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Diego Calvetti*, Miguel Luiz Ribeiro Ferreira

Innovative approaches to productivity monitoring: Integrating work sampling and electronic performance monitoring

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Abstract: Electronic performance monitoring (EPM) in workforce productivity lacks quantitative indexes, such as labour rating factors (LRFs). This study introduces an integrated method using smartphones and work sampling (WS) to measure productivity based on LRF. An experiment with 10 welders in a pipe shop demonstrated the method's effectiveness. This research aims to fill this gap using the design science research (DSR) methodology to introduce an integrated method based on electronic devices (smartphones) and human observation WS to measure productivity based on LRF. To demonstrate and evaluate this method, an experiment was carried out with industrial workers while welding steel pipes in low-carbon alloy using tungsten inert gas (TIG) and flux-cored arc welding (FCAW) methods. The results indicate the feasibility of this integrated method based on the complementarity of the WS and the EPM approach tested. The LRF using WS was determined to be 55.52% while the EPM factor was 57.78%. Also, welders are directly engaged in the welding process 75.55% of the time. Considering a standard productive state average of 50%, EPM results can represent an accuracy of 84%–96% of the LRF. The electronic method based only on the workers' location has the limitation of not identifying idleness within the production zone (PZ); as a result, some calibration is provided by the WS method. This research contributes a low-cost, accessible approach for continuous productivity improvement. The integrated method allows for both quantitative measurement and qualitative diagnosis of productivity factors, bridging the gap between traditional and modern monitoring techniques.

***Corresponding author: Diego Calvetti,** CONSTRUCT/GEQUALTEC, Faculty of Engineering, University of Porto, Porto, Portugal.
E-mail: diegocalvetti@fe.up.pt
Miguel Luiz Ribeiro Ferreira, School of Engineering, Federal Fluminense University, Niterói, Brazil

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1 Introduction

Electronic performance monitoring (EPM) uses technology to evaluate workforce performance, such as from the productivity perspective (Alder 2001). Labour rating factors (LRFs) are connected to the productive state, for example, directly conducting activities, supporting actions or idleness (Adrian 2004). The deployment of lean construction tools on labour efficiency can enhance overall productivity on-site (Aziz and Hafez 2013; Costella et al. 2018). Also, lean implementation is useful for small companies (Pereira and Tortorella 2018). The work sampling (WS) method allows a detailed analysis of the on-site work performance (Shehata and El-Gohary 2011; Lindhard 2023; Wandahl et al. 2023; Jacobsen et al. 2024). Finally, exploring EPM deployment connected to labour productivity assessment methodologies can lead to mixed methods with significant outputs.

Labour productivity is a keyword and theme that has always been studied in the construction industry. In most countries, labour costs represent 30% of the project's total cost (Jarkas and Bitar 2012). Also, on-site lower labour productivity can increase greenhouse gas (GHG) emissions and sanitary wastewater generation in an overscheduled project (Calvetti et al. 2021a). Poor site management and lack of supervision are frequent high-impact factors in project delays and over costs (Yap et al. 2021; Daoud et al. 2023).

Industry and Construction 4.0 are strictly connected to companies' digital transformation capabilities (Wang et al. 2024). Digital construction sites using Internet of Things (IoT) can support accurate data collection (Lopes Miranda et al. 2017). Delivery of digital skills to employees is crucial to accelerating 4.0 initiatives (Siriwardhana and Moehler 2024). For centuries, organisations have been monitoring their employees. Important information for workforce development can be obtained by monitoring.

In the same way, technological advances in electronics are transforming the way the performance of employees is evaluated (Alder 2001). It should be noted that the results of each research in different cultures are still not widely known. In this way, it is possible to obtain only a certain frequency of monitoring in some localities due to a multicultural formation and different implantation policies.

This research aligns with the ongoing digital transformation in construction and manufacturing, often referred to as Industry 4.0. The integration of EPM with traditional WS methods represents a step towards the smart construction concepts central to Industry 4.0. By leveraging smartphone technology and data analytics, our approach contributes to the broader goal of creating more efficient, data-driven work environments.

The WS method allows the collection of data from specific workers and crews (Lindhard 2023). WS can be used to categorise work activities from different perspectives, such as productive, non-productive, supporting, transporting, or walking (Lindhard 2023; Lee et al. 2024). Using WS enables on-site performance monitoring, such as establishing benchmarking (Shehata and El-Gohary 2011), finding improvement potential (Lindhard 2023), measuring mechanisation levels (Calvetti et al. 2021b) and realising sources of productive wastes (Aziz and Hafez 2013). Wandahl et al. (2023) envisaged that sensor-based technologies might automate WS data collection (Wandahl et al. 2023). Studies applying WS and using smartwatches targeted monitoring workforce direct work performance by analysing location and walking travelling (Pérez et al. 2022; Wandahl et al. 2023). Also, research was made applying WS correlated to workers' physical disposition using heart rate sensors (Jesus et al. 2024).

This research is set to design, demonstrate and evaluate the potential for monitoring workers' locations to measure LRF using smartphones supported by the WS method of activity performance. It uses the design science research (DSR) to analyse the proposed EPM-WS method. The demonstration and evaluation are performed in an experiment with 10 welders in an industrial pipe shop. Finally, LRF monitoring can lead to benchmarking, labour waste elimination and overall productivity improvement.

2 Theoretical background

Electronic performance monitoring is related to using computer-based technologies for data collection and analyses to run informational reports on workers' performance (Panina and Aiello 2005). Navon and Goldschmidt presented a model for automated control demonstrating that work labour can be electronically measured and controlled (Navon and Goldschmidt 2003a, 2003b). The concept generated is that the geographical locations of workers automatically measured at regular intervals are prone to be collected discreetly and analysed through computerised algorithms as a result of labour (Navon and Goldschmidt 2003a, 2003b; Navon 2005).

Navon (2005) directly compared labour productivity to a study conducted by Navon and Goldschmidt (2003a, 2003b), which investigated the hypothesis that the worker's position could be used as an indirect measure of performance (Navon 2005). This hypothesis stems from pieces of evidence that when a construction/assembly element is executed, the worker must physically contact the component to perform the work. In a study on the application of mobile technology with Global Positioning System (GPS) (Navon and Goldschmidt 2003b), the electronic result is compared to a sampling performed manually, where it is represented whether the worker is or not inactivity. Twelve activities were evaluated, and the difference between methods reached a difference of less than 12% in most activities (Navon and Goldschmidt 2003b).

Image-based monitoring was tested for construction workers' occupation cycle of activities, achieving an accuracy of 86.7%–81.2% (Gong and Caldas 2011). Radio frequency based on ultra-wideband (UWB) was applied to determine travel times, waiting and working and occupation zones such as work, storage and rest (Cheng et al. 2013). Also, Cheng and Teizer (2013) proposed the use of the technology of Radio-Frequency Identification (RFID) in combination with GPS and UWB to assess workers' location (Cheng and Teizer 2013). Teizer et al. (2013) published work aimed at the indoor training of construction workers (Teizer et al. 2013). The technology applied to tracking the movement of workers was hardware with UWB (Teizer et al. 2013). In their 2015 study, Jiang et al. detailed the creation of a real-time work activities measurement system combining geographic information system (GIS), GPS, and 3rd generation (3G) telecommunications (Jiang et al. 2015).

Using Bluetooth beacon technology (BLE), it was possible to determine and validate task duration (started-finished) using carpenter workers' presence data and self-report performance (Zhao et al. 2021). Also, using BLE beacon-based, a simulated experiment shows the feasibility of collecting data from the productivity state (direct work, support work and delay) (Khazen et al. 2024). Using data from smartphone sensors, such as accelerometer, gyroscope and linear acceleration, makes it possible to assess workers' posture (Nath et al. 2017). Also, using smartphone data sensors, it is possible to classify the activities the workers are conducting, such as fetching and placing rebars, sawing, or being idle (Akhavian and Behzadan 2016; Zhang et al. 2018; Yang et al. 2019). Finally, it is also possible to classify workers' activities using wearable devices, collecting acceleration data (Calvetti et al. 2022; Gong et al. 2022).

According to Adrian (2004), work labour is correlated with the activity it performs, e.g., ironworkers, painters or welders (Adrian 2004). Another possible classification is related to the state in which a worker presents when developing certain tasks (Adrian 2004). Most of the techniques to identify workers' activities are time-driven or data post-evaluation (Meyers and Stewart 2002; Adrian 2004; Groover 2007; Niebel and Freivalds 2013). Moreover, post-evaluation data models are most effective in businesses where the manufacturing process is consistently repeated (Yang et al. 2015). However, in industries, such as construction, where projects often have unique characteristics and less repetition, the benefits of these post-data evaluation techniques are likely to be marginal and require more effort to be statistically valuable (Yang et al. 2015). It is highlighted that in the manufacturing industry, productive time can be found at a rate of 88% and non-productive at 12%; at the same time, in the construction process, it can be found at a rate of 43%, accounting for non-productive times of 57% (Aziz and Hafez 2013). As an example of human observation-based techniques, it can highlight the normative methodology for productivity measurement, the multi-factor model for productivity measurement and the multiple criteria technique for productivity measurement (Sink 1985). The WS approach allows for the assessment of productivity based on the observation of workers' activities (Sink 1985; Meyers and Stewart 2002; Adrian 2004; Groover 2007; Niebel and Freivalds 2013).

Using the WS method mixed with EPM to evaluate the correlation with physical disposition, fatigue and stress related to production performance was feasible using heart rate measuring (Jesus et al. 2024). A WS tool empowered by sensors can provide real-time data to increase performance (Jesus et al. 2024). Also, mixing the WS method and GPS location from smartwatches for indoor activities in a building renovation could correlate productive and non-productive work and workers' positioning and travelling walking (Pérez et al. 2022; Wandahl et al. 2023).

The Maynard operation sequence technique (MOST) was studied to implement activity-based costing based on timing measurements (Ganorkar et al. 2019). The lean production and Six Sigma techniques focus on reducing waste and eliminating defects (Groover 2007). The definition of workstations and production processes goes through studies about the ergonomics of workers and the analysis of their movements and occupations (Adrian 2004; Groover 2007; Niebel and Freivalds 2013). Productivity is a learning process; learning curve evaluation processes are relevant to measuring workers' performance (Adrian 2004; Groover 2007).

3 Methodology

3.1 DSR methodology

This research applies the DSR methodology (Nunamaker and Purdin 1990; Peffers et al. 2007) to demonstrate and evaluate the development of a mixed method using

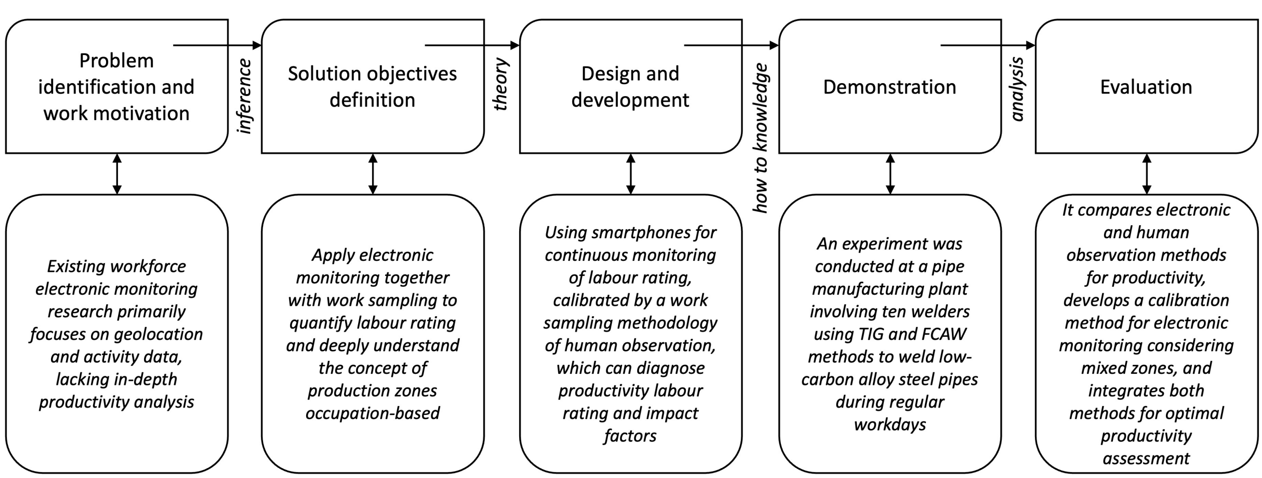


Fig. 1: Research method.

electronic monitoring and WS for labour rating assessment. Figure 1 presents the research method developed based on the DSR methodology.

Existing research on workforce location-based performance monitoring has primarily focused only on geolocation and activity information without being able to do a deep quantitative and qualitative assessment of productivity and its correlated impact factors. On the contrary, a few studies applied modelling process techniques to qualitative and quantitative productivity measurements. Also, manually collecting data by observations can be time-consuming, costly and labour-intensive.

Hence, this study contributes to knowledge by designing/developing, demonstrating and evaluating an integrated method to assess workers' productivity through (a) using smartphones, which is a very available technology nowadays, (b) for continuous monitoring of labour rating, calibrated by (c) a WS methodology of human observation, which can (d) diagnose productivity labour rating and impact factors. Consequently, this work aims to provide an integrated method using new technologies and a traditional modelling process technique to assess and empower the continuous improvement of the workforce's productivity cycling.

3.2 Sample

The experiment was conducted at a pipe shop in the State of São Paulo, Brazil. The plant has a total area of 73,117.00 m^2 with a constructed area of 16,492.00 m^2 and stands out in the manufacture of pipes for numerous Brazilian heavy construction industry projects. The experiment was carried out at the service fronts of the 10 welders under analysis during their usual activities on regular working days, see Figure 2. During the assessment period, the welders conducted activities involving welding low-carbon alloy steel pipes using Tungsten inert gas (TIG) and flux-cored arc welding methods (FCAW) techniques. This study was conducted in compliance with ethical guidelines for research involving human subjects. All participating welders were informed about the nature of the study and provided written consent for their involvement. Worker privacy was maintained by anonymising all collected data, and participants were given the option to withdraw from the study at any time without consequence.

3.3 Electronic (smartphone-based) performance monitoring method developed

This work evaluates the effectiveness of a methodology to monitor and quantify workers' productive and unproductive activities. In this sense, considering that the worker must be close enough to handle tools and materials to perform a certain task (Navon and Goldschmidt 2003a, 2003b; Navon 2005). The work area was divided into three distinct zones based on their relevance to the welding process: Production zone (PZ), the primary area where welding activities occur; Idle zone (IZ), an area where workers are present but not actively engaged in production and Mixed zone (MZ), transition areas between PZ and IZ. These zones were defined based on GPS coordinates and mapped to specific activities observed during the WS process. Figure 3 presents the concept of productive zones based on workforce occupation.

To achieve autonomous data collection using electronic devices, smartphones with proprietary embedded software were used, with subsequent data collection and processing by web software, as well as developed proprietary technology for the experiment. Preliminarily, the work areas were geographically registered in the system. In this way, the zone of productive occupation was identified. Workers must carry the device throughout

Fig. 2: Welders use smartphones, and researchers conduct the WS. WS, work sampling.

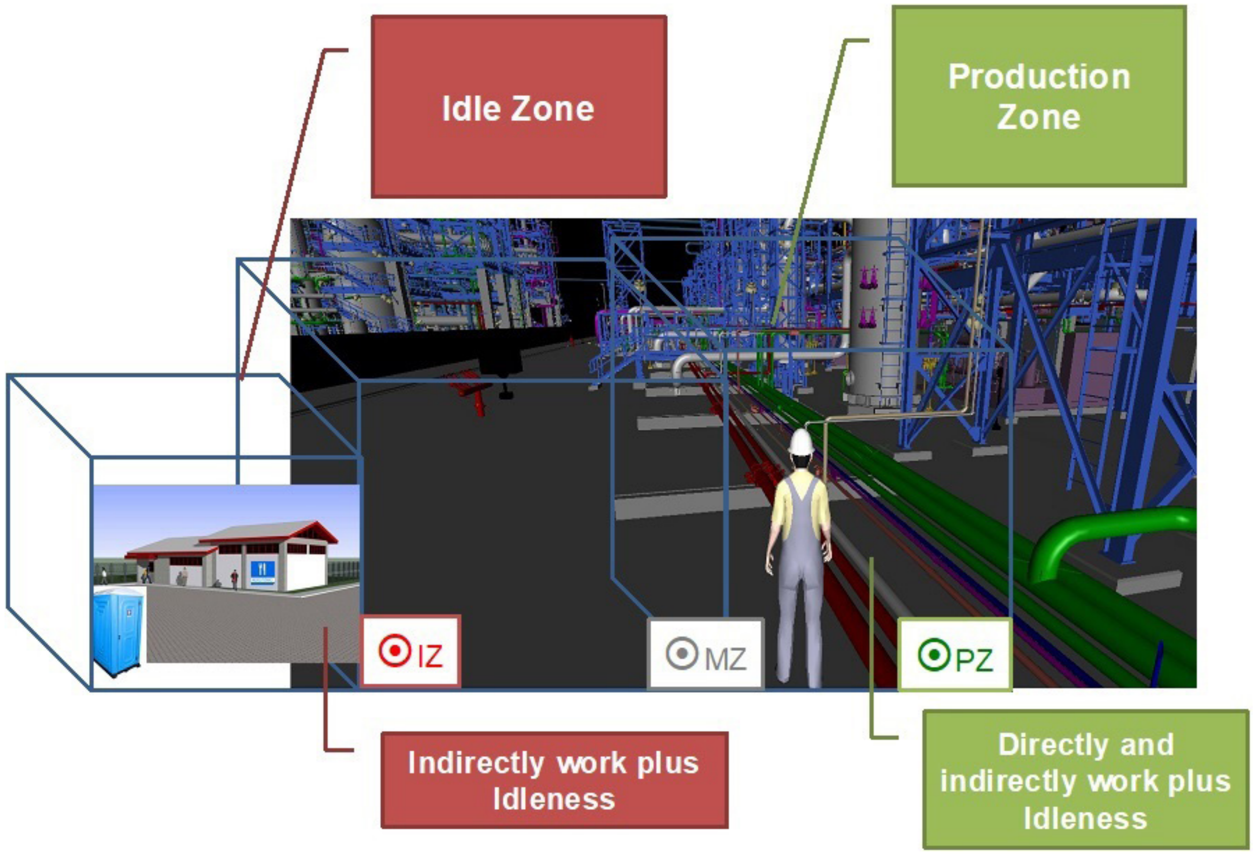


Fig. 3: Productive zones are a concept related to workers' occupations. IZ, idle zone; MZ, mixed zone; PZ, production zone.

the working day so that their geographical position can be detected every minute. The developed app uses GPS, Wi-Fi and mobile networks to determine the location of smartphones. According to the system response, the latitude and longitude data were captured for the experiment in a timeslot-based manner with the highest accuracy. At the beginning and end of the welding of a joint, the employee should take a picture of the barcode that identifies the spool. Through the Wi-Fi network and/or 3G, the data stored on the device are sent to the web software for data storage and analysis. Figure 4 illustrates the electronic monitoring process applied. The process involves (1) workers carrying smartphones with proprietary software, (2) continuous GPS location tracking, (3) barcode scanning of spools at the start and end of welding tasks, and (4) data transmission to web software for storage and analysis. This system enables near real-time productivity monitoring and calculation of the electronic factor of the production zone (EPZ).

These tools enabled by the proprietary web software allowed the development of an internal method that indicates the percentage of occupation of the welders inside and outside the PZs previously registered with the export of these points within a precision of 10 m. The following is the ordered sequence of steps that has been established to perform this procedure and which represents the process applied:

- Identify and remove the points related to days with single-area sampling;
- Identify and remove the collected points with an indicative accuracy greater than 10 m;
- Identify and remove the points collected before the delivery of the devices to the welders;
- Identify and remove the points collected after the return of the devices by the welders;
- Identify and remove the points with anomalous velocities;
- Identify and remove the abnormal points in relation to their successors and predecessors;
- Identify and remove the points with repetition of coordinates in small spaces of time;
- List the final points and attributes.

Thus, it was established that the EPZ percentage is the ratio between the sums of the number of points

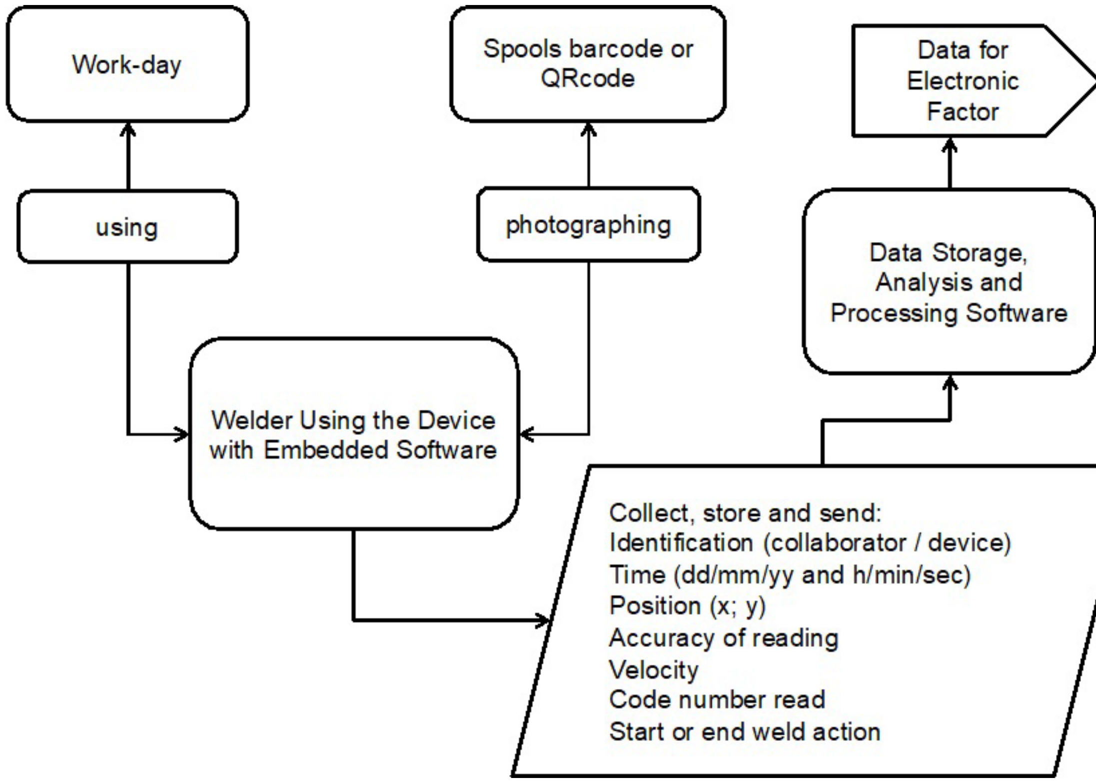


Fig. 4: Schematic representation flow of the EPM process conducted. EPM, electronic performance monitoring.

contained in the area recorded as productive in relation to the total points collected. In the same way, to obtain the electronic factor of the idle zone (EIZ), the non-productive zone occupation consists of the sum of the points counted outside of the productive zone concerning the total ratio of points. Finally, as described in the methodology of the sampling proportion, the averages were validated through the Monte Carlo analysis, and based on the number of points collected in this sample, the confidence limit of the results of the electronic methodology was delimited.

3.4 WS and labour factor methodologies

In the WS methodology, the data are collected through human observation and randomly performed and stratified according to the productive state, whether performing an activity (productive) or not (non-productive) (Sink 1985; Meyers and Stewart 2002; Adrian 2004; Groover 2007; Niebel and Freivalds 2013). The number of individual observations in each variable is transformed into a percentage value based on the ratio of the total observations. According to Adrian (2004), the sum of the percentage values of the activities considered productive determines the LRF (Adrian 2004). Therefore, the sum of the percentage values of the activities considered non-productive determines the idleness rating factor (IRF), according to Eqs. (1) and (2) (Adrian 2004).

$$\mathrm{LRF} = \frac{\text{Total observations of productive state}}{\text{Total observations}} \tag{1}$$

$$\mathrm{IRF} = \frac{\text{Total observations of non-productive state}}{\text{Total observations}} \tag{2}$$

To ensure the validity and reliability of the WS observations, two trained observers were employed in addition to the primary researcher. All observers underwent a comprehensive training programme to ensure consistent understanding and application of the observation protocol. A detailed observation guide was developed, clearly defining each activity category and providing classification guidelines. Observations were conducted according to a randomised schedule to prevent systematic bias. Inter-observer agreement was calculated using Cohen's kappa coefficient, with a result of 0.85, exceeding the recommended threshold of 0.80 for qualitative research (Finkler et al. 1993). This high level of agreement demonstrates the consistency and reliability of the observational data collected.

This WS methodology is noteworthy because it relies solely on the count of observations without requiring

Tab. 1: Adrian (2004), confidence limits

Sample sizes (95% confidence limits)					
Category proportion (%)	**Limits of error (%)**				
	1	**3**	**5**	**7**	**10**
50	9,600	1,067	384	196	96
40/60	9,216	1,024	369	188	92
30/70	8,064	896	323	165	81
20/80	6,144	683	246	125	61
10/90	3,456	384	138	71	35
1/99	380	42	15	8	4

continuous time measurement (Sink 1985; Meyers and Stewart 2002; Adrian 2004; Groover 2007; Niebel and Freivalds 2013). Increasing the recorded observations will directly correlate with an increase in confidence and a decrease in the error limit (Adrian 2004). However, irrespective of the sample size, there can always be an inherent uncertainty in the results (Adrian 2004). The uncertainty rate in modelling is quantified using three statistical concepts: confidence limits, error limits and category proportions (Adrian 2004); see Table 1.

The data collection procedure aimed to detect workers' activities that were considered productive or non-productive. Observations are taken on a timely basis, whether the timing is registered, but assuring action marking of the welder is performed at the very moment of observation. During the data collection of this experiment, the observation of the activity of each welder occurred in a time not less than 5 min for the same welder, where at random during the working day, data of the 10 welders who participated in the experiment were collected.

The simulation using the Monte Carlo technique is utilised to develop the probability distribution function (PDF) of LRF and IRF. The software @risk 7.5 (Palisade Company, LLC, Ithaca, NY 14850, United States) was employed for this purpose. The PDF obtained corresponds to the sum of the functions, representing each event's behaviour as productive or non-productive considering the population of all actions observed. The simulation process basically follows the steps (Calvetti and Ferreira 2018):

- Clustering the observation data collected in MS Excel worksheets according to the classification within productive state and non-productive state;
- Determining the suitable probability distribution function (PDF) using an Akaike information criterion (AIC) as the measure for model selection;
- Simulating the data using Monte Carlo with 5,000 iterations;
- Ensuring the number of iterations is sufficient by analysing the convergence using the computational programme. If it is observed that the number of iterations is not enough, it should be increased until a positive evaluation of the convergence analysis occurs. In case of inadequacy, one must select another generating function;
- Selecting the statistical parameters to perform the analysis;
- Performing the cumulative/density probability distribution;
- Developing the functions and performing the statistical parameters.

Finally, based on Adrian (2004), the sampling observation proportion model was applied and compared to validate the PDFs Monte Carlo modelling (Adrian 2004). This analysis compares the average values of the functions and their standard variations for deviations/coefficients to the calculated values. It also compares the error limits obtained using Table 1 to assess the accuracy of the results.

3.5 Comparative analysis and calibration

To compare the adhesion of the results obtained through electronic methodology and human observation, each method's averages and probability density function curves are analysed individually and in relation to each other. Likewise, the impact factors identified in the rating factors and their occurrence zones were evaluated.

In addition, based on the data obtained, a methodology of calibration for the electronic monitoring was developed, which incorporates the possibility of the occurrence of idleness within the established PZ. Finally, an integrated analysis is made to achieve the best workforce productivity assessment based on both methodologies.

4 Demonstration and evaluation

4.1 EPM

The electronic methodology generated 10,544 points regarding the positioning of the 10 welders under analysis, identifying that 6,092 of these points occurred within the PZ. Thus, the EPZ reached 57.78%; consequently, the EIZ was 42.22%. Applying the confidence limit methodology proposed by Adrian (2004) within the same parameter selected for the sampling allows it to assess the limit

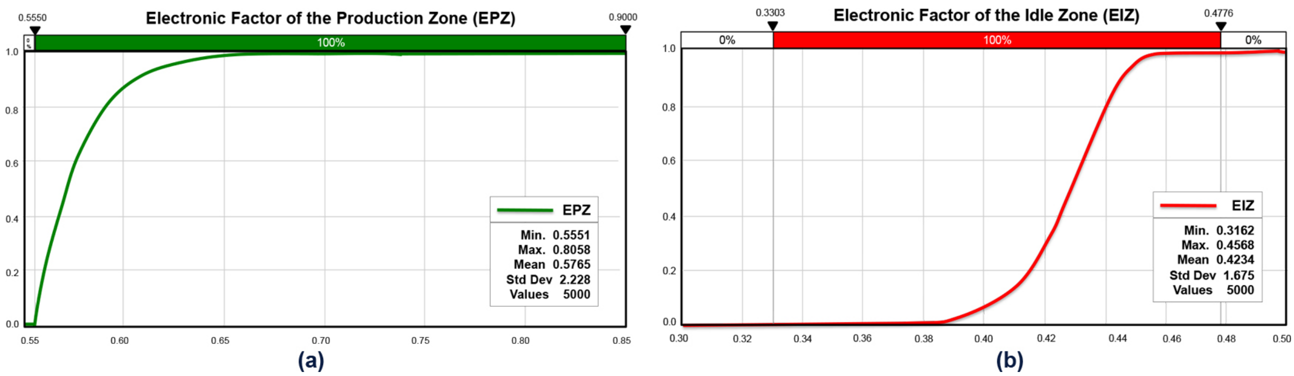


Fig. 5: PDF: (a) EPZ; (b) EIZ. EIZ, electronic factor of the idle zone; EPZ, electronic factor of the production zone.

error in relation to the electronic sample obtained (Adrian 2004).

Thus, for the sample relative to 10,544 observations and interpolating the values from Table 1, the limit error of approximately 0.78%, within a 95% confidence limit, is reached for the proportion category 50%. These results make it clear that the higher number of points sampled in the electronic method guarantees a lower limit error than that produced by human observation sampling. Considering a limit error of 2.41% obtained in the human observation method and 0.78% in the electronic method, a difference of the order of 309% is observed. This fact is mainly due to the following points: time of data collection; human observation leads to the mobilisation of a team of researchers in front of the service and the electronic method is autonomous, allowing the uninterrupted collection of data.

The PDF of the EPZ obtained by Monte Carlo simulation from the sample data of each of the 10 welders considered as independent variables, where an average of 57.649% is obtained, accounting for a deviation of 2.228, max. of 80.581, min. of 55.512 and a variation coefficient of 0.0386; see Figure 5a. This value is very close to that obtained by the total sampling, corresponding to 57.78%, which validates the function. The mean value of the PDF of the EIZ was 42.336%, with a standard deviation of 1.675, a maximum of 45.677, a minimum of 31.623 and a coefficient of variation of 0.0396, which is very close to the value obtained by the total sampling of 42.22%, which validates the function determined, see Figure 5b.

4.2 Human observation performance monitoring

The information gathered from the welders' work was organised based on their activities, amounting to 3,577 recorded observations. Depending on the welding process

Tab. 2: Work sampling of the productive state

Productive state	Observations	Percentage (%)
Welding	1,070	53.88
Grinding	430	21.65
Closing activities, organising and cleaning the workplace	164	8.26
Evaluating the task	114	5.74
Changing diffusers/torch-nozzle or tungsten sharpening	75	3.78
Spool adjustments and alignments	70	3.52
Recording the signet (Id)	32	1.61
Closing spool openings to purge	24	1.21
Cleaning the work area	7	0.35
Total	1,986	100.00

Tab. 3: Work sampling of the non-productive state

Non-productive state	Observations	Percentage (%)
Walking	666	41.86
Human physical conditions	337	21.18
Waiting for the crane operation	239	15.02
Management, health and safety meetings	152	9.55
Awaiting quality inspection	81	5.09
No joints released to start welding	53	3.33
No welding machine or defective machine	51	3.21
Interruption of activities due to the tubes Rigging	12	0.75
Total	1,591	100.00

involved, these activities were classified as productive or non-productive. Consequently, Table 2 showcases the number of observations in each action correlated with the productive state, and Table 3 shows the observation regarding the non-productive state. The dataset has been used and presented in early research and will be used to compare the WS method and the electronic one, serving as a base for EPM calibration (Calvetti and Ferreira 2018). The productive activities listed in Table 2 were determined through direct observation of the welding processes in the study environment. While these activities align with common practices outlined in standards such as ISO 3834 series, the list is not exhaustive and may vary depending on specific project requirements and welding techniques employed. At the same time, the non-production activities presented in Table 3 were identified through a systematic WS process. This process involved an initial observation period, iterative refinement of activity categories and expert validation by industry professionals. To manage experimental and methodological bias, several measures were implemented, including rigorous observer training, randomised observation schedules, multiple observers, blind recording techniques and regular inter-observer reliability checks. A continuous feedback loop was established to ensure consistent activity classification, and data triangulation was employed where possible to verify observational accuracy. These methodological safeguards were crucial in ensuring the reliability and validity of the identified activities, providing a robust foundation for subsequent analysis of workforce productivity.

The LRF density curve was generated via simulation and is the cumulative result of functions connected to the productive state. The probability distribution function (PDF) computed average is 0.5529, with a standard deviation of 0.0525, Figure 6a (Calvetti and Ferreira 2018). The PDF reaches a max. of 0.7942 and dips to a 0.3262 minimum, with a variation coefficient recorded at 0.09 (Calvetti and Ferreira 2018). In the same way, the density curve of the IRF is a result of the functions simulated and associated with the non-productive state. The value average of the IRF-PDF is 0.4549, with a deviation of 0.1035 (Calvetti and Ferreira 2018). The IRF-PDF reaches a max. of 0.9692 and a min. of 0.1785, with a variation coefficient of 0.23, Figure 6b (Calvetti and Ferreira 2018).

The LRF and IRF are calculated by comparing the ratio of absolute observations in each state to the total observations collected (Adrian 2004). Therefore, considering the sample of 3,577 observations, where 1,986 were clustered as productive state and 1,591 as non-productive state, the LRF was found to be 55.52%, and the IRF was 44.48% (Calvetti and Ferreira 2018).

Additionally, it can determine the relative error limits regarding the sample size within a given confidence interval. Based on Table 1, a category of 50% proportion was selected within a 95% confidence limit; subsequently, given the number of observations of 3,577, the error of 2.41% was calculated (Calvetti and Ferreira 2018). Therefore, the LRF found is considered in the range of 53.11% and 57.93% (±2.41%) (Calvetti and Ferreira 2018). At the same time, the LRF obtained by the PDF simulation of 55.30%, with a standard deviation of 5.25%, can be found in the range of 50.05% and 60.55% (Calvetti and Ferreira 2018). The Monte Carlo simulation of the LRF exhibits its expected variability due to the sum of its constituent random variables, and the resulting PDF accurately represents the LRF's behaviour, as confirmed by its close alignment with sampling chart results.

Analogously to the LRF, the proportion of IRF determined by the sampling observations is 44.48% (Calvetti and Ferreira 2018). Using the same category and confidence limit, the IRF is considered in the range of 42.07% and 46.89% (Calvetti and Ferreira 2018). Also, the IRF-PDF presented 45.49% as the mean value, with 10.35% of the standard deviation (Calvetti and Ferreira 2018). In this case, the IRF-PDF indicates results ranging from 35.14% to 55.84% (±10.35%) (Calvetti and Ferreira 2018). The IRF

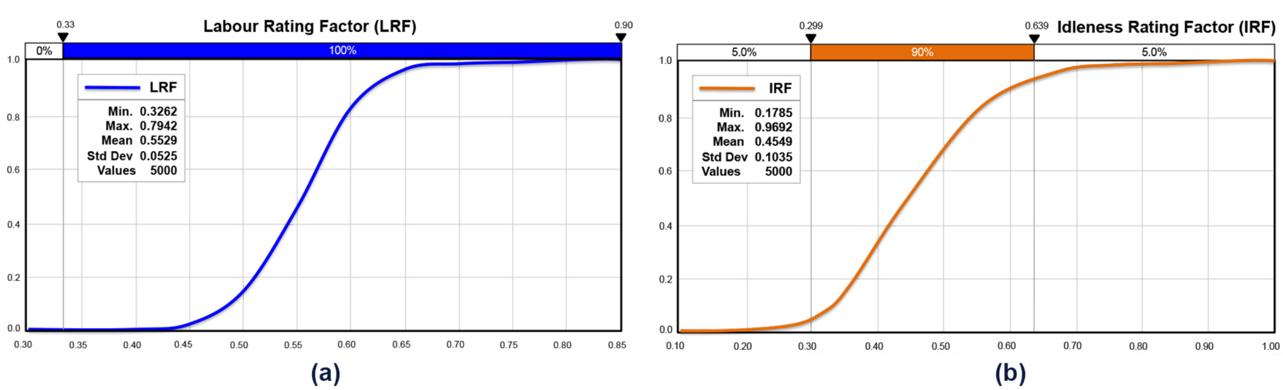


Fig. 6: The PDF: (a) LRF-PDF (Calvetti and Ferreira 2018); (b) IRF-PDF (Calvetti and Ferreira 2018). IRF, idleness rating factor; LRF, labour rating factor.

results show a greater dispersion in its PDF than the LRF due to the complexity and diversity of variables found in the sample, leading to increased dispersion in the Monte Carlo simulation (Calvetti and Ferreira 2018). However, the methodology can still be considered suitable, where improving activity modelling and increasing observations can reduce this dispersion found (Calvetti and Ferreira 2018).

A study using the WS method to evaluate tiling crew activity in an industrial building measures a level of active production of 65.43% and non-productive time of 34.57% (Shehata and El-Gohary 2011). Using the WS method, the active classification rate for prefabricated concrete elements was 42.00% direct work rate at 42.0%, 27.20% supporting activities and 30.80% non-productive activities (Lindhard 2023). Different case studies measured productive state rates for building renovation as (Wandahl et al. 2023): 25.03% carpenter work; 21.62% diverse renovation works, such as replacement of balconies, kitchens and bathrooms, replacing windows, adding insulation and putting up drywall; 34.57% works of new facades, new roofs and completely new installations; 38.96% new works on brick facades, roof, windows, additional and new insulations and 31.19% new facades, balcony, kitchen, bathroom and installations (Wandahl et al. 2023). A study of Danish renovation projects of a building measured a rate of 29% of productive actions for the crews in analysis (Pérez et al. 2022). For plumbing activities, a productivity rate of nearly 38% was found (Nassri et al. 2023). The different results using the WS method from distinguished use cases can indicate reasonableness in observing more productivity occupancy in works with more industrial characteristics.

4.3 Comparative analysis

Considering the results of 55.52% for the LRF and 57.78% for the EPZ, an absolute difference of 2.26% was observed between the results of the different methods. The difference obtained is low, considering that the electronic methodology does not detect idleness in the PZ. However, in this study, this fact may have influenced this outcome once workers knew they were being monitored. However, it is worth mentioning that idleness in the PZ can be measured using the human observation method, allowing it to be considered when implementing the electronic method. At the same time, due to the IRF in a simple perspective being the difference between the total and the LRF and appearing with high dispersion in the PDF simulation, it is more valuable to calibrate the electronic method correlating only EPZ and LRF.

As such, the difference between the methods of human observation and the electronic methodology is given by the limitation of the electronic detection of idleness occurring within the PZ. Likewise, based on the analyses of the observations, it is possible to characterise the actions identified according to their place of occurrence and their proportional percentage.

Productive state:

- Welding, 29.91% (PZ);
- Grinding, 12.02% (PZ);
- Closing activities, organising and cleaning the workplace, 4.58% (MZ);
- Evaluating the task, 3.19% (PZ);
- Changing diffusers/torch-nozzle or tungsten sharpening, 2.10% (PZ);
- Spool adjustments and alignments, 1.96% (PZ);
- Recording the signet (Id), 0.89% (PZ);
- Closing spool openings to purge, 0.67% (PZ);
- Cleaning the work area, 0.20% (MZ).

Non-productive state:

- Walking, 18.62% (IZ);
- Human physical conditions, 9.42% (MZ);
- Waiting for crane operation, 6.68% (MZ);
- Management, health and safety meetings, 4.25% (IZ);
- Awaiting quality inspection, 2.26% (MZ);
- No joints released to start welding, 1.48% (MZ);
- No welding machine or defective machine, 1.43% (MZ);
- Interruption of activities due to the tube rigging, 0.34% (PZ).

In this case, it is observed that the characteristic productive actions, which determine the LRF, occur in the vast majority, 91.39%, according to Eq. (3), within the PZ. Except for the following activities: ‘Closing activities, organising and cleaning the workplace’ and ‘Cleaning the work area’. The activities are part of the PZ and part of the IZ, that is, in the MZ, as previously mentioned.

The analysis indicates that these two activities have a low impact on the average LRF output. It is also observed that the action ‘Interruption of activities due to the tubes rigging’ is idle and occurs in the PZ. Just like actions 2 and 3 above, the actions: ‘No joint released to start welding’, ‘Waiting for crane operation’, ‘Awaiting quality inspection’, ‘Human physical conditions’ and ‘No welding machine or defective machine’ occur in the MZ. The actions that occur only in the IZ are: ‘Walking’ and ‘Management, health and safety meetings’.

To consolidate the registered data of the actions by zone of occurrence, the following results are obtained: 51.08% in the PZ, 22.87% in the IZ and 26.06% in the MZ. Based on the result of 57.78% of the EPZ, compared to 55.52% of the LRF, as well as 91.39% of the occupancy in the PZ, it can be inferred that employees within the PZ tend to occupy themselves. This fact can be justified by the occurrence of superior supervision and of their peers within the front of service because greater idleness is identified in places outside the PZ.

$$\text{Ocupation on the } PZ = 1 - \frac{\text{action } 2 + \text{action } 3}{\text{LRF}} \times 100 \qquad (3)$$

where:

Action 2 = Closing activities, organising and cleaning the workplace;
Action 3 = Cleaning the work area;
LRF = 55.52 total of the LRF.

4.4 EPM calibration

As shown in Figure 7, based on the result of 57.78% of the EPZ, compared to 55.52% of the LRF, there are differences between the probability distribution functions. As discussed above, it mainly arises from interpreting the labour rating in the MZ.

To compare the behaviour between the curves obtained by both methodologies, several functions derived from the PDF of the EPZ were generated, Figure 8. The plotted curve of +2% covers the upper limit until 82.58%. On the contrary, to cover the bottom limit until 35.50%, a plotted curve of –20.00% is needed. Based on the intersection of the curves, the correlation limit is determined to be between 82.58% and 58.00%, and the correlation of the electronic value related to the human observation method is ±2.00%. In this hypothesis, a determined EPZ of 60.00% is calibrated as an LRF of 58.00% until 62.00%. For instance, the calibration abacus shows respectively for values between 54.50% and 58.00% a correlation limit of ±4.00%, 52.00% until 54.50% correlation ±6.00%; 50.00% until 52.00% correlation ±8.00%; 47.50% until 50.00% correlation ±10.00%; 45.50% until 47.50% correlation ±12.00%; 40.50% until 45.50% correlation ±17.00% and 35.50% until 40.50% correlation ±22.00%.

According to Adrian (2004), it is expected that, in construction projects, on a workday of 8 h, only 4 h is productivity (Adrian 2004). As a result, it is anticipated to be at least 50% of productivity, indicating an accuracy of 84%–96% for the model.

5 Discussion

The electronic methodology cannot identify idleness within the PZ. In this sense, it is necessary to adjust the method that can mitigate this limitation, which can introduce a significant degree of inaccuracy to the results obtained using this methodology. Observing human behaviour allows for precisely identifying workers' actions, while electronic methodology only records the total time spent in specific zones. Therefore, it is recommended that, in view of the continuous use of the electronic method, at

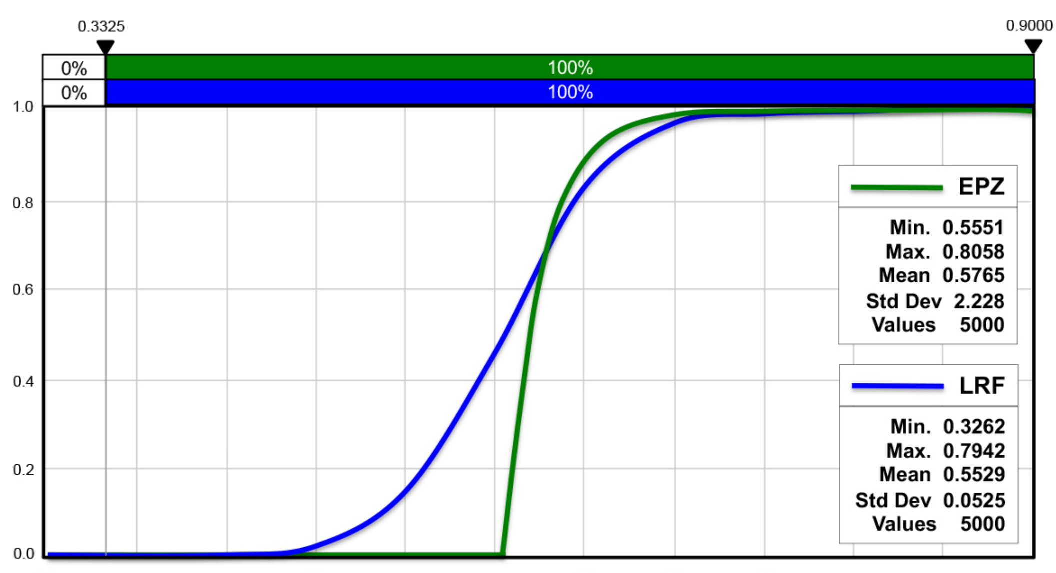
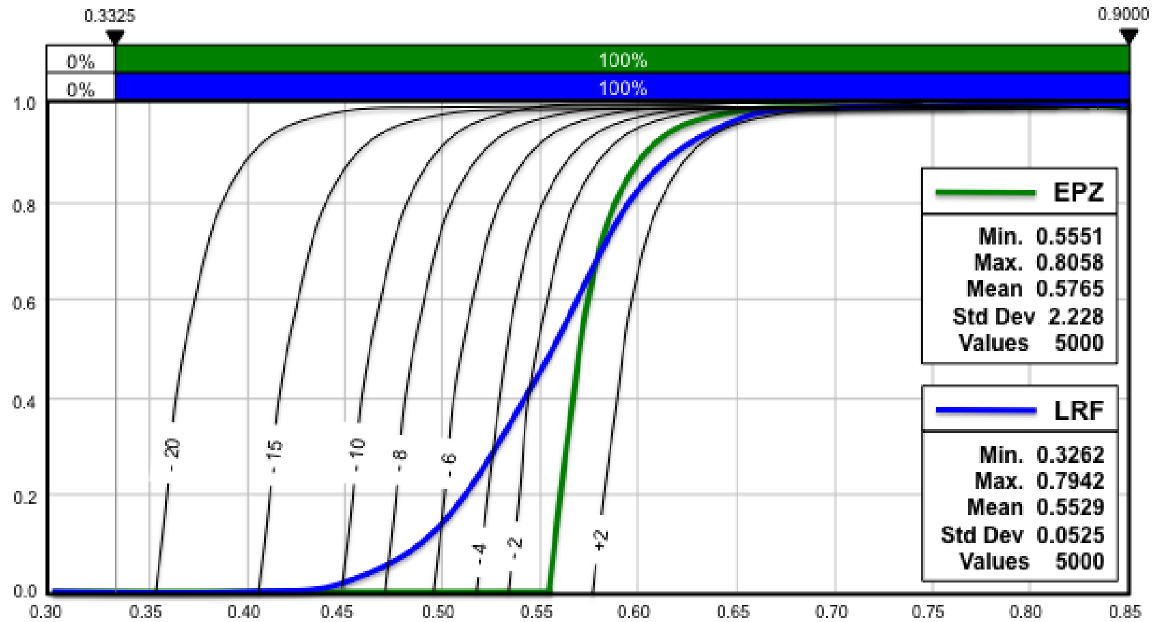


Fig. 7: Probability distribution functions of EPZ and LRF comparison. EPZ, electronic factor of the production zone; LRF, labour rating factor.



35.50	40.50	45.50	47.50	50.00	52.00	54.50	58.00	82.58	EPZ curve derivation %
20	15	10	8	6	4	2	0	0	Bottom correction (-) %
2	2	2	2	2	2	2	2	2	Top correction (+) %
22	17	12	10	8	6	4	2	2	Correlation Limit (+/-) %

Fig. 8: Calibration abacus EPZ to LRF. EPZ, electronic factor of the production zone; LRF, labour rating factor.

the beginning of the introduction of this monitoring technique, the human observation method should be used to develop the necessary calibration to reduce the inaccuracies mentioned above.

Based on the results, it is concluded that the methodologies of electronic and human observation are complementary. The use of electronic methodology will enable data to be collected in almost real-time, allowing efficient and fast monitoring of productivity. On the contrary, through the methodology of human observation, it is possible to develop parameters to correct the limitations of the electronic method. It should be emphasised that the human observation method, used with the support of the Monte Carlo method and the sensitivity analysis technique, considering the various functions that describe the behaviour of productive activities and idleness, will allow us to evaluate which factors impact productivity most. Thus, it will be possible to determine qualitatively and quantitatively which events generate idleness and which actions should be prioritised to boost the performance of the productive process. While this research provides valuable insights into EPM and WS for welders, it is important to acknowledge several limitations:

- **Sample Size:** This study was conducted with only 10 welders in a single pipe shop, which may limit the generalisability of the results to other settings or larger workforce populations.
- **Hawthorne Effect:** The awareness of being monitored electronically and through human observation may have influenced the welders' behaviour, potentially leading to higher productivity rates than usual.
- **Indoor GPS Accuracy:** The use of smartphone GPS for indoor positioning may have achieved reduced location accuracy compared to more specialised indoor positioning systems.
- **Limited Duration:** This study was conducted over a relatively short period, which may not capture long-term trends or seasonal variations in productivity.
- **Calibration Requirements:** The electronic monitoring method requires initial calibration using WS, which can be time-consuming and may need periodic updates to maintain accuracy.
- **Technology Limitations:** The smartphone-based monitoring system may have limitations in battery life, connectivity, or durability in industrial environments.

These limitations provide opportunities for future research to expand upon this work and address these constraints in subsequent studies.

Recent advancements in construction technology have revolutionised on-site performance monitoring practices, with several groundbreaking studies employing innovative techniques to enhance accuracy and efficiency. For example, Chen and Yu (2024) have developed an automated method for counting repetitive actions of construction workers using 3D pose estimation and self-similarity matrices, achieving 91.5% accuracy in identifying repetitive actions. The research by Altheimer and Schneider (2024) explores a machine learning-based framework using smart-watch accelerometers to recognise construction worker activities with hand-held power tools, achieving high accuracy in classifying activities and contributing to improved health, safety and productivity monitoring on construction sites. A research on sensor-based productivity monitoring integrates deep learning algorithms to automatically recognise and evaluate construction workers' actions, providing a novel framework for real-time productivity measurement (Cheng et al. 2023). Complementary methodologies, such as smartphone-based EPM and WS, to assess labour productivity can also integrate advanced action recognition algorithms and multiple sensors to enhance the precision and automation of productivity data collection.

Wang et al. (2025) provided a comprehensive review of sensor adoption barriers in the construction industry, identifying 11 key challenges, including data accuracy, site complexity and user acceptance, while proposing strategies to overcome these obstacles through standardisation, data-driven decision-making and user-centric innovations. Shamsollahi et al. (2024) presented an innovative method that integrates data from deep learning-based object recognition models and UWB systems to provide comprehensive information about tracked components in construction sites, including visual data, unique identifications and precise 3D locations. Xu et al. (2025) emphasised that sensor-based technologies, such as RFID and laser scanning, enhance interoperability, scheduling and production traceability in the manufacturing and assembly stages of industrialised construction. Finally, the work from these authors aligns with the ongoing efforts in this research to leverage sensor-based technologies for improving construction worker productivity, particularly in the context of Industry 4.0 initiatives.

The EPM results, showing an EPZ of 57.78%, demonstrate the potential for real-time productivity monitoring in industrial settings. This method can be applied in the following ways:

1. **Real-time performance dashboards**: Implement digital dashboards that display live EPZ data, allowing managers to identify productivity issues as they occur.
2. **Automated alerts**: Set up a system that sends notifications when EPZ falls below a certain threshold, enabling swift intervention to address productivity dips.
3. **Data-driven shift planning**: Use EPZ trends to optimise shift schedules and workforce allocation, potentially increasing overall productivity.

The combination of WS and EPM methods provides a more comprehensive view of productivity, and this integrated approach can be utilised to:

1. **Calibrate electronic monitoring**: Use WS results to periodically calibrate and validate EPM systems, ensuring accuracy over time.
2. **Identify non-productive activities**: The detailed breakdown of non-productive activities from WS can guide targeted interventions to reduce idle time.
3. **Training Programmes**: Develop tailored training programmes based on the specific non-productive activities identified, such as reducing waiting times or improving equipment reliability.

Based on the finding that welders are directly engaged in welding 75.55% of the time, with 24.45% spent on auxiliary activities, the following strategies could be implemented:

1. **Streamline auxiliary tasks**: Analyse and optimise the 24.45% of time spent on auxiliary activities to increase direct welding time.
2. **Equipment optimisation**: Given that 91.39% of productive actions occur within the PZ, focus on optimising equipment layout and accessibility to further increase productivity.
3. **Targeted idle time reduction**: Address the specific non-productive activities identified, such as 'waiting for crane operation' (6.68%) and 'management, health and safety meetings' (4.25%), to reduce overall idle time.

Long-term productivity tracking utilising the EPM method, which boasts an accuracy of 84%–96% for productivity values above 50%, indicates its potential for sustained productivity monitoring:

1. **Trend analysis**: Implement systems to analyse long-term productivity trends, enabling the identification of seasonal variations or gradual declines that require attention.
2. **Benchmarking**: Use the EPZ and LRF metrics to establish internal benchmarks and compare productivity across different teams or facilities.

3. **Continuous improvement programmes**: Integrate these metrics into continuous improvement initiatives, setting incremental targets for EPZ and LRF improvements.

6 Conclusions

In the study of productive activities, it was found that 75.55% of the time, welders are directly engaged in the welding process, while 24.45% of the time is spent on auxiliary activities. The electronic methodology has a limitation in detecting idleness occurring within the PZ. However, it is observed that 91.39% of the productive actions occur within the PZ. Most importantly, expecting values above 50% of productivity, the electronic method has an 84%–96% accuracy. Using the WS method, the LRF was found at a rate of 55.52%; whereas, the EPZ using the welders' location achieved 57.78%. Compared with studies applying the WS method, which results in productive rates ranging from those found by Shehata and El-Gohary (2011), Pérez et al. (2022), Lindhard (2023), Nassri et al. (2023), and Wandahl et al. (2023), indicating coherence in the results obtained.

This study successfully combined EPM using smartphones with traditional WS, providing a more comprehensive approach to productivity measurement in industrial settings. Also, the EPM method enables near real-time productivity tracking, allowing for swift interventions when productivity dips are detected. It developed a calibration abacus that correlates EPZ with LRF, addressing the limitation of EPM in detecting idleness within the PZ. Finally, the use of smartphones as monitoring devices offers a low-cost, accessible approach for continuous productivity improvement in manufacturing and construction.

One advantage of using smartphones as hardware is that users are used to the technology. Also, the GPS approach demands less infrastructure. However, the indoor position precision is lower than that of other technologies; similar research using GPS in indoor environments also activated reasonable results (Navon and Goldschmidt 2003a, 2003b; Pérez et al. 2022; Wandahl et al. 2023).

The WS methodology enables the swift and accurate recognition of actions carried out by the welders in the experiment. This method involves intermittently recording the productive or non-productive status, eliminating the need for continuous time monitoring. The data gathered through WS, which groups non-productive events, can be analysed using Monte Carlo simulations. This process allows the analysis of the PDF and validation of the WS results, and it also allows further comparison, for example, with the electronic method.

The results showed that the electronic and human observation methods are complementary and may be applied in an integrated way. The electronic method allows monitoring and controlling to be carried out almost in real time. At the same time, the human observation method (in this case, WS) is crucial to diagnosing productivity impact factors. Likewise, using the human observation method makes detecting idleness inside the PZ possible, which does not occur with the electronic method. So, correcting the results obtained by the electronic method inside the PZ is possible.

Electronic methodologies offer opportunities to monitor and manage productivity in almost real time. It enables the collection of large, accurate samples of data and their analysis, which is crucial for gaining insights into production processes. The results obtained from WS can be verified and compared with those obtained from the electronic method. In essence, these methodologies contribute to comprehending and enhancing productivity in various fields, from manufacturing to other domains. Through their integration and careful application, companies can improve their ability to optimise processes and achieve better results.

Future research directions in computer vision integration may target the development and testing of computer vision algorithms to automatically detect and classify worker activities within the PZ, addressing the current limitation of EPM in identifying idleness. At the same time, it is worth investigating the use of machine learning techniques to create self-adjusting calibration models that reduce the need for frequent manual WS, and also, exploring the integration of wearable sensors (e.g., accelerometers and heart rate monitors) with the smartphone-based EPM to provide more detailed activity and physiological data. Privacy-preserving techniques are relevant to the next steps of research. Research and implement advanced anonymisation and data protection methods to address potential privacy concerns associated with continuous electronic monitoring. Finally, it is relevant to conduct studies to adapt and validate the integrated EPM-WS method across various industries, such as construction, manufacturing and logistics, to establish its broad applicability.

The main contribution of this work is the potential for continuous productivity improvement through an accessible, low-cost method. The EPM technique allows monitoring and controlling productivity almost in real time, and human observation is the key to diagnosing the main impact factors. Thus, the methodology proposed in this study allows for a quantitative and qualitative evaluation of labour productivity. Likewise, the proposed model can be adapted to be applied to any type of hardware device, including integrating more than one.

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