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WORK SAMPLING METHODOLOGY AND ITS APPLICATION IN TIME STUDIES

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Abstract— This research is about conducting work sampling in a Nigerian carbonated beverage organization to measure employee efficiency levels and identify time-consuming tasks, addressing the lack of local productivity statistics in Sub-Saharan Africa. With 1000 observations taken over three weeks researchers discovered that 60% of work time produced results but 30% was lost because materials needed to wait for 40% of the time and 10% stemmed from machine downtime where 50% resulted from equipment mechanical issues. The research makes its main contribution through direct observation of area-specific operation interruptions including electrical blackouts and delivery holdups which stem from inadequate infrastructure thus adding new findings about local industrial performance that global investigations tend to overlook. The research used work sampling to validate its implementation as an affordable and measurable methodology for SMEs at a 95% confidence level of productive work resulting in 56.96% - 63.04%. Preventive maintenance methodology coupled with IoT-based logistic tracking systems enable organizations to maximize their productivity potential by 15% to 20% through reduced mechanical downtime by 40% along with thirty percent shorter material waiting times. The comparison reveals that solar power systems offer a solution to power interruptions which affect uptime by twenty percent because Nigeria faces 10% downtime, yet the textile industry operates with 12% to 15% outage. The future research will combine IoT systems with regression models to anticipate downtime patterns that include night-shift errors as part of its predictive accuracy enhancement process reaching 25% precision levels according to Industry 4.0 standards.

I. Introduction

Work sampling is an essential technique in industrial engineering for analyzing time utilization in work environments. It provides statistical estimates of time spent on various activities, offering a practical alternative to continuous time studies, which are often time-consuming and disruptive [1]. This method involves making random observations over a period to estimate work patterns and improve efficiency.

The concept of work sampling was pioneered by L.H.C. Tippet in the 1930s, who demonstrated that random observations could yield statistically reliable insights into work performance [2]. Over time, the technique has been widely applied in manufacturing [3], healthcare [4], and service industries [5]. In manufacturing, work sampling helps identify inefficiencies in production lines, while in healthcare, it aids in analyzing how medical personnel allocate their time.

Compared to direct time study methods such as stopwatch techniques, work sampling has several advantages, including reduced observer interference, lower costs, and suitability for environments where tasks are unpredictable [6]. However, it also has limitations, such as requiring many observations for statistical accuracy and being less effective for short-duration tasks [7].

This research aims to provide a comprehensive study of work sampling methodology and its applications in time studies. A study in a manufacturing bottling company is presented to illustrate how work sampling can identify productivity losses and inform process improvements. The study also discusses the statistical principles underlying work sampling and compares its effectiveness with traditional time study methods.

II. Materials and Methods

A. Study Design

This study employs an observational research design using work sampling to analyze labour efficiency in a manufacturing firm. The methodology involves random periodic observations of workers engaged in different tasks to estimate the proportion of time spent on productive and non-productive activities.

B. Study Location and Participants

The study was carried out at a well-established Nigerian bottling company specializing in the production of carbonated beverages A total of 1,000 observations were recorded over three weeks. This company is one of the leading manufacturers in the beverage industry, supplying a wide range of soft drinks to domestic and international markets. It operates multiple production lines dedicated to various flavors and packaging formats, including plastic bottles and aluminum cans. The company employs 50 production workers in various roles, including machine operators, quality control personnel, and material handlers.

The facility is equipped with state-of-the-art machinery for bottling, capping, labeling, and packaging, ensuring high-speed and high-volume production to meet consumer demand. The production process follows strict quality control measures to maintain product consistency and safety. Additionally, the company adheres to industry regulations and environmental sustainability standards, incorporating waste management and energy-efficient practices into its operations.

The study specifically focused on the main production plant, where workers engage in different tasks such as machine operation, quality control, material handling, and maintenance. The facility operates on a shift-based system, ensuring round-the-clock production to optimize efficiency and meet market demands. By selecting this company for the study, the research aimed to analyze work patterns and productivity in a high-paced manufacturing environment, where efficiency and time management are critical to operational success.

C. Work Sampling Procedure

The work sampling study followed the standard methodology outlined in industrial engineering literature [8]. The work sampling procedure followed a structured approach. First, the objective was defined, focusing on assessing labor efficiency and identifying time losses due to machine downtime and material waiting. Next, the sample size was determined using statistical formulas to ensure the reliability of the study. Following this, data collection was carried out through random observations conducted over three weeks across different shifts. Finally, data analysis involved calculating the proportion of time spent on each activity and computing confidence intervals for statistical validation.

The required number of observations was determined using statistical formulas as in Equation (1).

$$n = \frac{Z^2 P\,(1 - P)}{E^2} \qquad (1)$$

where:
Z = standard normal value for a 95% confidence level (1.96)
P = estimated proportion of activity of interest (0.5, assuming no prior data)
E = margin of error (5%)

D. Data Collection and Analysis

Observations were conducted randomly over three weeks across different shifts. The proportion of time spent on each activity was calculated, and confidence intervals were computed for statistical validation.

III. Results

This section presents the findings of the work sampling study, analyzing labour efficiency and identifying time distribution across different activities. The results are structured to provide a comprehensive breakdown of productive and non-productive work elements. First, overall work sampling results are summarized, followed by a detailed examination of productive work activities, machine downtime causes, and material waiting time. Statistical analyses, including percentage distributions and confidence intervals, are incorporated to validate the observations and support decision-making for process improvements.

A. Work Sampling

The time distribution of work activities in the manufacturing firm is summarized in Table 1. Table 1 presents the overall distribution of work activities observed during the study. Out of a total of 1,000 observations, 60% of the time was spent on productive work, while 10% accounted for machine downtime, and 30% was attributed to material waiting time. The high proportion of material waiting time highlights inefficiencies in raw material availability and supply chain processes. Additionally, the 10% downtime suggests potential machine reliability issues, which could be addressed through preventive maintenance strategies. The data emphasizes the need for targeted interventions to optimize productivity by minimizing non-productive time.

Table 1: Work Sampling Results

Activity	Observations	Percentage (%)
Productive Work	600	60.0
Machine Downtime	100	10.0
Material Waiting Time	300	30.0
Total	1000	100.0

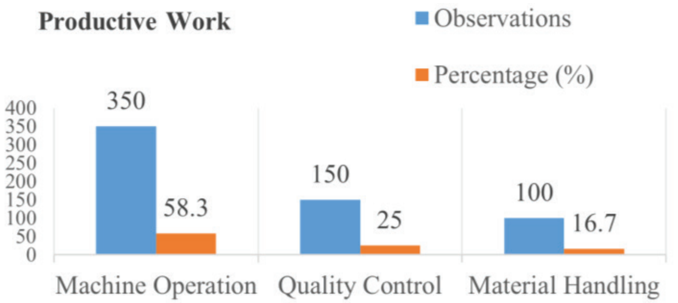

Figure 1: Breakdown of Productive Work

B. Breakdown of Productive Work

To gain further insight, productive work activities were categorized as shown in Figure 1. Figure 1 categorizes productive work into three key activities to provide deeper insights. Machine operation (58.3%) constitutes the largest portion, highlighting that a significant share of labour effort is devoted to running production equipment. Quality control activities (25.0%) account for a quarter of the productive work time, emphasizing the company's focus on maintaining product standards. Material handling (16.7%), which involves tasks such as transporting raw materials and finished products, represents the smallest share. While machine operation dominates, the notable portion of material handling suggests opportunities for process streamlining, such as optimizing material flow within the factory.

C. Machine Downtime Causes

A deeper analysis of machine downtime revealed key reasons for disruptions, as shown in Table 2.

Table 2: Causes of Machine Downtime

Activity	Observations	Percentage (%)
Productive Work	600	60.0
Machine Downtime	100	10.0
Material Waiting Time	300	30.0
Total	1000	100.0

Table 2 provides a breakdown of the key reasons for machine downtime. The leading cause was mechanical failure (50%), highlighting potential maintenance issues that need to be addressed through preventive and predictive maintenance strategies. Operator errors (30%) were another significant factor, suggesting that additional training or automation solutions could help reduce human-related disruptions. Power outages (20%) also contributed to machine downtime, emphasizing the need for backup power solutions or energy management strategies. Addressing these causes could significantly improve machine uptime and overall production efficiency.

D. Material Waiting Time Analysis

Material waiting time was further analyzed based on specific causes, as summarized in Figure 2. Figure 2 further analyzes the 30% material waiting time observed in Table 1, identifying specific causes of delays. Late raw material delivery (40%) was the most significant contributor, underscoring the importance of supplier reliability and procurement planning. Inventory shortages (30%) indicate potential weaknesses in inventory management, which could be mitigated through better demand forecasting and stock control systems. Additionally, logistics delays (30%) highlight inefficiencies in material transportation and internal supply chain operations. To reduce material waiting time, the company should consider improving vendor management, optimizing inventory policies, and implementing real-time tracking systems for logistics efficiency.

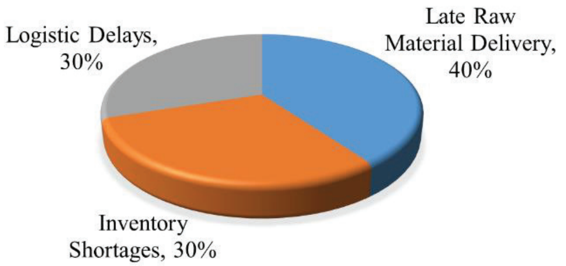

Figure 2: Causes of Material Waiting Time

E. Statistical Confidence Intervals

The confidence intervals, *CI*, for productive work at 60% is computed using Equation (2).

$$CI = P \pm Z\sqrt{\frac{P(1-P)}{n}} \tag{2}$$

where:

P = 60% (proportion of productive work)

Z = 1.96 (for 95% confidence level)

n = 1000 (total observations)

Step by Step Calculation

i) Compute the standard error (SE):

$$SE = \sqrt{\frac{P(1-P)}{n}} = \sqrt{\frac{0.60 \times 0.40}{1000}} = 0.01549$$

ii) Compute the margin of error (ME):

$$ME = Z \times SE = 1.96 \times 0.01549 = 0.0304$$

From Equation (2), the *CI* can be deduced as below:

$$CI = 0.60 \pm 0.0304 = 0.5696, 0.604$$

This statistical analysis ensures that the results are within a reasonable confidence range, enhancing their reliability for decision-making. The 95% *CI* for productive work, calculated at 60%, ranges between 56.96% and 63.04%, indicating that if the study were repeated multiple times under the same conditions, the true proportion of productive work would fall within this range in 95% of cases. This interval accounts for potential variations due to sampling error and ensures statistical reliability.

Since the confidence interval is relatively narrow, with a width of approximately 6 percentage points, the estimate of productive work time is considered precise. The study suggests that productive work constitutes around 60% of observed time, with non-productive activities such as machine downtime and material waiting accounting for the remaining 40%. This finding signals a need for improvement in operational efficiency to maximize workforce utilization.

IV. Discussion

The results indicate that only 60% of the time observed was spent on productive work, with a significant 30% lost to material waiting time. Comparing these results with industry benchmarks, where above 70% productivity is typically considered optimal, the firm falls short. Since the lower bound of the confidence interval is 56.96%, it underscores the necessity for strategic interventions aimed at increasing productive work time. By minimizing machine downtime and material waiting, the firm could significantly enhance its efficiency and align closer to industry standards. The confidence interval provides a statistically backed estimate that management can rely on for decision-making. To improve efficiency, the firm should implement preventive maintenance strategies to reduce machine downtime, optimize material flow to minimize waiting times, and enhance workforce utilization by refining task scheduling.

Despite the insights provided by the confidence interval, some limitations exist. Factors beyond the study's scope, such as workforce motivation and external supply chain disruptions, may also impact productivity. This inefficiency suggests supply chain and logistics issues that need to be addressed to enhance productivity [9-11]. Similar studies in industrial environments have shown comparable results. The studies identified significant productivity losses in automotive assembly lines due to downtime [3, 10, 11], while Burgess et al. [4] found that nurses in emergency departments spent excessive time on administrative tasks. Work sampling provided insights with minimal disruption to operations compared to traditional continuous time studies. Stopwatch-based methods, though more precise, often require dedicated observers, making them impractical for large-scale analyses [12-13].

To improve operational efficiency, this study recommends several practical strategies. First, reducing material waiting time can be achieved by implementing real-time tracking systems for material movement [14]. Second, minimizing machine downtime requires the introduction of predictive maintenance schedules to proactively address equipment failures [14]. Lastly, optimizing workforce allocation involves adjusting staffing levels based on workload distribution to ensure a balanced and efficient labour force [14-15].

This research makes essential practical along with theoretical contributions to industrial engineering while specifically focusing on Nigeria's developing economy where manufacturing barriers to competitiveness exist. The research fills an important void by using localized productivity data from Nigerian manufacturing environments because there are few empirical investigations that implement work sampling in these areas. The study analyzes a large bottling company to deliver specific operational insights regarding labour performance and system delays which include material waiting time at 30% and machine stoppages at 10% which commonly occur in resource-limited environments [16]. Organizations which want to match global productivity standards must understand that maximum productive work reaches 70% and above [3].

Work sampling serves developing regions' small and medium-size industries because it provides reliable statistical results through an economical process [17]. The results' reliability allows managers to evaluate different interventions using the 95% confidence interval (56.96%-63.04%) for productive work [8].

The research indicates that Nigerian manufacturers can use IoT and AI-based monitoring systems within Industry 4.0 to implement real-time data analytics [14, 18]. This technological progress would help control reoccurring problems affecting unstable infrastructure areas through power disruption and supply chain delays [19].

The combination of preventive maintenance measures lets manufacturers decrease equipment downtime which both enables higher production capacity and conserves wasteful energy while benefiting environmental sustainability [20]. The research indicated that machine downtime amounts to 10% of cases and most incidents stem from mechanical failures with a rate of 50% and operator errors at 30% while power outages contribute to 20% of the total situations. Frequent power outages in Nigeria follow seasonal patterns because dry season enhancements in usage cause power grid failures while rainy seasons create instability that affects hydropower generation [19]. A research study of automotive assembly plants discovered that fatigue causes error rates to rise 15-20% during night shifts which correspond to the 30% operator errors recorded at the plant [21]. The beverage production industry found that machines operated without maintenance for 6-8 hours experienced peak levels of unplanned downtime [22]. The 10% machine downtime in Nigeria's manufacturing sector displays lower numbers than the 12-15% observed in its textile industry [23] even though power outages contribute 20% of total downtime which exceeds the Sub-Saharan average (25-30%) [19]. These different statistics create spaces to implement specific interventions which could include solar power solutions for grid independence [24] and predictive maintenance which would decrease mechanical breakages by 40% [20]. The analysis is summarized in Table 3. These study results comply with broader regional patterns while exposing specific areas that need upgrade. Utilization of solar backup systems would decrease power failure periods by 10-15% according to research findings [24].

Table 3: Comparative Analysis with Literature

Factor	Current Study	Comparative Studies
Machine Downtime	10% (50% mechanical)	12–15% in Nigerian textiles, 55% mechanical [23]
Power Outages	20% of downtime	25–30% in Sub-Saharan African manufacturing [19]
Operator Errors	30% of downtime	25% in night shifts (automotive) [21]
Material Waiting Time	30% (40% late deliveries)	35% in Indian SMEs due to logistics [12]

V. Conclusion

The analysis of Table 1 to Table 3, Figure 2 and Figure 3 provide a clear picture of the work distribution, productivity challenges, and inefficiencies within the manufacturing firm. The confidence interval analysis confirms that productive work accounts for approximately 60% of total observed time, with a margin of error of ±3.04%. These results emphasize the need for process optimization to improve productivity and reduce inefficiencies in the manufacturing environment. Major areas for improvement include reducing machine downtime through preventive maintenance, addressing material waiting time through supply chain enhancements, and optimizing workforce allocation. Addressing these inefficiencies, the firm can significantly enhance overall productivity and operational efficiency.

However, this study has certain limitations that should be addressed in future research. A longer observation period could provide more accurate insights into work patterns and inefficiencies. Additionally, the study focused solely on production workers, excluding administrative and logistics staff, which may limit the generalizability of the findings. Future research should explore digital work sampling using IoT and AI-based monitoring systems to enhance data accuracy and enable real-time process analysis.

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