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MODERN APPROACHES TO TOOL MANUFACTURING AND REPAIR IN GENERATOR AND ELECTROTECHNICAL PRODUCTION

Summary. *The stable operation of generator and electrotechnical production depends heavily on tooling provision: stamps, molds, cutting tools, and assembly fixtures. Modern methods of tool manufacturing and repair are a critical factor in the continuity of production processes, product quality, and the operational efficiency of enterprises in the sector. Drawing on a combination of many years of practical experience in managing a tooling department in heavy electrotechnical engineering and a systematic review of current scientific literature, this article examines organizational approaches to toolroom operation, predictive-maintenance methods, and tool wear monitoring. It proposes an original three-tier tool resource management model ("condition assessment and record-keeping – proactive reconditioning – digital monitoring integration") that combines shop-floor organizational practice with elements of digital technology. The empirical basis of the model is practical reconditioning-rate indicators (70–80% for stamps and molds, 40–50% for cutting tools) recorded at a generator and electrotechnical manufacturing enterprise. The analysis shows that combining disciplined repair planning with the possibilities* *of digital monitoring can reduce tooling costs, cut downtime, and support the fulfillment of export contracts.*

Key words: *toolroom management, tool repair, predictive maintenance, generator manufacturing, electrotechnical production, tool wear monitoring.*

Introduction. Generators and electrotechnical equipment form the backbone of energy and industrial infrastructure: electricity supply, transport operation, and the continuity of production processes at the manufacturing enterprises themselves all depend on them. Every generator consists of thousands of precise components – thin copper winding plates, insulation elements, housing assemblies – the manufacture of which is impossible without specialized tooling: stamps, molds, cutting tools, and assembly fixtures. This tooling is manufactured and serviced by tooling departments (toolrooms), which function as the technical "heart" of the enterprise [1; 14].

Practice shows that it is the condition of the tooling stock, rather than the capacity of the main technological equipment, that most often determines the rhythm of production. The breakdown or wear of a stamp or milling cutter halts the production line, causes defects, and disrupts delivery deadlines, which is especially critical for enterprises fulfilling export contracts with strict quality requirements [2; 14]. At the same time, there is a systemic shortage of qualified tooling engineers and electromechanical specialists on the labor market [20], which increases the value of well-documented, systematic approaches to organizing this segment of production.

In recent years, a substantial body of research has emerged on the digitalization of maintenance – from the concept of predictive maintenance within Industry 4.0 [10; 21] to the application of machine- and deep-learning methods for monitoring cutting-tool wear [3; 4; 5; 7]. However, these studies are mostly focused on the algorithmic side of the problem and are rarely linked to the organizational practice of specific tooling departments in heavy engineering, where the deployment of complex sensor systems is often constrained by budget and infrastructure.

The purpose of this article is to analyze modern approaches to tool manufacturing and repair in generator and electrotechnical production and, by combining practical experience in managing a tooling department with a systematic review of the scientific literature, to propose an applied tool resource management model suited to enterprises with limited digitalization capacity. To achieve this purpose, the article examines the organizational aspects of toolroom operation, approaches to predictive maintenance and tool wear monitoring, and practical reconditioning indicators recorded over many years of engineering practice. The article is structured as follows: a literature review across four thematic areas, a description of the research methodology, results presented as empirical indicators and tables, a discussion of the proposed three-tier model, and conclusions with practical recommendations.

Literature Review

Organization of toolroom operations

A toolroom is traditionally defined as a centralized unit responsible for the storage, accounting, issuance, repair, and manufacture of tooling [1; 14]. Effective management of this area requires clear tool accounting, workload planning, and timely maintenance, all of which directly affect the productivity of the main production process [14]. Sources emphasize that a well-organized toolroom provides not only storage but also safety, standardized issuance procedures, and control over equipment condition [1]. Practice shows that the quality of such a unit's work depends not only on technical equipment but also on the human factor – staff qualifications and interaction with shop-floor foremen and design departments [14].

Special attention should be paid to the shortage of personnel in electromechanics and tool manufacturing: specialists in this field combine knowledge of electrical engineering, mechanics, and metalworking technologies, which makes training such personnel lengthy and costly [20]. This reinforces the value of management systems that enable efficient use of available staff and resources, in particular through rational workload planning, reduced equipment downtime, and improved labor efficiency [8].

Predictive maintenance within Industry 4.0

A large share of current research is devoted to the transition from reactive and scheduled preventive maintenance to predictive maintenance, which relies on the analysis of data about equipment condition [10; 21]. Systematic reviews indicate that predictive maintenance reduces unplanned downtime, lowers repair costs, and extends equipment service life by intervening precisely when technically justified rather than on a fixed schedule [11; 21]. At the same time, researchers emphasize that deploying predictive systems requires investment in sensor infrastructure, data collection and storage, and staff training [13], and that maintenance-strategy optimization is increasingly framed as a problem that can be solved with reinforcement learning and other decision-making methods under uncertainty [19].

Methods for monitoring cutting-tool wear

A separate and technologically dense strand of literature is devoted to monitoring cutting-tool wear using computer-vision and deep-learning methods. Researchers propose approaches based on digital image processing of cutting edges to automatically determine the degree of wear [3], as well as combined image-processing pipelines that merge expert rule-based analysis with neural-network models [7]. Other studies propose intelligent multi-step tool-wear prediction models based on deep neural networks [4] and hybrid architectures that convert signals into images for classification with ResNext-type networks to analyze multi-channel signals during milling [5]. Similar approaches are applied to other machining processes – for example, tool wear monitoring in high-speed broaching with carbide tools [6].

These studies demonstrate high accuracy in recognizing tool condition under laboratory or controlled production conditions, but they largely disregard the organizational context: how exactly monitoring results should be translated into decisions about repair, replacement, or modernization of tooling at the level of shop-floor planning.

Reviews and critical analyses of tool condition monitoring systems

Comprehensive reviews of artificial intelligence systems for tool condition monitoring in machining indicate that, despite significant algorithmic progress, practical deployment is constrained by the complexity of integrating models into production information systems and by the absence of standardized datasets for different types of equipment [12]. Reviews of machining process monitoring generally confirm that combining sensor data (cutting force, vibration, acoustic emission) with analytical methods improves process stability, though this level of maturity is mainly characteristic of large-scale, high-technology production [17]. Studies on optimizing the parameters of long short-term memory (LSTM) models for predictive maintenance confirm the effectiveness of deep recurrent networks for forecasting remaining useful life [9], while studies on industrial robots show that combining data with expert knowledge improves production stability under conditions of intelligent manufacturing [18].

Reconditioning and restoration technologies

A less represented but practically significant strand of research concerns tool reconditioning technologies. Studies on reconditioning diamond-coated cutting tools show that restored tooling can retain acceptable performance characteristics when machining composite materials [15], confirming the economic viability of repair over full replacement. Directed energy deposition (DED) additive manufacturing is considered a promising technology for restoring worn surfaces of stamps and molds through local metal deposition [16], combining repair with a form of localized modernization of tooling geometry.

The literature review shows that scientific approaches to wear monitoring and predictive maintenance are technologically mature but are mostly oriented toward high-technology production with developed sensor infrastructure. The practice of tooling departments in traditional heavy engineering, which includes generator and electrotechnical production, requires adapted, less resource-intensive management models that combine organizational discipline with elements of accessible digital solutions. It is precisely this gap that the model proposed in this article aims to fill.

Methodology. This is an analytical study that combines two sources of data: (1) a systematic review of scientific literature on toolroom organization, predictive maintenance, and tool wear monitoring (21 sources, 2020–2026); and (2) empirical data from practical experience managing a tooling department (production preparation bureau) in generator and electrotechnical manufacturing, accumulated over more than twenty years of engineering practice, including a period of direct departmental leadership.

The practical data include indicators of the share of reconditioned tooling (stamps, molds, assembly fixtures, and cutting tools) by category, the number of repeated reconditioning cycles for individual items of tooling, and a qualitative description of the tool-preparation production cycle – from the shop's request submission to the delivery of finished tooling to production. These data are used as an illustrative case reflecting typical practice at a heavy electrotechnical engineering enterprise that fulfills both domestic and export orders (India, Tajikistan, Germany, Canada).

The analysis was carried out using thematic synthesis: sources were grouped into four areas (toolroom organization, predictive maintenance, wear monitoring, reconditioning technologies), after which the principles identified in the literature were compared with elements of the practical tool-management cycle. Based on this comparison, an original three-tier tool resource management model was formulated, structuring existing practice as a sequence of management tiers and identifying points at which elements of digital monitoring from the reviewed research can be integrated into traditional organizational practice. A limitation of the methodology is that the practical indicators relate to a single enterprise and do not constitute a statistical sample; the model should therefore be regarded as a conceptual, rather than a statistically verified, tool suitable for further empirical testing.

Findings

Analysis of the practical production-preparation cycle showed that the tooling department's work is structured as a sequence of six stages: receipt of a request from the shop floor or design department → entry of the task into the monthly plan → calculation of material consumption norms → machining of the workpiece (turning and milling operations) → heat treatment (hardening) and final grinding → marking, database registration, and delivery to the shop. Task priority is determined by an urgency flag, and conflicts arising when several urgent tasks arrive simultaneously are resolved through an operational review of workload together with management (See Figure 1).

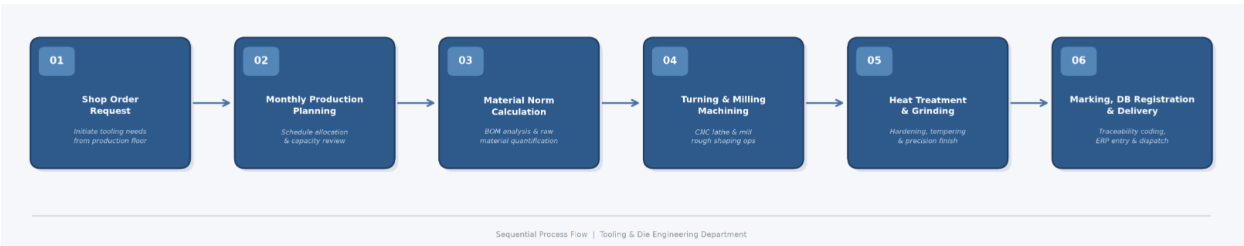

Fig. 1. Diagram of the tool-preparation production cycle

A key empirical finding concerns the share of tooling returned to service through repair and refurbishment rather than full replacement (Table 1). For the category of stamps, molds, and assembly fixtures, the share of reconditioned tooling was 70–80%, with individual items undergoing repeated reconditioning three to five times. For the category of cutting tools (mills, drills), the reconditioning rate was lower – 40–50%: expensive milling cutters were reground to a smaller diameter for other tasks or restored by brazing new carbide inserts.

Table 1

Tooling reconditioning indicators by category

Tooling category	Reconditioning rate, %	Typical reconditioning method	Number of repeated reconditioning cycles
Stamps, molds, assembly fixtures	70–80%	Regrinding of working surfaces, replacement of worn components	up to 3–5 times
Cutting tools (mills, drills)	40–50%	Regrinding to a smaller diameter, brazing of carbide inserts	1–2 times

These indicators confirm that preventive repair carried out before critical tooling failure is more cost-effective than reactive replacement, consistent with findings on the economics of predictive maintenance [10; 13; 21] and with research on cutting-tool reconditioning technologies [15]. At the same time, the lower reconditioning rate for cutting tools compared to stamps is explained by more intensive physical wear of cutting edges during direct contact with metal, which is consistent with tool-wear-monitoring studies that record nonlinear wear dynamics on cutting surfaces [3; 4; 5].

A second important finding is confirmation of the impact of export-contract requirements on tool-manufacturing technology: orders for European customers required the development of tooling from more wear-resistant steels to work with new grades of insulation materials and alloys, illustrating the practical need for adaptability in tool production, consistent with findings on the stability and adaptability of machining processes [17].

The findings thus confirm two claims: (1) the large majority of tooling in heavy electrotechnical engineering can and should be reconditioned rather than replaced; and (2) the effectiveness of this reconditioning depends on disciplined, forward-looking repair planning, which forms the basis for the model proposed in the following section.

Discussion. Based on the comparison of practical experience with the results of the literature review, a three-tier tool resource management model is proposed (Figure 2, Table 2), structuring the work of the tooling department in generator and electrotechnical production as three sequential but cyclically repeating tiers.

Tier 1. Condition assessment and record-keeping. The foundation of the model is systematic accounting of all tooling – from stamps to cutting tools – recording manufacture date, number of usage cycles, and previous repairs. This tier draws on classical toolroom-organization principles: centralized storage, standardized issuance, and condition control [1; 14]. In departmental practice, this tier is implemented by registering each item of tooling in a database after manufacture or repair, creating a usage history necessary for subsequent decisions.

Tier 2. Proactive reconditioning. The second tier formalizes the practice implemented in the case described: tooling is sent for repair before critical wear or failure occurs, rather than after a breakdown. This approach is supported both by empirical indicators (70–80% reconditioning of stamps and molds through timely intervention) and by research on the economic effectiveness of predictive and preventive maintenance [10; 13; 21], as well as by technologies for reconditioning cutting edges [15] and additive restoration of worn surfaces [16]. The essential difference between the proactive approach and scheduled preventive maintenance "by calendar" is that the repair decision is based on the actual condition of the tooling, recorded during a regular inspection, rather than solely on a fixed time interval.

Tier 3. Digital monitoring integration. The third tier is forward-looking and envisages the gradual integration of automated wear-monitoring methods developed in the reviewed literature – computer vision for analyzing cutting-edge images [3; 7], deep-learning models for forecasting remaining useful life [4; 5; 9], and signal analysis in machining processes [6]. Unlike laboratory studies, where such systems are deployed as standalone solutions, in the proposed model digital monitoring is treated as an addition to Tier 1 (record-keeping) and Tier 2 (proactive reconditioning): monitoring data automate precisely the repair-decision moment that is currently performed manually by an engineer based on experience and scheduled inspection (See Figure 2).

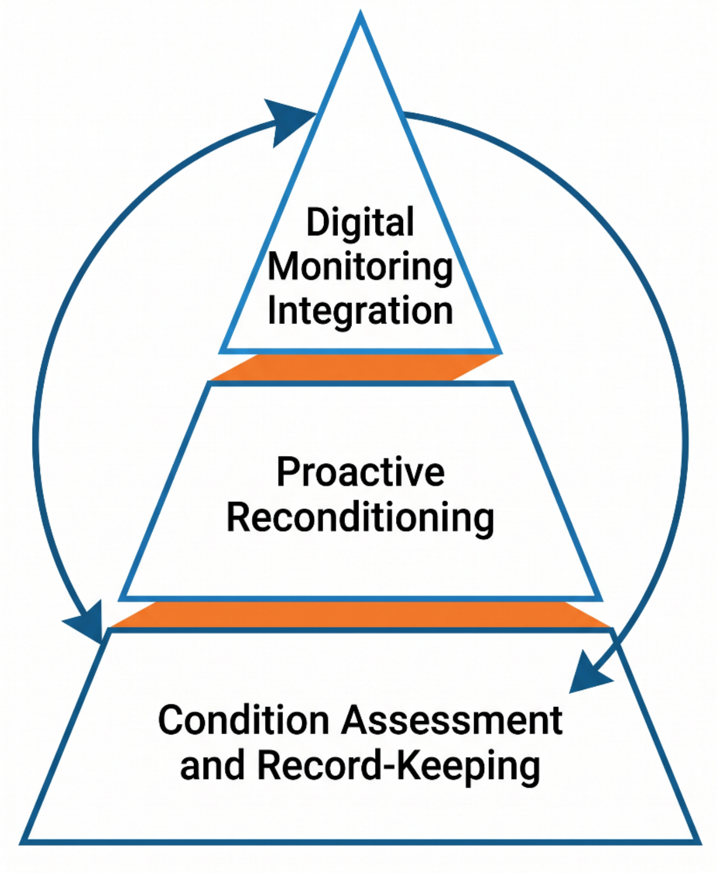

Fig. 2. Three-tier tool resource management model

Table 2

Structure of the three-tier tool resource management model

Tier	Content	Sources	Practical implementation
Tier 1. Condition assessment and record-keeping	Centralized accounting of tooling, usage and repair history	[1; 14]	Registration of each item of tooling in a database after manufacture or repair
Tier 2. Proactive reconditioning	Repair before critical wear occurs, based on scheduled inspection	[10; 13; 15; 16; 21]	Rule of forward repair for stamps and molds; regrinding and brazing of cutting tools
Tier 3. Digital monitoring integration	Automated wear detection using computer vision and deep learning	[3; 4; 5; 6; 7; 9]	Pilot deployment for the most expensive and critical tooling items (export orders)

The key managerial advantage of the model is that it does not require a one-time deployment of expensive sensor infrastructure. Enterprises with limited budgets can implement Tiers 1 and 2 using purely organizational means, achieving significant economic benefit – as evidenced by the reconditioning-rate indicators presented above – and gradually, as resources permit, add elements of Tier 3 for the most critical or expensive tooling items, such as complex stamps for export orders. This staged approach is consistent with review findings that the success of predictive-maintenance deployment depends largely on an enterprise's organizational readiness, not solely on the technological availability of algorithms [12; 21].

The model's economic effect manifests in three ways. First, reduced spending on new tooling procurement through multiple reconditioning cycles (up to 3–5 for stamps), directly lowering product cost [8; 13]. Second, reduced production-line downtime through forward repair rather than emergency repair, consistent with findings on reduced unplanned time losses when transitioning to predictive maintenance strategies [10; 11; 18]. Third, support for an enterprise's ability to fulfill export orders with elevated quality requirements for tooling, since systematic record-keeping and disciplined reconditioning allow tooling to be quickly adapted to new material grades [17] (See Figure 3).

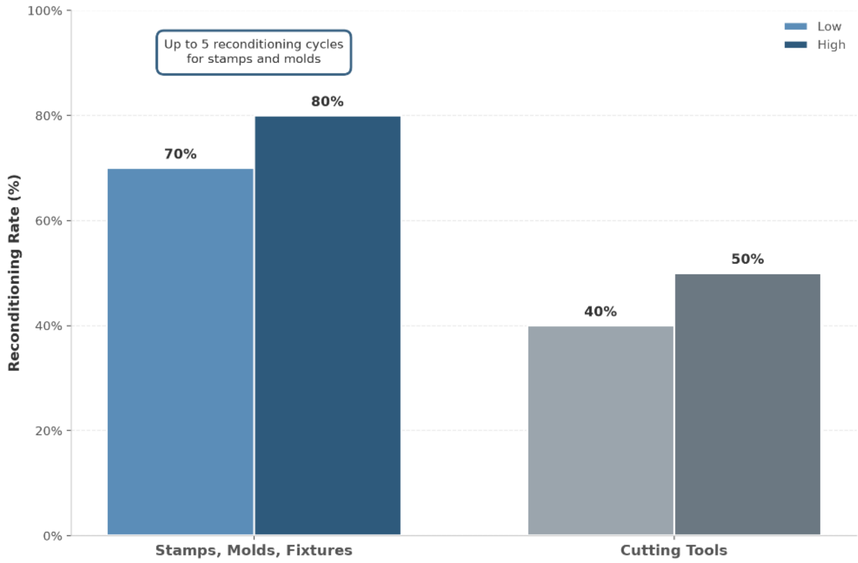

Fig. 3. Comparison of reconditioning rates by tooling category

The model also has limitations. It is built on a single-enterprise case and requires further verification at other manufacturers with a different range of tooling. In addition, Tier 3 of the model is formulated largely on the basis of laboratory research and requires a separate pilot deployment to confirm economic feasibility under serial rather than mass generator production. Further research could be directed toward quantitatively assessing the impact of Tier 3 deployment on reconditioning rates relative to the current 70–80% and 40–50%, as well as toward developing adaptive, low-cost repair-decision strategies based on reinforcement learning [19], tailored to the resource constraints of heavy-engineering enterprises rather than only the high-technology manufacturers for which most of the systems reviewed in the literature were developed.

Conclusions. Modern approaches to tool manufacturing and repair in generator and electrotechnical production combine the traditional organizational practice of tooling departments with the new possibilities of digital wear monitoring. The analysis showed that disciplined, forward-looking tooling reconditioning allows up to 70–80% of stamps and molds and 40–50% of cutting tools to be returned to service, substantially reducing spending on new tooling procurement and cutting production downtime.

The proposed three-tier tool resource management model – condition assessment and record-keeping, proactive reconditioning, and digital monitoring integration – structures existing practice and offers enterprises a staged path toward deploying elements of predictive maintenance without requiring large one-time investments in sensor infrastructure. The model is grounded in a combination of many years of practical experience managing a tooling department in heavy electrotechnical engineering and a systematic review of current scientific research on tool wear monitoring and predictive maintenance.

The model's practical significance lies in its applicability to enterprises with limited digitalization resources, including manufacturers of generators and turbines operating in both domestic and export markets. Further research should focus on quantitatively verifying the model at other enterprises in the sector and on developing affordable sensor solutions for Tier 3 of the model.

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