuts where the contextual model outperformed the probabilistic model (%)	23.88
Number of DT cuts where the contextual model outperformed the probabilistic model	47
Percentage of DT cuts where the contextual model outperformed the probabilistic model (%)	69.12

Abbreviated Python code used to generate Table A3 is provided below.

```

    tbf_context_better = (
        validation_results['Context_TBF_error_%'] <
        validation_results['Prob_TBF_error_%']
    ).sum()

    dt_context_better = (
        validation_results['Context_DT_error_%'] <
        validation_results['Prob_DT_error_%']
    ).sum()

    summary_context_vs_prob = pd.DataFrame({
        'Metric': [
            'TBF cuts where contextual model outperformed probabilistic model',
            'TBF percentage (%)',
            'DT cuts where contextual model outperformed probabilistic model',
            'DT percentage (%)'
        ],
        'Value': [
            tbf_context_better,
            tbf_context_better/67 * 100,
            dt_context_better,
            dt_context_better/68 * 100
        ]
    })

```

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