

Proof of Performance for Remote Operations Services of Mechatronic Systems

Artur Krause^{1,2}, Franziska Speh², Pascal Kull¹, Steffen Wagenmann²,
Maximilian Rolle², Philipp Humbeck², Nikola Bursac¹

¹ISEM - Institute for Smart Engineering and Machine Elements, Hamburg University of Technology, Germany

²TRUMPF SE + Co. KG, Germany

Abstract: This study develops a data-driven Proof of Performance to quantify productivity gains enabled by Remote Operations Support in complex mechatronic systems during operation. Remote Operations Support provides centralised, data-based monitoring and remote troubleshooting of machines, allowing error cases to be addressed without immediate on-site presence and thereby reducing downtime. The Proof of Performance operationalises productivity as additional running-state time between remote error resolution and the next error or the end of the shift, complemented by resolution-time segmentation to explain performance effects. Iterative refinement of report structure and KPI logic results in a robust measurement framework that supports consistent, comparable reporting. The developed Proof of Performance provides confirmation that Remote Operations Support can substantially enhance productivity improvement by accelerating recovery from disturbances and increasing productive machine time.

Keywords: Remote Operation; Data-driven; Data analysis; Resource consumption; Sustainability

1 Motivation

Sheet-metal components are widely used across numerous industries, including the manufacture of aircraft, vehicles, and frames for television and computer screens (Qin, 2010). These parts are typically produced from steel or aluminium, materials that dominate industrial sheet-metal applications due to their availability and favourable mechanical properties (Cooper et al., 2017). Growing global populations and expanding economies increase demand for both materials and intensify the need for efficient, scalable production (Simon et al., 2023). Global crude steel production reached approx. 1.89 billion tons in 2023, underscoring the scale at which sheet-metal-related value chains operate (C. Schmidt, 2024).

Industrial manufacturing relies on a broad range of sheet-metal forming processes that require specialised equipment and benefit from continuous technological innovation in mechanics, control, and automation (Boljanovic, 2004). Metal forming machines are complex mechatronic systems that integrate multiple subsystems and technologies, including electronics, mechanics, and hydraulics, which increases both system capability and operational complexity (Merschak & Hehenberger, 2019). Manufacturing complex sheet-metal components, therefore, involves high capital investment and substantial energy consumption, making energy and resource efficiency central drivers for both cost reduction and sustainability objectives (Cooper et al., 2017).

Operational machine data combined with resource consumption data enables the quantification of energy demand by machine state and the identification of high-consumption phases, such as start-up, transient behaviour, and non-productive operation. Analyses based on this linkage support measures that increase performance, improve resource efficiency, and reduce environmental impact by targeting the states and subsystems that contribute most to overall consumption (Krause et al., 2024).

Non-productive states contribute to avoidable energy consumption, especially during machine idling, when auxiliaries, control systems, or hydraulics continue to draw power without producing parts. Remote operations technologies can reduce these losses by enabling remote access, monitoring, and intervention, which shortens reaction times and supports faster recovery from disturbances. Operators in a remote operations center can diagnose issues and resolve certain machine stoppages without being physically present at the machine, reducing downtime and enabling extended operating hours without continuous on-site staffing (Mislán, 2022).

Remote operations centers integrate real-time data from machines, sensors, and service systems to provide a consolidated operational view and to support standardised decision-making across multiple assets (Feng, 2024). Service quality and reliability are key determinants of customer satisfaction, particularly when production interruptions translate directly into delivery and cost risks (Paluch & Blut, 2013). Data collected through remote operations can document interventions, generate performance and availability reports, and improve service delivery by enabling transparency and continuous improvement across the installed base (T. Schmidt, 2016).

2 Literature Review

2.1 Remote Operations within Autonomous Operations as a Service

The Business-to-Business sector is subject to increasing competitive pressure, as technological differentiation has decreased in many markets. Innovation is therefore treated as a key lever for sustaining competitiveness. A frequently applied approach is servitisation, meaning the systematic extension of products through services to strengthen product and process innovation (Goffin et al., 2021). Product–service systems (PSS) combine tangible products and intangible services that are designed and integrated to jointly satisfy customer needs (Tukker & Tischner, 2006). In many industrial settings, differentiation increasingly depends on operational outcomes such as availability, responsiveness in case of disturbances, and transparency over performance rather than on hardware features alone. In parallel, the use of large datasets gains relevance for identifying customer requirements, operationalising service quality, and quantifying delivered value. Delivered value can be expressed through measurable operational indicators, for example, availability, downtime and recovery time, throughput, quality outcomes, or resource-related measures such as energy per produced part. The combination of product, service, and data can support competitive differentiation but is typically associated with the development of new business models and organisational adjustments, especially regarding digital capabilities and lifecycle responsibilities (Fischer et al., 2022). The term business model is not uniformly defined in the literature (Schallmo, 2018). Teece (2010) defines a company’s business model as “the manner by which the enterprise delivers value to customers, entices customers to pay for value, and converts those payments to profit”. Business models evolve in response to technological developments and changing customer expectations, influencing how value is created, delivered, and captured (Rajim, 2024). In industrial equipment markets, this evolution is reflected in a shift from transaction-oriented sales toward recurring revenue models that depend on sustained operational performance over the lifecycle. Equipment-as-a-Service (EaaS) represents an example of a business model based on a subscription approach (Relayr, 2021). It combines the physical product with the services required to operate and maintain the equipment, consolidating them into a single, integrated offering (Rösler & Friedli, 2021). The concept of EaaS involves the provision of machines to customers on a subscription basis, whereby the customer does not acquire the machine but rather pays a recurring fee to access it. The subscription fee is calculated based on the delivered value, which may include factors such as machine availability, usage duration, or the performance outcomes derived from its utilisation (Evckenko et al., 2022). This setup shifts operational and financial risk toward the provider, which increases the relevance of systematic monitoring, rapid fault isolation, and standardised intervention processes to meet agreed service levels. These elements are incorporated in the Autonomous Operations as a Service framework, which comprises a technical component (autonomous operation) and a business model component (“as a service”).

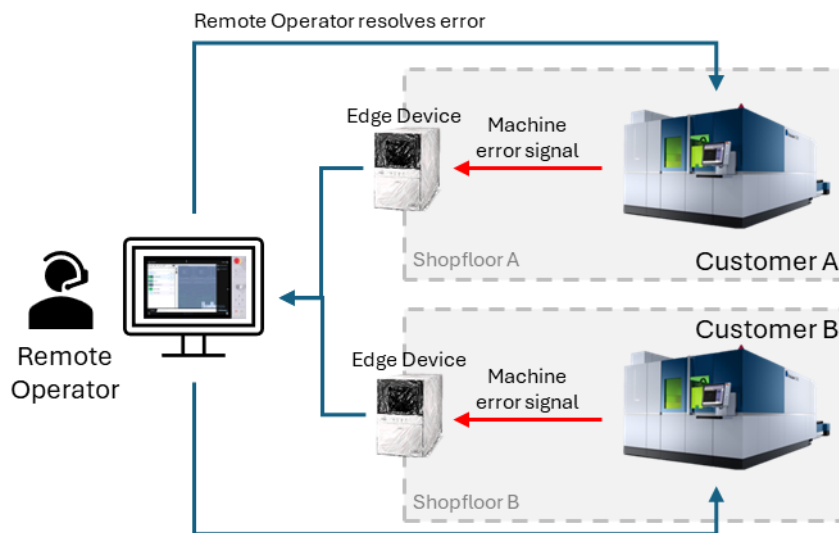


Figure 1: Simplified description of the Remote Operation Service

The technical component targets operation with reduced dependence on physical specialists on-site by enabling centralised support and intervention. For original equipment manufacturers (OEMs), the framework provides a basis for integrating operational responsibility into service-oriented business models. For OEMs, this also includes the capability to manage performance and availability across a distributed installed base. Remote operations serves as an enabling capability because monitoring and troubleshooting can be conducted at customer sites via digital technologies (Wirth et al., 2024). Remote operations can be understood as a human-in-the-loop operational concept that stabilises production and generates structured operational knowledge, while autonomous functions can be introduced incrementally based on validated use cases and data. Remote operations are carried out from centralised remote operations centers, where real-time data

integration consolidates information from sources such as machine sensors, controller signals, condition monitoring systems, and production databases. Integration typically includes event and alarm streams, machine-state information, historical maintenance and service records, and contextual production information, enabling consistent diagnosis and targeted interventions to restore operation and stabilize performance (Feng, 2024).

2.2 Data-Driven Decision Making

Remote control from centralized remote operations centers and timely operational interventions require real-time integration of data from heterogeneous sources, including machine sensors, controller signals, condition monitoring systems, and production databases (Feng, 2024). Data-driven decision-making refers to an approach in which data is collected and analyzed to extract relevant patterns and facts that inform organizational decisions. Decisions are thus grounded in empirical evidence rather than intuition or informal observation (Joubert, 2019).

To support informed decision-making and generate data-driven insights, data-driven decision-making frameworks provide structured process models that guide activities such as data collection, analysis, and interpretation. These frameworks aim to increase decision quality and efficiency by establishing repeatable steps and clearly defined analytical outputs (Pothineni, 2022). The Cross-Industry Standard Process for Data Mining (CRISP-DM) is a widely used framework in data mining and analytics (Khare et al., 2024). It distinguishes six phases: Business Understanding, Data Understanding, Data Preparation, Modeling, Evaluation, and Deployment. The phases are iterative rather than strictly linear, and transitions between phases are required as insights and constraints emerge during project execution (Chapman, 2000). Another established approach is the SPALTEN method, which provides a generally applicable methodology for solving problems under varying boundary conditions and degrees of complexity (Albers et al., 2016). SPALTEN frames product development and its individual phases as problem-solving tasks and emphasizes the transformation from an actual state to a required target state under constraints such as available time, information availability, complexity, and scope (Albers et al., 2005).

Despite advances in literature, the systematic use of field-gathered operational data to derive actionable insights and support decision-making in product development based on field-gathered operational machine data has received limited attention within industrial practice. This limitation is particularly relevant for complex mechatronic systems, where operational data can support the management of system interactions and emergent behavior. Wagenmann et al. (2022) address this gap by proposing a data-driven process for requirement validation in product development. The approach maps the fundamental activities of CRISP-DM to the elements of the SPALTEN problem-solving methodology, linking data mining activities to established development logic. The proactive and systematic use of field-gathered data therefore offers potential to improve decision-making efficiency during development. Machine data combined with resource consumption data can reveal improvement potential for sustainability objectives by reducing environmental impact while increasing system efficiency and performance (Krause et al., 2024). Product Carbon Footprint calculations and sustainability assessments based on operational data require technical system architectures that support data acquisition, data quality management, and data mining strategies as integral design elements. Operational data integration into development processes is increasingly recognized as a mechanism for sustainability-oriented improvement of mechatronic systems. Sustainable Engineering through Data-driven Design is a methodology developed for this purpose and supports data-driven product development aimed at minimizing environmental impact associated with the operation of new generations of complex mechatronic systems (Krause, 2025).

3. Methodological approach and Research Questions

This research was conducted at a German machine tool manufacturer and contributes to the investigation of Remote Operations Support and its effects on productivity and sustainability during machine operation. The objective of this study is to develop a data-driven Proof of Performance for Remote Operations Support that quantifies productivity effects and sustainability-related impacts during machine operation using relevant KPIs. In accordance with the research objective the following research questions are derived to operationalize the objective:

RQ1: What influencing factors and challenges can be identified for a data-driven proof of performance to evaluate remote Operations Support?

RQ2: How can a data-driven performance evaluation for Remote Operations Support be designed to enhance sustainability during machine operation?

RQ3: What benefit does a data-driven Proof of Performance of Remote Operations Support provide in identifying and deriving to enhance sustainability during machine operation?

In order to systematically address the research questions, the Design Research Methodology by Blessing and Chakrabarti (2009) is applied. To answer the first research question (Descriptive Study I) multiple analyses are conducted to identify

relevant influencing factors and challenges for a data-driven Proof of Performance. Resolved fault cases from machines in the field are analyzed together with several Remote Operators. The analysis combined recorded fault messages, corresponding machine signals, and video recordings of the respective fault situations. These machine-generated data are systematically compared with the fault causes identified by the Remote Operators and the measures actually applied to resolve the faults. In this way, the available machine data are validated against the practical knowledge and actions of the Remote Operators. The resulting understanding of relevant signals, fault patterns, and resolution measures are incorporated into the development of the Proof of Performance and its KPIs. To answer the second research question, the Prescriptive Study focuses on the iterative development of the data-driven Proof of Performance. This approach enables development-relevant insights from field data, such as recurring fault patterns, relevant operating conditions, and improvement potentials, to be transferred into product development and used to support the development of new system generations. To answer the third research question, Descriptive Study II evaluates the added value of the developed Proof of Performance and Remote Operations Support for sustainability-oriented machine operation. The evaluation examines how productivity- and sustainability-related effects, such as resolved fault cases, reduced downtimes, avoided on-site interventions, and improved machine availability, can be made transparent and used to derive measures for reducing environmental impacts during operation.

4 Identified factors and challenges in the development of a proof of performance

Within the scope of this study, a factor is defined as an element that influences the Proof of Performance or the KPIs it contains. A challenge refers to an existing or potential obstacle that can lead to misinterpretation or hinder the accurate calculation of KPIs. The analysis identified six factors that affect the reliability and interpretability of the current Proof of Performance. These factors cluster along three themes: selection of a suitable database, correctness of KPI calculations already implemented, and completeness of KPI coverage required for attribution of effects. Table 1 summarises the identified factors that directly influence KPI computation and KPI coverage and outlines their implications for the reliability and interpretation of the reported results.

Table 1: Identified factors influencing the Proof of Performance and its KPIs

Factor category	Factor	Description	Implication for reliability
Database	OPC UA-based data source (event-level)	Provides machine states, measured values, parameters, and alarms via a standardised interface; supports event-based evaluation with high temporal granularity.	Enables time-accurate KPIs and consistent sequencing of errors and interventions.
Database	Batch-based data source (60-minute heartbeat)	Computes multiple states in batch mode; heartbeat-driven updates can introduce timing delays and duration deviations.	Risks distorted durations and misaligned timestamps; limits suitability for time-critical KPIs.
KPI correctness	Total production time (incorrect calculation)	Current calculation logic yields incorrect production time values.	Distorts the utilisation baseline and affects all derived comparisons
KPI correctness	Number of error cases (incorrect calculation)	Current calculation logic yields an incorrect count of error cases.	Biases frequency-based interpretations (disturbance rate, workload, intervention volume).
KPI correctness	Increased productivity (incorrect calculation)	Current calculation logic yields incorrect productivity gains.	Undermines the central performance statement communicated to customers.
KPI completeness	Missing KPIs for remote assistance and access-right constraints	Remote assistance effects are not represented; periods without access rights are not captured.	Prevents attribution of productivity effects and can misrepresent resolvability and response performance.

In addition, three challenges were identified that do not change KPI values directly, but systematically reduce reproducibility, comparability, and the feasibility of sustainability-related reporting. Table 2 summarises the identified challenges that constrain reproducibility, comparability, and sustainability-related reporting, and specifies their implications for the practical use of the Proof of Performance.

Table 2: Identified challenges affecting use, comparability, and sustainability reporting

Challenge category	Challenge	Description	Implication for reliability
Documentation	Missing documentation of sources and KPI logic	Data sources, signal semantics, and KPI calculation logic are not comprehensively documented.	Reduces reproducibility; complicates correction, extension, and handover.
Configuration	Non-standardized dashboard configuration	No formalised guidelines for dashboard settings prior to customer transmission.	Enables inconsistent settings; reduces comparability across customers and time.
Sustainability data	Missing input data for sustainability KPIs	Required input data for Product Carbon Footprint and saved resource consumption are not implemented in the existing version.	Prevents reliable sustainability KPI computation; sustainability evaluation remains incomplete.

The development of the Proof of Performance in this study can be based on one of two databases that differ in the way data is transmitted and in temporal resolution. The database used in the current version provides data via OPC UA and enables structured transmission of machine-related information such as operational states, measured values, parameters, and alarms. This data source supports event-based evaluation with high temporal granularity and is treated as real-time within the reporting logic used for the Proof of Performance. The second database is used for other internal reports and computes multiple states in batch mode with a heartbeat frequency of 60 minutes. Batch-wise processing with heartbeat updates can introduce delays between control signals and their registration, affecting recorded durations and contributing to deviations compared to event-based sources (IBM, 2024). Because several KPIs depend on accurate timestamps and short-term state transitions (e.g., reaction time, active time, productivity increase), the higher-resolution data source constitutes the appropriate basis for the Proof of Performance within this study. Beyond the database decision, the Proof of Performance can contain incorrect calculations for three KPIs: total production time, number of error cases, and increased productivity. These errors affect the reported magnitude of productivity effects and distort comparisons between periods with and without Remote Operations Support.

In addition, KPI coverage is incomplete for two aspects required for the consistent interpretation of productivity effects. First, productivity increases achieved through remote assistance are not represented by dedicated KPIs. Second, the absence of information on time periods during a shift in which remote operators lack access rights limits the interpretability of response and resolution performance, because non-actionable cases cannot be distinguished from delayed cases. While such factors directly influence KPI computation and KPI coverage, the practical reliability of the Proof of Performance is additionally shaped by the conditions under which the report is created and interpreted. Limited documentation reduces traceability, as the underlying data sources, signal semantics, and KPI calculation logic are not specified in sufficient detail for systematic verification. Consequently, reported values cannot be reproduced and checked with the required rigour, and necessary adjustments become difficult to implement without risking unintended effects on other KPIs. Simultaneously, the customer-facing dashboard is prepared without formalised configuration guidelines. This increases the probability that different settings, such as evaluation periods, filters, aggregation rules, or shift definitions, are applied across customers or reporting cycles. Such variability can change KPI outputs independently of actual machine behaviour, deteriorating comparability and complicating the interpretation of differences between reports. Sustainability-related evaluation is further constrained by missing input data. Product Carbon Footprint and saved resource consumption are considered as KPIs to assess sustainability, and Product Carbon Footprint is widely used as an understandable environmental indicator in industrial contexts (Sanyé-Mengual et al., 2014). However, the data required for Product Carbon Footprint calculation are not implemented in the existing Proof of Performance, which prevents reliable computation and limits the substantiation of sustainability-related conclusions derived from the report.

5 Development of data-driven Proof of Performance of increased Productivity

The development of the Proof of Performance follows an iterative refinement process supported by regular alignment with the Remote Operations team lead. Across 11 iterations, the report structure and the underlying KPI logic are consolidated and specified in a way that supports consistent interpretation. The revised version corrects the calculation logic for total production time, total number of error cases, and increased productivity. In addition, productivity enabled through remote assistance are explicitly represented through increased productivity remotely assisted, complementing increased productivity for remotely resolved cases. To improve interpretability, the KPI set is organized into four functional groups that reflect the analytical purpose of the measures and are summarized in Table 3.

Table 3: KPI groups included in the Proof of Performance

KPI group	Purpose in the Proof of Performance	Included KPI elements
Error volume and remote contribution	Establish baseline of disturbance volume and quantify remote-resolution share for attribution of effects	- Total number of error cases - Number of remote solved error cases
Productivity effects	Quantify additional running-state time attributable to remote resolution and remote assistance as well as normalise effects against baseline production time	- Total production time - Production time without increased productivity - Increased productivity - Increased productivity remotely assisted - Percentage increase of production time - Days with exactly one remotely solved case - Days with more than one remotely solved case - Days without a remotely solved case
Response and resolution performance	Explain productivity effects through time-to-response and time-to-resolution characteristics to support benchmarking and outlier-aware interpretation	- Average reaction time - Average processing time - Average inactive time - Average error resolve time segmented by resolution method - Minimum resolve time - Maximum resolve time - Median resolve time - Processing time per machine per night in hours - Period-level and day-level processing time averages - Average increased productivity of days with remotely solved error cases
Energy-, cost-, and emissions-related indicators	Extend evaluation toward sustainability-related implications and quantify scenario-based savings potential during machine idle phases	- Energy consumption - Energy costs - Energy-related emissions - Total duration of energy consumption - Energy consumption during machine operation - Total duration of idle phases - Scenario comparison of costs, energy consumption, and emissions - Absolute and percentage savings

The first group establishes baseline context by quantifying disturbance volume and the contribution of remote resolution. This baseline is captured through the total number of error cases and the number of remote solved error cases, which together provide the reference for interpreting time-based effects and separating case volume from performance per case. The second group quantifies productivity effects by relating running-state time to the contribution of remote support. Total production time is reported as the running-state duration within the evaluation period. The productivity gain attributable to Remote Operations Support is reported as increased productivity, while productivity gain enabled through guided on-site resolution is represented through increased productivity remotely assisted. Production time without increased

productivity is derived by subtracting both gain components from total production time, and the percentage increase of production time provides a normalised view of the effect. To reduce the risk that period averages conceal concentration effects, daily distribution measures differentiate days with exactly one remotely solved case, days with more than one remotely solved case, and days without a remotely solved case. The third group explains productivity outcomes through response and resolution performance. The time structure of case handling is represented through reaction time, processing time, and inactive time. Reaction time captures the interval between error occurrence and first response, processing time reflects the period of active work on the case, and inactive time accounts for interruptions when remote resolution is not possible and the case is resumed later. These segments are aggregated into average indicators and complemented by minimum, maximum, and median resolution time to support outlier-aware interpretation. Resolution performance is further segmented by resolution method, distinguishing remotely solved cases, remotely assigned cases, and on-site cases. Workload distribution and comparability across periods are supported by processing time per machine per night in hours, together with averages computed over the evaluation period and over days with remote resolutions; the average increased productivity of days with remotely solved error cases links productivity gain to the temporal distribution of remote activity. The fourth group extends the report toward sustainability-related indicators by linking energy consumption to cost and emissions factors and by providing operational aggregation. Energy costs are derived from energy consumption and the respective country-specific electricity price, while energy-related emissions are derived from energy consumption and the respective country-specific CO₂ intensity. Aggregations capture both the total duration of energy consumption and energy consumption during machine operation, and idle behaviour is represented through the total duration of idle phases grouped by switchability. A scenario comparison contrasts costs, energy consumption, and emissions for a baseline without shutdown with a scenario that excludes consumption during switchable idle phases; the resulting differences are reported as absolute savings in euros, kilowatt-hours, and CO₂e, complemented by percentage savings.

6 Added value of the developed Proof of Performance

The developed proof of performance increases the reliability and interpretability of reported effects by refining KPI logic at boundary conditions that previously produced systematic distortions. One improvement concerns the KPI for the total number of error cases. In the existing implementation, the system counts error cases based on case start time without verifying whether the case is also completed within the selected shift window. The revised logic introduces a shift-consistency constraint so that only error cases with a start time after shift start and an end time before shift end are counted. This adjustment aligns the KPI with the intended operating window and reduces the risk that cross-shift cases bias results for a given evaluation period.

A second improvement addresses the measurement of productivity gains when running substates that extend beyond the shift boundary. In such situations, recorded running durations may include time outside the evaluated shift and therefore overstate the productivity effect attributed to remote support. The revised KPI logic applies a boundary rule that distinguishes whether the relevant running substate is fully contained within the shift window. When a running substate occurs between two error cases that both start and end within the shift, the full recorded duration is retained. When a running substate continues beyond shift end, only the interval from the start of the running substate to shift end is counted as increased productivity. This rule confines the quantified productivity gain to the selected shift and supports comparability across reporting periods. The calculation of total production time is improved through an explicit case-based interpretation of running substates relative to the shift window. If a running substate starts before shift starts and ends during the shift, only the interval from shift start to the end of the running substate is counted as productive time. If a running substate starts during the shift and ends after the shift end, only the interval from the start of the running substate to the shift end is counted. If both start and end occur within the shift, the full recorded duration is used. Running substates that do not meet these conditions are excluded, including substates that occur entirely outside the shift window. This treatment reduces ambiguity and prevents production time from being overstated through the inclusion of non-relevant operating periods.

Beyond improved correctness of productivity-related KPIs, the developed proof of performance provides added value by enabling a structured assessment of operational efficiency measures aimed at sustainability, such as targeted shutdowns during downtime. Qualitative expert assessments indicate heterogeneous expectations regarding overall sustainability impact. One position emphasises that the largest leverage may lie in reducing energy consumption during active peak times rather than in reducing idle times, and that energy-related emissions represent only a minor share of total CO₂ equivalents once material-related emissions are included. Another position highlights that long idle periods can occur over extended time horizons and therefore offer measurable potential for resource-efficiency improvements through targeted shutdown strategies. Across perspectives, the measure is generally regarded as practically feasible, while the estimated contribution to total emissions depends on the system boundary applied. These qualitative assessments are complemented by a quantitative analysis based on operational data enabled by the developed dashboard. Data from 118 machines over a twelve-month period were evaluated.

The aggregated savings associated with targeted shutdown during idle phases amount to approximately 142 200 euros in energy costs, approx. 1 mio. kWh in energy consumption, and about 316 300 kg CO₂e in energy-related emissions. On a per-machine basis, this corresponds to average annual savings of approximately 1 205 euros, 8 475 kWh, and 2 681 kg CO₂e. The reduction in energy-related emissions is of the same order of magnitude as the annual emissions of an average combustion-engine passenger car driven roughly 14 000 km (Federal Statistical Office, 2022).

7 Discussion and Outlook

This research develops a data-driven proof of performance for Remote Operations Support and its contribution to sustainability-oriented operations. The work builds on established research on remote repair, remote diagnostics, telemaintenance, remote monitoring, and predictive maintenance, which has shown the relevance of operational data for improving equipment availability, supporting fault diagnosis, and reducing service effort in industrial contexts. While this literature demonstrates the value of remote access and operational data for service and maintenance activities, the present work extends this perspective by focusing on a data-driven evaluation logic that makes the effects of Remote Operations Support transparent for customers and usable for internal product development.

The findings indicate that a reliable Proof of Performance requires more than the definition of additional KPIs. This observation is consistent with performance measurement literature and standards for manufacturing operations management, which emphasize that KPIs require clearly specified definitions, data inputs, calculation rules, time behavior, and interpretation logic to support comparability and decision-making. In the context of Remote Operations Support, these requirements are particularly relevant because performance effects are evaluated across machines, shifts, fault cases, and customer-specific operating conditions. Therefore, the existing Proof of Performance is analyzed to examine the current evaluation logic and to identify factors that influence KPI validity and comparability. The results provide the basis for targeted adjustments, particularly regarding data sources, time-window logic, and calculation rules, which are required to avoid systematic distortions such as those occurring at shift boundaries. The developed proof of performance improves practical applicability through two mechanisms. First, the KPI set is extended with resource-related indicators, enabling sustainability-oriented comparisons based on operational data. This extension positions the proof of performance as a framework for combining operational improvements with ecological indicators, while maintaining a shared measurement logic. Second, the introduction of structured documentation and a standardised preparation guide addresses previously identified limitations in reproducibility and report comparability. The documentation specifies KPI definitions, data inputs, and calculation logic, reducing the risk of misinterpretation. The preparation guide standardises filter and configuration settings for customer-facing reporting, supporting week-to-week comparability and consistent communication of results.

The findings indicate that the developed proof of performance provides a transparent basis for data-driven assessment of productivity gains enabled by remote troubleshooting. At the same time, the integration of resource-related KPIs demonstrates how the reporting logic can be extended toward sustainability evaluation. This extension supports the use of the proof of performance as a measurement layer for future comparisons and for prioritising improvement measures based on quantifiable effects rather than assumptions. Further development opportunities follow directly from the implemented KPI structure and from observed interpretation limits. Sustainability-related KPIs can be expanded to provide customers with additional insight into the environmental implications of operational decisions, complementing productivity reporting. Usability can be improved through filter functions that enable structured selection by machine, evaluation period, and shift hours, thereby increasing flexibility without compromising comparability. The KPI set also enables validation of business-case assumptions, for example, by using processing time per machine and shift to identify systems with consistently longer troubleshooting durations. Combining this information with error frequency supports the identification of recurring and time-intensive error types that can be prioritised for corrective actions.

Further benefit arise from the decomposition of total resolution time into reaction time, processing time, and inactive time. This separation supports a more precise interpretation of prolonged downtime by indicating whether delays originate from late response, extended active troubleshooting, or interruptions when remote resolution is not possible. In particular, inactive time highlights cases in which remote support cannot complete resolution and escalation becomes necessary, which provides a measurable indicator for technical limitations of remote resolvability and for potential improvements in diagnostics, access rights, or intervention capabilities.

The proof of performance also enables broader pattern analyses. For example, the relationship between the number of days with remotely resolved cases and the associated productivity increase can be evaluated to estimate average productivity effects under different levels of remote activity. Daily indicators showing whether none, one, or multiple cases were resolved remotely support this analysis, while interpretation requires caution. A day without remotely resolved cases may reflect absence of errors, lack of access rights, or technical non-resolvability. Combining these indicators with processing times and error volume can support more robust inferences, such as identifying periods with complex error types that require further investigation.

Overall, the developed proof of performance provides value for both external reporting and internal decision-making. It supports evidence-based evaluation of Remote Operations Support performance and creates a consistent reporting basis that improves transparency in operational monitoring. The combination of an extended KPI set, clarified calculation logic, and standardised documentation establishes a foundation for continuous refinement and for future integration of sustainability evaluation into operational performance reporting.

Future work can build on the data foundation established for the Proof of Performance to develop AI-based approaches for fault detection and resolution support. The combination of recorded fault messages, machine signals, video data, and documented resolution measures provides a suitable basis for identifying recurring fault patterns and deriving recommendations for Remote Operators. By extending this data basis with additional contextual information and validated resolution knowledge, future systems could support Remote Operators in diagnosing faults more efficiently and selecting suitable corrective actions. Such approaches represent a direct transfer of insights gained from operational data into product development and can support the further development of Remote Operations Support for future system generations.

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