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RESEARCH ARTICLE

Integration of Wearable Electromyography Sensors With Cloud-Based Analytics for Biomechanical Overload Monitoring and Ergonomic Evaluation

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ABSTRACT Work-related musculoskeletal disorders (WMSDs) remain a pressing issue in industrial environments, posing both health and legal risks. This study explores the feasibility of a wearable system for assessing biomechanical overload risk using surface electromyography (EMG). The proposed approach integrates wearable EMG sensors, a mobile application, and a cloud-based information system to facilitate reliable, real-time data acquisition and preliminary analysis. A pilot experiment was conducted on a diverse group of subjects to evaluate signal processing robustness and to test four hypotheses related to physiological and ergonomic variability. Results indicate the system's potential for capturing muscle load dynamics and generating interpretable indicators of physical workload. While promising, the method's current validation is limited in scale and focused on signal-level analysis rather than long-term occupational outcomes. This study serves as a foundational step toward scalable ergonomic evaluation using wearable biosensors, with further validation required in diverse and larger industrial settings.

INDEX TERMS Ergonomic risk assessment, Industry 4.0, muscle activity measurement, physical workload monitoring, real-time data acquisition, surface electromyography.

I. INTRODUCTION

Despite predictions that Industry 4.0 would significantly reduce manual labor through automation, manual tasks continue to form a substantial part of industrial production, exposing workers to ongoing risks of work-related musculoskeletal disorders (WMSDs) [1]. WMSDs, caused primarily by ergonomic stressors such as repetitive movements, lifting heavy loads, and awkward postures, remain prevalent across various industrial sectors. Recent European

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surveys underline the persistent nature of these risk factors, with increasing awareness and reporting of issues like repetitive hand or arm movements and lifting or moving heavy loads between 2014 and 2019 [2], [3]. However, despite greater recognition, the implementation of preventive measures has remained stagnant, indicating a clear gap between risk identification and effective mitigation [2].

Traditional risk assessment methods include observational, self-reporting, and direct measurement techniques. While observational and self-reporting approaches offer ease of use, they can suffer from subjective bias and inconsistency [4]. Conversely, direct methods involving optical motion capture and wearable inertial sensors objectively measure motion and posture but fail to capture essential parameters of muscle activity, which are critical for evaluating biomechanical overload during tasks involving repetitive object manipulation or sustained exertion.

Electromyography (EMG) provides a promising direct measurement approach that objectively quantifies muscle activation, exertion levels, peak activity, and cumulative muscle load [4], [5]. Previous studies have demonstrated EMG's reliability and accuracy in assessing muscular fatigue and physical workload objectively, establishing it as a standard tool for ergonomic evaluations in industrial and occupational health contexts [4], [6], [7]. Nevertheless, existing EMG-based methodologies still exhibit significant limitations, particularly concerning their deployment in real-world industrial settings. These limitations include the lack of real-time data processing capabilities, insufficient synchronization among multiple EMG sensor channels, inadequate error correction procedures for continuous data collection, and limited integration with established ergonomic regulations [4], [5], [6].

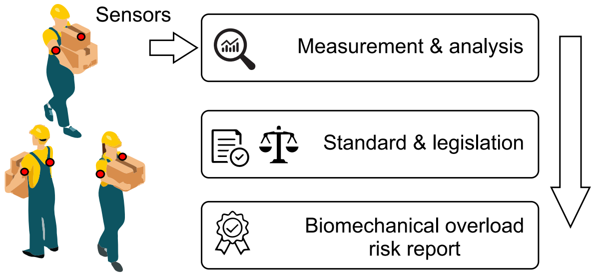

FIGURE 1. Biomechanical overload assessment: measurement and analysis from wearable sensors, followed by evaluation according to standards and legislation to produce a biomechanical overload risk report.

The assessment of the biomechanical overload related to manual material handling is a fundamental step in the prevention of WMSDs. Figure 1 illustrates the procedure for this type of assessment. The current methods for assessing biomechanical overload are categorized as observational, self-reporting, and direct methods [4]. Among these, direct methods are the most objective, based on optical motion capture systems, wearable systems, or EMG systems. Optical motion capture systems and wearable systems use accelerometers and inertial sensors, and goniometers can assess various motion and posture parameters. However, these instruments do not provide information about muscular activity and physical load, which are crucial parameters for assessing physical load on the upper limbs during manual operations, such as repetitive manipulation of objects and grasping objects of various sizes and weights. The application of surface EMG measurement sensors, which measure muscular activity, offers detailed information about muscle activation, muscle exertion, mean values, peaks, percentiles, cumulative exposure, and rate of change. This provides an objective assessment of physical load that can be quantified for each measured individual.

Existing EMG-based ergonomic assessment methods still suffer from several critical limitations: a lack of reliable multi-channel synchronization, insufficient handling of data loss in continuous recordings, and only limited alignment with regulatory standards. These shortcomings hinder their deployment in real-world industrial environments. This study addresses these identified gaps by proposing a novel, integrated method that combines wearable EMG sensors, a mobile application, and a cloud-based information system. Our approach introduces advanced multi-channel synchronization techniques, intelligent error detection and correction algorithms, and real-time signal processing to deliver robust and reliable ergonomic assessments. Specifically, the study applies these comprehensive EMG measurements to biomechanical overload assessments aligned explicitly with the Czech Republic's Government Regulation No. 361/2007 Coll., which shares core principles with international ergonomic standards such as ISO 11228 and ILO guidelines. This regulatory grounding ensures compatibility with globally accepted approaches while allowing for local compliance.

While the Czech regulation provides a specific national framework, the general methodology for quantifying muscle load, relative force, and repetitive movements is compatible with international risk assessment standards. This enables the proposed system to be adapted to various national contexts that rely on similar physical workload thresholds, such as those defined by the European Agency for Safety and Health at Work or National Institute for Occupational Safety and Health (NIOSH) in the United States.

The primary contributions of this research include:

1) System concept definition: Integration of wearable EMG sensors with mobile and cloud technologies to create a scalable, reliable solution for ergonomic monitoring.
2) Comprehensive EMG processing methodology: Introduction of multi-channel synchronization, intelligent error detection and correction, and precise muscle load quantification.
3) Regulatory-grounded assessment framework: Alignment of the developed methodology with Government Regulation No. 361/2007 Coll. and international ergonomic standards, enabling practical applicability and compliance in occupational health contexts.

To support the validation of the proposed system, we formulated four hypotheses grounded in established ergonomic and physiological principles. These hypotheses examine whether the relative force values derived from EMG data ($\%F_{\max}$) reflect sex-based strength differences, muscle group physiology, handedness, and correlations between absolute strength and relative workload. This hypothesis-driven structure ensures scientific rigor and enhances the interpretability of results in ergonomic contexts.

The remainder of this paper is organized as follows. Section II reviews related work in EMG-based ergonomic assessments. Section III describes the methodology, including the EMG measurement setup, data processing techniques, and system architecture. Section IV outlines the experimental protocol for validating our approach. Section V presents the results, Section VI discusses the implications, limitations, and ethical considerations, and Section VII concludes the study with recommendations for future research.

II. RELATED WORK AND RESEARCH GAP

This section provides a review of recent studies applying electromyography (EMG) to assess biomechanical overload risks in occupational and industrial contexts. The aim was to identify common methodologies, existing limitations, and areas in need of improvement, with a focus on real-time, field-deployable systems integrated with ergonomic standards.

The literature review was conducted following the principles of the PRISMA 2020 guidelines to ensure transparency in the search, screening, and inclusion process. Publications from the period 2015–2024 were considered, as this timeframe captures the most recent advances in wearable electromyography, ergonomic risk assessment, and Industry 4.0/5.0 contexts. The databases Scopus and Web of Science (WoS) were selected for their broad multidisciplinary coverage, indexing of peer-reviewed engineering, biomedical, and ergonomics journals, and the ability to provide reproducible export and citation tracking. While other sources such as IEEE Xplore, Medline, or Google Scholar could also have been considered, the combination of Scopus and WoS was sufficient to capture a representative set of studies relevant to the objectives of this work.

Search Parameters: The review was conducted using the keywords *"EMG" AND "load" AND "ergonomic"*. We searched two major scientific databases—Scopus and Web of Science (WoS). A total of 32 studies were initially screened. After applying inclusion and exclusion criteria based on relevance to biomechanical overload assessment in work or industrial settings, 18 studies were included in the final review (14 were excluded).

The included studies cover a wide range of applications, such as repetitive task analysis, tool use, lifting and carrying loads, paramedic operations, and ergonomic intervention evaluation. They utilize different EMG configurations, signal processing pipelines, and evaluation strategies, including both laboratory and field-based measurements. The findings of this review are categorized and analyzed in the following paragraphs.

Surface electromyography (sEMG) is a well-established, non-invasive technique for assessing muscle activity and has been extensively used in ergonomics for evaluating biomechanical load, fatigue, and the risk of work-related musculoskeletal disorders (WMSDs). The integration of wearable sEMG sensors with real-time analytics is transforming the landscape of occupational health and ergonomic assessment.

Table 1 provides an overview of selected recent studies that utilize surface electromyography (sEMG) for ergonomic assessment. The table summarizes the methodological focus, strengths, and limitations of each work, highlighting the diversity of application domains and technical approaches. It includes studies addressing real-world deployments, tool-use evaluations, high-density sensor applications, and methodological innovations. This comparison serves to contextualize the current study within the broader research landscape and to identify common challenges such as limited generalization, the need for calibration, or lack of integration with workplace standards.

The studies summarized in Table 1 demonstrate substantial progress but also illustrate that existing solutions typically address only a subset of the challenges. None of them combine synchronized multi-channel acquisition, real-time correction of transmission losses, and direct integration with enforceable ergonomic standards. This unique constellation of features defines the novelty of the present system.

A foundational challenge in sEMG analysis lies in the standardization of amplitude estimation methods. Campanini et al. [6] discussed how commonly used low-pass filtering procedures affect signal interpretation, highlighting the need for standardized processing protocols to ensure reliable ergonomic assessments. In a complementary review, the same authors [6] identified barriers to the application of EMG in neurorehabilitation and clinical ergonomics.

Occhipinti and Colombini [8] and Ranaldi et al. [9] emphasized methodological limitations in sEMG signal interpretation, especially under dynamic conditions. They noted the impact of cross-talk, electrode placement, and inter-individual variability, all of which must be considered in ergonomic applications.

To quantify fatigue effects, Campanini et al. [6] investigated how sEMG signal features change with muscular fatigue during hand grasp tasks, showing significant reductions in force estimation accuracy over time. Similarly, Koizumi et al. [10] found that power-assisted tools significantly reduced adductor pollicis muscle fatigue in repetitive hand tasks, emphasizing the importance of ergonomic tool design. García-Jaén et al. [11] analyzed lumbar, dorsal, and shoulder muscle activity under different postural conditions, providing practical insights for physical training and workplace posture strategies.

Wang [12] introduced a reinforcement learning-based optimization model that minimizes musculoskeletal stress by adjusting task parameters in repetitive motion tasks—an approach particularly promising for real-time ergonomic feedback. Skovlund et al. [13] offered a review of wearable sensor systems enhanced with artificial intelligence, concluding that while sensor technology is mature, challenges remain in data fusion, feature selection, and generalizability across job tasks.

Campanini et al. [6] and Skovlund et al. [13] further stressed that, despite growing interest, clinical and field adoption of sEMG in ergonomics is still limited by practical barriers such as user-friendliness, cost, and analytical complexity. In particular, Skovlund et al. [13] demonstrated how lifting height and load mass significantly influence muscular workload, assessed through EMG during supermarket stocking.

Celiński et al. [14] applied sEMG to study ergonomic risk in ambulance-based rescue operations, showing that stretcher height and ambulance configuration contribute to overload in paramedics' back and shoulder muscles. Martinez et al. [15] used high-density sEMG (HD-sEMG) to model grasp force from transient signals, demonstrating how spatial resolution improves estimation accuracy during complex motor tasks.

Ranavolo et al. [5] focused on the myoelectric manifestation of fatigue in repetitive tasks using miniaturized sensors. Their work showed that temporal and spectral EMG features can effectively track fatigue, especially in industrial settings. Meanwhile, in the context of human-centric manufacturing, Papetti et al. [16] emphasized the role of new technologies in reducing MSDs, calling for integrated biomechanical monitoring in Industry 5.0.

Grip force and upper-limb fatigue have also become focal points in occupational risk analysis. Alam and Khan [17] consolidated ergonomic studies that relate arm-hand workload to task repetition and posture, laying the groundwork for sensor-based risk classification systems.

Kumari et al. [18] used EMG to analyze the effects of push–pull loads in agricultural settings, showing significant fatigue in shoulder and lower back muscles during extended tasks. Khan et al. [19] offered a methodological review on EMG and EEG feature extraction and classification strategies for assistive devices, underscoring how robust classifiers can improve ergonomic intervention systems.

Giannini et al. [4] developed a sensor fusion system using sEMG and IMUs to evaluate biomechanical overload in real-time, referencing International Organization for Standardization (ISO) 11228 ergonomic risk thresholds. Hota et al. [20] applied EMG and machine learning to classify workloads during tractor operations, identifying high strain on the gastrocnemius and soleus muscles during clutch/brake use.

Merbah et al. [7] conducted a surgical case study showing how prolonged operations lead to detectable fatigue in deltoid and trapezius muscles, measurable through wearable EMG. Finally, Johnen et al. [21] challenged the validity of non-weighted cumulative load models, showing that such models significantly underestimate actual muscular and cardiovascular strain, thus advocating for the inclusion of EMG-based physiological data in ergonomic evaluation.

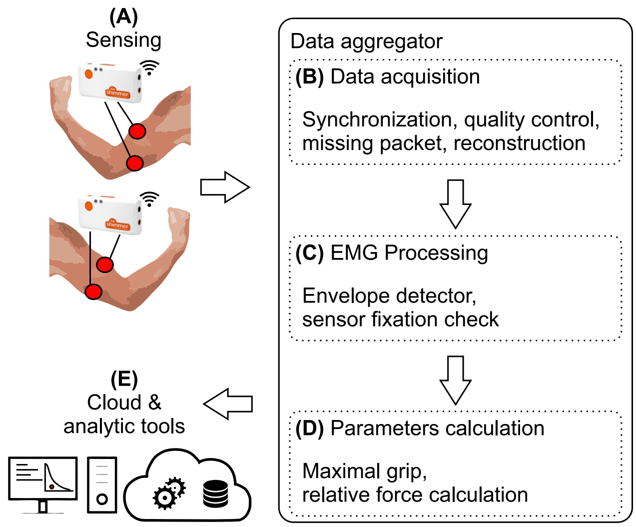

FIGURE 2. Block diagram of the proposed solution: (A) Shimmer wireless EMG sensors are attached to a worker. (B) Data acquisition involves synchronization, signal quality control, and missing packet reconstruction. (C) EMG signal processing applies filtering, envelope detection, and a sensor fixation check. (D) Parameter calculation determines the maximal grip and the relative force. (E) Cloud and analytic tool for advance data processing.

Several studies reviewed in Table 1 reference ISO 11228 or national guidelines (e.g., US OSHA, Canadian CSA) as baseline criteria, highlighting a broader trend toward standardized regulatory integration. This reinforces the need for adaptable systems that can align EMG-based assessments with both national and international benchmarks.

Despite the growing use of wearable electromyography (EMG) in ergonomic assessments, current solutions often fall short in providing a reliable, real-time, and scalable system for evaluating biomechanical overload risk in real-world industrial environments. Most existing approaches either rely on isolated sensor data without proper synchronization, lack mechanisms for error detection and correction, or remain confined to offline analysis without integration into regulatory frameworks or mobile/cloud infrastructure.

Moreover, while numerous studies emphasize muscle fatigue and workload quantification, few translate raw EMG data into actionable ergonomic insights based on binding national legislation or workplace health regulations. There remains a significant gap in methods that not only acquire and process EMG signals comprehensively but also operationalize the results in accordance with specific occupational health standards.

This study addresses these limitations by proposing a novel, fully integrated solution that combines wearable EMG sensors, a mobile application, and a cloud-based information system. It introduces a robust EMG processing methodology that incorporates multi-channel synchronization, intelligent error correction, and real-time force analysis. Importantly, the proposed system supports practical implementation of

TABLE 1. Comparison of related work on EMG-based ergonomic assessment.

Author	Methods	Strengths	Limitations
Skovlund et al. 2022 [13]	EMG during supermarket stocking tasks	Real-world data; considers lifting height and mass	Focuses on specific task; limited generalizability
Occhipinti et al. 2016 [8]	Review of ergonomic assessment methods including EMG	Comprehensive methodology comparison	No implementation or system validation
Ranavolo et al. 2018 [5]	Miniaturized sEMG sensors for repetitive tasks	Portable and suitable for field use	Limited signal quality under dynamic conditions
Papetti et al. 2024 [16]	Human-centric ergonomics in Industry 5.0	Contextualizes modern ergonomic needs	Conceptual; lacks technical implementation
Ranaldi et al. 2018 [9]	Discussion of EMG measurement and limitations	Addresses signal integrity and reliability	Theoretical; lacks field validation
Kumari et al. 2023 [18]	EMG assessment during agricultural push-pull tasks	Task-specific fatigue analysis	Small sample size; lab conditions
Johnen et al. 2022 [21]	Critique of cumulative load models	Highlights flaws in conventional assessment	Does not offer EMG-based alternative
Martinez et al. 2020 [15]	HD-sEMG for hand grasp force estimation	High spatial resolution	Complex hardware setup
Merbah et al. 2023 [7]	Wearable EMG during surgery	Real-time fatigue tracking in professional task	Limited to upper-body regions
Khan et al. 2020 [19]	Review of EMG/EEG features and classifiers	Useful for interface design	No ergonomic focus
Hota et al. 2023 [20]	EMG and machine learning in tractor operation	Machine learning workload classification	Task- and equipment-specific
Alam et al. 2024 [17]	Grip force and posture literature	Links force with ergonomic indicators	Narrative review without implementation
Giannini et al. 2020 [4]	Wearable EMG and Inertial Measurement Unit system for handling risk	Standards-based overload detection	Needs calibration for each worker
Garcia Jaen et al. 2021 [11]	Muscle activation in bench vs standing row	Posture-based comparison	Lab-based; fitness focus
Celinski et al. 2025 [14]	EMG in ambulance trauma rescue	Application in paramedic ergonomics	Limited to small group and task type
Wang et al. 2024 [12]	Reinforcement learning for reducing musculoskeletal stress	Adaptive task regulation	Simulation-based; not tested in real environments
Campanini et al. 2020 [6]	Barriers to clinical sEMG use	Covers regulatory and technical issues	Does not propose new system
Koizumi et al. 2024 [10]	Scissor tool impact on hand fatigue	Demonstrates tool design benefit	Small sample; narrow application

biomechanical overload assessment based on the Czech Republic's Government Regulation No. 361/2007 Coll., thus bridging the gap between advanced biosignal analytics and enforceable workplace safety legislation.

III. METHODS

This section outlines the methodology employed to quantify physical workload. The system architecture is described, and a mathematical formulation for processing the measured signals is formulated.

Figure 2 presents a block diagram of the proposed solution for assessing physical workload using EMG sensors. The diagram illustrates five main components, each representing a step in the workload analysis. Block (A) depicts the sensing procedure, during which workers are equipped with Shimmer wireless EMG sensors. Blocks (B–D) depict the data aggregator, designed as a mobile application. Block (B) describes the data acquisition stage, which involves synchronization, quality control, and the reconstruction of missing data packets. Block (C) is dedicated to EMG processing and includes filtering, detection of the signal envelope, and sensor fixation checks. Block (D) deals with the calculation of parameters for maximal grip and relative force. Finally, Block (E) represents the cloud and analytic tools used for advanced data processing.

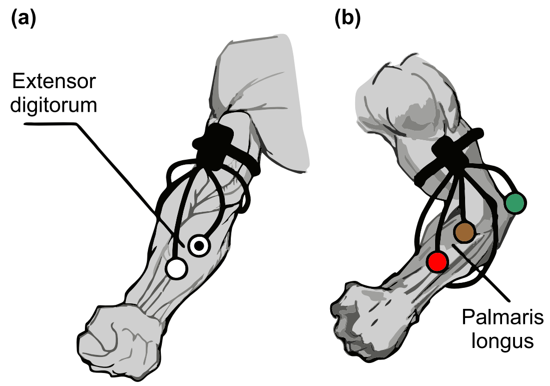

FIGURE 3. Attaching electrodes and sensors to the arm: (a) Fixation to extensor digitorum (b) Fixation to palmaris longus.

A. EMG WIRELESS SENSORS AND MEASUREMENT METHODOLOGY

The initial physical workload analysis involves measurement of muscle activity via wireless EMG sensors. This section highlights critical aspects of the measurement procedure, including the necessity for accurate sensor placement.

Figure 3 illustrates the placement of dual-channel EMG sensors on the forearm for precise muscle activity monitoring. The workload is measured by wireless units fixed to each arm.

This dual-channel configuration includes five electrodes: two sets of measuring electrodes and a common ground. The electrodes are placed directly on the skin over the targeted muscles to ensure the most effective detection of muscle activity. Optimal electrode positioning is achieved through alignment with the mid-line of the muscle in the area of the largest muscular bulk. The Extensor Digitorum and Palmaris Longus muscles are specifically monitored to assess physical workload, while the common potential electrode is affixed to the elbow, away from active muscle regions, to reduce artefacts from muscle activity.

To ensure methodological standardization and inter-laboratory reproducibility, the electrode placement followed the recommendations of the SENIAM Project (Surface ElectroMyoGraphy for the Non-Invasive Assessment of Muscles) [22]. This European concerted action, carried out under the BIOMED II program, developed comprehensive guidelines for EMG sensor properties and placement procedures based on literature reviews, expert workshops, and multi-laboratory validation. The SENIAM guidelines provide detailed protocols for electrode positioning on 27 muscles and have become the reference standard in SEMG-based biomechanical studies. By adhering to these recommendations, the present study ensures both scientific rigour and practical relevance in the assessment of muscular workload.

B. DATA ACQUISITION

The data acquisition process is facilitated by two wireless EMG sensors. The aim of data acquisition is to ensure the appropriate quality and consistency of data for subsequent processing. Since the wireless EMG sensors do not share a common time base, they must be unified. Although the wireless EMG sensors used in this study are commercially available and widely validated for physiological signal acquisition, short-term data loss can occur during measurement. While the Bluetooth communication protocol used for wireless transmission is a confirmed and reliable standard, it is still susceptible to temporary disruptions caused by electromagnetic interference in industrial environments. Moreover, data loss is not solely attributable to wireless transmission issues—another contributing factor is the limited size of the internal buffer memory within the physical EMG sensor devices. If data cannot be offloaded from the sensor to the mobile application quickly enough (e.g., due to temporary transmission delays), the buffer may overflow, resulting in missing samples.

To mitigate the impact of such losses, a signal reconstruction algorithm is implemented that restores short gaps using a trend-preserving linear interpolation. This technique was selected for its low computational complexity, real-time applicability, and its ability to preserve the spectral characteristics essential for further EMG signal processing, such as envelope extraction and force estimation. This method represents one of several possible approaches for gap restoration. All reconstructed samples are flagged in the dataset, enabling selective inclusion or exclusion in downstream analysis depending on the application context. Although this method has proven effective in the present study, a comparative evaluation with alternative imputation methods will be part of future investigations.

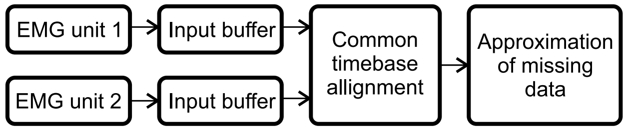

FIGURE 4. Data acquisition and preprocessing of the EMG signals. Data are transmitted from the EMG units to the input data buffer and aligned to a common time base. Missing data are then corrected.

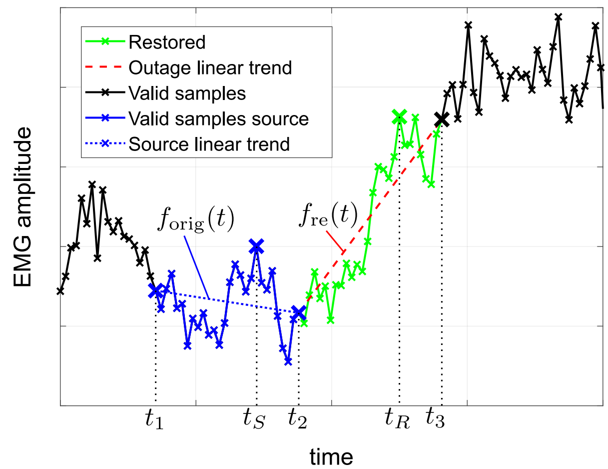

FIGURE 5. Principle of restoring missing samples – Missing samples are replaced with previous valid samples, containing an adjusted linear trend, resulting in a restored sample.

Figure 4 outlines the data acquisition and preprocessing procedure for EMG signals. Measured values are transmitted via Bluetooth from the EMG units to the input buffers. The EMG devices mark the samples stored in the input buffers with timestamps, which can vary. The common time base is constructed as follows: First, a time base is created, then each sample from the input buffers is assigned to the nearest time in the time base. After this alignment, some samples in the common time base might remain empty as a result of data loss during transmission. These empty samples are not denoted as numbers.

The data are transmitted via a Bluetooth serial profile, and the EMG unit manufacturer acknowledges the possibility of data loss. This loss is explicitly indicated in the communication protocol as a ratio of lost to transmitted data.

Figure 5 illustrates the principle of restoring a missing sample. In this process, the cluster of missing samples (red dashed line) is replaced with a copy of the previous valid samples (solid blue line). To ensure signal continuity, the linear trend of the cluster is adjusted. This approach preserves the signal's spectral properties and continuity, which are important for subsequent signal processing. First, the parameters k_1 and q_1 of the linear equation $f_{orig}(t) = k_1 t + q_1$, which spans the first and last samples of the source cluster, are calculated according to (1). The source cluster must be two samples longer than the number of missing values.

$$k_1 = \frac{y(t_1) - y(t_2)}{t_1 - t_2};\ q_1 = y(t_1) - k_1 t_1 \tag{1}$$

The linear trend of the missing data is then calculated using the last valid sample occurring before the gap and the first valid sample occurring after the gap. The parameters k_2 and q_2 of the linear function $f_{re}(t) = k_2 t + q_2$ are then calculated using (2).

$$k_2 = \frac{y(t_2) - y(t_3)}{t_2 - t_3};\ q_2 = y(t_2) - k_2 t_2 \tag{2}$$

The repaired sample is calculated using equation (3):

$$y(t_R) = y(t_S) - (k_1 \cdot t_S + q_1) + (k_2 \cdot t_R + q_2) \tag{3}$$

where $y(t_R)$ is the value of the restored sample in t_R, and $y(t_S)$ is value of the source sample in t_S.

Each sample is associated with a corresponding flag that indicates one of three states: a valid sample, a short gap, or a long gap. After the processing phase, the flags are used to remove the interpolated areas of the signal and provide signal quality information to the user.

While the linear interpolation method proved sufficient for supporting real-time operation and preserving the spectral integrity of the EMG signals, more advanced reconstruction approaches could be considered. Techniques such as spline interpolation or machine learning–based imputation could be integrated on the cloud side of the architecture, where computational resources are less constrained.

C. EMG PROCESSING

After the restoration of missing sequences, the signal is processed. The EMG signal is subject to distortions from noise and the electric potential of the human body, resulting in signal fluctuations. Several processing steps are therefore required to obtain sufficient signal quality.

Figure 6 illustrates the EMG processing procedure. The input is the pre-processed raw signal from the EMG wireless devices, with common time-based corrections and restoration of missing samples. First, the direct current component and any high frequencies that cause noise are reduced by a 6th-order Butterworth band-pass filter set to 20–120 Hz. This initial filtering ensures noise cancellation and aligns the resulting signal to a single baseline. As this signal is alternating, the next step involves rectifying the signal by calculating the absolute value of each sample. The signal is then filtered by a low-pass filter to reduce frequencies that arise during the rectification process. A 6th-order Butterworth low-pass filter set to 5 Hz is used for this purpose. The final step of EMG signal processing is envelope detection, which is calculated by the Root Mean Square (RMS) from one-second windows.

D. ASSESSMENT EVALUATION

To assess the biomechanical overload, the relative force and number of movements must be calculated as defined in the

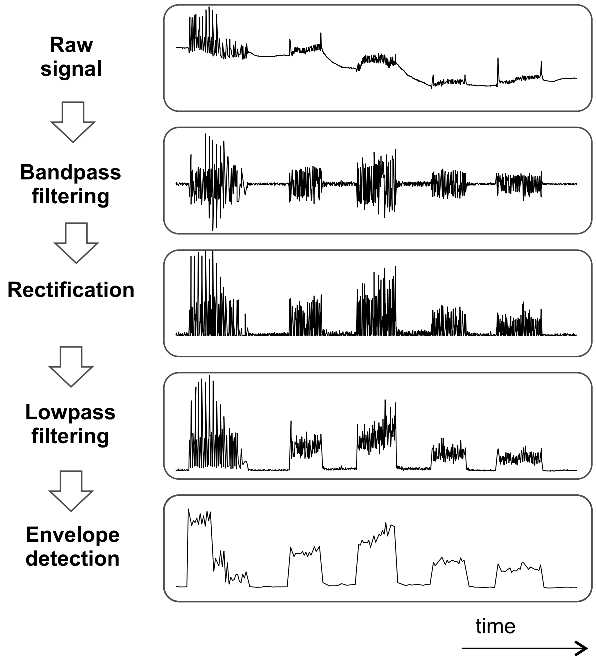

FIGURE 6. EMG block processing diagram.

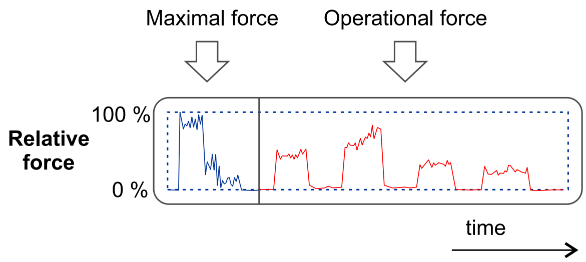

FIGURE 7. Force scaling – Operational force is scaled to the previously measured maximal force.

Czech Republic's legislation, Government Regulation No. 361/2007 Coll.

This regulation defines relative force as scaled to the previously measured maximal force. Figure 7 illustrates the scaling process. The maximal force is calculated as the maximal value of the envelope signal determined by RMS over one-second windows. The maximal force is also measured with a dynamometer to ensure that the subject's maximal force falls within the expected range.

The overload assessment is evaluated using both the average relative force ($\%F_{\max}$) and the total number of movements executed over an eight-hour period, as specified in Regulation 361/2007 Coll. Figure 8 presents the limit values for the average relative force $\%F_{\max}$ and the total number of movements.

The relative force $\%F_{\max}$ is calculated as the average value from RMS one-second windows over the entire shift (8 hours). The total number of movements is determined by an external system, for example manually from video recordings.

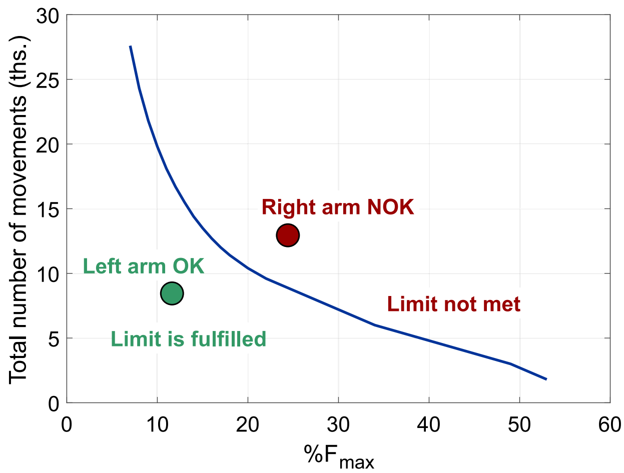

FIGURE 8. Evaluation of force according to Government Regulation No.361/2007 Coll., appendix 5 for an eight-hour working shift.

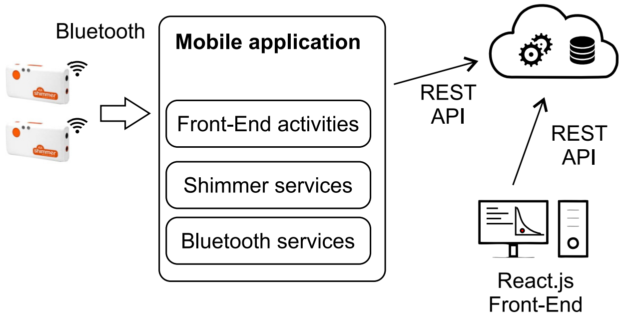

FIGURE 9. System architecture – Wireless EMG nodes transmit raw data via Bluetooth to the mobile application for data processing. The mobile application communicates with cloud services via a REST and React.js front-end server to manage data and measurements.

E. SYSTEM ARCHITECTURE

The system architecture for the biomechanical overload assessment method integrates multiple components to ensure accurate and real-time data collection, processing and analysis. Back-end services such as data management, administration tools, and a user web application are also integrated.

The system architecture (Figure 9) consists of wireless EMG sensors connected via Bluetooth to a mobile application, which runs on an Android-operated mobile phone or tablet. The mobile application communicates with a cloud server using a representational state transfer (REST). The cloud server hosts a React.js front-end application, providing customer services and management, measurement management, and analytic tools.

IV. EXPERIMENT

The experimental evaluation of the biomechanical overload assessment method was approved by an ethical committee, formalised in N. 72/2016, issued by Palacky University Olomouc, Czech Republic. The authors confirm that all experiments were performed in accordance with relevant guidelines and regulations. Informed consent was obtained from all participants involved in this study. The first experiment was designed to evaluate the EMG processing methodology, and the second experiment was designed to demonstrate the validity of the approach, tested on a group of subjects. The subjects were selected from among academic staff and students.

TABLE 2. Tasks performed for EMG processing evaluation.

N	Activity	Weight (kg)
1	$F_{\max}$ on the dynamometer	-
2	Holding the dynamometer at a constant force	10, 20, 30
3	Manipulation with small weight	0.65
4	Manipulation with dumbbell	2.5, 5, 7.5
5	Holding a dumbbell	7.5, 10, 5, 2.5
6	Wrist rotation with dumbbell	2.5
7	Multiple movements with dumbbell	2.5
8	$F_{\max}$ on the dynamometer	-

A. EMG PROCESSING EVALUATION

Although the proposed EMG signal processing pipeline employs standard techniques such as band-pass filtering, rectification, and envelope detection, its novelty lies in its integration into a real-time, wearable system designed for field conditions with limited computational resources. In contrast to many offline or lab-based systems, our approach includes additional components such as synchronization of asynchronous wireless channels, intelligent gap restoration for Bluetooth transmission losses, and signal quality flagging to support continuous workplace monitoring. Therefore, evaluating the efficacy of this combined processing pipeline is essential to demonstrate its robustness under real-world conditions, which include noise, movement artifacts, and data interruptions that are not typically addressed.

The aim of this experiment is to demonstrate the EMG processing methodology. The experiment is designed to highlight different types of activity in the EMG signal. To achieve this, the experiment employed various loads and load types, and tasks performed with these loads. These tasks were designed to test EMG processing under both low and high loads and demonstrate the robustness of the EMG processing methodology.

Table 2 summarizes the tasks performed to evaluate the EMG processing methodology. To calculate the relative force, the first step of the experimental procedure involved pressing the dynamometer with maximal power to determine the $F_{\max}$ (1). Next, to assess the relationship between the hand grip force and the amplitude of the EMG envelope, the subject held the dynamometer at a constant force (2). To emulate a repetitive manual industrial workload, the subject lifted and placed four joined ice hockey pucks forward and backward over a distance of 30 cm, followed by a break (3). The same activity was then performed with a heavier load on a dumbbell (4). To evaluate static load, in the next step, the subject held the dumbbell with weights of 7.5, 10, 5, and 2.5 kg. This sequence was optimized to limit the number of weight changes on the dumbbell (5). The next test added wrist rotation, representing an activity where the subject simultaneously holds the load and manipulates an object

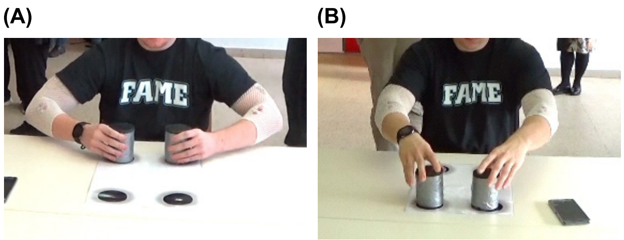

FIGURE 10. Emulation of the manual labour performed by manufacturing operators: (A) Side grip test. (B) Top grip test.

TABLE 3. Descriptive statistics of the subjects.

Parameters	Value
Subject count	20 (10 males, 10 females)
Handedness	20 Right-handedness
Age	20–45 years (mean 24, median 23, std 5.14)
Height	160–200 cm, (mean 173.35, median 172, std 10.74)
Weight	45–100 kg, (mean 70.5, median 69.5, std 14.95)

(6). Sequence (7) combined static and dynamic movements, integrating the previous steps. Finally, the maximal power was measured again to verify the validity of the initial maximal power measurement (8).

B. TESTING THE VALIDITY OF THE APPROACH

The aim of this experiment is to evaluate the proposed solution on a group of subjects. A representative test involving a manual repetitive process was selected to simulate the typical workload of manufacturing operators.

The procedure comprised several steps:

1) The tested subject was fitted with wireless sensors and electrodes, attached to the appropriate muscles.
2) The maximal force was measured for both arms, using a dynamometer to assess hand grip strength.
3) Maximal flexion and extension forces were determined.
4) A three-minute side grip test was performed. During the side grip test, the subject lifted weight sets (0.65 kg) and moved them a distance of 30 cm, with a frequency of 55 movements per minute (Figure 10A).
5) After the side grip test, the subject rested for three minutes.
6) A top grip test was then performed. This test followed the same procedure as the side grip test, but the subject instead held the weight sets from the top with their fingers (Figure 10B).
7) After the tests, the maximal force for both arms was measured again with the dynamometer to verify the initial maximal force measurement.

Table 3 summarises details of the subjects involved in the experiment. Twenty subjects participated, with an equal number of males and females. All subjects were right-handed, with ages ranging from 20 to 45 years. The heights of the subjects ranged from 160 to 200 cm, and their weights ranged from 45 to 100 kg.

To connect the experimental validation with the overall aim of developing a reliable ergonomic assessment method, four hypotheses were formulated. These hypotheses were designed to explore whether the processed EMG signals and derived $\%F_{\max}$ values meaningfully correlate with physiological and ergonomic principles. The purpose was to test the method's sensitivity in detecting known inter-individual and inter-limb differences, such as sex-based strength differences (H1), muscle group physiology (H2), handedness (H3), and the relationship between absolute strength and relative workload (H4). By confirming these expected patterns, the study aimed to validate the method's applicability in real-world ergonomic contexts.

The formulation and testing of the following hypotheses serve a dual purpose. First, they are designed to evaluate whether the system's output—specifically the computed $\%F_{\max}$ values—aligns with well-established physiological and ergonomic principles. This helps verify that the proposed method produces valid, interpretable results that reflect real-world biomechanical differences. Second, confirming these hypotheses supports the practical utility of the system for occupational health applications, as it indicates the method's sensitivity to key ergonomic factors (e.g., sex-based strength differences, muscle group properties, and handedness). Thus, hypothesis testing provides a structured way to validate the system's robustness, accuracy, and relevance for workplace use.

To evaluate the proposed solution and demonstrate the validity of the approach, we formulated four hypotheses based on anticipated results.

Hypothesis 1 (H1): *Sex-based difference: This hypothesis tests whether the EMG-based relative workload assessment reflects the known physiological differences in maximal grip strength between males and females. The expectation is that for the same task, females—who generally have lower absolute strength—will exhibit a higher* $\%F_{\max}$.

Hypothesis 2 (H2): *Muscle group size: Flexor muscles are typically smaller and may fatigue more easily than extensors during repetitive gripping tasks. This hypothesis evaluates whether* $\%F_{\max}$ *can capture this physiological difference, indicating a higher strain on flexors.*

Hypothesis 3 (H3): *Hand dominance: Most individuals exhibit greater strength in their dominant hand. This hypothesis assesses whether* $\%F_{\max}$ *is lower in the dominant hand due to greater force-generation capacity, validating the method's sensitivity to inter-limb variability.*

Hypothesis 4 (H4): *Strength correlation: This hypothesis explores whether there is an inverse relationship between a subject's maximal force and the* $\%F_{\max}$ *recorded during standardized tasks. A significant inverse correlation would indicate that the EMG-based relative workload measure effectively reflects strength-normalized exertion, supporting its ergonomic relevance.*

Although the participants were recruited from an academic setting, the sample was deliberately composed of individuals with varied physical constitutions, age, height, weight, and strength characteristics. This was intended to reflect the diversity of real-world worker populations. The equal gender distribution further supports the generalization of the findings, especially in relation to sex-based ergonomic differences.

V. RESULTS

The results section presents the findings of two key experiments. The first experiment aimed to evaluate the efficacy of the EMG processing methodology. The second experiment focused on validating this approach by testing it on a diverse group of subjects.

A. EMG PROCESSING RESULTS

This section presents the results of the EMG signal processing procedure, examining its performance for various conditions. The experiment involved a range of loads and load types, and multiple tasks performed under these conditions. By testing the EMG processing methodology under both low and high loads, the robustness and reliability of the EMG processing techniques were evaluated, and their effectiveness was demonstrated in a range of scenarios.

Figure 11 shows the results of EMG processing procedure. Figure 11A shows the raw signal in millivolts, which captures the unprocessed muscle activity data, characterized by noise and fluctuations. Figure 11B shows the bandpass signal, where a bandpass filter has been applied to retain frequencies within a specific range, resulting in a more structured signal that highlights muscle activity more clearly. Figure 11C shows the absolute value signal, where negative values have been removed, Figure 11D shows the lowpass signal, where a lowpass filter has been applied to smooth the data, reducing high-frequency noise and providing a cleaner trend of overall muscle activity. Finally, Figure 11E shows the envelope signal, which presents the processed data in a simplified, smoothed form that is easier to interpret.

Figure 11E illustrates the processed EMG signal envelope across various experimental conditions designed to demonstrate the method's ability to differentiate muscle load types based on EMG amplitude. Segment (1) represents the initial maximal force ($F_{\max}$) exerted on a dynamometer, establishing a baseline scaled from 0 to 100% for relative force comparisons in subsequent segments. Segment (2) shows a proportional relationship between grip force and EMG peak amplitude. Segments (3) and (4) represent tasks involving relatively low loads of 0.65 kg, 2.5 kg, 5 kg, and 7.5 kg, respectively. Despite the low weight, similar EMG values were observed, indicating that subjects applied effort primarily to move their hands, with minimal influence from the load itself. Segment (5) clearly illustrates higher EMG amplitudes corresponding to static tasks involving progressively heavier weights, highlighting the relationship between static muscle load and EMG amplitude. Segment (6), depicting wrist rotation tasks, demonstrates relatively lower EMG amplitudes due to lower muscle activation requirements. Conversely, segment (7) captures significantly higher EMG amplitudes generated by dynamic, repetitive

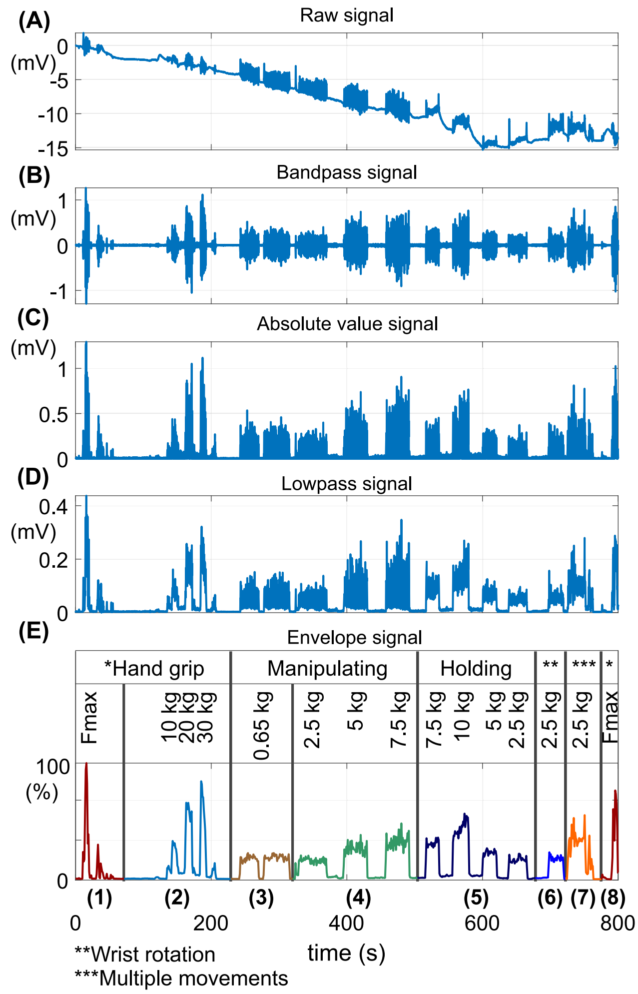

FIGURE 11. EMG signal processing results – (A) Raw EMG; (B) Signal after bandpass filtering; (C) Signal after absolute value; (D) Signal after low pass filtering; (E) Resulting EMG envelope.

movements, reflecting greater muscular activation from frequent motion. Segment (8), a maximal force measurement taken after completing the series of tasks, shows a lower amplitude compared to the initial maximal measurement in segment (1).

B. APPROACH VALIDITY RESULTS

The validity test results provided the data to assess both the performance of the test conducted on the subjects and the hypotheses. After data validation, two subjects were removed from the dataset on account of errors that occurred during measurement: the equipment experienced a signal dropout (Subject 005), and an electrode detached during testing (Subject 018).

Although the number of valid participants in this study was relatively small (18), each subject contributed four independent EMG channels, substantially increasing the overall data volume and supporting the robustness of the statistical analysis. This explains why clear gender-related differences, as tested in H1, reached high levels of

TABLE 4. Approach validity results: statistical parameters of each combination of the grip test (side and top), arms, and muscle group (flexor and extensor).

	n	mean	sd	med	min	max	skew	kurt
SRF	18	4.39	2.38	3.58	1.59	10.95	1.24	0.80
SRE	18	10.65	4.74	9.93	3.91	23.54	1.36	1.56
SLF	18	6.44	5.28	5.11	2.37	24.59	2.13	4.88
SLE	18	13.77	6.15	12.77	5.68	24.93	0.51	-1.21
TRF	18	5.11	2.32	4.87	1.73	9.02	0.19	-1.38
TRE	18	12.07	5.30	10.98	4.48	22.63	0.43	-0.92
TLF	18	7.47	4.39	7.04	2.67	20.97	1.42	2.32
TLE	18	16.71	8.08	16.13	6.37	35.02	0.63	-0.60

S – Side grip, T – Top grip, R – Right arm, L – Left arm, F – Flexor, E – Extensor

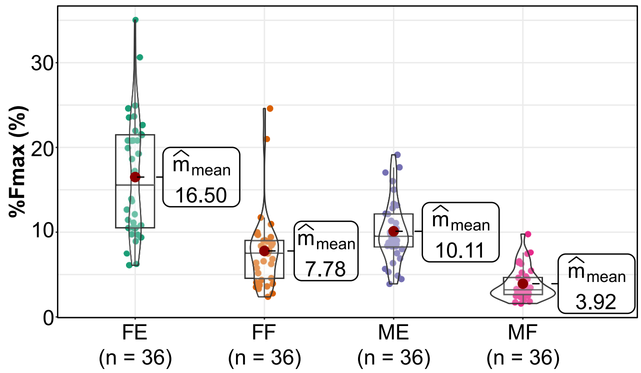

FIGURE 12. Comparison of each muscle, grouped by type and sex. FE – female extensor, FF – female flexor, ME – male extensor, MF – male flexor.

significance despite the modest sample size. Nevertheless, the participants were recruited from an academic environment rather than from an industrial workforce, which limits the direct generalization of the results. Future studies with larger and more diverse cohorts from real working environments are needed to further validate the observed patterns. Non-parametric tests such as the Wilcoxon rank-sum test and Spearman's rank correlation, which do not assume a normal distribution of the data, are well-suited to smaller sample sizes and have been widely used in similar ergonomic and biomedical signal studies. The statistical significance achieved in our results (p < 0.001 in multiple tests) indicates that the observed differences are robust and unlikely due to chance, even with 18 participants. Additionally, the balanced representation of sex and controlled experimental conditions support the reliability of the findings. While a larger sample could improve generalization, the current cohort size is sufficient for the study's validation goals and hypothesis-driven comparisons.

Table 4 summarises the experiment's descriptive statistics. The dataset contains 18 values of $\%F_{\max}$ and each combination of the grip test (S – side and T – top), arms (L – left and R – right), and muscle group (F – flexor and E – extensor). The statistical parameters described are number of values (n), mean, standard deviation (sd), median, minimum (min), maximum (max), skewness (skew), and kurtosis (kurt).

H1 proposes that females will show a higher average $\%F_{\max}$ because they generally exhibit less muscle strength than males. A Wilcoxon rank-sum test with continuity correction was performed to compare the values between males and females. The test was significant ($W = 3747.5,\ p < 0.001$), suggesting that the distribution of $\%F_{\max}$ differs between the sexes. The female group's mean $\%F_{\max}$ is 12.14 %, while the male group's mean is 7.01 %, supporting H1.

Figure 12 plots the results for each muscle, grouped by type and sex, using a combination of violin plots and box plots. The violin plot displays the distribution density, represented by the width of the violin. The box plot indicates the 25th, 50th (median), and 75th percentiles of the dataset, and $\hat{m}_{mean}$ represents the mean values of $\%F_{\max}$ in each muscle group. The plotted points were randomly distributed (using the jittering technique) on the horizontal axis to improve the readability of the graph. The results in Figure 12 indicate that the $\%F_{\max}$ for male subjects' extensor and flexor muscles is significantly lower than that of the corresponding muscle groups in the female subjects. H1 is therefore supported.

H2 proposes that the because the flexor is a smaller muscle group, it will exhibit a greater average $\%F_{\max}$. A Wilcoxon rank-sum test with continuity correction was conducted to compare the values between different muscle groups. The test was significant ($W = 4583.5,\ p < 0.001$), suggesting that the distribution of values differs between the muscle groups. The mean value of $\%F_{\max}$ for the extensor is 13.30 %, while the mean value for the flexor is 5.85 %, supporting the hypothesis. The results in Figure 12 also support H2, exhibiting similar values for females and males, indicating that the flexor produces a higher load.

H3 proposes that the dominant (right) hand is stronger and will exhibit a lower average $\%F_{\max}$. A Wilcoxon rank-sum test with continuity correction was conducted to compare the values between the left and right hands. The test was significant ($W = 3169,\ p = 0.021$), suggesting that the distribution of values differs between the hands. The mean value of $\%F_{\max}$ for the left hand is 11.10 %, while the mean value for the right hand is 8.06 %, supporting the hypothesis.

Figure 13 plots the relationship between the maximal hand grip force measured by the dynamometer and the relative load $\%F_{\max}$ for each subject in both side and top grip tests. Linear regression also demonstrates this relationship. Figure 13A and Figure 13B show the results for the left and right hands, respectively. The results in Figure 13 support H3, indicating that the right hand, which is the dominant hand in all subjects, produced significantly lower values.

H4 proposes an inverse correlation between strength and average $\%F_{\max}$, suggesting that greater strength on the dynamometer will result in a lower average $\%F_{\max}$. A Spearman's rank correlation was conducted to assess the relationship between the values from dynamometer and the $\%F_{\max}$, revealing a significant negative correlation between the variables ($\rho = -0.28,\ S = 638131,\ p < 0.001$). The results in Figure 13 support the hypothesis since the linear regression function exhibits a downward trend.

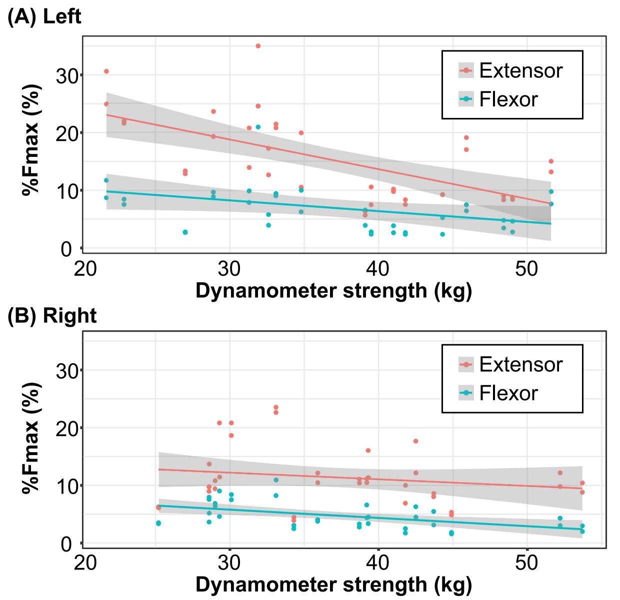

FIGURE 13. Relationship between strength from dynamometer and $\%F_{max}$.

VI. DISCUSSION

This section discusses the technical, methodological, and deployment advantages of the proposed solution and outlines its limitations and potential ethical concerns.

In comparison with prior EMG-based ergonomic tools, the proposed method does not merely replicate existing measurement capabilities but operationalizes them in a manner directly applicable to workplace monitoring. Where previous approaches often required laboratory calibration, tolerated unsynchronized data streams, or offered only conceptual regulatory links, the present system demonstrates that synchronized multi-channel EMG acquisition, robust error handling, and explicit regulatory grounding can be achieved within a single framework. This provides a qualitatively different level of readiness for occupational deployment.

The proposed wireless solution for biomechanical overload assessment offers several theoretical and methodological advantages that differentiate it from existing solutions discussed in Section II. These include improved user comfort due to the wireless setup, increased flexibility and freedom of movement during data acquisition, and integration capabilities with mobile and cloud-based platforms. The solution leverages readily available commercial EMG units, promoting accessibility and adaptability across different regulatory frameworks. Although the current study focuses on demonstrating the validity and effectiveness of the proposed method rather than a comprehensive comparative evaluation, Section II provides a review of existing EMG-based ergonomic assessment methodologies, highlighting limitations such as isolated sensor usage, lack of real-time capabilities, and limited synchronization of multiple sensor channels. Addressing these gaps, the presented approach offers synchronized multi-channel EMG data processing, real-time error correction, and integration with existing regulatory standards, providing a robust foundation for future comparative analyzes against specific competing solutions.

In comparison to existing EMG-based ergonomic studies summarized in Table 1, our proposed solution uniquely integrates several crucial aspects. While recent studies [4], [7] leverage wearable EMG sensors for real-time monitoring, these systems either require individual calibration for each worker or focus on restricted muscle groups and application scenarios. Other reviewed methodologies often lack field validation [9], operate within narrowly defined experimental conditions [10], [18], or do not implement technical systems suitable for broad industrial adoption [16], [17]. Unlike these approaches, our method combines multi-channel synchronization, real-time intelligent data restoration, and comprehensive signal processing, providing robust and scalable real-world applicability. Moreover, our approach directly integrates with regulatory standards, explicitly addressing a gap identified in studies [8], [21], where ergonomic insights remain disconnected from enforceable workplace safety guidelines. Therefore, this study extends previous research by offering a practically deployable solution that effectively bridges technological advancements and ergonomic assessment standards.

However, the proposed solution also has certain limitations:

1) Battery Life – The dependency on battery power restricts the operational time. Charging events must be planned carefully to align with scheduled measurements.
2) Wireless Transmission Problems – Conducting measurements in manufacturing areas involves exposure to high electromagnetic noise, which can adversely affect signal quality.
3) Maximal Force Measurement – The accuracy of relative force calculations depends critically on maximal force measurement. If the subject does not exert maximal grip force, this can lead to an inaccurate increase in the relative force value. It is therefore essential for a specialist to validate the maximal force measurements. A maximal force check at the conclusion of the measurement procedure can also confirm whether the initial maximal force was correctly measured.
4) Electrode Problems – Data quality can be degraded by problems related to electrodes, for example the quality of skin-electrode contact. This contact quality can be affected by ambient conditions or human sweat and hair.

The deployment of our solution also raises several ethical considerations. Employees might feel apprehensive about being monitored, fearing that data collected could be used to evaluate their work performance rather than for its intended health and safety purposes. There is also a risk of data breaches, which could result in unauthorized access to sensitive personal information.

Beyond formal ethics approval and informed consent, the deployment of wearable monitoring systems in workplaces must comply with relevant data protection laws, including the General Data Protection Regulation (GDPR) in the European Union. In the proposed system, all collected EMG data are pseudonymized, with identifiable information stored separately and protected by access controls. Equally important is how the purpose of the system is communicated to employees: measurements should be clearly presented as a health and safety measure aimed at preventing musculoskeletal overload rather than as a tool for performance surveillance. This framing can substantially increase acceptance and trust, while participatory elements such as involving workers in decisions about data use and privacy settings further support adoption. To maintain data reliability, the methodology also incorporates a repeated maximal force measurement at the end of each session; because approximate maximal strength is known from initial calibration, this step enables the detection of inconsistencies and safeguards against intentional or unintentional non-cooperation. Together, these measures strengthen both the validity of the ergonomic assessment and the likelihood of its successful implementation in industrial practice.

Although the present study aligns with Czech Government Regulation No. 361/2007 Coll., the underlying methodology is transferable to other regulatory contexts. The core parameters—relative force ($\%F_{\max}$) and movement counts—remain identical, while only the threshold values and evaluation windows differ across standards such as ISO 11228, ILO guidelines, or OSHA/NIOSH recommendations. Since these values are implemented in the cloud-based system as configurable parameters, the architecture readily supports dynamic adjustment to the specific requirements of different regions without modifying the measurement hardware or processing pipeline.

An important consideration in our system is the reconstruction of missing EMG data. While Bluetooth provides a standardized and confirmed communication protocol, data loss can still occur due to two main factors: environmental interference during wireless transmission and the physical limitations of the internal memory buffers in the EMG sensor units. If data cannot be transferred to the receiving mobile device fast enough, buffer overflows may lead to sample loss.

Although each step in the EMG processing pipeline—band-pass filtering, rectification, low-pass smoothing, and RMS envelope extraction—is standard and widely validated, their individual impact on overall signal robustness was not isolated in this study. Initial pilot tests confirmed that all steps are necessary to maintain signal interpretability in real time, especially under varying load conditions. However, a more detailed sensitivity analysis, assessing how each stage contributes to noise reduction and stability of relative force estimation, will be part of future work aimed at further refining the system for embedded deployment.

While the processing pipeline itself is independent of the complexity of the performed movements, its performance should also be confirmed in real-world industrial settings. Unlike controlled laboratory tasks, workplace conditions involve longer durations, variable loads, sustained exertion, and environmental noise, all of which may introduce additional artefacts or transmission issues. Future validation in such environments will therefore provide a more stringent test of robustness and ensure the applicability of the proposed system in practice.

The proposed linear interpolation-based method for restoring these missing samples was designed to preserve the temporal and spectral integrity of the signal. During the controlled experiments presented in this study, the occurrence of data loss was minimal, and the interpolation mechanism was activated only for short sequences of missing samples. All restored samples were flagged, and the overall share of interpolated data remained marginal across all participants. This low incidence of data loss supports the feasibility of real-time deployment under typical usage conditions. However, we recognize that in harsher environments or during extended measurements, more complex imputation strategies may be required. Therefore, comparative analysis with alternative reconstruction methods will be part of our future work.

Although this approach proved sufficient for supporting the integrity of our workload assessments and was indirectly validated through hypothesis testing and statistical consistency, it is only one of many possible methods. More advanced techniques, such as spline interpolation or machine learning-based imputations, may further improve signal fidelity under certain conditions. Therefore, a detailed evaluation of the effectiveness and limitations of this reconstruction strategy—compared to other alternatives—will be a key focus of future studies.

While the current study demonstrates the method's validity under controlled experimental conditions, future work will focus on deployment in real manufacturing environments. Testing the system in diverse operational contexts will allow us to evaluate long-term usability, integration into existing workflows, and responsiveness to industrial stressors such as sustained workload, variable ambient conditions, and different task typologies.

The present study employed non-parametric tests to validate the formulated hypotheses, as these methods are robust for small sample sizes. While this approach was sufficient to confirm expected differences, it does not allow for full examination of interactions between grip type, muscle group, gender, and handedness. Future studies with larger and more diverse cohorts will therefore employ mixed-effects models or repeated-measures ANOVA to capture within-subject variability and higher-order interaction effects.

VII. CONCLUSION

The study introduced a novel approach to biomechanical overload assessment using wearable EMG sensors. The experimental evaluation demonstrated the robustness and reliability of the EMG processing methodology under various load conditions. The results validated the proposed approach, confirming its effectiveness in providing detailed and objective assessments of muscle activity and physical load. This validation was supported by statistical analysis of the collected data, which corroborated our hypotheses regarding muscle load variations across different groups and conditions.

By addressing the combined limitations identified in previous studies, the proposed system moves beyond incremental improvements and establishes a benchmark for scalable ergonomic risk evaluation. Its integration of technical robustness with regulatory compliance positions it as a practical alternative to existing EMG-based assessment methods.

Despite its advantages, the proposed solution also has certain drawbacks. These include the dependency on battery life, potential problems with wireless transmission in high electromagnetic noise environments, and the critical importance of accurate maximal force measurement for reliable relative force calculations. Data quality can also be compromised by electrode-related problems, such as skin-electrode contact and ambient conditions.

Future research can focus on addressing these identified limitations and exploring the potential for integrating automated movement detection to further enhance the proposed solution's capabilities. Future work will also explore the integration of advanced techniques such as machine learning-based workload classification, posture recognition using multimodal sensor fusion (e.g., EMG and IMU data), and real-time feedback mechanisms for users and supervisors. These extensions would transform the system from a passive monitoring tool into an active assistant capable of delivering personalized ergonomic recommendations, early warnings of overload risk, and adaptive task guidance in real-world environments. Such capabilities align with emerging paradigms in Industry 5.0, where human-centered and AI-assisted systems are increasingly deployed to support occupational health and performance. Future work also will focus on systematically comparing the current lightweight interpolation with higher-order and machine learning–based reconstruction techniques to quantify trade-offs in accuracy, spectral fidelity, and deployment feasibility within cloud-integrated ergonomic assessment systems.

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