2025 IMEKO TC-6 International Conference on
Metrology and Digital Transformation - M4DConf 2025
Benevento, Italy, September 3-5, 2025

Innovative Approach in Industry 5.0: Use of Multiple Sensors in a Real Production Process to Enhance Workers' Well-Being

Matteo Zendri[1], Francesco Pilati[2], Francesca Calabrese[3], Qingwei Cai[4]

[1] *Research Fellowship, Department of Industrial Engineering, University of Trento, matteo.zendri@unitn.it*
[2] *Associate Professor, Department of Industrial Engineering, University of Trento, francesco.pilati@unitn.it*
[3] *Assistant Professor, Department of Industrial Engineering, University of Trento, francesca.calabrese@unitn.it*
[4] *PhD Student, Department of Industrial Engineering, University of Trento, qingwei.cai@unitn.it*

Abstract – This paper presents a novel application for Industry 5.0: the first global implementation of multiple wearable sensors in a real industrial environment.

With minimal investment in IoT infrastructure, the proposed system enables the collection of useful data on operator activities, including self-reported fatigue after specific tasks.

These data are fundamental for analyzing the relationship between assembly tasks and self-reported fatigue by operators, allowing optimization of product design and assembly processes.

By adopting this approach, industries can enhance worker well-being and decrease the incidence of occupational diseases. The final goal of the project is to develop and validate an algorithm capable of predicting, in real-time, the perceived fatigue experienced by operators upon completing specific tasks.

I. INTRODUCTION

Industry 5.0 is a new concept that follows the evolution of Industry 4.0. This previous concept is centered on efficiency optimization and improvement of the production processes using IoT, data analysis and Artificial Intelligence. With Industry 4.0 there are innovative concepts like collaboration between man and machine, adaptability and continuous training of the operators. With Industry 5.0 the focus is moved from the manufacturing processes to human centricity and well-being. This is necessary due to the particular European situation and especially in Italy where the population is becoming older without an increase in birth in new generations.

A. Birth rate

In the following figure, the official Eurostat report explaining the birth trend in European countries is shown [1].

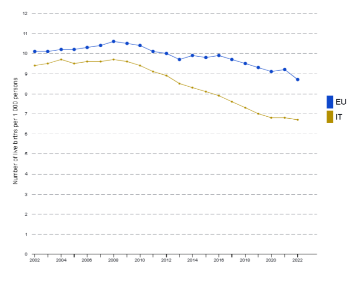

Figure 1: *Birth rate trends (2002-2022).*

B. Population age

In the following figures, the official Eurostat report shows the ageing of the European population [1].

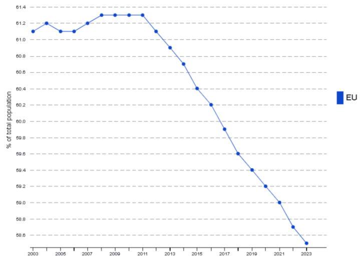

Figure 2: *European population between 20-64 years (2002-2022).*

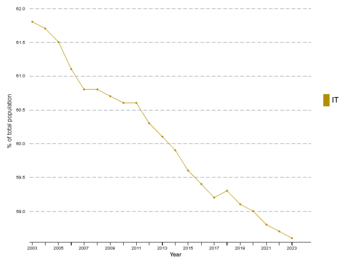

Figure 3: *Italian population between 20-64 years (2002-2022).*

C. Occupational diseases

In the following graph it is possible to see a continuous increase of occupational diseases with the exception of the period 2020-2023, when the Covid-19 pandemic led to a temporary decrease in cases. Each disease impacts production and represents a high cost and profit loss for companies, as the operator is unable to continue the activity, thereby reducing productivity. Multiple factors may contribute to these conditions, such as repetitive movement at high velocity, handling of heavy components, or assembly tasks performed with poor posture. These causes are not always easy to detect, and assessing the severity of the impact on the operator can be difficult [2].

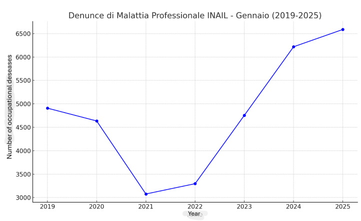

Figure 4: *Occupational diseases over the last 6 years.*

For these reasons, Industry 5.0 introduces a new human-centric approach, aiming to preserve operator health over time.

II. LITERATURE REVIEW

In comparison, the study by Bonakdar et al. (2025) [3] analyzed fatigue during manual handling tasks (MHT) using a methodology based on inertial measurement units (IMUs) to monitor joint angles and coordinative variability. The key findings revealed an increase in both mean and peak joint angles as fatigue intensified, except for the knee joint, where both decreased. Additionally, a decline in coordination between adjacent joints was observed, as indicated by reduced information transmission measured through mutual information theory. This study reports tests conducted in a controlled laboratory environment, tracking three distinct activities performed repeatedly over time: lifting, carrying, and moving. To collect data for these activities, eight participants volunteered for the experiment and were asked to wear six IMUs each. The accuracy achieved with this approach was 74%.

Another relevant paper is the study conducted by Munguia Tapia et al. [4], which focuses on the real-time recognition of physical activities using wireless accelerometers and a heart rate monitor. The goal was to identify 30 different activities during gym sessions in a controlled environment. Involving 21 participants, the dataset covered 16.6 hours of data.

Using a different approach, the authors attempted to identify activities based on individual subjects, achieving an accuracy of 94.6%. However, when subject information was excluded, the accuracy dropped to 80.6%.

An important result was the increase in accuracy (1–2%) when heart rate information was included.

The study conducted by Tryon and Trejos [5] aimed to develop models that classify task weight using EEG–EMG fusion. To achieve this goal, 32 healthy subjects (mean age 24.9 ± 5.4 years) performed elbow flexion–extension motions under different conditions of speed and weight. The experimental setup included EEG sensors and encoders, and an accuracy of 83.01 ± 6.04% was reported in classifying three weight levels.

By contrast, the present study introduces an innovative use of multiple sensors in a real industrial environment, without control over external perturbations or noise typical of real-world manufacturing conditions. The objective is to classify different tasks and predict the operator's fatigue level.

III. ARCHITECTURE DESCRIPTION

The most important factor for effective data analysis is the dataset quality. The initial phase of the project is focused on constructing a well-structured dataset.

The system architecture includes wearable sensors, a server, and a Raspberry Pi. After initial lab testing, the components were installed at the partner company.

During assembly tasks, operators wear the following devices:

- Three quaternions:
  - One on the back to measure posture variations
  - One on the dominant hand to track movements
  - One on the non-dominant hand to track movements
- One Bitalino with four channels:
  - ECG to measure heart rate
  - EMG to monitor muscle activity in the arm
  - EMG to monitor muscle activity in the trapezius
- UWB bracelet to track the operator's position
- RFID glove on the dominant hand to detect touched objects

The quaternions and Bitalino send data to the Raspberry Pi; RFID gloves send data to a smartphone, and the UWB bracelet sends data to the POE. The POE is connected via Ethernet to the server, while Raspberry Pi and smartphones communicate through Wi-Fi.

The system includes a simple interface that allows the operator to start and stop data collection. The same interface also displays sensor status in real time. A more technical interface supports remote monitoring of sensor functionality, detecting disconnections or temporary malfunctions.

IV. MONITORED PROCESS DESCRIPTION

The project involves collaboration with a company based in the province of Trento (Italy) that produces items using a C-shaped production layout. Product weight ranges from 30 to 180 kg, and heights vary between 500 and 1300 mm. Assembly involves tools, manual handling, and movement. Each shift typically includes 6 to 12 items, with model variation affecting the process.

The company shared production cycles for all products, breaking them down into 20 specific assembly tasks. This segmentation helps identify tasks that contribute most to perceived fatigue.

Training sessions guided operators to wear sensors correctly and manage data acquisition autonomously. During the learning period (7–10 days), support was provided to resolve any operational challenges.

The participant group included operators of varying age and handedness. Despite defined production cycles, task execution varies due to operator habits and tool use, creating process variability. The use of precedence diagramming is under consideration to reduce variability and complexity.

A minimum of 100 assembled items has been set to ensure a consistent dataset for analysis. Human error and potential disconnections during data gathering are also considered.

The power of this innovation lies in the use of multiple sensors. The post-processing rules automatically filter out noise and irrelevant information, increasing the algorithm's accuracy by focusing on meaningful signals.

VI. ALGORITHM DEVELOPMENT

The data preprocessing phase focuses on methods for effectively cleaning and integrating the collected information, as sensors recorded continuous hours of activity without interruption, including short pauses or routine operator duties. The first step involves distinguishing valuable data from irrelevant segments. It is also necessary to isolate data sections affected by brief sensor disconnections, as these periods prevent complete tracking of the operator's actions.

During the assembly process, variations may occur due to human errors or defective components that require substitutions or corrective actions. Data related to these exceptional cases are excluded from the analysis to reduce variability and maintain consistency.

Several machine learning models have been developed, including deep learning architectures, recurrent neural networks (RNNs), and long short-term memory (LSTM) networks. In addition, intelligent algorithms have been implemented to identify and prioritize value-added data within the dataset.

The analysis of sensor signals aims to identify the tasks most strongly correlated with operator-reported fatigue. From a managerial perspective, this information is highly valuable, as it enables tracking the evolution of fatigue across tasks and entire shifts. This, in turn, allows for the adaptation of production plans to the physical capabilities of individual operators, enabling recovery periods after more demanding activities.

Such insights support the optimization of assembly processes and product design with the objective of minimizing operator strain.

The overarching goal of the project is to implement an algorithm capable of predicting, in real time, the perceived fatigue level of operators following the execution of specific tasks.

VIII. CITATIONS AND REFERENCES

References

[1] Eurostat, "Demography report 2023," European Commission, 2023.

[2] INAIL, "Reports of occupational injuries and diseases - INAIL data for January 2025," INAIL Press Release, March 2025.

[3] A. Bonakdar et al., "Fatigue assessment in multi-activity manual handling tasks through joint angle monitoring with wearable sensors," Univ. of Alberta, 2025.

[4] E. Munguia Tapia et al., "Real-Time Recognition of Physical Activities and Their Intensities Using Wireless Accelerometers and a Heart Rate Monitor," MIT, Stanford, Boston Med. Center.

[5] J. Tryon and A. L. Trejos, "Classification of Task Weight During Dynamic Motion Using EEG–EMG Fusion," IEEE Trans. on Neural Systems and Rehabilitation Engineering, vol. 31, pp. 1071–1080, 2023.

[6] M. Calzavara, M. Faccio, and I. Granata, "Multi-objective task allocation for collaborative robot systems with an Industry 5.0 human-centered perspective," The International Journal of Advanced Manufacturing Technology, 2023. [cite: 3461, 3462, 3463, 3090, 3091, 3092]

[7] Z. Wang and J. Yan, "Multi-sensor fusion based industrial action recognition method under the environment of intelligent manufacturing," Journal of Manufacturing Systems, vol. 74, pp. 575-586, 2024. [cite: 4267, 4268, 4269, 3809, 3810, 3811]

[8] J. Yang, T. Liu, Y. Liu, and P. Morgan, "Review of Human-Machine Interaction Towards Industry 5.0: Human-Centric Smart Manufacturing," in Proceedings of the ASME 2022 International Design Engineering Technical Conferences and Computers and Information in Engineering Conference, 2022. [cite: 5023, 4694]

[9] M.M. Falerni, V. Pomponi, H.R. Karimi, M. Lavit Nicora, L.A. Dao, M. Malosio, and L. Roveda, "A framework for human-robot collaboration enhanced by preference learning and ergonomics," Robotics and Computer-Integrated Manufacturing, vol. 89, p. 102781, 2024. [cite: 5697, 5327, 5568]

[10] C.B. Erdaş and S. Güney, "Human Activity Recognition by Using Different Deep Learning Approaches for Wearable Sensors," Neural Processing Letters, vol. 53, pp. 1795-1809, 2021. [cite: 7617, 7618, 7340, 7341]

[11] B. Gaffinet, J.A.H. Ali, Y. Naudet, and H. Panetto, "Human Digital Twins: A systematic literature review and concept disambiguation for industry 5.0," Computers in Industry, vol. 166, p. 104230, 2025. [cite: 8366, 8367, 8368, 8369, 8370, 8371, 8372, 8373, 7872, 7890, 7953, 7990, 7991, 8057, 8133, 8179, 8236, 8237, 8331]