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Advancing Predictive Maintenance in the Field: Assisted Diagnostics and Remote Collaboration

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Abstract

The paper addresses the introduction of predictive maintenance for military ground equipment under field conditions through assisted diagnostics and remote expert collaboration. It proposes a "field-level PdM" process–data framework linking on-site evidence capture, standardized recording of maintenance events, and subsequent analytics, including remaining useful life (RUL) prognostics. The approach is examined via scenario-based pilot testing that evaluates time to fault identification, record quality, and robustness under degraded connectivity. Expected outcomes include reduced downtime, improved asset availability, and enhanced data readiness for PdM analyses. The discussion situates the approach within current initiatives of the Czech Armed Forces and highlights ergonomic and safety considerations associated with long-term use of hands-free devices. The study provides a basis for further operational and economic assessment.

KEY WORDS: *military ground equipment, predictive maintenance, condition-based maintenance (CBM), assisted field diagnostics, remote expert collaboration*

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1. Introduction

Maintenance is often perceived primarily as a cost factor - an unavoidable activity focused on restoring equipment only after a failure has occurred. Such a reactive view, however, no longer matches the current requirements for reliability, availability, and life-cycle efficiency, particularly for complex vehicle fleets and mission-critical ground systems. In military settings, any unexpected downtime directly affects operational readiness, increases the burden on logistics, and can compromise safety. As a result, maintenance is increasingly approached as a strategic capability that supports sustained availability through systematic planning, data-driven decision-making, and continuous improvement across the equipment life cycle [1,2,14]

A key shift in this evolution is the move from corrective and time-based preventive maintenance toward condition-based maintenance (CBM), which relies on technical diagnostics and continuous or periodic monitoring of the actual health state of components and subsystems [6,7]. Within CBM, predictive maintenance aims to anticipate failures and schedule interventions at an optimal time, while proactive maintenance goes further by identifying degradation mechanisms and addressing root causes before faults propagate into functional failure [5,6]. These approaches depend on the availability of operational data (e.g., from onboard diagnostics and vehicle networks), its integration with maintenance records, and analytical methods that support fault detection, diagnostics, and prognostics such as remaining useful life (RUL) estimation [9-11].

A distinctive challenge for military ground equipment is that diagnostic assessment and maintenance decisions must often be performed in the field, under time pressure, with limited workshop infrastructure, and in demanding environmental conditions. In this context, digitally assisted diagnostics and remote collaboration can significantly enhance maintenance effectiveness. Hands-free operation supports safe work procedures and reduces cognitive load during inspections and troubleshooting. High-quality visual documentation (photos/video) and real-time communication enable remote expert guidance, faster fault isolation, and more consistent reporting. Moreover, structured capture of field observations can improve the quality and completeness of data inputs required for predictive models. This paper therefore focuses on the role of assisted diagnostics and remote collaboration as an enabling layer for implementing predictive and proactive maintenance concepts in military field conditions, linking operational practice with the data and workflows needed for sustainable fleet readiness [18,19].

2. Design and Pilot Verification of Predictive Maintenance in Field Conditions

The methodological procedure is conceived as an applied, design-oriented approach aimed at designing and verifying a process-data framework for predictive maintenance that is feasible under field conditions. The point of departure is grounded in the concepts of condition-based maintenance and predictive/prognostic maintenance, particularly with regard to implementation aspects, the standardization of procedures, and the linkage between diagnostics and maintenance decision-making throughout the entire cycle of recording and evaluation [7,15]. Based on a synthesis of relevant literature and experience from applications in the field of military vehicles, an analysis of field maintenance requirements is conducted, with emphasis on typical sources of diagnostic uncertainty, points at which information is lost, and stages where the decision-making cycle is prolonged due to limited expertise, equipment, or infrastructure [1,18]. The output of this part is the definition of a target "field-level PdM" architecture that connects field-based collection of evidence and observations, including visual inspection, symptom description, and selected operational parameters from onboard systems, with structured storage in maintenance records and subsequent analytical processing. The proposal also includes a data taxonomy for the uniform and reproducible recording of symptoms, operational context, and actions performed, so that records can be aggregated and used for diagnostic and prognostic methods, including estimates of remaining useful life (RUL) [10,11].

The pilot verification is carried out through scenario-based testing, which translates the proposed framework into a set of representative situations corresponding to typical failure and degradation states of land equipment. Each scenario includes predefined decision-making steps, required inputs, and expected outputs in the form of intervention prioritization, recommended corrective action, and a standardized record [7,15]. The scenarios are conducted under conditions approximating field deployment and involve the use of assisted diagnostics and remote expert collaboration, including a variant with degraded connectivity, in order to verify the robustness of the process under limited communication conditions [19]. The evaluation focuses on practically measurable indicators, particularly the time required to identify a fault and reach a decision, the frequency of repeated diagnostic steps, the need for escalations, and the completeness and consistency of the documentation produced. At the same time, the assessment examines whether the records generated in this way provide a sufficiently high-quality basis for subsequent analytical use in predictive maintenance and for linkage to prognostic procedures, including RUL estimation, or for the gradual development of a data base for longer-term predictive modelling [10,11]. The outcome of the methodology is a refined proposal for the implementation of predictive maintenance in field conditions, supplemented by recommendations for integrating assisted diagnostics and remote collaboration into the maintenance cycle in such a way that the approach is transferable and scalable within military logistic support [18,19].

3. Expected Benefits of Assisted Diagnostics in the Field

The expected outcomes are based on the premise that the integration of assisted field diagnostics and remote expert collaboration represents a practical "accelerator" for the implementation of predictive maintenance under field conditions, as it simultaneously shortens the decision-making cycle and improves the quality of evidence concerning technical condition. The anticipated benefit should therefore not be assessed solely in terms of immediate repair support, but primarily from the perspective of systematic improvement of the maintenance process, standardization of records, and the creation of a data foundation for CBM/PdM analytical methods [7,18,19].

At the first level, assisted diagnostics is expected to accelerate fault identification and the selection of an appropriate corrective action through the possibility of synchronous consultation with an expert located outside the intervention site. The field technician can share the inspection view, supplement it with targeted visual documentation, and receive immediate feedback on diagnostic hypotheses and subsequent steps. This mechanism should reduce repeated diagnostic procedures, decrease the frequency of escalations caused by incomplete descriptions of symptoms, and shorten the period during which equipment remains out of service, particularly in situations where local personnel do not possess the full range of expertise or diagnostic tools required. In the environment of military vehicles, where operational data and maintenance events are combined, a stronger link is also expected between field findings and their subsequent entry into maintenance records, which is a prerequisite for meaningful evaluation of failure trends and recurring faults [1,2,18]. At the second level, improvements are expected in occupational safety and the ergonomics of procedures performed under field conditions. The hands-free mode reduces the need to manipulate handheld devices during inspection and enables tasks to be carried out while using personal protective equipment, including in demanding environments characterized by noise, dust, or restricted space. At the same time, a reduction in cognitive load may be assumed, as the operator is not required to constantly shift attention between the technical object and the search for instructions or contact with support personnel. Another important expected outcome is a higher degree of standardization in records concerning equipment condition: the introduction of a unified approach to capturing visual evidence and describing symptoms, including time, location, severity, context, and actions performed, has the potential to improve the consistency of records across units and to generate "comparable" records suitable for subsequent analysis [7, 15,19].

The third level of expected results concerns data quality and prognostics. It is assumed that higher-quality and more complete field records will support the development and validation of predictive procedures by reducing the proportion of ambiguous or poorly interpretable cases in the maintenance database. From the perspective of PdM analytics, contextual information is particularly valuable, including the circumstances under which a symptom emerged, the actions performed, and the system response. Such information is often lost in routine practice, despite its substantial influence on the interpretation of failure phenomena. Evidence enriched in this way may support both simpler approaches based on rules and threshold values and more advanced data-driven methods, including anomaly detection, fault classification, and the gradual implementation of remaining useful life prognostics [10-12]. In relation to studies focused on combining time-series data with maintenance events, it can also be expected that field records will become more readily "linkable" to operational data, which is important both for model training and for the retrospective evaluation of intervention effectiveness [2,11].

Overall, a measurable impact on equipment operational availability is expected through reduced downtime, improved quality of maintenance decision-making, and enhanced ability to plan interventions on the basis of actual technical condition. In the longer term, this combination of process acceleration and higher-quality evidence is expected to create conditions for the more systematic implementation of predictive and proactive maintenance in modern, technologically complex ground platforms, where failures often do not arise in isolation but rather as a consequence of complex degradation mechanisms [1,4,18].

4. Current Status of Introducing Assisted Diagnostics and Remote Maintenance Support in the Czech Armed Forces

Within the Czech Armed Forces, recent developments indicate a deliberate effort to move selected elements of digital transformation from conceptual discussions to verifiable operational practices, particularly in the field of logistics support and the maintenance of ground equipment. In this respect, the facilities associated with the Centre of Deployable Systems in Lipník nad Bečvou are increasingly perceived as a key test and implementation environment, where technologies are systematically refined and introduced with the ambition to reshape how equipment is maintained, how expertise is transferred, and how logistics processes are managed under the conditions of the modern battlefield [18,19].

Fig. 1 The image captures a field diagnostic activity during the inspection of technical equipment, in which a modern hands-free diagnostic device with assisted-reality capabilities and support for remote collaboration is used.
Source: spojar.mo.gov.cz [19]

A concrete manifestation of this trajectory is the ongoing testing of assisted diagnostic solutions designed to support maintenance and training for newly introduced equipment, referenced in connection with the KOVVŠ M2 platform. The introduction of such capabilities is framed as a shift in practical work routines: instead of relying on static manuals and time-consuming information searches, the approach emphasizes immediate access to digital procedures, technical data, and diagnostic functions during task execution. [19] This creates conditions for greater process standardization in the field - namely, a more uniform sequence of diagnostic steps and more reproducible documentation of observed symptoms across units - an aspect that is particularly important for systems characterized by extensive electronic integration and sensorization [7,15]. In parallel, the Czech Armed Forces are developing a component of remote maintenance support aimed at strengthening field-level decision-making without requiring the physical deployment of specialists to the site of intervention [18,19]. The operational mechanism consists of online connectivity between the field technician and an off-site expert, with shared visual streams from the inspection enabling targeted step-by-step guidance and faster verification of diagnostic hypotheses. [19] This support model has the potential to reduce the frequency of costly deployments of specialized teams, shorten equipment downtime, and improve repair consistency by ensuring that decision-making does not depend solely on locally available experience. From the perspective of operational sustainment, emphasis is also placed on efficiency and on reducing the time and financial demands of interventions, which aligns with the broader trend of moving from improvised repairs toward planned and managed maintenance [1,18].

A feature with a direct link to predictive maintenance is the extension of field diagnostics through comparative modes based on a defined "normal" state - for example, the use of thermal maps to identify components exhibiting deviations (e.g., overheating) before a failure becomes manifest. [19] In this way, field diagnostics progresses beyond the detection of already-developed problems toward the early capture of degradation phenomena and the timely scheduling of interventions at an optimal moment [6,15]. In practice, this also entails generating more structured and archivable diagnostic artefacts that can be linked to maintenance records and subsequently used when assessing recurring fault patterns [7,15].

The emerging solution is additionally framed by requirements for usability in demanding conditions and compatibility with military standards. Attention is drawn to Czech-language voice control, all-shift endurance, and, in particular, integration with tactical communication assets via the data link of MPU-5 radios, complemented by the use of high-speed 5G networks. These parameters suggest that the objective is not an isolated "digital aid," but rather a robust communication–diagnostic support capability suitable for operational environments in which connectivity availability and transmission security constitute critical prerequisites for remote collaboration. [19] Overall, the current state in the Czech Armed Forces can be interpreted as a practically grounded transition toward digitally supported maintenance that enhances diagnostic capability in the field while creating conditions for the gradual maturation of predictive approaches for modern ground platforms [1,5,6,18,19].

5. Ergonomics, Fatigue, and User Workload in the Use of a Hands-Free Diagnostic Device

Deploying assisted reality smart glasses in Czech Army maintenance and logistics represents a promising pathway for digitalizing "work at the point of action" and improving information availability during task execution. In practice, the expected benefits include faster procedural work through in-field guidance displayed in the user's field of view, reduced error rates when handling technical documentation, more efficient communication with specialized units via remote expert support, and improved continuity of intervention records. These benefits align well with the broader shift toward proactive maintenance, where decisions about interventions rely on rapid access to contextual information (equipment condition, fault history, recommended actions) and clear guidance for technicians.

At the same time, the long-term sustainability of such deployment depends not only on device functionality, but also on human-centered factors: visual strain, fatigue, cybersickness-like symptoms, cognitive workload, and wearing comfort during extended shifts. In a military setting - where maintenance and logistics are performed under variable conditions (noise, vibration, changing illumination, limited infrastructure) - systematic assessment of these factors is essential both for occupational safety and for user acceptance.

From a psychophysiological perspective, one of the most frequently discussed limitations of smart glasses is visual load. This may arise from the presence of virtual content within the field of view, as well as from repeated attentional switching between the physical object (e.g., a component being repaired) and the virtual information layer (instructions, checklists, step highlighting). In maintenance and logistics, this is particularly relevant for tasks that demand sustained visual inspection and fine manual work, for which susceptibility to ocular fatigue may be heightened. Evidence from field studies suggests that head-mounted AR devices can alter behaviors associated with visual comfort, such as blink rate, which is commonly used in ergonomics as an indirect indicator of dry-eye risk and subsequent subjective eye strain. Marklin et al. conducted a field study comparing multiple device types, including the monocular RealWear HMT-1 and an optical see-through headset, during procedural work and confined-space operations. They reported task- and device-dependent differences in blink rate and emphasized that, for some tasks, reduced blinking may signal elevated eye-strain risk [20]. For pilot testing, this finding is important because it indicates that "generic" manufacturer claims regarding ergonomics are insufficient; instead, impacts on visual comfort must be validated for specific task categories (diagnostics, adjustments, inspection routines, picking), exposure durations, and operational conditions.

Beyond eye strain, the literature increasingly addresses visually induced motion sickness (VIMS) and cybersickness, associated with symptoms such as nausea, dizziness, headaches, disorientation, and oculomotor discomfort. Although cybersickness has traditionally been discussed primarily in virtual reality, research shows that optical see-through AR can also elicit meaningful symptomatology in certain scenarios. Kaufeld et al. demonstrate that optical see-through AR can induce severe VIMS under specific conditions, with symptom profiles strongly dependent on the nature of the displayed content (static versus dynamic; simulation versus simple procedural guidance) [22]. In the context of field operations, this dimension is critical from a safety standpoint: technicians operate in active environments, handle materials, work near machinery or vehicles, and sometimes perform tasks in confined spaces. Any disorientation or decline in attentional stability can increase the likelihood of incidents. A practical advantage of research focused on AR cybersickness is that it provides methodological guidance for measurement and mitigation. Hughes et al. address the psychometrics of cybersickness in AR and argue that safe and sustainable deployment requires standardized assessment protocols (e.g., SSQ) and organizational measures (limiting exposure duration, structuring work into blocks, implementing adaptation phases) [23]. Such recommendations are transferable not only to training but also to routine logistics, where smart glasses may be considered for “full-shift” use.

The organizational-operational dimension of fatigue is increasingly linked to work–rest scheduling. This is especially relevant because cumulative effects may emerge late in a shift or across repeated daily exposures, even if the technology appears acceptable in short trials. Hsiao et al. propose work–rest schedules for visual tasks using optical head-mounted displays based on measurements of visual fatigue and VIMS recovery. Their approach yields practical inputs for internal guidelines - specifically, how to define realistic work blocks and rest intervals [21]. This framework is applicable both to logistics (picking, inventory, receiving/issuing) and to maintenance (repetitive inspection routines), where the technology is likely to be used intermittently throughout the shift rather than continuously.

Equally important is wearing comfort and user acceptance, because these factors often determine whether the technology will be adopted in real operations. In logistics tasks such as picking, empirical work shows that even when performance remains stable, discomfort (pressure points, perceived obstruction, distraction) and psychosocial factors (nervousness, concerns about making mistakes) may undermine sustained use. Smith et al. analyze comfort during picking and putting tasks with smart glasses and show that comfort is multidimensional and can influence not only willingness to use the device but also the long-term stability of performance [24]. This implies that pilot evaluation should not be limited to time and error metrics; it must also include systematic assessment of comfort, perceived strain, and acceptance across user groups (experience level, physical characteristics, task profiles, shift length). In maintenance, the same logic applies, with additional complexity introduced by protective equipment, variable postures, and the need to communicate in noisy environments - factors that can further elevate overall load.

6. Limitations

The limitations of this study stem primarily from the fact that it focuses on the conceptual design and pilot verification of introducing predictive maintenance into operational practice, rather than on a full quantification of impacts. The work does not provide a detailed calculation of the economic effect (e.g., TCO/LCC, return on investment) or the costs associated with process change, personnel training, and integration into existing maintenance information systems. Another limitation relates to the complexity of modern ground platforms and the resulting volumes of heterogeneous data (operational parameters, maintenance records, visual documentation), whose management, standardization, and analytical processing can significantly influence real-world feasibility and the scope of implementation. For these reasons, the results should be interpreted as a starting point for subsequent, more detailed operational and economic assessment.

7. Conclusions

Predictive maintenance represents a promising direction for military ground equipment, enabling a shift from predominantly reactive interventions toward condition-based maintenance management and timely planning of maintenance actions. However, under field conditions, the benefits of this approach do not arise solely from deploying analytical methods; they depend primarily on establishing a functional process–data chain that links field diagnostics, maintenance records, and subsequent evaluation [7,15]. The proposed framework indicates that assisted diagnostics and remote expert collaboration can serve as practical enablers of this chain: they accelerate fault identification, reduce decision uncertainty, and simultaneously increase the completeness and consistency of field records. Such records are essential for building a reliable data foundation and for downstream prognostic tasks, including remaining useful life (RUL) estimation [10,11].

At the same time, the introduction of similar capabilities within the Czech Armed Forces is already supported institutionally and is being pursued through targeted validation in an operational context. This suggests that integrating assisted diagnostics into maintenance workflows for modern equipment is practically feasible. [19] In the broader perspective of military sustainment, such a solution supports faster knowledge transfer between the field and specialized facilities, reduces the need for physical deployments of experts, and contributes to shortening equipment downtime. [18,19] Beyond technical and process-related aspects, it is necessary to account for human factors associated with long-term use of hands-free devices, including wearing comfort, visual load, fatigue, and cybersickness-like symptoms, which may affect both occupational safety and user acceptance. [20-24]

Future work should therefore focus on pilot validation through representative scenarios and on assessing the impact on equipment availability, record quality, and “data readiness” for predictive analytics. Only on this basis will it be possible to formulate scalable recommendations for implementing field-level predictive maintenance for highly complex ground platforms.

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