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IMPLEMENTATION OF A PREDICTIVE MAINTENANCE SYSTEM
IN AN AUTOMOTIVE ENTERPRISE: ECONOMIC IMPACT AND
PRODUCTION RESULTS

D.T. Aldasheva¹, O.S. Salykova², K.S. Maulenov², G.M. Baenova^{3*}

¹*Kostanay Engineering and Economics University named after M. Dulatov,
Kostanay, Kazakhstan*

²*Akhmet Baitursynuly Kostanay Regional University, Kostanay, Kazakhstan*

^{3*}*L.N. Gumilyov Eurasian National University, Astana, Kazakhstan*

**Corresponding author: baenova_gm@enu.kz*

Abstract

The article presents the results of the pilot implementation of the predictive equipment maintenance system at the SaryarkaAvtoProm LLP automotive industry enterprise. The system is based on an ensemble of machine learning algorithms trained on multichannel sensor data (vibration, temperature, pressure, flow rate of process fluids) and failure logs. The prototype of the online monitoring system was integrated with two priority assembly lines of the machine assembly shop (engine and transmission units).

For two months, the system analyzed sensor data streams in real time and generated warnings when the failure probability threshold of 0.7 was exceeded. During this period, 14 alarm notifications were generated, nine of which corresponded to the actual pre-failure conditions of the equipment, and in five cases pronounced signs of wear were detected, eliminated as part of scheduled repairs. It is shown that the introduction of a predictive maintenance system has reduced total maintenance costs from 1,000,000 to 720,000 conventional units (savings of about 28%) and reduced the duration of unplanned downtime from 340 to 200 hours (a decrease of $\approx 41\%$). The economic impact factors are analyzed: advance planning of repairs, reduction of the number of emergency situations, optimization of stocks and reduction of the volume of emergency purchases.

The pilot implemented sensor-data acquisition and preprocessing, ensemble-based risk estimation, an alert interface, and feature-contribution explanations. Digital twins and federated learning were not part of the experimental system and are considered only as directions for future scaling.

Keywords: Predictive maintenance, machine learning, online monitoring, economic efficiency, downtime, automotive industry, sensor monitoring.

**АВТОМОБИЛЬ КӘСІПОРНЫНДА БОЛЖАМДЫ ҚЫЗМЕТ КӨРСЕТУ
ЖҮЙЕСІН ЕНГІЗУ: ЭКОНОМИКАЛЫҚ ТИІМДІЛІК ЖӘНЕ
ӨНДІРІСТІК НӘТИЖЕЛЕР**

Алдашева Д.Т.¹, Салыкова О.С.², Мауленов Қ.С.², Баенова Г.М.^{3*}

¹*М. Дулатов атындағы Қостанай инженерлік-экономикалық университеті,
Қостанай, Қазақстан*

²*Ахмет Байтұрсынұлы атындағы Қостанай Өңірлік университеті,
Қостанай, Қазақстан*

^{3*}*Л.Н. Гумилев атындағы Еуразия ұлттық университеті, Астана, Қазақстан*
**Хат-хабар үшін автор: baenova_gm@enu.kz*

Аңдатпа

Мақалада SaryarkaAvtoProm LLP автомобиль өнеркәсібі кәсіпорнында жабдыққа болжамды қызмет көрсету жүйесін тәжірибелік-өнеркәсіптік енгізу нәтижелері келтірілген. Жүйе көп арналы сенсорлық деректерде (діріл, температура, қысым, технологиялық сұйықтықтарды тұтыну) және сәтсіздік журналдарында оқытылған Машиналық оқыту алгоритмдерінің ансамбліне негізделген. Онлайн мониторинг жүйесінің прототипі Механикалық құрастыру цехының екі басым құрастыру желісімен (қозғалтқыш және трансмиссия тораптары) біріктірілген.

Екі айдың ішінде нақты уақыттағы жүйе сенсорлық деректер ағындарын талдап, сәтсіздік ықтималдығы шегі 0,7-ден асқан кезде ескертулер жасады. Көрсетілген кезеңде 14 дабыл хабарламасы жасалды, олардың тоғызы жабдықтың нақты алдын ала болжанған жай-күйіне сәйкес келді, ал бес жағдайда жоспарлы жөндеу шеңберінде жойылған тозудың айқын белгілері анықталды. Болжалды қызмет көрсету жүйесін енгізу жалпы қызмет көрсету шығындарын 1 000 000-нан 720 000 шартты бірлікке дейін төмендетуге (шамамен 28% үнемдеу) және жоспарланбаған тоқтап қалу ұзақтығын 340-тан 200 сағатқа дейін қысқартуға мүмкіндік берді (≈41% төмендеу). Экономикалық әсер факторлары талданады: жөндеуді алдын-ала жоспарлау, Төтенше жағдайлар санының төмендеуі, қойма қорларын оңтайландыру және шұғыл сатып алу көлемінің төмендеуі.

Пилот шеңберінде сенсорлық деректерді жинау және алдын ала өңдеу, ансамбльдік тәуекелді бағалау, хабарландыру интерфейсі және белгілер үлесін көрсету іске асырылды. Цифрлық егіздер мен федеративті оқыту эксперименттік жүйеге кірген жоқ және жүйені болашақта масштабтау бағыттары ретінде ғана қарастырылады.

Кілт сөздер: Болжалды қызмет көрсету, машиналық оқыту, онлайн бақылау, экономикалық тиімділік, тоқтап қалу, автомобиль өнеркәсібі, сенсорлық бақылау.

**ВНЕДРЕНИЕ СИСТЕМЫ ПРЕДИКТИВНОГО ОБСЛУЖИВАНИЯ
НА АВТОМОБИЛЬНОМ ПРЕДПРИЯТИИ: ЭКОНОМИЧЕСКИЙ ЭФФЕКТ И
ПРОИЗВОДСТВЕННЫЕ РЕЗУЛЬТАТЫ**

Алдашева Д.Т.¹, Салыкова О.С.², Мауленов Қ.С.², Баенова Г.М.^{3*}

¹*Қостанайский инженерно-экономический университет им. М. Дулатова,
Қостанай, Казахстан*

²*Қостанайский региональный университет имени Ахмет Байтұрсынұлы,
Қостанай, Казахстан*

^{3*}*Евразийский национальный университет им. Л.Н. Гумилева, Астана, Казахстан*
**Автор-корреспондент: baenova_gm@enu.kz*

Аннотация

В статье представлены результаты опытно-промышленного внедрения системы предиктивного обслуживания оборудования на предприятии автомобильной промышленности SaryarkaAvtoProm LLP. В основу системы положен ансамбль алгоритмов машинного обучения, обученных на многоканальных сенсорных данных (вибрация, температура, давление, расход технологических жидкостей) и журналах

отказов. Прототип системы онлайн-мониторинга был интегрирован с двумя приоритетными сборочными линиями механосборочного цеха (двигательные и трансмиссионные узлы).

В течение двух месяцев система в реальном времени анализировала потоки сенсорных данных и формировала предупреждения при превышении порога вероятности отказа 0,7. За указанный период сгенерировано 14 тревожных уведомлений, девять из которых соответствовали реально предотказным состояниям оборудования, а в пяти случаях были выявлены выраженные признаки износа, устраненные в рамках плановых ремонтов. Показано, что внедрение системы предиктивного обслуживания позволило снизить суммарные затраты на обслуживание с 1 000 000 до 720 000 условных единиц (экономия порядка 28 %) и сократить длительность незапланированных простоев с 340 до 200 часов (уменьшение на ≈41%). Анализируются факторы экономического эффекта: заблаговременное планирование ремонтов, снижение количества аварийных ситуаций, оптимизация складских запасов и уменьшение объема экстренных закупок.

В рамках пилота были реализованы сбор и предобработка сенсорных данных, ансамблевая оценка риска, интерфейс оповещений и представление вклада признаков. Цифровые двойники и федеративное обучение в экспериментальную систему не входили и рассматриваются только как направления дальнейшего масштабирования.

Ключевые слова: предиктивное обслуживание, машинное обучение, онлайн-мониторинг, экономическая эффективность, простой, автомобильная промышленность, сенсорный мониторинг.

Introduction

For an automotive assembly shop, equipment reliability is not an abstract technical indicator: a single stop on a critical line can interrupt the planned output of engine or transmission units. At SaryarkaAvtoProm LLP, this problem was considered together with the cost of emergency repairs, loss of production time and the need to keep maintenance work within scheduled windows. Preventive maintenance alone does not always detect the beginning of degradation, while reactive repair records the problem only after it has already affected the line.

The ICT basis for solving this task is the continuous use of industrial sensor data. Vibration, temperature, pressure and flow-rate measurements can be processed as time series and converted into diagnostic features for decision support. In this sense, Industry 4.0 technologies, IIoT infrastructure and data analytics are used here not as a general digitalization background, but as the information layer that links equipment condition, failure logs and maintenance decisions.

Published studies on predictive maintenance show that data-driven maintenance can reduce the losses associated with unplanned stops and poorly timed repairs [1-3]. The main mechanism is practical: sensor streams are analyzed to detect anomalies, classify pre-failure states and estimate the remaining useful life of components [4-6]. AI-based analysis of IIoT data has been used both for predictive-maintenance decisions and for operational monitoring of connected transport systems [7, 8]. In maintenance applications, warnings issued before complete failure support earlier diagnostics and repair planning [7].

This logic is especially important for automotive production. Assembly operations are tightly connected, and the failure of one drive, bearing unit, hydraulic element or gearbox may stop not only a local machine but also the following operations in the chain. Therefore, the article treats early diagnosis as a production-data task: the system must recognize the beginning of degradation early enough for the repair team to react without creating a new production bottleneck.

The transition to PdM is relevant in automotive production because machine-learning-based maintenance cases must satisfy reliability, safety and production-continuity requirements

at the same time [20]. Studies on prognostics and health management report that condition-based diagnostics can improve equipment availability and reduce maintenance costs [9]. Research on optimization and machine learning in automotive manufacturing also shows that maintenance decisions are increasingly linked with production planning rather than considered separately [10].

For online use, the speed and location of data processing are important. Edge analytics and workshop-level preprocessing reduce the delay between a sensor change and a warning in the interface [11]. Similar fault-detection tasks have been reported for industrial autonomous transporters and automobile engines [12, 13], and neural-network models are also used in related diagnostics of vehicles and infrastructure [14].

Several research directions are relevant to later scaling. Federated learning allows sites to improve models without transferring raw operational data [15]. Explainable AI is also relevant because engineers need to know why a warning was generated and which signals influenced it [16]. Digital twins can support equipment condition assessment, fault prediction, and predictive maintenance planning [17]. In this pilot, the interface displayed feature contributions, risk trajectories, and links between alerts and maintenance-log events; digital twins and federated learning were not implemented.

The economic result of PdM is formed mainly at the moment when an emergency stop is replaced by planned work. For this reason, the assessment in the article includes not only the cost of repair operations, but also production losses during downtime, urgent procurement and overtime work of maintenance teams.

Although the literature on PdM is extensive, many papers remain at the level of models trained on historical datasets. Fewer studies describe what happens after a model is placed into an operating production circuit and begins to generate warnings for real maintenance personnel. This gap is the reason for focusing the article on pilot operation, not only on algorithm training.

The ensemble machine learning models used in this study were developed and trained at an earlier stage of the project using multichannel sensor data. This study focuses on the practical implementation of these models in a real automotive production environment, describing system architecture, online monitoring operations, operational and economic outcomes, organizational integration, and prospects for scaling.

The purpose of this article is to evaluate the effectiveness of implementing a predictive maintenance system at SaryarkaAvtoProm LLP based on an analysis of operational and economic indicators, as well as to identify organizational and technological factors influencing the success of integrating such systems into the production circuit of an automotive enterprise.

The study is positioned within the field of information and communication technologies, specifically at the intersection of Data Science, Applied Artificial Intelligence, Industrial IoT, and Smart Manufacturing. The ICT contribution lies not only in the use of machine learning algorithms, but also in the integration of sensor data acquisition, online preprocessing, decision-support software, and interpretable alert generation in a real production environment.

To achieve the stated purpose, the following research tasks were addressed: (1) to describe the architecture of the predictive maintenance system; (2) to formalize the data flows and machine learning models used for online monitoring; (3) to evaluate warning quality during trial operation; (4) to assess the economic effect of the predictive strategy compared with reactive maintenance; and (5) to identify organizational, technological and methodological limitations for further scaling.

Scientific novelty of the study

For this study, the engineering and applied novelty is defined by four points: (1) an ICT architecture for PdM was deployed in a real automotive assembly environment; (2) Random Forest, gradient boosting and CNN-LSTM outputs were combined for multichannel industrial sensor streams; (3) the models were tested in continuous online monitoring, not only on archived data; and (4) diagnostic results were connected with maintenance costs and downtime, which made it possible to evaluate the system by both technical and economic indicators.

Materials and methods of research

The object of the research is the maintenance process for critical equipment of an automotive mechanical assembly shop. The subject of the research is a data-driven method for predicting pre-failure equipment states based on multichannel sensor data and machine learning models.

The study is experimental and data-driven: it combines industrial sensor monitoring, machine learning validation and a production-economic assessment of the pilot implementation. The computational implementation was prepared in Python using standard data-analysis and machine learning tools: pandas and NumPy for preprocessing, scikit-learn for Random Forest and metric calculation, XGBoost/LightGBM for gradient boosting, and TensorFlow/Keras for the CNN-LSTM model. The online monitoring prototype was integrated with the enterprise sensor infrastructure and notification interface.

Only aggregated operational indicators and anonymized event descriptions were released for publication. Raw sensor streams, detailed maintenance logs, implementation costs, and asset identifiers remain inside the enterprise information system; this limits independent reproduction of the numerical results.

Experimental scope. The pilot covered two priority assembly lines for engine and transmission units in the mechanical assembly shop. The monitored contour included selected bearings, gearboxes, hydraulic cylinders, and drive mechanisms rather than the entire plant. Four sensor modalities were processed: vibration, temperature, pressure, and process-fluid flow. Features were calculated over 30-second and 5-minute windows, the risk estimate was updated every 60 seconds, and online operation lasted two months. Sensor coverage varied by equipment unit; to avoid identifying individual assets, the contour is reported only in aggregate.

The predictive maintenance system comprises four interrelated components:

Data Collection Subsystem. Vibration, temperature, pressure, and process fluid flow sensors were installed on critical equipment components (bearings, gearboxes, hydraulic cylinders, and drive mechanisms). High-frequency vibration signals were captured with minimal delay, while temperature and pressure readings were collected less frequently but provided essential context for condition assessment. All data were timestamped and transmitted to a centralized processing unit.

Preprocessing and Aggregation Module. This module filters outliers, restores isolated gaps, synchronizes timestamps, and computes aggregated features over fixed time windows (30 seconds and 5 minutes). Feature normalization and logarithmic transformation are applied as needed to mitigate scale differences.

Computational Module with Ensemble Models. Equipment failure predictions are generated by an ensemble of three models:

- Random Forest for tabular aggregated features;
- Gradient Boosting (XGBoost/LightGBM) to capture nonlinear interactions;
- hybrid CNN and LSTM Neural Network for analysis of raw vibration time series.

Each model outputs the probability of a component being in a pre-failure state. In the deployed ensemble, the three model probabilities were combined by averaging to form the integrated prediction used by the notification system.

User Interface and Notification System. The interface displays aggregated indicators by production line, forecast history, and current risk levels for each component. If the integrated probability exceeds a threshold of 0.7, the system generates an alert for the maintenance team, specifying the component and the type of potential failure.

Historical monitoring data from the equipment of the SaryarkaAvtoProm LLP mechanical assembly plant was used to train and test machine learning models. The observations included multi-channel time series generated by sensors for vibration, temperature, pressure, and flow of process fluids.

Data collection was carried out continuously during the long period of operation of the equipment. The frequency of registration of vibration signals was up to several kilohertz, while the temperature and pressure parameters were recorded with a lower frequency.

The database included several million time-series observations and maintenance-log records describing failures and repair actions. The logs were used to label normal and pre-failure conditions. The enterprise did not release the numbers of training and test windows, the class distribution, or the count of historical failure episodes, so sample-level replication is not possible.

The forecast update rate was 60 seconds, reflecting the actual frequency of sensor data input and the allowable calculation delay. The alarm threshold was set at 0.7: if the integral probability of failure issued by the ensemble exceeded this threshold, the system classified the equipment condition as critical and generated a notification indicating the specific node and the type of possible malfunction.

The models were trained on labelled historical data containing normal operating modes and intervals preceding documented failures. The validation scheme consisted of a training sample and a held-out test sample; no separate fixed validation subset was used. Hyperparameters were selected by cross-validation within the training sample, after which the ensemble was evaluated on the held-out test sample.

Aggregated statistical features based on time windows of observations were used for Random Forest and gradient boosting models. The neural network model of CNN and LSTM was trained directly on the initial time series of vibration signals, which made it possible to take into account time dependencies and characteristic patterns of equipment degradation.

Hyperparameters were selected by cross-validation within the training sample, and the final ensemble was formed by averaging the three model probabilities.

The alarm threshold of 0.7 was selected during validation as an operational, risk-oriented compromise between missed failures and redundant diagnostics. It was not derived from a separately reported optimization across multiple threshold values. Because a false negative may cause emergency downtime, component destruction, or cascading damage, the selected operating point prioritizes Recall while keeping the alert volume manageable for maintenance personnel. The metrics reported below therefore apply only to the 0.7 operating threshold.

Table 1. The main features used in the models

Feature group	Examples
Vibration parameters	RMS vibration, spectral energy
Temperature parameters	Average temperature, temperature gradient
Pressure parameters	Average pressure, dispersion
Operating parameters	Equipment load mode

To increase the information content of the models, a set of statistical and spectral features was formed from the initial signals, shown in Table 1.

During the experiment, the system operated in continuous online monitoring mode, analyzing incoming sensor data and making predictions about the technical condition of the equipment. Information about the warnings was transmitted to the repair and maintenance service of the enterprise, where decisions were made on additional diagnostics or planning repairs.

The trial operation of the system was carried out for two months under real enterprise conditions. During this period, the system generated 14 alarm notifications on the monitored lines. Subsequent analysis revealed the following:

- 9 notifications were found to be correct: during emergency diagnostics of the equipment, pre-emergency conditions were recorded (abnormal vibration growth, steady overheating of certain components, pressure instability in the hydraulic system, etc.). Timely intervention prevented the development of failures and avoided a complete shutdown of the line.

- 5 notifications did not lead to immediate failures; however, during the planned disassembly of the units, noticeable signs of wear were revealed (developed bearing defects, early signs of gear damage, etc.). The replacement or restoration of components was carried out within the framework of pre-planned stops, which minimized the impact of repair work on the overall production schedule.

The five warnings that did not end in immediate failure were still useful for maintenance planning: inspection during planned stops revealed early wear in the corresponding units. In this setting, a moderate number of additional warnings is acceptable because the cost of missing a real failure is higher than the cost of checking a component during scheduled maintenance.

Table 2. System activation results

Type of operation	Quantity	Share
Confirmed pre-failure states	9	64%
Early signs of wear	5	36%
Total warnings	14	100%

Of the 14 warnings summarized in Table 2, nine corresponded to confirmed pre-failure conditions. This supports the ability of the ensemble to detect early signs of equipment degradation.

According to reviews from engineering and technical staff, early warnings allowed:

- more flexible planning of maintenance work and distribution of workload among repair teams;
- reduction of stress on staff associated with emergency situations;
- reduction of the risk of cascading damage to neighboring equipment components.

In terms of the quality of the algorithms, the main classification quality metrics were calculated to quantify the effectiveness of the system. Based on the results of trial operation, the following indicators were obtained: Precision – 0.64, Recall – 1.0, F1-score – 0.78. A high Recall value indicates the system's ability to detect almost all potentially dangerous equipment conditions, which is critically important for industrial diagnostics tasks.

The relationship between Precision and Recall should be interpreted in the context of industrial risk management. For the pilot metrics, a warning linked to a documented pre-failure state was treated as a positive prediction; a warning that revealed wear but was not followed by an immediate pre-failure event was not counted as a confirmed positive, although it remained operationally useful. Precision of 0.64 indicates that 9 of 14 alerts corresponded to confirmed pre-failure states, while Recall of 1.0 means that no confirmed dangerous event documented during the pilot interval was missed. With only 14 alerts, the Wilson 95% confidence interval for Precision is approximately 0.39-0.84; the metric is therefore a pilot estimate rather than a definitive long-term value.

The ensemble decision logic was also compared with simpler approaches used in maintenance practice. A single threshold rule based only on vibration or temperature is transparent but reacts poorly to combined weak signals and transient operating modes. Individual machine learning models are more flexible, but Random Forest and gradient boosting mainly process aggregated windows, whereas CNN-LSTM captures temporal vibration patterns. Combining their outputs was intended to reduce model-specific errors and to provide a more stable warning logic under heterogeneous sensor data.

The production interface retained integrated ensemble alerts and their explanations, but not synchronized outputs from each component model. A retrospective comparison of model-level Precision, Recall, and F1-score would therefore be unreliable. The next validation stage should log all component-model outputs against a common held-out benchmark; the pilot metrics reported here apply only to the deployed ensemble.

For this type of industrial task, redundant warnings are less damaging than missed failures. Additional diagnostics require time, but a false negative may lead to line stoppage, emergency procurement and cascading damage. The selected strategy therefore gives priority to completeness of pre-failure detection, while the number of warnings remains low enough for maintenance personnel to process them manually.

Assessment of economic efficiency

To quantify the economic impact of transitioning to predictive maintenance, a comparative analysis of two strategies was conducted:

- reactive maintenance – repair after failure, previously used in the company;
- predictive maintenance – planning maintenance activities based on forecasts from an ensemble of models.

The calculation included:

- direct costs of planned and unplanned repairs;
- losses from unplanned downtime;
- additional expenses for urgent purchases and overtime work of maintenance personnel.

Table 3 presents enterprise-aggregated values calculated on the same comparison basis. Monetary values are expressed in conventional units because the underlying accounting records are confidential.

Table 3. Comparison of Maintenance Strategies

Service strategy	Total cost, conv. units	Unplanned downtime, h	Reduced downtime, %	Savings vs. reactive, %
Reactive maintenance	1 000 000	340	–	–
Predictive maintenance (ML ensemble)	720 000	200	≈ 41	≈ 28

Using the values in Table 3, total maintenance costs decreased by 280,000 conventional units (28.0%), while unplanned downtime was reduced by 140 hours (41.2%). These figures apply to the enterprise comparison used for the pilot and are not universal industry coefficients.

The key sources of savings were:

- advance planning of repairs. Thanks to the system's forecasts, maintenance activities were scheduled during periods of minimal line load, reducing the impact of shutdowns on the production program;

- reduction of emergency failures. Early detection of component degradation allowed major emergency repairs to be avoided, the cost of which typically far exceeds that of planned maintenance;

- inventory and procurement optimization. Advance information about upcoming part replacements enabled planning of purchases, avoiding emergency orders at inflated prices and reducing the volume of “frozen” stock;

- reduction of overtime and use of external contractors. Transitioning from reactive “fire-fighting” repairs to planned maintenance decreased the need for urgent work, further easing the burden on the enterprise's budget.

A model of total equipment maintenance costs was used to quantify the economic effect of implementing a predictive maintenance system. The total cost of operation can be represented by the following expression:

$$C_{\text{total}} = C_{\text{repair}} + C_{\text{downtime}} + C_{\text{inventory}} + C_{\text{emergency}} \quad (1)$$

where C_{repair} is the cost of repair work; C_{downtime} is losses related to the shutdown of the production line; $C_{\text{inventory}}$ is the cost of holding spare-parts inventory; $C_{\text{emergency}}$ includes urgent procurement, overtime work, and external contractors.

First-year ROI was used to relate the annual net operating benefit to the initial implementation investment:

$$\text{ROI}_{1y} = ((E_{\text{ann}} - C_{\text{impl}}) / C_{\text{impl}}) \times 100\% \quad (2)$$

Here, E_{ann} is the annual net operating benefit (gross savings minus recurring operating costs) before recovery of the initial investment, and C_{impl} is the one-time implementation cost. Equation (2) therefore gives first-year ROI. The payback period is:

$$T_{\text{payback}} = C_{\text{impl}} / E_{\text{ann}} \quad (3)$$

A payback period below one year requires $C_{\text{impl}} < E_{\text{ann}}$. Internal financial statements meet this condition, but the implementation and component-level cost data are confidential. The exact ROI and payback are therefore management-accounting estimates rather than

independently reproducible results. The released data support the observed cost difference of 280,000 conventional units and downtime difference of 140 hours.

The size of the economic effect depends on the cost of line downtime and on how intensively the equipment is used. In highly loaded automotive production, even a relatively small decrease in unplanned stops can give a noticeable financial result.

Organizational Aspects and Impact on Safety.

The practical implementation of the predictive maintenance system required several organizational changes:

- revision of interaction rules between operational and maintenance personnel;
- inclusion of system alarms in maintenance planning procedures;
- development of standard operating procedures (SOPs) for responding to high-risk failure notifications.

Engineers needed to see why an alert had been issued, a requirement also emphasized in work on explainable AI for predictive maintenance [16]. The implemented interface displayed:

- the contribution of key features (temperature, vibration along individual axes, pressure) to the ensemble's final forecast;
- the dynamics of the predicted probability of failure over time;
- the association of specific warnings with corresponding events in the maintenance logs.

Training sessions for engineering and technical personnel covered Precision, Recall, F1-score, and the response procedure for system alerts. The sessions linked model output with the maintenance decisions expected from staff.

From the perspective of industrial safety, the predictive system allowed:

- reduction of the likelihood of serious accidents involving component destruction and risks to personnel health;
- reduction of the likelihood of cascading damage, where failure of one unit leads to damage to several neighboring units;
- safer execution of maintenance activities by transferring them to scheduled windows and eliminating the urgency typical of emergency repairs.

The literature identifies accident prevention and reduction of critical incidents as important effects of PdM implementation [9, 19, 20]. The pilot results at SaryarkaAvtoProm LLP are consistent with this interpretation: early warnings did not eliminate the need for human diagnostics, but they gave repair teams more time to inspect risky components before emergency conditions developed.

Table 4. Comparison of PdM implementation results

Study	Cost reduction	Reduced downtime
Bucay-Valdiviezo et al., 2023	20–25%	≈30%
Meddaoui et al., 2024	≈30%	≈35%
This study	≈28%	≈41%

The data in Table 4 place the pilot results within the range reported in comparable PdM studies [2, 5]. The obtained cost reduction of about 28% and downtime reduction of about 41% do not by themselves prove universal applicability, but they support the practical relevance of machine-learning-based maintenance under the conditions of the monitored lines.

The study also has clear boundaries. The pilot covered only a limited number of production lines, and the two-month observation period is too short to describe seasonal load

changes or long-term ageing of equipment. In addition, not every unit was covered by the same set of sensors, which means that some failure modes could remain less visible to the model.

These limitations directly affect the transferability of the results: models trained on a narrow set of lines may reflect specific equipment modes, sensor placement and maintenance practices. Therefore, before deployment in other workshops or enterprises, the models should be recalibrated on local data and revalidated under new operating regimes. The obtained results should be interpreted as evidence of technical and economic feasibility rather than as a universal benchmark for all automotive enterprises.

Reproducibility is limited by undisclosed sample counts, asset-level sensor coverage, per-model alert logs, and implementation cost. These gaps do not change the recorded pilot outcomes, but they restrict statistical comparison and independent verification of payback.

Discussion and results

The pilot results are close to the ranges reported in the PdM literature, but their interpretation should remain cautious. In the present case, the economic effect was achieved because warnings were linked with actual maintenance planning: repairs could be moved to less loaded periods, and emergency interventions became less frequent. This connection between prediction and maintenance scheduling is more important than the isolated accuracy of the model.

The diagnostic quality of the proposed approach depends on the completeness of sensor coverage, the quality of failure-log annotation and the stability of operating regimes. Missing sensors, irregular maintenance records or changes in production load can shift the data distribution and reduce model generalizability. For this reason, periodic recalibration, monitoring of model drift and validation after major equipment changes should be treated as necessary elements of the PdM lifecycle.

The architecture used in the pilot also shows why local preprocessing is useful. If all raw signals are transferred without aggregation, the monitoring loop becomes slower and more difficult to maintain. Computing features at the workshop level and sending compact risk estimates to the interface is a more practical option for near-real-time maintenance decisions, especially for mobile or autonomous industrial equipment [11].

The remaining discussion concerns possible extensions, not components of the pilot. Digital twins, federated, transfer and reinforcement learning, added acoustic or visual inputs, and MES/ERP integration require separate validation.

The next development step is to connect the monitoring system with a digital twin of the production line. Such a model would make it possible to:

- conduct simulation experiments to assess the impact of various maintenance strategies;
- predict the consequences of failures without risking real equipment;
- optimize repair schedules based on production programs and resource availability.

Federated learning is another option for scaling, especially when several enterprises or sites operate similar equipment but cannot exchange raw data. In that case, each site can train on its own operational history, while the shared model receives only aggregated learning updates. For automotive enterprises, this is important because sensor logs, workloads and maintenance records may contain commercially sensitive information.

From a diagnostic perspective, additional data types can be integrated:

- acoustic signals, which have been successfully used to detect engine defects;
- data on road conditions and external operating environments, applied in similar tasks for predicting roadway degradation;
- video images and computer vision analysis for assessing wear of exposed components.

Further improvement of the system may also require transfer learning and reinforcement learning. Transfer learning can reduce the amount of new data needed when the model is moved to another line, while reinforcement learning may be used to select maintenance actions under resource constraints [4, 18, 19]. These methods should be tested carefully, because a scheduling model that is efficient in simulation may behave differently under real production interruptions.

At the enterprise level, PdM should eventually be connected with MES and ERP systems rather than remain a separate diagnostic dashboard. Such integration would allow warnings to influence spare-parts planning, repair-team workload and the production schedule. This is the point at which predictive maintenance begins to move toward prescriptive maintenance: the system not only reports risk, but also supports the choice of a repair window and resource allocation [4].

In the long term, this transition can change the role of the maintenance service from emergency response to planned lifecycle management of production equipment.

The SaryarkaAvtoProm LLP case should therefore be considered as a pilot implementation of industrial AI under real operating constraints. Its value lies not in replacing engineering expertise, but in showing how sensor data, model outputs and maintenance decisions can be joined in one operational workflow.

Conclusions

The study showed that machine learning methods can be used for predictive maintenance in an operating automotive production environment. The conclusions below correspond to the tasks stated in the introduction.

1) The proposed ICT architecture brings together sensor monitoring, preprocessing, ensemble models and an alert interface. In practice, this turns raw equipment signals into a decision-support tool for the maintenance service.

2) The ensemble based on Random Forest, gradient boosting and CNN-LSTM models detected early degradation patterns in multichannel data. During the two-month pilot, 14 warnings were generated; 9 were linked with confirmed pre-failure states, and 5 led to the detection of significant wear during scheduled maintenance.

3) The 0.7 alarm threshold was an operational, recall-oriented setting rather than the result of a separately reported threshold-optimization study. At this setting, the pilot metrics were Precision = 0.64, Recall = 1.0, and F1-score = 0.78, but the small number of observed events requires longer validation.

4) Compared with reactive maintenance on the reported enterprise comparison basis, the predictive strategy reduced total maintenance costs by 280,000 conventional units (28.0%) and unplanned downtime by 140 hours (41.2%). Because implementation cost data are confidential, the internal estimate of payback within one year is not presented as an independently reproducible result.

5) The implementation changed maintenance organization as well as diagnostics. Alerts were added to planning procedures, engineers received explanations of the model output, and earlier inspections reduced the probability of cascading equipment damage.

6) The article's applied contribution is the demonstration that PdM can be evaluated by a combined set of indicators: classification metrics, production downtime, maintenance costs and organizational effects. This gives a broader view than model accuracy alone.

7) Further work should extend the observation period, include more production lines, retain synchronized outputs from each component model, and add acoustic, visual, and environmental data. Digital twins, federated learning, transfer learning, and reinforcement

learning were not implemented in the present pilot and must be evaluated separately before they can be treated as system components.

The pilot supports machine-learning-based PdM as one component of industrial digital transformation. Its practical effect depends on sensor-data quality, maintenance-log discipline, and the enterprise's ability to incorporate model warnings into routine repair planning.

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Information about the authors

D.T. Aldasheva – Master of Pedagogical Sciences, senior teacher of the Department of Information Technology and Automation, Kostanay Engineering and Economics University named after M. Dulatov, Kostanay, Kazakhstan; e-mail: aldasheva.dinara@mail.ru; ORCID: 0009-0000-4990-4308;

O.S. Salykova – Candidate of Technical Sciences, Head of the Software Department, Akhmet Baitursynuly Kostanay Regional University Akhmet Baitursynuly, Kostanay, Kazakhstan; e-mail: solga0603@mail.ru; ORCID: 0000-0002-8681-4552;

K.S. Maulenov – PhD, Head of the Department of Digital Technologies and Artificial Intelligence, Akhmet Baitursynuly Kostanay Regional University, Kostanay, Kazakhstan; e-mail: k.maulenov070693@gmail.com; ORCID: 0000-0003-4147-3843;

G.M. Baenova – corresponding author, PhD, senior teacher of the Department of computer and software engineering, L.N. Gumilyov Eurasian National University, Astana, Kazakhstan; e-mail: baenova_gm@enu.kz; ORCID: 0009-0009-6191-458X.