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Trends in the Implementation of Artificial Intelligence for the Diagnosis and Prevention of Emergency Situations

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Abstract

The article provides an analysis of the systemic causes of the low economic return and limited accuracy of artificial intelligence (AI) systems when diagnosing emergency modes in the heavy industry segment. The aim of the work is to empirically substantiate the need to shift from the Data Filtering paradigm (algorithmic cleansing) to the Data Readiness concept (engineering preparation of assets). The methodological basis includes a systematic literature review and a four-year longitudinal case study of spiral classifiers modernization. Within the framework of the study, the transition from mechanically unstable open gear transmissions to IP66-rated direct drives equipped with torque arms was implemented. It is demonstrated that this engineering intervention eliminated the root cause of mechanical noise, reducing drive vibration from 7.8 mm/s to values below 2.0 mm/s. This mechanical stabilization allowed for the reliable identification of weak defect signatures (0.3 mm/s) that were previously masked by noise, thereby significantly increasing diagnostic accuracy. The study argues that implementing the Data Readiness strategy enables the transition from reactive anomaly detection to full-scale Prognostics and Health Management (PHM). The key results indicate that this approach creates a verified foundation for high-accuracy hybrid digital twins, leading to a reduction in unplanned downtime and the prevention of complex cascading failures. The conclusion is that the effectiveness of AI in heavy industry is achieved through the symbiosis of deep mechanical modernization and advanced data analytics. The presented results and approaches are oriented toward reliability engineers, industrial enterprise management, and data science specialists involved in the implementation of Industry 4.0 technological solutions.

Keywords: *Artificial Intelligence, Data Readiness, Data Filtering, Prognostics and Health Management (PHM), Remaining Useful Life (RUL), Digital Twin, Mechanical Noise, Heavy Industry, Spiral Classifier, Predictive Maintenance (PdM).*

INTRODUCTION

The implementation of the Industry 4.0 paradigm has led to increased capital investments in industrial artificial intelligence and predictive maintenance (PdM) systems [1]. Such investments in AI and digital innovations prepare countries for the creation of new business models and participation in the global economy. According to UNESCO, AI may add 13 trillion US dollars to the global economy by 2030 and increase global GDP by 1.2% [2]. However, behind these macroeconomic indicators lies a systemic contradiction that can be designated as the AI paradox. Despite the declared return on investment of these technologies, a significant share of practical projects for the implementation of PdM in heavy industries (mining and metallurgical industries) is characterized by low predictive accuracy, high false alarm rates, and limited economic effectiveness [3, 4].

Low SNR and Mechanical Noise In the context of heavy industry, this problem transcends the domain of IT and enters the domain of applied mechanics. The critical constraint is the fundamental quality of the primary signal recorded from mechanically unstable equipment. The central issue is the extremely low Signal-to-Noise Ratio (SNR) caused by dominant mechanical noise. In systems with worn open gear transmissions, the vibration background generated by the drive (reaching 7.8 mm/s) does not merely mask the weak signal of an emerging defect (e.g., 0.3 mm/s in a bearing) but physically suppresses it. In this scenario, the useful signal lies below the physical noise floor, making the SNR mathematically unrecoverable [9]. Consequently, the AI system is fed “blind” data, rendering it incapable of correct diagnosis regardless of the algorithm’s complexity.

Current academic and industrial literature predominantly addresses this issue through the Data Filtering paradigm. A substantial body of research is devoted to wavelet transforms [6, 7], autoencoder architectures, and digital filters for cleansing noisy signals [8]. However, there is a significant research gap: existing studies virtually ignore the engineering aspect of the problem. Mechanical preparation of the asset (Data Readiness) is rarely considered an integral part of an AI project. The prevailing approach assumes that equipment is a constant, and all improvements must come from the mathematical processing of the output signal. There is a lack of empirical studies that view mechanical modernization not as a repair task, but as a mandatory prerequisite for generating AI-compliant data.

The aim of this study is to empirically substantiate that the effective implementation of AI in heavy industry requires a paradigm shift from Data Filtering (algorithmic cleaning) to Data Readiness (engineering elimination of noise sources). To achieve this aim, the study addresses the following **objectives**:

– To analyze the limitations of algorithmic methods when operating under conditions of high coherent mechanical noise.

– To demonstrate, through a longitudinal industrial experiment, that mechanical stabilization of the asset (specifically, the transition to direct drives) is the only way to achieve a readable SNR for micro-defect detection.

– To prove that establishing a Data Readiness framework is a necessary condition for transitioning from simple anomaly detection to high-precision Prognostics and Health Management (PHM).

The author's hypothesis is that investments in eliminating the root causes of mechanical noise, that is, in engineering modernization and structural stabilization of equipment, are not an alternative but a necessary precondition for the cost-effective implementation of any advanced AI systems, including prognostic maintenance (PHM) and digital twins.

The scientific novelty of the work is determined by empirical evidence, based on a four-year industrial study, that the mechanical stabilization of an asset (Data Readiness) is a critical and previously underestimated determinant of accuracy, whose influence on the final quality of prognostics surpasses the effect of increasing algorithmic complexity and sophistication of data filtering methods.

MATERIALS AND METHODS

To achieve the stated objective and test the proposed hypothesis, a mixed research methodology was employed, combining qualitative analysis of prevailing industrial and academic trends with a quantitative assessment based on a long-term industrial experiment.

At the first stage, a systematic analysis of academic sources in leading databases (Scopus, IEEE Xplore, SpringerLink), as well as authoritative industry reports for the period 2019–2024, was carried out. The aim of the review was to identify prevailing approaches to PdM, including methods based on the Data Filtering paradigm, and to record key barriers to their practical implementation. Special attention was paid to data quality requirements imposed by prognostics and health management (PHM) systems, remaining useful life (RUL) estimation models, and digital twin solutions.

The theoretical provisions and the main analytical section of the article are based on an in-depth analysis of a four-year industrial comparative test of modernized spiral classifiers at a beneficiation plant. The case in question is treated not as an illustrative example, but as an experimental validation of the basic hypothesis.

– Object: 2KSN-30 spiral classifiers.

– Control group: Standard classifiers with a conventional drive based on an open gear transmission.

– Experimental group: Modernized classifier with direct drive (sealed gear motor) and a torsion lever that completely eliminates the open transmission.

RESULTS AND DISCUSSION

The currently prevailing Data Filtering approach is based on the axiom that a noisy signal from a primary sensor can be mathematically cleaned and thereby the useful component contained in it can be recovered. In the terminology of this approach, the key problem is formulated as the presence of noise that masks the informative signal. For heavy industry, such a formulation is fundamentally incorrect.

The critical flaw lies in the nature of the noise itself: under the conditions under consideration it is not a stationary Gaussian process that can be suppressed by simple averaging or linear filtering. Rather, it is a coherent, high-amplitude vibration background generated by other, substantially more massive and mechanically unstable components of the unit. In classical spiral classifiers, the main source of such a background is the open gear drive. Wear of the tooth profile and the inevitable misalignment of the shafts produce a powerful, structured vibration background that floods the measurement channel.

Data from a four-year longitudinal study demonstrate that the amplitude of this background is 4,5–7,8 mm/s in terms of the root-mean-square vibration velocity. At the same time, the signature of an incipient defect in the form of a microcrack in a bearing yields a vibration response on the order of only 0,3–0,5 mm/s. Thus, the dynamics of the defect initially lie below the level of the background vibration field. No processing algorithm, whether a wavelet transform or a deep neural network, can reconstruct a signal that is physically absent from the recorded data stream. This leads to an algorithmic dead end: attempting to apply AI in such a configuration is equivalent to trying to discern a whisper next to a loudspeaker during a rock concert.

The Data Readiness paradigm [18] radically changes the initial problem formulation: the focus shifts from noise filtering to eliminating its source at the level of the unit's design and kinematics. The starting point of the process is not the work of a data scientist, but engineering and mechanical analysis and targeted modification of the equipment.

The longitudinal study provides direct experimental confirmation of the effectiveness of this approach.

Problem: a traditional drive with an open gear train generating a vibration background of 4,5–7,8 mm/s.

Solution: deep mechanical modernization — complete elimination of the open gear train and its replacement with a sealed (IP66) direct drive with a torsion arm.

Result: elimination of the root cause of mechanical instability and, consequently, a radical reduction of the vibration background at the source level.

As shown by the results of the four-year tests, such an engineering redesign pays for itself autonomously, even before any AI deployment. The comprehensive quantitative results of the comparative study are presented in Table 1.

Table 1. Comparative operational and reliability characteristics (author's data)

Indicator	Standard	Modernized	Change
Throughput, t/h	100	133	+33%
Classification efficiency, %	58	69	+19%
Availability, %	84.7	100	+15.3%
Maintenance cost, $/year	15,000	12,000	−20%
Unscheduled drive repairs/year	3	0	−100%
Vibration RMS, mm/s	4.5–7.8	<2.0	~70–75% reduction
Lubricant consumption, L/year	400	20	−95%

A visual confirmation of the formation of a Data-Ready platform is presented in Fig. 1.

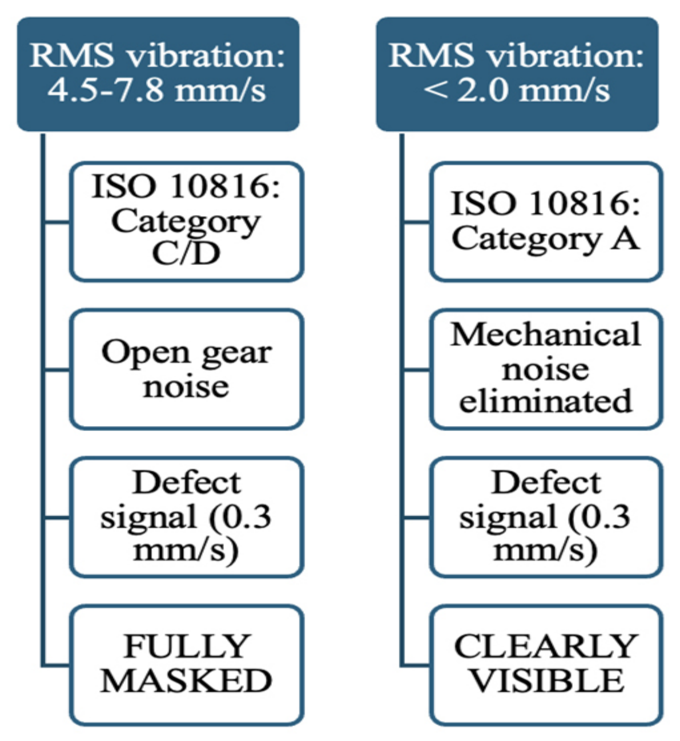

Fig. 1. Conceptual diagram of vibration noise reduction during the transition to the "Data-Ready" platform (compiled by the author based on [18]).

The key meaning of this trend is that equipment modernization is not merely an increase in the MTBF indicator, but essentially the transformation of the asset into a generator of high quality data. A stable low vibration level (< 2.0 mm/s) forms a quiet background, that is, the most appropriate representation of the healthy state of the unit. Against this background, AI for the first time obtains a physical possibility to identify the earliest weak signatures of defect initiation (in bearings, the shaft and other components) that previously remained virtually invisible.

The classical concept of PdM, especially when operating on dirty data, essentially reduces to an anomaly detection system. Its functionality is limited to binary classification: normal / anomaly. Such an approach is inherently reactive. In this mode, AI only records the fact that an anomaly has been detected or that a failure is expected within 24 hours. In essence, this is not failure prevention but only a statement of an almost inevitable event.

The next evolutionary stage is Prognostics and Health Management (PHM) [25]. The central function and main value of PHM consist in the capability to compute the Remaining Useful Life (RUL — Residual Useful Life) [11].

RUL estimation is no longer a binary classification problem but a reconstruction and tracking of the continuous degradation trajectory of the asset [21]. To construct such a trajectory, AI must observe the defect evolution from the very moment of its initiation, recording the gradual evolution of the state rather than only the final failure phase. The literature explicitly emphasizes that high quality data with a high SNR are a necessary condition for the correct operation of data driven RUL models [12].

At this stage, a direct link with Trend 1 becomes apparent. On dirty data: the noise level is 7.8 mm/s. The signal of an incipient crack (0.3 mm/s) and the signal of a developed crack (0.6 mm/s) are equally invisible, both falling below the noise threshold. In such a situation, AI is not able to observe the degradation process itself; it registers only the final failure, when vibration exceeds the threshold value.

On cleaned data: the noise level decreases to < 2.0 mm/s. Under these conditions, AI clearly registers the emergence of the 0.3 mm/s signal and subsequently tracks its growth to 0.6 mm/s. As a result, AI obtains a continuous degradation trajectory suitable for extrapolation and, accordingly, for RUL estimation.

Thus, Data Readiness (Trend 1) serves as a necessary engineering prerequisite for the transition to PHM/RUL (Trend 2). This conceptual shift is illustrated in Fig. 2.

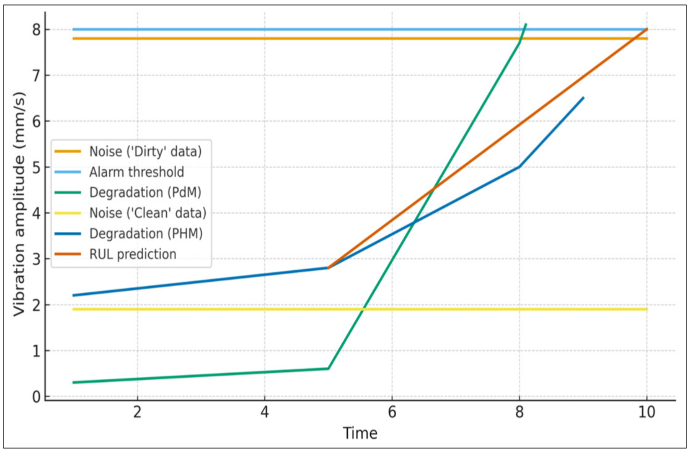

Fig. 2. Comparison of the capabilities of PdM and PHM depending on the data quality (author's data).

The presented graph is conceptual in nature. The Degradation (PdM) curve illustrates a situation in which the diagnostic signal remains indistinguishable up to the moment of failure, that is, the process of increasing degradation is effectively masked by the noise level. In contrast, the Degradation (PHM) curve demonstrates that, when operating with a clean noise background, the defect signal is consistently observed above this background, which creates the possibility not only to record its evolution but also to construct an RUL Forecast in the form of a dashed extrapolation. The transition from PdM to PHM in this context should be regarded not as a purely technical upgrade but as a qualitative business transformation, whose nature and implications are collectively summarized in Table 2.

Table 2. Conceptual comparison of PdM and PHM depending on data quality (compiled by the author based on [20, 23, 24]).

Characteristic	Predictive Maintenance (PdM) on dirty data	Prognostics and Health Management (PHM) on clean data
Basis (Data)	Low SNR, Data Filtering	High SNR, Data-Ready (Trend 1)
Primary objective	Anomaly detection	Estimation of degradation trajectory
Key metric	Binary (Normal / Anomalous)	Remaining Useful Life (RUL) (continuous)
Time horizon	Reactive (hours, days)	Prognostic (weeks, months)
Business outcome	Reduction of downtime (with risk of false alarms)	Asset optimization (maintenance planning, MRO)

The third and most advanced trend consists in the development of high accuracy digital twins capable of actually preventing emergency situations rather than only analysing them post factum. In contrast, the overwhelming majority of existing digital twins essentially represent either passive three dimensional visualisations or simulation models relying predominantly on averaged design data rather than on real operating data [15, 16].

In the academic literature it is emphasised that dirty data constitute a constant threat to the reliability of a digital twin: a digital twin supplied with noisy, incomplete, or incorrectly verified data very quickly loses synchronisation with the real object, which leads to the generation of false recommendations and, ultimately, to the practical uselessness of such a system [13].

A truly prognostic digital twin must have a hybrid structure, synthesising the advantages of two methodological approaches:

– Physics-based Model. A physically grounded model (for example, based on the finite element method, computational fluid dynamics methods, and related numerical approaches) that describes the behaviour of the system under idealised, strictly defined conditions and specifies the normative reference dynamics of the object [22].

– Data-driven Model. A data oriented machine learning model that uses actual sensor data for continuous calibration, refinement, and adaptive correction of the physical model in real time [16].

At this level Data Readiness (Trend 1) and PHM (Trend 2) become fundamentally important, forming the foundation for the implementation of Trend 3. A Data-Ready class platform provides a stable, verified stream of clean data that corresponds to the most appropriate standard of vibration background (< 2.0 mm/s). This reliable stream of measurements serves as the basis for constructing a genuinely prognostic digital twin.

This approach opens up the possibility of achieving the highest level of maturity, namely the modelling of cascading failures:

– Detection (Trend 1). AI algorithms operating against a background of clean vibration signal (< 2.0 mm/s) are capable of instantaneously detecting a weak anomaly on the order of 0.3 mm/s, interpreted as the early stage of the initiation of a bearing defect.

– Prognosis (Trend 2). The PHM model then tracks the evolution of the detected anomaly and computes the remaining useful life (RUL) of the corresponding bearing.

– Simulation (Trend 3). The hybrid digital twin receives this verified diagnostic signal, introduces the corresponding defect into its physics-based model, and initiates a system-level simulation. As a result, the digital twin reproduces the development of a cascading failure at the level of the entire installation; for example, it predicts the emergence of shaft misalignment after 15 days and then, induced by this misalignment, an overload of the drive and its emergency shutdown after 18 days.

In such an architecture AI is no longer limited to a simple message that there is a problem (PdM) or that the bearing will fail in 20 days (PHM). It explicitly demonstrates the probable trajectory of the development of a system level accident, providing engineers with temporal resources for taking preventive measures, for example the timely ordering of a complete set of critically important components rather than only the bearing. The conceptual architecture of such a system is presented in Fig. 3.

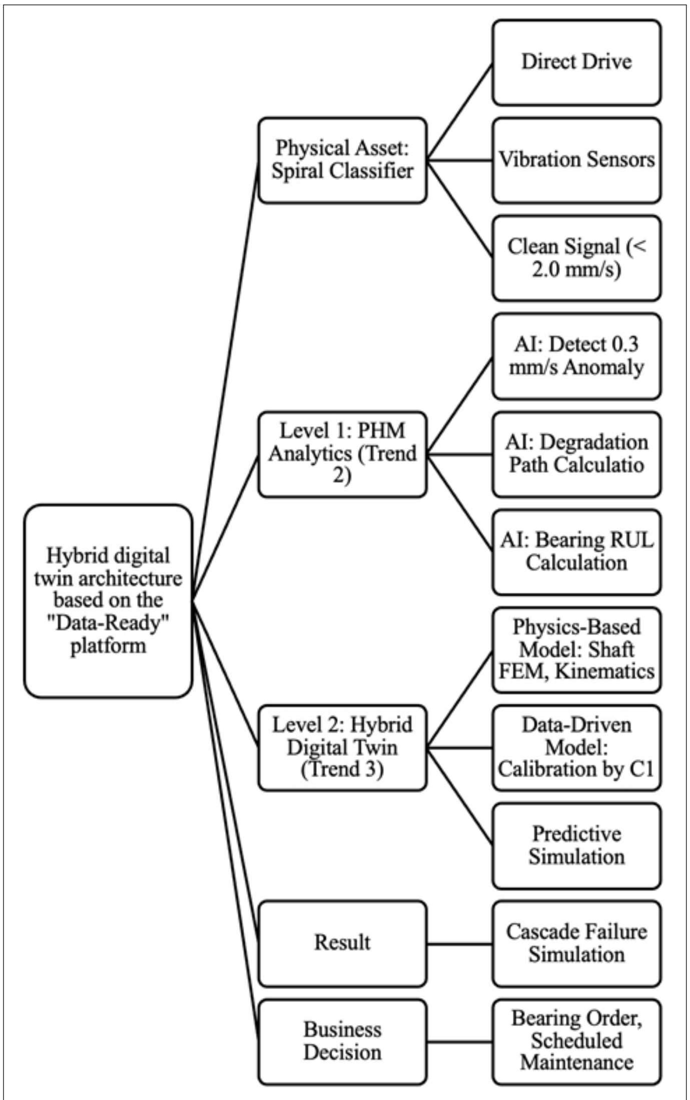

Fig.3. Hybrid digital twin architecture based on the "Data-Ready" platform (compiled by the author based on [10, 14, 17, 19]).

The issues addressed within the framework of the four-year case study are by no means local or unique in nature. As demonstrated in the Introduction, they represent typical, systemically significant barriers encountered by Industry 4.0 at the global level. The AI paradox, that is, the divergence between the scale of investments and the achieved effect, is to a significant extent caused by the fact that the basic structural problems of working with data are either underestimated or remain completely outside the focus of attention.

Figure 4 below presents the main existing barriers to the implementation of industrial AI.

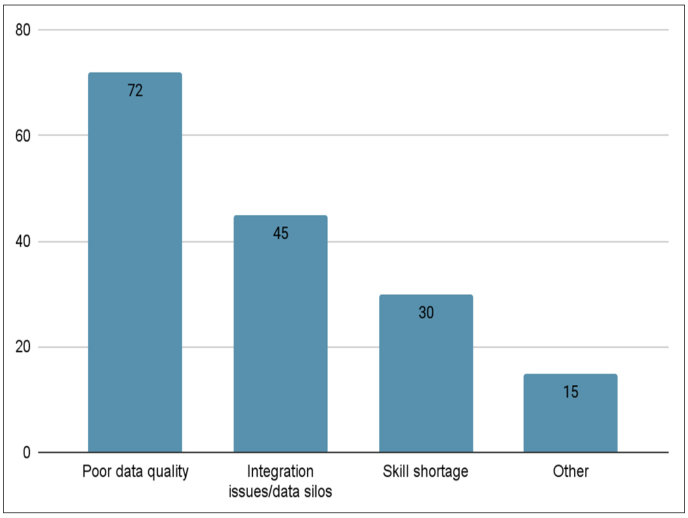

Fig. 4. Key barriers to the implementation of industrial AI (compiled by the author based on [4, 5, 24]).

As follows from the analysis presented in Fig. 4, the key limiting factor is constituted precisely by data-related issues, namely their quality and integration, which form the predominant share of the aggregate barriers. The concept of Data Readiness addresses this bottleneck at the level of primary information sources, making it possible to eliminate low data quality prior to subsequent processing and thereby directly mitigating approximately 72% of the overall barrier.

At the same time, despite the identified limitations, the economic motivation for implementing AI in industry not only does not weaken but is strengthening. The segment of technologies for data processing at the production level (Edge AI) demonstrates stable growth dynamics, which increases both external and internal pressure on enterprises and in fact forces them to move toward a systematic solution to the problem of data quality.

Thus, the conducted study allows us to conclude that, on the one hand, the market demonstrates a clear demand for AI-based solutions, while on the other hand, a significant share of implemented projects proves to be unsuccessful precisely because the data do not meet the requirements of such systems. The Data Readiness strategy, verified in the course of a four-year study, under these conditions represents the only practically feasible and sustainable approach to overcoming the specified barrier and to unlocking the potential declared by PHM technologies and Digital Twins.

CONCLUSION

The conducted study allows us to formulate the following final conclusions regarding the applicability of AI in heavy industry diagnostics.

The four-year longitudinal experiment empirically confirmed that the primary barrier to AI efficiency is not algorithmic imperfection, but the low quality of the primary physical signal. The implementation of the Data Readiness strategy—specifically the mechanical modernization of spiral classifiers (transition to IP66 direct drive)—yielded the following quantitative results:

– Noise Reduction: The root mean square vibration velocity of the background noise was reduced from 7.8 mm/s to values below 2.0 mm/s.

– Diagnostic Sensitivity: The signal-to-noise ratio (SNR) was improved to a level that allows the reliable detection of incipient defect signatures with amplitudes as low as 0.3 mm/s, which were previously physically indistinguishable.

– Prognostic Capability: The stabilization of the mechanical baseline enabled the transition from binary anomaly detection (PdM) to the construction of continuous degradation trajectories and the calculation of Remaining Useful Life (RUL).

The theoretical contribution of this work to the field of PHM and Industrial AI consists of the following:

– Redefinition of the Hierarchy: The study substantiates that "Data Readiness" is not merely a preliminary data cleaning step, but a distinct cyber-physical layer of the Industry 4.0 architecture. Proved that mechanical determinism is a prerequisite for digital stochastic modelling.

– Limits of Data Filtering: The work defines the physical boundaries of the applicability of Data Filtering methods. It is shown that under conditions of coherent mechanical noise, algorithmic filtering is mathematically untenable; thus, the solution must shift from the domain of Data Science to the domain of Precision Engineering.

– Symbiotic Design: A methodological approach is proposed in which the mechanical design of equipment is optimized not only for torque or durability but specifically for diagnostic transparency, treating the machine as a generator of high-quality data for Digital Twins.

For industrial management, the conclusion is unequivocal: investments in reducing mechanical instability should be interpreted not as operating expenditures (OPEX) for repairs, but as a mandatory capital investment (CAPEX) in digital infrastructure. The highest effectiveness of AI is achieved only through the symbiosis of deep mechanical modernization and advanced analytics. Thus, a "quiet" machine is the only valid foundation for a "smart" factory.

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