METHOD FOR PREDICTING PRE-FAILURE STATES OF MICROELECTRONIC MANUFACTURING EQUIPMENT BASED ON DIGITAL TWIN AND INTELLIGENT ANALYSIS OF PROCESS PARAMETERS

Kyrylo Horovyi
Kharkiv National University of Radio Electronics
Ukraine, 61166, Kharkiv, Nauky Ave., 14
E-mail: kyrylo.horovyi@nure.ua

Annotation: The paper proposes a method for predicting pre-failure states of microelectronic manufacturing equipment based on Digital Twin technology and intelligent analysis of process parameters, providing equipment health monitoring, anomaly detection, and simulation of equipment degradation scenarios. The method employs machine learning models and time-series analysis to predict the probability of a pre-failure state, estimate the Remaining Useful Life (RUL), and calculate a dynamic risk index. The integration of prediction results with a decision support system and a continuous learning loop creates the prerequisites for a transition from reactive maintenance to proactive prediction and prevention of equipment failures.

Key words: Digital Twin; microelectronic manufacturing; pre-failure state; equipment health prediction; machine learning; Remaining Useful Life (RUL); dynamic risk index; predictive maintenance.

МЕТОД ПРОГНОЗУВАННЯ ПЕРЕДАВАРІЙНИХ СТАНІВ ОБЛАДНАННЯ МІКРОЕЛЕКТРОННОГО ВИРОБНИЦТВА НА ОСНОВІ DIGITAL TWIN ТА ІНТЕЛЕКТУАЛЬНОГО АНАЛІЗУ ТЕХНОЛОГІЧНИХ ПАРАМЕТРІВ

Кирило Горовий
Харківський національний університет радіоелектроніки
Україна, 61166, Харків, пр. Науки, 14
E-mail: kyrylo.horovyi@nure.ua

Анотація: У роботі запропоновано метод прогнозування передаварійних станів обладнання мікроелектронного виробництва на основі технології Digital Twin та інтелектуального аналізу технологічних параметрів, який забезпечує моніторинг технічного стану, виявлення аномалій і моделювання сценаріїв деградації обладнання. Метод передбачає застосування моделей машинного навчання та аналізу часових даних для прогнозування ймовірності передаварійного стану, оцінювання залишкового корисного ресурсу RUL і формування динамічного індексу ризику. Інтеграція результатів прогнозування із системою підтримки прийняття рішень і контуром безперервного навчання створює передумови для переходу від реактивного технічного обслуговування до проактивного прогнозування та попередження відмов обладнання.

Ключові слова: Digital Twin; мікроелектронне виробництво; передаварійний стан; прогнозування технічного стану; машинне навчання; залишковий корисний ресурс (RUL); динамічний індекс ризику; прогнозне технічне обслуговування.

The relevance of the research is determined by the need to improve the reliability and operational safety of high-precision microelectronic manufacturing equipment, whose failure may lead to disruptions in technological processes, deterioration of product quality, and the occurrence of emergency operating conditions. Traditional technical monitoring methods are primarily focused on detecting existing deviations, whereas modern manufacturing requires early prediction of the transition of equipment from a normal to a pre-failure state. The use of Digital Twin technology provides continuous representation of the current state of physical equipment in a digital environment and enables simulation of its behavior under various combinations of process parameters and external influences. The integration of the Digital Twin with intelligent data analysis methods makes it possible to identify hidden patterns and anomalous changes in parameters, assess the dynamics of equipment health, and predict the probability of critical deviations. The development of such a method creates the prerequisites for a transition from reactive maintenance to predictive maintenance and proactive prevention of pre-failure states in microelectronic manufacturing equipment. The structural diagram of the method for predicting pre-failure states of microelectronic manufacturing equipment based on Digital Twin is presented in Figure 1.

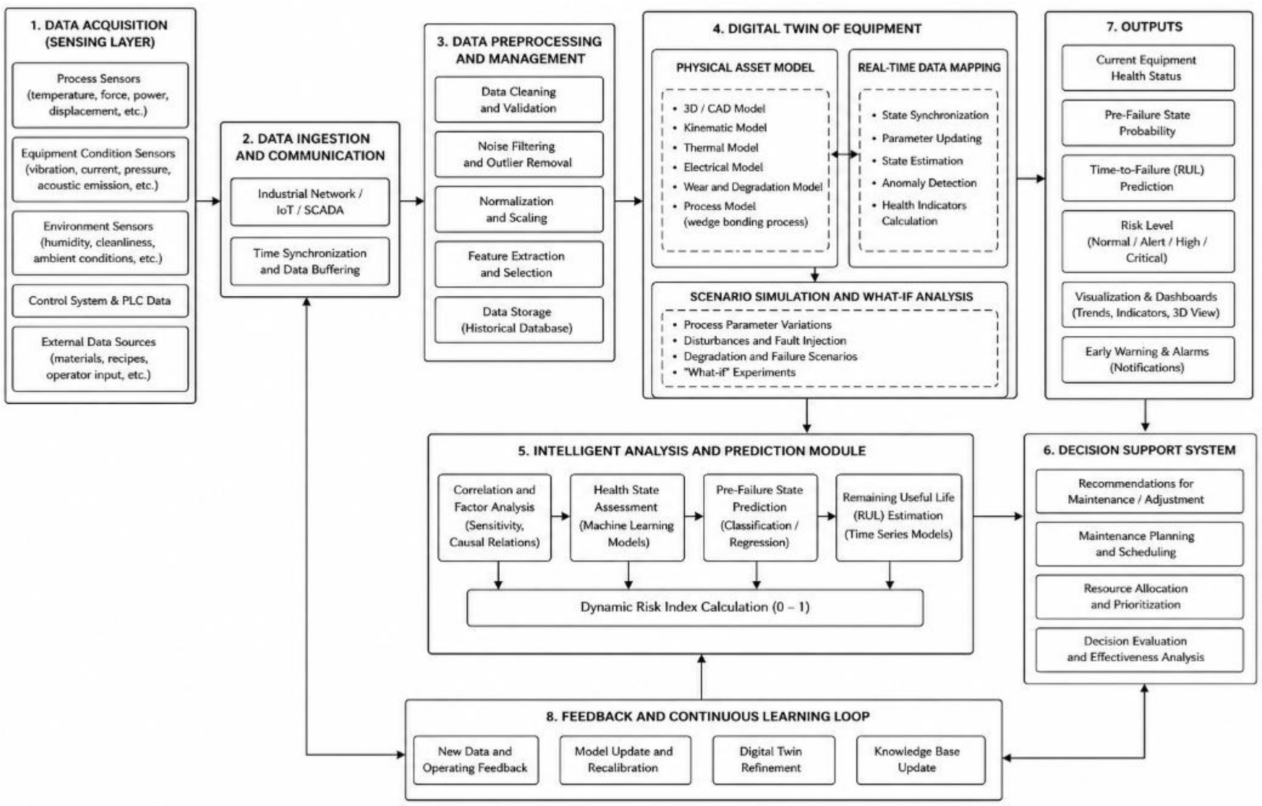

Figure 1 – Structural Diagram of the Method for Predicting Pre-Failure States of Microelectronic Manufacturing Equipment Based on Digital Twin

The operating principle of the method for predicting pre-failure states of microelectronic manufacturing equipment based on Digital Twin (Fig. 1) is based on the continuous acquisition, processing, and intelligent analysis of process parameters, followed by prediction of changes in the equipment health state. The Data Acquisition (Sensing Layer) block provides primary data from process sensors monitoring temperature, force, power, and displacement; condition-monitoring sensors measuring vibration, current, pressure, and acoustic emission; environmental sensors; the control system and PLC; as well as external information sources concerning materials, process recipes, and operator actions. The Data Ingestion and Communication block is designed to transmit the acquired information through an industrial network, IoT, or SCADA infrastructure and provides time synchronization and buffering of data streams required to form a consistent time sequence of process parameters. The Data Preprocessing and Management block performs data validation and cleaning, noise filtering and outlier removal, parameter normalization, and extraction and selection of informative features, after which the processed data are stored in a historical database for further analysis and model training. The central component of the method is the Digital Twin of Equipment block, which creates an up-to-date digital representation of the physical equipment and ensures its synchronization with the actual technological process. The Physical Asset Model component integrates 3D/CAD, kinematic, thermal, and electrical models, equipment wear and degradation models, as well as a technological process model, particularly the wedge bonding process, making it possible to reproduce the relationships between process operating modes and the equipment health state. The Real-Time Data Mapping component provides real-time synchronization between the states of the physical equipment and its Digital Twin, updates the parameters of the digital model, assesses the current equipment condition, detects anomalies, and calculates diagnostic health indicators.

The Scenario Simulation and What-if Analysis block is used to investigate the behavior of the Digital Twin under changing process parameters, simulated faults and external disturbances, degradation processes, and various failure scenarios, making it possible to study pre-failure operating conditions without hazardous experimental impacts on the physical equipment. The results of current monitoring and scenario simulation are transmitted to the Intelligent Analysis and Prediction Module, where the Correlation and Factor Analysis component identifies the most significant process factors and determines their correlation, sensitivity, and cause-and-effect relationships with equipment health degradation. At the next stage, Health State Assessment uses machine learning models to evaluate the current health state of the equipment, while Pre-Failure State Prediction performs classification or regression-based prediction of the system's transition to a pre-failure state. The Remaining Useful Life (RUL) Estimation component uses time-series models to estimate the remaining useful life and the predicted time until a critical state or failure occurs, while the results of all intelligent analysis components are integrated into Dynamic Risk Index Calculation, where a normalized dynamic risk index ranging from 0 to 1 is calculated. The Outputs block presents the results in terms of the current equipment health state, probability of a pre-failure state, predicted RUL, risk level classified as Normal, Alert, High, or Critical, trend visualization, early warnings, and emergency alerts. The obtained results are transmitted to the Decision Support System, which generates recommendations for maintenance or adjustment of process operating modes, determines maintenance schedules, supports resource allocation and work prioritization, and evaluates the effectiveness of the decisions made. The final Feedback and Continuous Learning Loop block returns new operational data and actual equipment performance results for retraining and calibrating the intelligent models, refining the Digital Twin, and updating the knowledge base. Thus, the closed-loop cycle "sensor data → preprocessing → Digital Twin → scenario simulation → intelligent analysis → pre-failure state and RUL prediction → decision support → continuous learning" enables a transition from traditional failure detection to proactive prediction of equipment degradation and early prevention of pre-failure states.

The advantage of the developed method lies in the comprehensive integration of Digital Twin technology, intelligent data analysis, and continuous monitoring of process parameters, which enables timely anomaly detection and prediction of the transition of microelectronic manufacturing equipment to a pre-failure state. The use of scenario simulation and What-if Analysis makes it possible to investigate the effects of changes in process parameters, degradation, and potential faults within a digital environment without the risk of damaging the physical equipment. Integrated assessment of the equipment health state, pre-failure probability, Remaining Useful Life (RUL), and dynamic risk index enables the early generation of recommendations for adjusting operating modes and performing maintenance activities. The feedback and continuous learning loop provides adaptive refinement of intelligent models and the Digital Twin based on newly acquired operational data, thereby facilitating a transition from reactive equipment maintenance to a proactive and predictive maintenance strategy.

CONCLUSIONS. As a result of the research, a method for predicting pre-failure states of microelectronic manufacturing equipment is proposed, which integrates Digital Twin technology, continuous monitoring of process parameters, scenario simulation, and intelligent data analysis to assess the current and predicted health state of the equipment. The application of machine learning models enables prediction of the probability of equipment transitioning to a pre-failure state, estimation of the Remaining Useful Life (RUL), and calculation of a dynamic risk index, allowing critical changes in the technological process to be detected at an early stage. The integration of the obtained results with the Decision Support System enables the generation of recommendations for adjusting operating modes, planning maintenance activities, and prioritizing appropriate measures, while the continuous learning loop provides adaptive refinement of intelligent models and the Digital Twin based on newly acquired operational data. The proposed approach creates the prerequisites for a transition from reactive fault detection to proactive prediction of degradation and prevention of pre-failure states in high-precision microelectronic manufacturing equipment.

Reference

1. Barna, V., Ridzoňová, D., & Majlingová, A. (2026). Integrating Climate Change Adaptation, Disaster Risk Reduction, and Civil Protection for Sustainable Development: A Comparative Analysis of Central European Strategies. Sustainability, 18(9), 4548. https://doi.org/10.3390/su18094548
2. Nevliudov, I., Vladyslav, Y., & Horovyi, K. (2026). Model of the Technological Process of Wedge Bonding Based on FEK Delvotec 6400 in the Production of Hybrid Electronic Modules. Collection of scientific papers «SCIENTIA», (June 12, 2026; Chicago, USA), 170-173.
3. Modarres, MohammadReza and Almeida, Miguel and de Diego, Emilio and Torres, Luis and Asensio Martínez, Laura and Miranda, A. I., A Knowledge-Based Decision Support Framework for Multi-Hazard and Cascading NaTech Risk Assessment: Systematic Review and Multi-Criteria Evaluation. Available at SSRN: http://dx.doi.org/10.2139/ssrn.7003022
4. Yevsieiev V., Sezonova I., Demska N. Digital Twins and Cyber-Physical Systems as the Foundation for the Transformation of Civil Defense in the Context of Industry 5.0 // Paris Science and Education Forum : proceedings of the International scientific and practical conference (July 10-12, 2026). – Paris, France : - Pp. 12-14. https://doi.org/10.64828/conf-139-2026
5. Yevsieiev V., Stytsenko T. Intelligent Situational Awareness Systems for Civil Safety Based on Industry 5.0 Technologies // In VII Correspondence International Scientific and Practical Conference Science in Motion: Classic and Modern Tools and Methods In Scientific Investigations held on July 24th, 2026. P.181-184. DOI : https://doi.org/10.36074/grail-of-science.24.07.2026.
6. Benetti, L. (2026). Cyber Intelligence and Critical Infrastructure Protection: An Integrated Framework for Defending Against Hybrid Cyber-Physical Threats. Available at SSRN 6730318. https://dx.doi.org/10.2139/ssrn.6730318
7. Reza, M. H., Sibly, M. N. B., Rabbani, S. G., Sadi, S. H., Ahamed, M. F., Shafi, F. B., ... & Chowdhury, M. E. (2026). A comprehensive review of convolutional neural networks: foundations, enhancements and applications. Neural Computing and Applications, 38(4), 56. https://doi.org/10.1007/s00521-025-11827-w
8. Nevliudov I. Sh., Yevsieiev V., Sotnik S. Implementing Industry 5.0 Technologies in Civil Safety Systems for Intelligent Emergency Management // In Proceedings of the XII International Scientific and Theoretical Conference, July 17, 2026. San Francisco, USA: International Center of Scientific Research. -281. P. 85-88. https://doi.org/10.36074/scientia-17.07.2026
9. Nevliudov I., Yevsieiev V., Horovyi K. Analysis of the FEK Delvotec 6400 Wedge Bonding System // Débats scientifiques et orientations prospectives du développement scientifique: c avec des matériaux de la X conférence scientifique et pratique internationale, Paris, 5 juin 2026. P. 89-92. https://doi.org/10.36074/logos-05.06.2026
10. Abu-Jassar, A. T., Attar, H., Amer, A., Lyashenko, V., Yevsieiev, V., & Solyman, A. (2025). Development and investigation of vision system for a small-sized mobile humanoid robot in a smart environment. International Journal of Crowd Science, 9(1), 29-43. https://doi.org/10.26599/IJCS.2023.9100018