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Advancements in Data Analysis for the Work-Sampling Method

Borut Buchmeister * and **Natasa Vujica Herzog**

Faculty of Mechanical Engineering, University of Maribor, Smetanova 17, SI-2000 Maribor, Slovenia; natasa.vujica@um.si
* Correspondence: borut.buchmeister@um.si

Abstract: The work-sampling method makes it possible to gain valuable insights into what is happening in production systems. Work sampling is a process used to estimate the proportion of shift time that workers (or machines) spend on different activities (within productive work or losses). It is estimated based on enough random observations of activities over a selected period. When workplace operations do not have short cycle times or high repetition rates, the use of such a statistical technique is necessary because the labor sampling data can provide information that can be used to set standards. The work-sampling procedure is well standardized, but additional contributions are possible when evaluating the observations. In this paper, we present our contribution to improving the decision-making process based on work-sampling data. We introduce a correlation comparison of the measured hourly shares of all activities in pairs to check whether there are mutual connections or to uncover hidden connections between activities. The results allow for easier decision-making (conclusions) regarding the influence of the selected activities on the triggering of the others. With the additional calculation method, we can uncover behavioral patterns that would have been overlooked with the basic method. This leads to improved efficiency and productivity of the production system.

Keywords: work sampling; observations; analysis; proportions; correlations; interdependence between activities

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1. Introduction

Nowadays, the business world is more focused on sales and trade. We are paying less attention to how we work and how to organize and improve production in a high-quality way. It involves a well-thought-out, comprehensive, and systematic coordination of activities, as well as solving all problems that arise to achieve success.

Work-study, as one of the fundamental areas of scientific work organization, provides extensive possibilities for the analysis of any work, as well as the possibility of applying improved working methods and finding ways to determine the necessary times for the completion of the respective work. The processing times of activities can be determined for an existing operation from historical data, work sampling, or time studies [1]. The basic purpose of work-study and time study is to achieve optimal work effects in the performance of work tasks.

The basic requirements for a successful and rationalized business involve controlling and monitoring to reduce delays and time losses in the work process [2]. These delays and time losses are common in the business processes of companies in less developed countries, often to a greater extent when compared to companies in highly industrialized countries; the main reason for this is the relatively low level of work organization. Labor interruptions and downtime are elements that increase production costs and disrupt the production process. Therefore, one of the basic tasks of a work-study is to identify and determine these losses (or unproductive activities) and then use the analysis to separate excused (planned and unplanned) and unexcused work interruptions and time losses and propose measures to eliminate or reduce them to the lowest values. Losses are usually classified into the following:

- Planned losses (business conversations, editing of documentation, preventive maintenance, physiological needs, etc.);
- Unplanned losses (breakdown of working equipment, power outage, waiting for transport, etc.);
- Indiscipline (private absence, private conversations, etc.).

The methods that allow us to measure and analyze the use of time are as follows: the stopwatch time study and the work-sampling method.

Work sampling is a statistical work measurement method in which many observations are made over a period of time on a group of machines, processes, or workers to collect information about the percentage of time spent on specific activities [3].

In this article, we present our original contribution to the data analysis for the work-sampling method. To the usual calculations of percentage time spent, we add a correlation analysis of percentage activities by hours of the work shift to identify potential interdependencies between them pairwise. This can greatly facilitate the adoption of optimal decisions based on the results of the studies conducted, especially in the form of some changes in the process organization to reduce time losses.

We demonstrate the relevance of the research problem with a brief overview of the recent literature in the field of the article.

The scope of application of the work-sampling method in different areas is well covered (in manufacturing, maintenance, product development, construction, garment industry, food industry, logistics, pharmacy, hospitals, etc.). In our analysis, for reasons of relevance, we present some important publications from the last 10 years to emphasize the relevance of the method in question.

Our main focus is on applications in production plants. The work-sampling method is a very useful tool for setting standard times. Garcia et al. proposed a methodology to determine the allowance time based on the heart rate and sampling of a part of a production line consisting of thirteen stations operated by four workers [4]. The result was that the allowance time after the study was higher than before. Similarly, De la Riva et al. conducted an experimental study on work sampling, using a new technology available (heart rate measurement) to allocate the allowance time to a task during the workday [5]. The need for observations represents a considerable cost factor, which is why Martinec et al. introduced self-reporting. They described a self-reported work-sampling approach developed and adapted for production development and the application of the approach in an automotive supplier company [6]. The results provide insight into the engagement of group members at work and how their activity was related to the context, mode, and type of information transaction used.

Work sampling is mainly used as a stand-alone method but can also be used in combination with other methods. This is how Yuan et al. conducted the study, where three different methods were integrated: work sampling, computer simulation, and biomechanical modeling to investigate the physical demands of the job [7]. A work-sampling method was used to quantify the proportion of time spent on specific tasks. Work sampling can also provide key data in ergonomic studies. Dasgupta et al. collected data on the ergonomic strain of workers using the work-sampling method and identified several risk factors in the observed tasks [8]. Similarly, Javernik et al. assessed the workload of workers in collaborative workplaces under different workload conditions [9,10]. The results indicate the need for the individualized treatment of individuals to increase productivity and job satisfaction at the same time.

Work-study is the most important, but not the only, application of work sampling. Skec et al. [11] investigated work sampling in product development. They introduced a work-sampling application for cell phones that can greatly simplify and popularize the use of the method. Grznar et al., on the other hand, reported on the development of a special tool for workplace analysis [12].

In the field of construction, Fischer et al. introduced a hierarchical classification for activity recognition and used a hybrid deep learning model as an alternative to the work-sampling method. Based on the activity recognition results, a discrete event simulation was used to predict the progress of the process [13].

To improve the efficiency of the maintenance department, Dewi et al. analyzed the current workload of technicians and employees using the work-sampling method [14]. The study found that the workload of the maintenance department was so low that a reduction in the number of employees, the creation of more efficient work processes, and an expansion of the workplace were suggested.

Ünal and Güner conducted a work-study using work sampling in the garment industry [15]. They integrated work sampling and fuzzy logic. Since safety and productivity are critical in evaluating performance management in maritime transport and port management, Safa and Craig investigated activity analysis methods and selected work sampling as a suitable method for improvement policy [16].

Lee et al. presented a good overview of the novelties regarding the application of the work-sampling method in construction [17]. Their article contributes to the state of knowledge in construction management through a thorough understanding of the current state-of-the-art activity sampling techniques and research gaps. Their analysis includes a qualitative synthesis of the contributions of the reviewed articles. Mathiassen et al. developed a procedure to evaluate the statistical properties of work-sampling strategies that estimated categorical exposure variables and illustrated the applicability of this procedure to investigate the bias and accuracy of exposure estimates from different sample sizes [18].

Wahid et al. presented a case study on the SME food industry [19]. The results of this study show that work-sampling data can be used as reliable estimates to identify potential bottlenecks and idle times in a factory. Similarly, Rashid and Louis proposed a framework that extends the applicability of event data collection and process models by converting them into DES models for predicting future performance [20].

Examples of work-sampling studies can also be found in the field of hospital care. Wong et al. conducted a work-sampling study in two hospitals [21]. The results make it possible to optimize the workflow with a focus on spending more time on direct patient care. Gupta et al. conducted a work-sampling study with seven participating dentists who were referred to the field and patients who visited the on-site dental center [22]. They concluded that work sampling is a viable method for optimizing healthcare, with a focus on effective use.

The process of work sampling is traditionally carried out manually, which does not exclude more modern approaches with recording devices and automatic activity recognition. Luo et al. improved the work-sampling method and introduced an activity recognition method that accepts surveillance videos as input and generates different and continuous markers for the activity of individual workers in the field of view [23]. Their method can be the basis for effective and objective work sampling.

The remaining sections of the article are organized as follows: Section 2 describes the work-sampling method, the prescribed steps in conducting the observations, and the basic calculations. Section 3 comprehensively describes the factors and causes of production losses (62 factors in total)—as a result of our many years of experience, and as a guide for analysis and decision-making. Section 4 presents the upgraded analysis of the work-sampling results and its advantages. Section 5 provides an example of a work-sampling study in a manufacturing company, which confirms the relevance of upgrading the analysis of the results. Section 6 summarizes the results, presents concluding remarks, and discusses possibilities for future work.

2. Materials and Methods

Work sampling (also called activity sampling) is a statistical method that can be used to solve certain problems in the field of industrial engineering without the need for constant presence or an analytical approach. It is based on the theory of sampling and represents one of the possibilities for the practical application of mathematical statistics in industry. The method is also known in German-speaking countries as the method of observation at random points in time or "Multimomentverfahren". As an example, we identify preselected situations in which the person or object in question may be alone or in a group, using observations at random points in time. On this basis, we determine the expected proportion of this state in the total time with the prescribed accuracy and probability. The work-sampling method was first used by Tippet in the British textile industry in 1934 and described by Stanton [24].

Observations using this method are carried out without a stopwatch so that the analyst walks through all the workplaces belonging to him/her several times a day (e.g., 20 to 30 times) at randomly selected times over a period of two, three, or more weeks. The analyst records the data (a line) on the recording sheet, indicating the type of event, i.e., the activity that he/she notices at the moment of arrival (the recording is, of course, also possible using a computer application on a tablet, laptop, or mobile phone). For semi-automated processes, it is necessary to observe what the worker does and what the machine does. For example, the machine can perform a processing operation while the worker performs a completely different activity (around productive work or losses).

In this way, after recording the cumulative sum of observations of individual activities, a large total number of observations is obtained, which allows us to determine separately the proportion of the workday spent on a particular activity and, thus, actually obtain an objective picture of the structure of the workday at the observed workplaces. This in turn makes it possible to draw appropriate conclusions and make suggestions to improve the situation under investigation [25].

If the results obtained with this method are to be realistic, the following conditions must be met in addition to objective and accurate recordings: enough observations of events and a randomized observation schedule to observe one detail at a time. The time period for the study must be long enough to avoid production peculiarities, seasonal production, etc.

The areas of work and problems to which the work-sampling method can be applied are practically and objectively unlimited, e.g., the analysis of capacity utilization and planning, guidelines for work within a shorter workday, the determination of elements for setting standard times (time allowance coefficient), etc. If we use this method to analyze how to reduce idle times and increase work efficiency, the elements must be placed in such a way that they reveal bottlenecks that depend on the operator himself (e.g., arriving late, leaving work too early, etc.). Some elements can also show us various other organizational shortcomings (e.g., lack of materials, machine breakdowns, indiscipline, etc.). By incorporating the elements of the work-sampling method into a mathematical model, we obtain the results with a certain degree of accuracy. The method does not solve problems but points them out and calculates their probability and frequency [25].

The work-sampling method is characterized by a high degree of activity and economy, which is expressed in the following advantages:

- We can record several workplaces simultaneously and track a relatively large number of activities (time efficiency);
- The time and cost of observations are significantly lower than those of continuous recording with a stopwatch (from 35 to 80%); we obtain the information we need quickly, using fewer resources, and at a lower risk and cost (cost-effectiveness);
- The objectivity of recording the actual situation has an accuracy that is satisfactory in practice; work sampling provides statistically valid data for analyzing work patterns;
- Since the recording technique minimizes the influence of the observed workers on the recording results, the probability of false results is much lower than with continuous recording (less intrusive as it involves periodic observations over a period of time);
- Training analysts for recording is simple, fast, and straightforward; we do not need any special equipment (no timing devices) to carry out recordings;
- It can be applied to various types of work environments (flexibility);
- The study takes longer, minimizing short-term fluctuations;
- The recording can be interrupted or resumed, if necessary, as it does not affect the result.

Of course, this method also has its disadvantages:

- The recording of observations can involve a certain amount of subjectivity, which can lead to inconsistencies in data collection and interpretation;
- Difficulties in recording individual workplaces, especially if they are located further away;
- We cannot capture individual differences between workers as we are observing a group of workers;
- We cannot set standards by sampling work activities;
- It provides an overview of activities without detailed insights into specific tasks or processes;
- It does not capture short-term fluctuations that could be important for identifying inefficiencies or bottlenecks in the process;
- It is practically impossible to ensure adequate accuracy for activities that account for less than 1% of the share, as a very large number of observations (over 150,000) would be required;
- It is very difficult to identify the causes of employee work interruptions and absenteeism, as an understanding of the specific context and work environment is required.

The last one is exactly the area we are mainly contributing to in this article (described in Section 4).

2.1. The Recording Process of the Work-Sampling Method

Before the actual recording, we must study and prepare the necessary steps in detail, which include the following phases [26,27]:

1. Pre-recording preparations: Determining the scope and location of the workplaces, preparing the recording team (a single person can collect 400 to 600 observations per day), informing the workers, making a list of activities, drawing up a plan for random visits to the workplaces (the observation route), and defining the forms—usually recording and collecting sheets. Each analyst draws up the observation schedule randomly and according to the outline of the group of workplaces to be observed (the departure time for observation, the workplace where it starts, and the direction of movement) for each recording day.
2. Recording—collecting observations: preliminary (pilot) recording (usually 3 to 5 days; we check the adequacy of the list of activities and the schedule of random observations; we calculate the proportion of time spent on each activity) and the main (full) recording (we collect the number of observations required according to the most typical or important activity).

With the work-sampling method, a confidence level of 95% and a precision level of 0.05 of the results are completely sufficient, so that the required number of observations is as follows:

$$N = \frac{1.96^2 \cdot (1 - p_i)}{0.05^2 \cdot p_i} = 1537 \cdot \frac{(1 - p_i)}{p_i}, \tag{1}$$

where

N—denotes the number of observations required,

1.96—number of standard deviations from the mean reflecting the 95% level of confidence,

p_i—proportion of time spent on the major activity (between 0 and 1).

The equation for determining the upper and lower control limits (M_i) for a confidence level of 95% is as follows:

$$M_i = p_i \pm 1.96 \cdot \sqrt{\frac{p_i \cdot (1 - p_i)}{N}}, \tag{2}$$

2.2. Data Analysis and Calculations

After completing the recording, we calculate the percentage of occurrence of each activity and the accuracy achieved (ε_i) for individual or combined activities, as follows:

$$\varepsilon_i = \pm\, 1.96 \cdot \sqrt{\frac{1 - p_i}{N \cdot p_i}}, \quad (3)$$

We calculate the results of the activity shares for the entire recording period, by hours of the work shift, days, and shifts [26].

The time allowance factor (TA_f) is calculated according to the following equation:

$$TA_f = \frac{\sum PL}{\sum PW + \sum UL + \sum IN}, \quad (4)$$

where

PL—number of observations for planned losses,

PW—number of observations for productive work,

UL—number of observations for unplanned losses,

IN—number of observations for indiscipline.

3. Factors and Causes of Losses

When analyzing the level of work organization in manufacturing companies, we first look for the factors that cause overwork and the factors of production. As there are many of them, it is difficult to monitor them all at the same time. We, therefore, group them and carry out a selection of the most influential factors to monitor them. Based on work-sampling studies conducted in manufacturing companies to date, we identified the observed state of the factors or causes of losses (and thus poor capacity utilization), which we categorized into four groups: time losses, material losses, yield losses, and other losses. The following list of factors is part of our article contribution.

The most important factors (16) that cause time losses are as follows:

1—Improper use of personnel, qualifications, and skills of individuals are not matched to the requirements of the jobs;

2—Involvement of workers and officials in the work without prior familiarization with the conditions of the work environment and possible training;

3—Incomplete and inaccurate technical documentation and poorly organized instruction during work;

4—Unsuitable location of workplaces;

5—Irregular operation of workplaces;

6—Unsuitable work equipment;

7—Unstable and insufficiently monitored technological processes;

8—Irrational choice and use of means of transport;

9—Ineffective organization of quality control;

10—Weak organization of preventive, regular, planned corrective maintenance and full restoration of machinery or the general lack of a maintenance system for machinery and equipment;

11—Ineffective functioning of the production control department;

12—Unhealthy relationships between people;

13—Unrealistic time standards;

14—Unfavorable working conditions;

15—Insufficient and improper stimulation to save time;

16—Various unforeseen downtimes, unrealistic operating schedules, irregular power supply, etc.

The most important factors (14) that cause material losses are as follows:

1—Incomplete specification and poor quality of purchased material;

2—Insufficient use of standard materials;

3—Unrealistic material standards;

4—Insufficient and improper stimulation to save materials;

5—Insufficient knowledge of material properties and processing methods;

6—Inadequacy and inaccuracy of machinery and tools;

7—Use of material not fit for purpose, use of better-quality material in the absence of necessary additional processing, and the like;

8—Insufficient interest of workers in product quality;

9—Surplus stocks of materials, raw materials, and the like;

10—Improper and unprofessional handling of materials during placement and manipulation;

11—Improper and unprofessional manipulation of semi-finished and finished products during transport, placement, and packaging;

12—Poorly organized collection, classification, and use of waste materials;

13—Improper use of materials;

14—Ineffectively organized control of materials and semi-finished products.

The most important factors (12) that cause yield losses are as follows:

1—Unprofessional and irresponsible handling of machines, tools, equipment, etc.;

2—Insufficient knowledge of the technical and utilization characteristics of machines, tools, and equipment, as well as incomplete and disorderly maintenance of equipment records;

3—Abnormal use of production equipment;

4—Insufficient maintenance of machines and equipment that are not in use;

5—Indifferent ignoring of minor breakdowns of machines and tools;

6—Incomplete and uneven use of available capacities;

7—Mismatch between component capacities and production program, inappropriate production program, high degree of inconsistency, etc.;

8—Unrealistic operational planning;

9—Inefficient response to production disruptions, weak organization of dispatch service;

10—Inefficient coordination of component production processes;

11—Insufficient insight into production status, poor application of operational records and their use for operational monitoring and analysis of trends in results achieved;

12—Lack of adequate information system and automatic data processing.

The most important factors (20) that cause other losses are as follows:

1—Unsuitable location of factories, departments, workshops, and workplaces and, as a result, harmful crossing of the paths of workpieces and personnel;

2—loss of space due to irrational layout of machines, materials, semi-finished and finished products;

3—Inappropriate layout and maintenance of internal paths;

4—Improper selection and use of means of transport;

5—Disorganization at the workplace;

6—Improper set-up and functioning of the control network;

7—Insufficient lighting at the workplaces;

8—Ineffectiveness of protective measures for persons and property;

9—Weak work discipline;

10—Hesitancy with management bodies in making and implementing decisions;

11—Unfavorable working conditions, humidity, stuffiness, harmful vapors, high temperature, and the like;

12—Unhealthy relations between employees, especially between managers;

13—Poor functioning of the administration (trade unions);

14—Poorly organized meals (wrong timing of hot meals and poor quality of food);

15—High turnover of employees;

16—Lack of a systematic study of the organization and work methods;

17—Lack of instruments regulating inter- and intra-departmental relations;

18—Non-systematic and non-up-to-date monitoring, analysis, and presentation of the results achieved;

19—Insufficiently elaborated planning methodology and weak planning discipline;

20—Lack of a department systematically dealing with problems related to the improvement of production and the business in general.

The company requires consistency (optimization) between the individual factors that control the functions. The discrepancy between certain functions and groups of jobs also causes the occurrence of loss factors and poor utilization of production capacities. Therefore, it is necessary to localize the losses, but it is not possible to quantify them precisely, and therefore we cannot say whether we will first solve the problem of machine maintenance or labor discipline, for example.

4. Upgrade of the Analysis of Work-Sampling Results

We usually report the results of work-sampling study observations in the form of percentages of individual activities (or grouped) by hours, days, and work shifts [27]. We also calculate the achieved accuracy of the results and their control limits [28].

Many unplanned losses can be caused by certain superficially insignificant events, which in turn trigger new events in a chain, leading to extensive time losses. Since the work-sampling method gives us an insight into the activity proportions at the finest level in the workday hours, we can consider using the data from the activity plot by hour and comparing them with each other to identify possible correlations.

The most used measure of the linear relationship between two quantitative variables (two sets of data) is Pearson's correlation coefficient r, which assumes at least one interval type of the two variables analyzed and a linear relationship between the variables. The coefficient can assume values between -1 and 1. Pearson's correlation coefficient answers two questions, namely:

(a) Is there a linear relationship between the variables at all? and
(b) How strong is the linear relationship between the variables?

When we examine the existence of a linear relationship, we speak of two types of relationships. A positive correlation exists when the values of the first (x) and second (y) variables are high or low. In this case, the coefficient is positive and close to 1. If one variable changes, the other variable also changes in the same direction. A negative correlation exists if the values of the first (x) variable are high and the values of the second (y) variable are low or vice versa. The coefficient is then negative and close to -1.

To determine the strength of the interdependence between the activities, we use a modified coefficient value scale, which is presented above in Table 1.

Table 1. Strength of interdependence according to the value of the correlation coefficient.

Coefficient Value *r*	Strength of Interdependence
0.00	None
0.01–0.19	Very weak (negligible)
0.20–0.39	Weak
0.40–0.69	Moderate
0.70–0.89	Strong
0.90–0.99	Very strong
1.00	Perfect (functional)

It should also be emphasized that Pearson's correlation coefficient indicates the relationship between two variables, but not the influence of one variable on another. Therefore, the judgment of the analyst is necessary in accordance with their knowledge of the performance of the observed activities and the possible causes of the correlation.

Therefore, we calculate the correlations between the percentages of all activities by hour and find the correlation coefficient for all possible pairs within an 8 h work shift.

A sample size n = 8, values of pairs of variables are as follows: $(x_1, y_1), \ldots, (x_8, y_8)$.

Correlation value equation, adjusted for $n = 8$ (universal for all studies), is:

$$r = \frac{8 \cdot \Sigma xy - (\Sigma x) \cdot (\Sigma y)}{\sqrt{\left(8 \cdot \Sigma x^2 - (\Sigma x)^2\right) \cdot \left(8 \cdot \Sigma y^2 - (\Sigma y)^2\right)}}, \tag{5}$$

In our methodological development, we use the *t*-test for two independent samples (independent-samples *t*-test, two-tailed) and determine whether there are statistically significant differences in the average value of the two samples. It is a standard method to determine whether the correlation coefficient is statistically significant or not [29].

A 95% confidence interval can be defined as the interval spanning from the 2.5th to the 97.5th percentiles of the resampled r values (Figure 1). This corresponds to a significance level of 0.05. The sampling distribution of the studentized Pearson's correlation coefficient follows the Student's *t*-distribution with degrees of freedom (DOF) $n - 2$. To determine the critical values for r, the following function is applied [29]:

$$r = \frac{t}{\sqrt{n - 2 + t^2}}, \tag{6}$$

Degrees of freedom	Significance level .2	.15	.1	.05	.025	.01
1	3.078	4.165	6.314	12.706	25.452	63.657
2	1.886	2.282	2.920	4.303	6.205	9.925
3	1.638	1.924	2.353	3.182	4.177	5.841
4	1.533	1.778	2.132	2.776	3.495	4.604
5	1.476	1.699	2.015	2.571	3.163	4.032
6	1.440	1.650	1.943	2.447	2.969	3.707
7	1.415	1.617	1.895	2.365	2.841	3.499
8	1.397	1.592	1.860	2.306	2.752	3.355

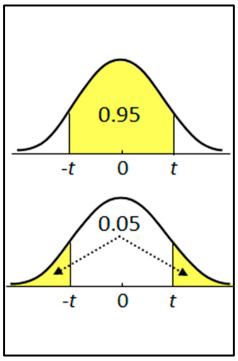

Figure 1. Critical values of t for two-tailed tests (part of the table), left [29] and the meaning of confidence interval, right.

In our case, we have the sample size $n = 8$, and from the *t*-distribution table (Figure 1), we take the value $t_{6,\,0.05} = 2.447$, resulting in $r = 0.707$. This is the threshold value for r, to decide which pairs of activities should be investigated regarding interdependence.

We consider coefficient values of 0.7 or more (and -0.7 or less) as a threshold for a more detailed investigation or for the search for a logical connection or interdependence between two activities, which gives us the opportunity to find the causes of losses and, consequently, improve the situation. We consider only those pairs where at least one of the activities is from the group of losses and both activities exceed 1% of the hourly share (adequate accuracy limit). The application is demonstrated using a selected real-life example of a study conducted in a company in the metalworking industry.

As already described, the work-sampling method consists of three steps, from the preparation of the recording and its execution to the analysis of the observations and calculations, with a discussion of the results and suggestions for improvement. The steps of the method are shown in Figure 2, with the addition of our original contribution to the method shown in red (in the third step).

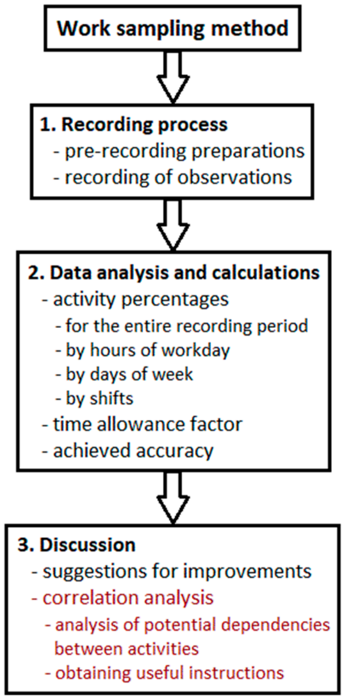

Figure 2. Steps of the work-sampling method with the addition of correlation analysis (in red).

5. Case Study

In the selected medium-sized metalworking company (with make-to-order production), we carried out the necessary observations as part of the work-sampling project. We selected a machining company (turning operations) with 17 workplaces (7 types of machines). The analyst's observation route is shown in Figure 3. Each visit was carried out in a random direction: clockwise or anti-clockwise. Two rounds per hour were possible (only one in the hour in which there was a 30 min break), so that we collected 255 observations in one shift (8 h: $7 \times 2 + 1 = 15$ observations per workplace, 17 workplaces).

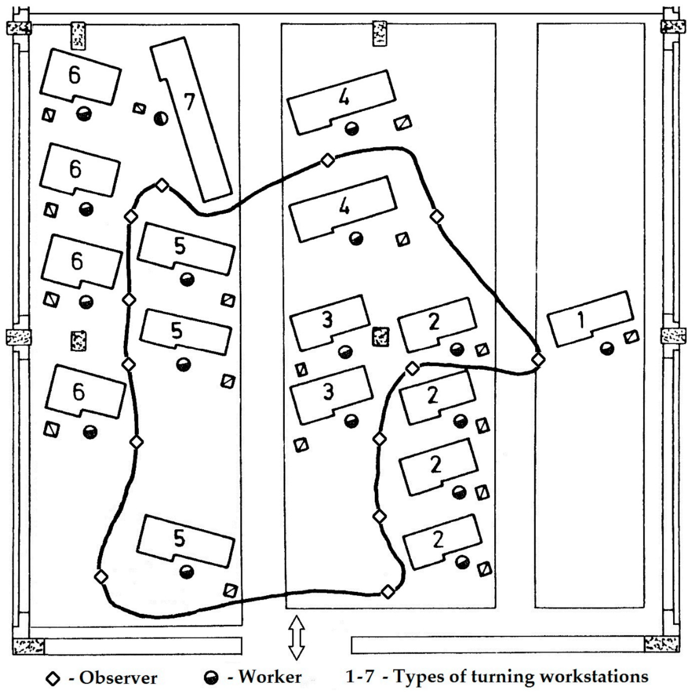

Figure 3. Analyst's observation route in the work-sampling study.

Through pilot recordings, we found that over 4000 observations were necessary and identified 23 operator activities:

Machining	Productive work
Clamping/unclamping the workpiece	
Dimensional control	
Tool movement in the machining position	
Clamping/unclamping of tool	
Workstation set-up	Planned losses
Study of working instructions	
Conversation about tasks	
Tool set-up	
Collecting/returning of tools	
Cleaning the machine	
Personal needs (toilet, washing, etc.)	
Annotation of work results	
Handover of work	
Waiting for transport	Unplanned losses
Waiting for documentation	
Machine failure	
Absence from company	
Business meeting	
Power outage	
Repair of defects	
Private conversation	Indiscipline
Private absence from the workplace	

During the main recording, 4131 observations were collected. We used the Drigus Multidata recording device shown in Figure 4. We observed labor in two shifts, from Monday to Friday. The results are summarized in Tables 2 and 3. The results for weekdays and shifts are not included.

Figure 4. Drigus Multidata recording device.

Table 2. The proportion of the workday spent on each activity.

Activity	Number of Observations	Portion (%)
1. Machining	2129	51.54
2. Clamping/unclamping the workpiece	176	4.26
3. Dimensional control	153	3.70
4. Tool movement in the machining position	19	0.46
5. Clamping/unclamping of the tool	27	0.65
Productive work	2504	60.61
6. Workstation set-up	34	0.82
7. Study of working instructions	49	1.19
8. Conversation about tasks	43	1.04
9. Tool set-up	201	4.87
10. Collecting/returning of tools	51	1.23
11. Cleaning the machine	114	2.76
12. Personal needs (toilet, washing, etc.)	214	5.18
13. Annotation of work results	38	0.92
14. Handover of work	6	0.15
Planned losses	750	18.16
15. Waiting for transport	11	0.27
16. Waiting for documentation	0	0
17. Machine failure	0	0
18. Absence from company	250	6.05
19. Business meeting	37	0.90
20. Power outage	0	0
21. Repair of defects	2	0.05
Unplanned losses	300	7.26
22. Private conversation	377	9.13
23. Private absence from the workplace	200	4.84
Indiscipline	577	13.97
Total	**4131**	**100.00**

Table 3. Activity proportions by workday hours (in %).

Activity	1	2	3	4	5	6	7	8
1. Machining	38.23	63.89	58.33	58.33	63.33	56.85	54.07	21.30
2. Clamping/unclamping the workpiece	11.49	3.33	5.00	4.17	2.78	2.22	3.33	1.85
3. Dimensional control	1.69	3.89	4.44	2.78	5.56	5.37	3.70	1.85
4. Tool movement in the machining position	0.38	0.37	0.74	0.83	0.56	0.56	0.37	0.00
5. Clamping/unclamping of the tool	1.13	0.93	0.37	0.00	0.93	0.56	0.19	0.93
6. Workstation set-up	6.21	0.00	0.19	0.00	0.00	0.00	0.00	0.00
7. Study of working instructions	6.78	0.56	0.74	0.83	0.19	0.00	0.37	0.00
8. Conversation about tasks	2.07	1.48	1.11	0.56	1.85	0.19	0.93	0.00
9. Tool set-up	6.97	4.44	6.67	6.39	5.19	4.81	4.26	0.74
10. Collecting/returning of tools	2.07	0.56	1.30	0.56	0.93	1.11	1.48	1.67
11. Cleaning the machine	0.00	0.00	0.00	0.00	0.00	0.00	1.67	19.44
12. Personal needs (toilet, washing, etc.)	9.79	2.96	2.41	2.22	3.52	10.00	8.15	1.48
13. Annotation of work results	0.00	0.00	0.00	0.56	0.00	0.19	1.67	4.81
14. Handover of work	0.00	0.00	0.00	0.00	0.00	0.19	0.56	0.37
15. Waiting for transport	0.00	0.56	0.74	0.56	0.19	0.19	0.00	0.00
16. Waiting for documentation	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
17. Machine failure	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
18. Absence from company	6.21	6.11	6.11	6.11	6.11	6.11	6.11	5.56
19. Business meeting	5.08	0.00	0.00	0.00	0.00	0.56	0.56	0.74
20. Power outage	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
21. Repair of defects	0.00	0.00	0.00	0.56	0.00	0.00	0.00	0.00
22. Private conversation	1.69	9.44	9.63	14.44	7.59	9.26	10.56	12.04
23. Private absence from the workplace	0.19	1.48	2.22	1.11	1.30	1.85	2.04	27.22
Productive work	**52.92**	**72.41**	**68.89**	**66.11**	**73.15**	**65.56**	**61.67**	**25.93**
Losses	**47.08**	**27.59**	**31.11**	**33.89**	**26.85**	**34.44**	**38.33**	**74.07**

The time allowance factor (TA_f) is calculated according to Equation (4):

$$TA_f = \frac{750}{2504 + 300 + 577} = 0.22$$

The accuracy achieved for the proportion of productive work is ±2.51% and for losses is ±3.86%. The lower and upper limits within which the actual shares of productive work are distributed are 59.1% to 62.1%, and 37.9% to 40.9% for losses.

As already mentioned, the calculation of Pearson's correlations between the activity proportions by workday hours represents a procedural enhancement of the analysis of the results of the work-sampling method. The correlations between all pairs of activities were calculated according to Equation (5) and are shown in Table 4; all values were multiplied by 10 and rounded (we have values between −9 and +9).

Table 4. Correlations between individual activities for the example shown.

A.	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23
1	\	−1	7	7	−3	−3	−3	3	5	**−7**	**−8**	0	**−8**	−4	5	0	0	**7**	−4	0	1	1	**−8**
2		\	−4	0	2	**9**	**9**	6	6	5	−3	4	−3	−3	−1	0	0	4	**8**	0	0	**−7**	−3
3			\	4	−1	−5	−5	0	1	−4	−5	0	−5	−1	2	0	0	3	−5	0	−2	0	4
4				\	−6	−1	0	1	8	−5	−7	0	−7	−5	6	0	0	6	−2	0	5	1	−7
5					\	4	4	4	−2	3	2	0	0	−2	−3	0	0	−1	5	0	−6	−6	2
6						\	**9**	5	4	6	−1	5	−2	−2	−3	0	0	3	**9**	0	−1	**−8**	−2
7							\	5	4	5	−2	4	−2	−3	−2	0	0	3	**9**	0	0	**−7**	−2
8								\	5	0	−5	1	−6	−5	0	0	0	6	4	0	−2	**−7**	−5
9									\	−1	**−8**	2	**−8**	−6	4	0	0	**8**	2	0	2	−3	**−8**
10										\	3	4	3	3	−6	0	0	−2	**7**	0	−4	−5	3
11											\	−3	**9**	5	−4	0	0	**−9**	0	0	−1	3	**9**
12												\	−3	2	−5	0	0	4	5	0	−3	−5	−4
13													\	6	−4	0	0	**−9**	0	0	0	4	**9**
14														\	−6	0	0	−4	−1	0	−2	2	4
15															\	0	0	2	−5	0	3	3	−3
16																\	0	0	0	0	0	0	0
17																	\	0	0	0	0	0	0
18																		\	2	0	1	−4	**−9**
19																			\	0	−2	**−8**	0
20																				\	0	0	0
21																					\	5	−1
22																						\	3

Note: values are multiplied by 10 and rounded. A—Activity.

Activities whose hourly shares never exceed 1% are not considered in the correlation analysis. Satisfactory accuracy of the result is not guaranteed for these activities, as already described in Section 2 (in the description of the disadvantages of the work-sampling method) and at the end of Section 4. The excluded activities can be found under reference numbers 4, 14, 15, and 21.

Discussion

When analyzing potential dependencies between activities, we must consider pairs that have a value less than −6 or greater than 6, bolded in Table 4. There are 27 such correlations (without excluded activities):

- Machining and collecting/returning of tools (−7)—more processing means less collecting or returning tools.
- Machining and cleaning the machine (−8)—when we are not machining, there is more cleaning of the machines (e.g., in the last hour of the work shift).
- Machining and annotation of work results (−8)—we record the results at the end of the work shift.

- Machining and absence from the company (7)—we cannot confirm the connection (false correlation).
- Machining and private absence from the workplace (−8)—more productive work means less absence and losses (and vice versa).
- Clamping/unclamping the workpiece and workstation set-up (9)—the relationship exists when the batch is started, not later.
- Clamping/unclamping the workpiece and study of working instructions (9)—the comment is the same as the previous one.
- Clamping/unclamping the workpiece and business meeting (8)—we cannot confirm the relationship (false correlation).
- Clamping/unclamping the workpiece and private conversation (−7)—more productive work prevents conversations—due to the distances between the workplaces (and vice versa).
- Workstation set-up and the study of working instructions (9)—there is a logical connection between the activities (we need to familiarize ourselves with the work instructions when setting up the machine).
- Workstation set-up and business meeting (9)—meeting with the aim of perfecting the settings and starting the batch.
- Workstation set-up and private conversation (−8)—when setting up the machine there is less private conversation—because of the distances between workplaces.
- Study of working instructions and business meetings (9)—we cannot confirm the correlation (false correlation).
- Study of working instructions and Private conversation (−7)—good documentation does not encourage the worker to go to another worker for a private conversation.
- Conversation about tasks and Private conversation (−7)—it is obvious that some instruction from the foreman is usually required before starting a new task, which of course precludes the need for a private conversation; the importance of competent managers (useful comment no. **1**).
- Tool set-up and cleaning of the machine (−8)—tool setting is at the start of machining and machine cleaning is usually at the end.
- Tool set-up and annotation of work results (−8)—tool setting is at the start of machining, and the recording of the results is at the end.
- Tool set-up and absence from the company (8)—we cannot confirm the connection (false correlation).
- Tool set-up and private absence from the workplace (−8)—more productive work means less absence (and vice versa).
- Collecting/returning of tools and business meeting (7)—there is a possibility that the worker goes to the tool store and inadvertently attends a short meeting.
- Cleaning the machine and annotation of work results (9)—usual procedure after the job's completion.
- Cleaning the machine and absence from company (−9)—the completion of activities clearly does not encourage absence for other work tasks.
- Cleaning the machine and private absence from the workplace (9)—the completion of a batch of products gives the worker the feeling that he can do some private matters after this; the reason may be the late arrival of a new work assignment or unfavorable working conditions (useful comment no. **2**).
- Annotation of work results and absence from company (−9)—completion of a batch clearly does not encourage absence for other work duties.
- Annotation of work results and private absence from the workplace (9)—completion of a batch with recording the results gives the worker the feeling that he can still do some private matters after this; it is important to check the timeliness of the assignment of a new work order or correct organization of dispatch service (useful comment no. **3**).

- Absence from the company and private absence from the workplace (−9)—it appears that workers do not abuse absence due to other work commitments to attend to personal matters (useful comment no. **4**).
- Business meetings and private conversations (−8)—it seems that private conversations do not continue after meetings, which would lead to additional losses.

We looked at 27 pairs of activities and obtained four useful instructions or hints on the necessary actions that would have been overlooked without this analysis. We can confirm that testing the correlations has given us an additional tool for evaluating the recording data. Even with simple examples, we find certain hints for critical thinking (usually three to five). Sometimes they are correct (there is a link between the activities) and require some changes in the organization of the production process, but it can also be that they are useless.

6. Conclusions

Work sampling offers several benefits in terms of cost efficiency, flexibility, and statistical validity. It is a statistical method for determining the proportion of time workers spend on various defined or identified activities. We observe workers at random times during the work shift and mark what they are doing each time. Work sampling enables rapid analysis, identification, and improvement of work responsibilities, tasks, outstanding competencies, and organizational processes. Its main advantage lies in the study of non-repetitive activities, but it can also be used to develop time standards for repetitive work.

In this article, we present a comprehensive list of the most important loss factors that have emerged from our studies over the last two decades. And the most important thing in this article is that we introduce a pairwise correlation comparison of the measured hourly shares of all activities to examine whether mutual dependencies exist. The results of the work-sampling method are presented in tables, and additional calculations are now made to enable a discussion among the members of the working group about possible shortcomings and the necessary improvements to the processes. With the correlation analysis, we obtain the first signal, where some activities can trigger the occurrence of another activity, which can be without added value or represent a loss. This is an essential contribution to decision-making regarding efficiency improvements. In the example shown, we obtained four useful tips that can contribute to a better organization of processes and higher productivity.

The work-sampling method has two traditional steps: the recording process and data analysis, which includes calculating the activity shares for the entire recording period, by hours of the work shift, by days or by shifts, and the accuracy achieved. We add an upgrade to the data analysis: a correlative comparison of pairs of activities according to their share in the hours of the working day, which can help us to find the causes of the occurrence of losses (causal relationship between activities). This original idea was tested in a case study and led to four further useful suggestions. Applying correlation analysis to work sampling is extremely useful for managers to improve the work performance and productivity of organizations. This work contributes both theoretically (a new idea for data analysis) and empirically (a test case) to labor productivity insights. The procedure requires knowledge of the observed work processes.

Future research will include more sophisticated statistical methods supported by artificial intelligence. Certainly, we can improve the performance of recording by using video recording technology, probably without the use of image processing technology, because it is impossible to determine (automatically) with sufficient reliability what is being done in the workplace. Manual review of video is more time-consuming than direct observation, so the traditional method of manual recording is still acceptable.

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