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New Approach of Process Cycle Time Measurement System with Sensor Application

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ABSTRACT

This paper introduces an innovative process cycle time measurement system with sensor applications designed for production line monitoring in manufacturing industries to address the challenges faced by manufacturing industries, such as inefficient production lines, machine downtime and manual production line recording. To tackle these issues, the research employs a methodology that integrates infrared sensors and microcontrollers, enabling real-time data capture and analysis. Three distinct case studies are conducted, involving balanced production lines, un-balanced production lines and production lines with machine downtime, to assess production line performance and efficiency. The results demonstrate the system's ability to accurately capture process cycle times and highlight areas for improvement in future studies. In conclusion, this research contributes to the field of production line monitoring, offering valuable insights for enhancing manufacturing processes and efficiency, with potential applications in real-world manufacturing industries.

1. Introduction

Malaysia's manufacturing sector is the second-largest contributor to economic growth, employing a significant number of Malaysians [1]. Malaysian manufacturing's leading sub-sectors include petroleum, chemicals, rubber, plastics, electricals, electronics and optical products [2]. While some segments of this sector are fully or semi-automated, with machines performing the majority of tasks with human assistance, certain manufacturing processes, such as wired harness assembly, remain to rely on manual operating systems [3,4]. Regardless of the manufacturing operating model, common challenges remain, such as machine downtime, bottlenecks and inefficient production line

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processes [5-7], reducing production efficiency and affecting company profitability. To address these issues, many industries have implemented lean manufacturing methods [8].

Lean manufacturing has gained widespread popularity due to its objective of increasing production productivity by reducing waste, including waiting times, overproduction, downtime and other non-value-added activities [9-13]. One critical parameter in lean manufacturing and line balancing is process cycle time, which plays a pivotal role in optimizing production efficiency [14,15]. Process cycle time is the total time required to complete one cycle of a specific process, from the arrival of raw materials to the production of a finished product. By optimizing cycle time through line balancing studies, manufacturers can reduce bottlenecks, minimize downtime, enhance output and ultimately improve overall production efficiency [16,17]. This approach aligns with the principles of lean manufacturing, which seek to eliminate waste and optimize operations for maximum efficiency. Reducing cycle time allows manufacturers to minimize idle time, streamline workflows and enhance overall output, as demonstrated by Rahul Patni [18], Taifa *et al.,* [19], Aikhuele *et al.,* [20] and Selamat *et al.,* [21].

As industries worldwide increasingly leverage innovations like artificial intelligence, the Internet of Things (IoT) and advanced sensors, the manufacturing sector is transitioning towards fully automated processes for monitoring, assembly, testing and quality inspection [22-24]. This paper introduces a novel sensor application system specifically designed for real-time process cycle time measurement, integrating IoT for lean manufacturing line balancing. Unlike existing systems, our approach offers precise real-time data capture across various production scenarios, including balanced, unbalanced and machine downtime environments. The proposed system enables continuous cycle time monitoring, addressing inefficiencies in production lines, particularly for conveyor-based systems. This contribution will facilitate not only the analysis of overall production line trends but also the identification of bottlenecks, ultimately improving production efficiency.

2. The Key Parameters in Lean Manufacturing

In the context of lean manufacturing, the optimization of production line processes relies on various parameters to ensure efficiency and smooth operations. Two key parameters that play a crucial role in achieving these objectives are takt time and cycle time. Takt time holds significant importance in lean manufacturing environments, representing the available time per production cycle that precisely matches the production rate to customer demand [25,26]. This parameter serves as a fundamental indicator used in the manufacturing industry to meet customer order deadlines. By calculating takt time obtained by dividing the available production time by customer demand within a specific time period as shown in Eq. (1), manufacturers can align their production processes with the pace required by customer demand.

$$Takt\ Time = \frac{Available\ Production\ Time}{Customer\ Demand} \tag{1}$$

Process cycle time, on the other hand, refers to the duration needed to complete a specific process or the entire production cycle, from raw material acquisition to the completion of the finished product [19,27]. It represents the time taken from the beginning to the end of a process, including any necessary wait times, processing time and additional activities involved in completing the cycle [28]. This also includes process micro-stoppage or idling time. Figure 1 depicts a block diagram illustrating the concept of process cycle time measurement for a line balancing study.

Fig. 1. Process cycle time concept [29]

Based on Figure 1, cycle time measurement comprises several important components, namely "product in," "process" (time measurement) and "product out." The cycle time count begins at the "product in" stage when the raw materials for manufacturing the product are entered into the process. Subsequently, the process takes place, during which the process cycle time is measured, taking into account factors such as downtime, bottlenecks or any other elements that contribute to delays in production. Finally, at the "product out" stage, the product is completed through assembly and the cycle time count comes to an end, enabling the determination of the final process cycle time for that product.

3. Recent Study on Real-Time Systems for Production Line Applications

Over the last few decades, numerous research studies related to monitoring systems have been conducted across various manufacturing industries, all with the shared objective of minimizing operational costs, optimizing production output, reducing waste and maintaining product quality. As a result, a comprehensive literature review was conducted to identify the most current real-time monitoring systems. Table 1 provides a summary of recent studies examining production line monitoring systems in various industries and applications. The table highlights the diverse parameters that are monitored to enhance production productivity and efficiency.

Table 1
Summary of findings of recent studies on IoT production line monitoring

Year	Connectivity	Production Type	Monitoring Parameter	Sensor Application	GUI Approach	Notification Feedback
2020 [30]	IoT	Hybrid	Worker Productivity	RFID	Desktop Application	None
2020 [31]	IoT	Hybrid	Machine Operational Status, Downtime	None	Web Application	None
2020 [32]	IoT	None	Biogas Volume	Flowmeter Sensor	Web Application	None
2021 [33]	IoT	None	Worker Productivity	RFID	Desktop Application	None
2021 [34]	IoT	None	None	None	Web Application	None
2021 [35]	IoT	None	Temperature, Humidity, Position, Product Output	DHT-11, Ultrasonic, Photoelectric Sensors	Desktop Application	None
2021 [36]	IoT	Discrete	Power Consumption, Machine Speed	Current, Meter Counter Sensors	Desktop Application	None

2021 [37]	IoT	None	Machine Operational Status	Camera	Mobile Application	None
2022 [38]	IoT	Discrete	Worker Productivity	Ultra-Wide Band Real-Time Locating System	Mobile Application	Smart Watches Notification
2022 [39]	IoT	Discrete	Production Delay, Production Level, Product Quality Assessment	None	Desktop Application	None

Table 1 reveals several significant research gaps within the area of real-time production line monitoring systems. Firstly, despite extensive studies on parameters such as machine operational status, product quality and worker productivity, a notable gap exists in the field of cycle time monitoring. This critical aspect of production line performance has not received sufficient attention and there is a lack of robust mechanisms for accurately measuring cycle time at individual workstations. Addressing this research gap underscores the necessity for this study to focus on real-time cycle time monitoring systems capable of data capture and analysis.

Furthermore, another conspicuous research gap is the absence of notification feedback mechanisms. When abnormal data signals issues like production machine failures, bottlenecks or downtime, there is currently no established mechanism for promptly notifying the responsible personnel. Consequently, the development of notification feedback systems to promptly alert relevant individuals to deviations in the monitoring system represents a crucial avenue for further research and development.

As a result, a new approach to the measurement of process cycle time, using sensor applications, has been proposed to address this research gap. The system will utilize an infrared sensor (IR) in conjunction with an ESP32 microcontroller and LabVIEW software for analysis. Additionally, LabVIEW will also serve as a graphical user interface for displaying results to users via the internet.

4. New Concept of Sensor Application

4.1 General Hardware Setup

The proposed system's general hardware setup is illustrated in Figure 2. This system was implemented at each of the assembly stations in the manufacturing industry's production line. Furthermore, the proposed system is compatible with both manual and automated types of assembly stations, whether they involve humans or machines.

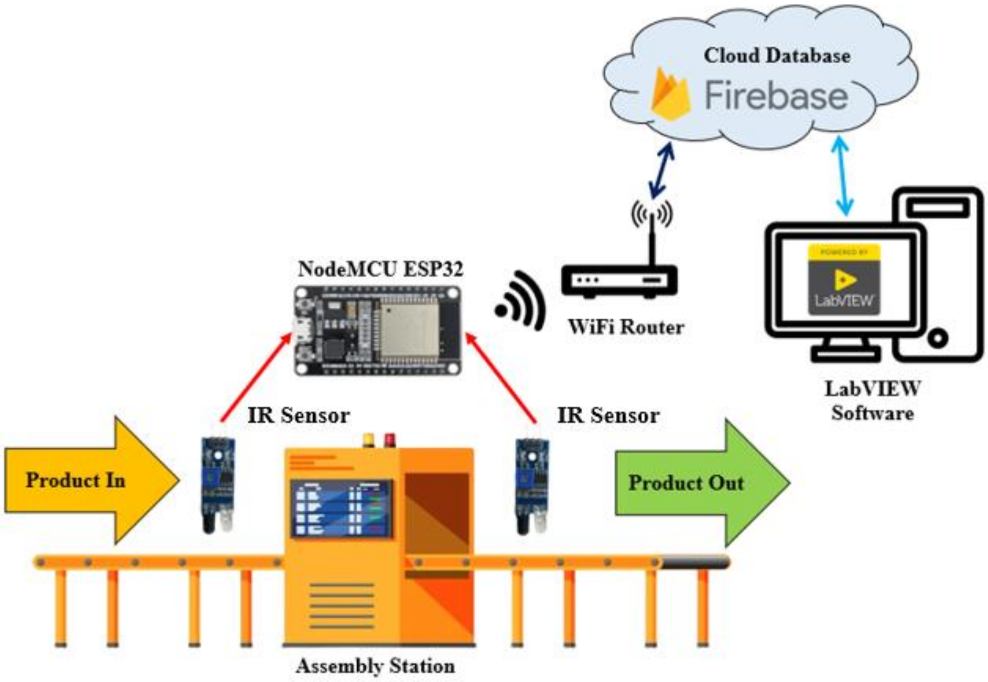

Fig. 2. General hardware setup

In this proposed system, IR sensors were utilized to detect the presence of an object on the conveyor belt at the assembly station. The IR sensor operates with an emitter emitting an infrared light that propagates through the air and is reflected when it encounters an object in front of it. The reflected infrared light is then received by the receiver, generating a voltage signal that is output to the microcontroller. Conversely, no voltage signal is generated if there is no object in front of the IR sensor. Figure 3 illustrates the working principle of the IR sensor in detail.

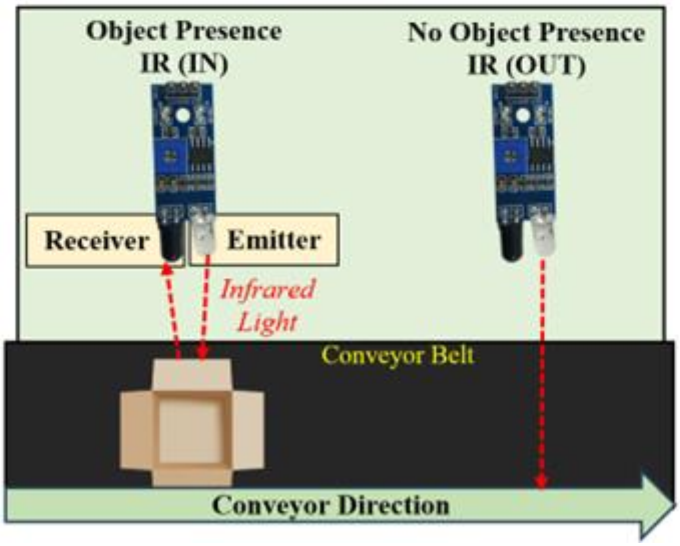

Fig. 3. IR sensor working principles

The system operates as an object passes through the IR (IN) and (OUT) sensors, generating a voltage signal and transmitting it to the NodeMCU ESP32 microcontroller. The microcontroller then converts the analogue voltage signal to a digital format and wirelessly transmits it to the LabVIEW software. In LabVIEW, a "true" and "false" condition is used to capture the timestamps of the IR (IN) and (OUT) signals. The captured timestamp data is then employed to calculate the process cycle time by subtracting the output timestamp from the input timestamp, as shown in Eq. (2). The analysed data was then processed and displayed in the LabVIEW Graphical User Interface (GUI) for the end user to view and store for future reference.

$$Process\ Cycle\ Time\ (PCT) = Timestamp\ (IR\ OUT) - Timestamp\ (IR\ IN) \qquad (2)$$

4.2 Conveyor System and Electrical Circuit Design for Simulation

Figure 4 illustrates the 2D design of the proposed straight line conveyor system for simulating manufacturing production lines, comprising four distinct processes. Each product enters from the right side of the conveyor and passes through four different types of processes at each assembly station before becoming a completed product.

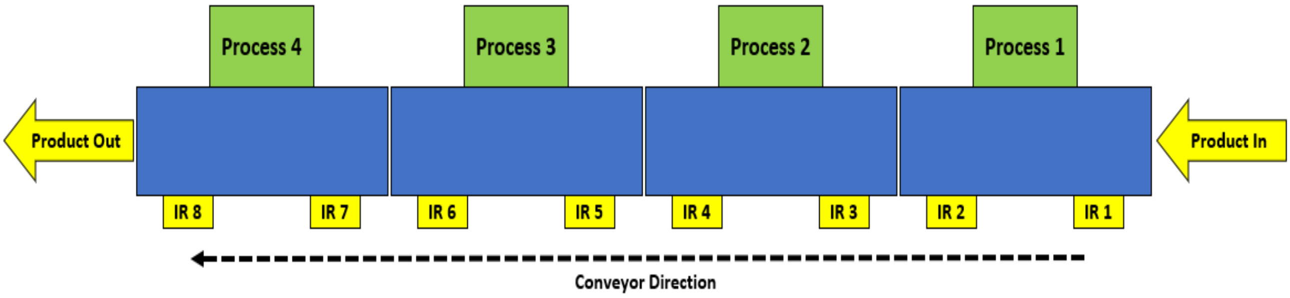

Fig. 4. 2D design of conveyor system

Next, a 3D conveyor system was designed using SolidWorks software and then 3D printed. The final result of the conveyor system is shown in Figure 5 below, consisting of four conveyors attached in a straight line to create a straight-line production system. Each conveyor station is equipped with a stepper motor to move the conveyor belt and a servo motor to temporarily block a product for a specific amount of time, known as the process cycle time. This represents a simulation of a typical manual or semi-autonomous production process using the servo motor mechanism. Additionally, an IR sensor is attached at the beginning and end of each conveyor station to capture the timestamp of the product entering and exiting.

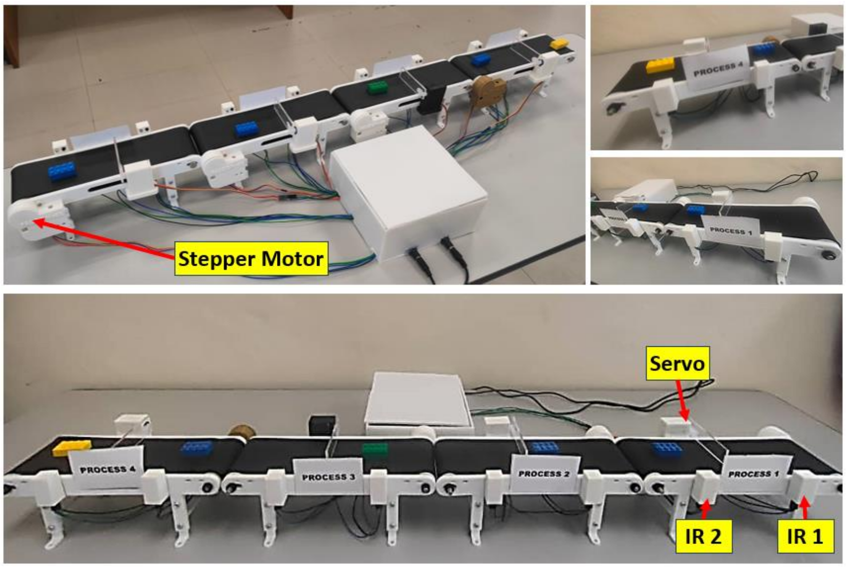

Fig. 5. Simulation of model scale production line

Moving on to the electrical circuit design part which is used to move the conveyor and capture data of the proposed system. It consists of two separated electrical circuits design with different proposed which is one of it used for capturing the process cycle time through IR sensor as shown in Figure 6 and another one is for simulating the conveyor system as shown in Figure 7.

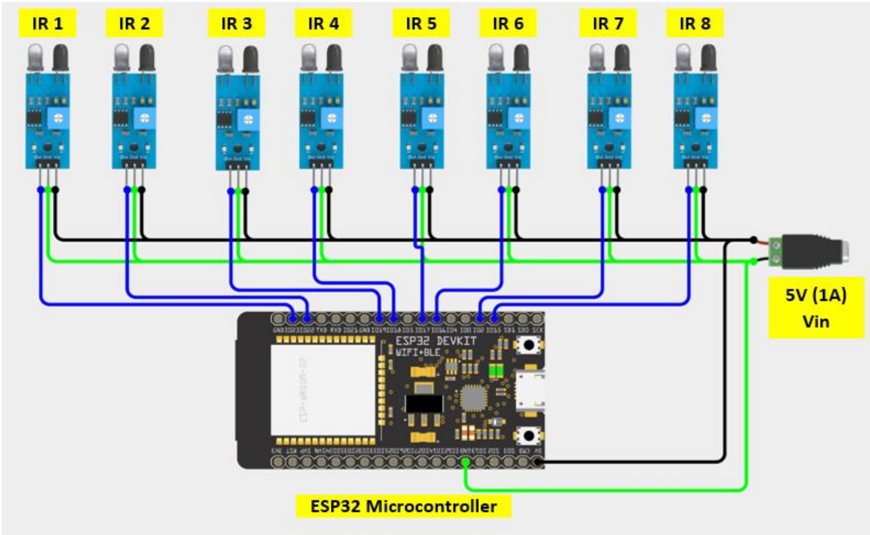

Fig. 6. Electrical circuit design for capturing the process cycle time

Figure 6 shows the electrical circuit comprising eight IR sensors connected to the ESP32 microcontroller, which is used to capture the timestamp of product entry and exit at each conveyor station. Both the IR sensors and ESP32 microcontroller are powered by a Direct Current (DC) power source with a voltage of 5 volts and a current of 1 ampere. The ESP32 microcontroller was programmed using the Arduino IDE, configured to transmit data wirelessly to Firebase and subsequently from Firebase to LabVIEW for further analysis and display.

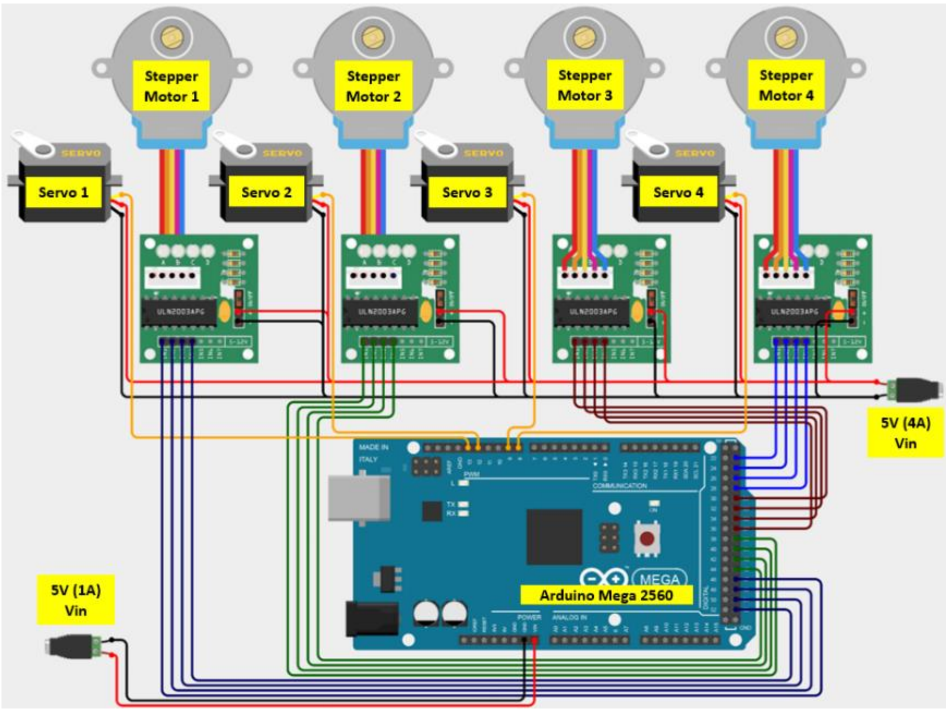

Fig. 7. Electrical circuit design for simulating the conveyor system

Figure 7 shown the electrical circuit design for controlling the stepper motor and servo motor of the conveyor system using the Arduino Mega 2560 microcontroller, powered by two separate sources one with 5 volts and 4 amperes of current and the other with 5 volts and 1 ampere of current. Each of the stepper motors is controlled using a ULN2003APG driver to move the belt at each conveyor station. Additionally, a servo motor is placed between the IR sensors to simulate the process of machine or human assembling a product. The servo is controlled by the Arduino Mega 2560 microcontroller, which is programmed to randomly block the product based on case study which will be discuss at result and discussion topic before releasing it to another station.

4.3 LabVIEW GUI Layout

Subsequently, all the analysis is performed within the LabVIEW software and displayed on the LabVIEW front panel interface. This is because LabVIEW excels at data visualization, allowing users to easily create custom user interfaces and dashboards with interactive graphs and controls for interpreting the analysed data. As a result, a LabVIEW GUI, as shown in Figure 8, was designed to interpret the analysed data for the proposed system.

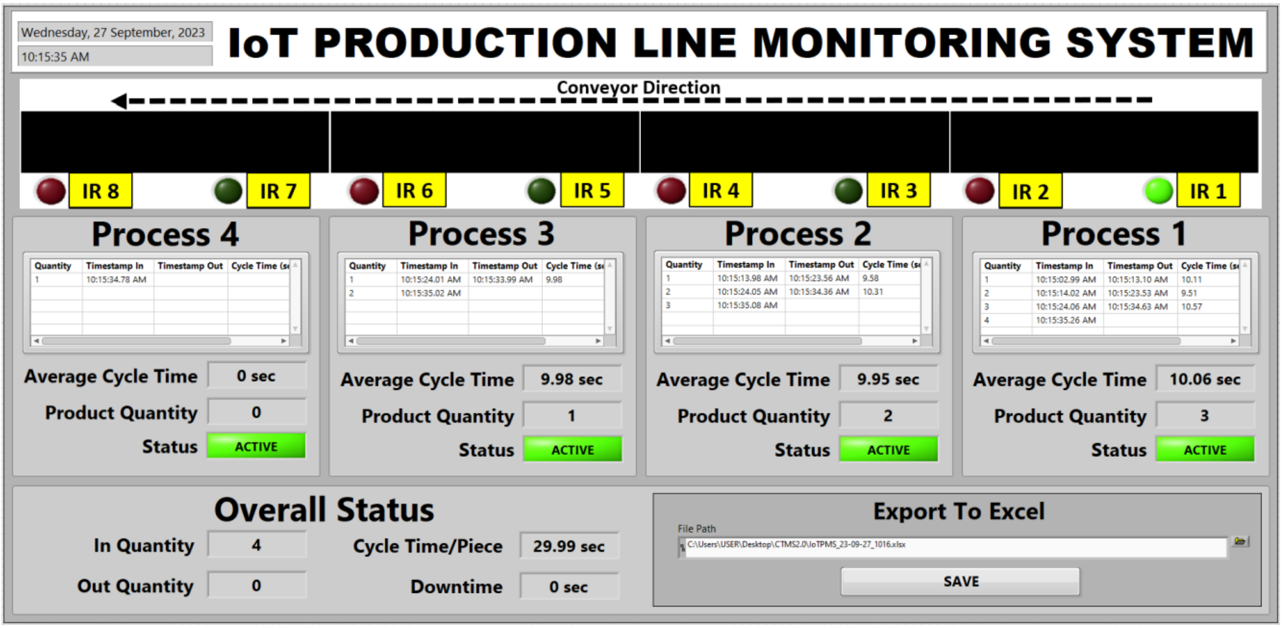

Fig. 8. Proposed system LabVIEW GUI

As shown in Figure 8, the LabVIEW GUI consists of two parts. The upper part displays data for each process at the conveyor station. The Light Emitting Diode (LED) at each process lights up to indicate that the IR sensor is detecting a product. The timestamp for entry and exit, along with cycle time data, is stored in the table for each process. This data is then used to determine the average process cycle time, product quantity and the status of the assembly station, which is displayed below the table. The "Status" serves as an indicator of whether the current conveyor is active or down, based on the analysed process cycle time. It will show "Down" if there has been no detection from the IR sensor for more than 5 minutes. The overall production data is displayed at the bottom part of the GUI, alongside an "Export to Excel" feature, which allows the captured data to be saved in Excel format for further analysis.

5. Results and Discussion

Takt time serves as a vital parameter for assessing the line balancing of the production line. It represents the ideal pace at which each process should operate to meet customer demand without overproduction or underproduction. This paper assumes a takt time based on real-world manufacturing industry situations, which typically involve a single shift and a 1-hour break. The production target in this scenario is 4000 units per day to meet customer demand. The calculated takt time of 9.9 seconds per unit is obtained using the previously mentioned Eq. (1) for each process of the production line.

For the purposes of this research, three comprehensive case studies were proposed to evaluate real manufacturing production lines. These case studies encompass balanced production lines, un-balanced production lines and production lines with machine downtime. The core of this simulation lies in the utilization of servo motors at each conveyor station to temporarily block the product, thereby emulating various real-world scenarios of human or machine product assembly in manufacturing production lines. Table 2 displays the randomized duration range of servo motor blocking for simulating different case studies of the production line based on the determined takt time.

Table 2
Simulation of three case studies

Servo Process Simulation	Case Study 1	Case Study 2	Case Study 3
	Balanced	Un-Balanced	Machine Down Time
Process 1 (Servo 1)	9-11 sec	9-11 sec	9-11 sec
Process 2 (Servo 2)	9-11 sec	8-14 sec	9-11 sec
Process 3 (Servo 3)	9-11 sec	10-20 sec	300-500 sec
Process 4 (Servo 4)	9-11 sec	6-9 sec	9-11 sec

Table 2 shown servo blocking time for different case study based on the determine takt time to meet the customer demand. So, in the Balanced case study, all processes are set within the range of 9-11 seconds. This aligns with the calculated takt time of 9.9 seconds, ensuring that each process operates efficiently and in harmony with the overall production pace. In the Un-Balanced case study, some processes have wider time ranges (e.g., Process 2 with 8-14 seconds) to simulate scenarios where certain processes operate slower or faster than the calculated takt time. This variation helps identify potential bottlenecks or inefficiencies in the production line. In the Machine Downtime case study, Process 3 has a significantly longer time range (300-500 seconds) to simulate extended machine downtime. This extreme variation represents a disruptive scenario in which one process experiences significant delays, impacting overall production efficiency.

Furthermore, the exported Excel file provides two additional datasets for analysis which are standard deviations and standard errors for each process. The standard deviation measures the variability or spread in the cycle time for each process. Smaller standard deviations indicate less variability in process cycle time, while larger ones suggest more variability. This data can be used to evaluate the performance of the human or machine in each specific process, offering insights for potential future research.

On the other hand, standard error serves as a measure of the precision of the sample mean when estimating the population mean. In this context, it quantifies the precision of estimating the assembly of 4000 products based on a sample of 5 products. Smaller standard errors indicate that the sample mean provides a more reliable estimate of the population mean.

5.1 Balanced Production Line

Table 3 presents the results for Case Study 1, which represents a balanced production line simulation. In this scenario, the research aimed to emulate an ideal manufacturing environment where processes are well-coordinated and have similar cycle times. The table provides data for process cycle times (PCT) across four different processes (Process 1 to Process 4) over five samples.

Table 3
Results for Case Study 1: Balanced production line

Sample	Process Cycle Time (PCT)			
	Process 1 (s)	Process 2 (s)	Process 3(s)	Process 4 (s)
1	10.25	9.27	9.98	10.23
2	10.07	10.31	10.05	10.45
3	10.52	10.69	9.68	9.92
4	10.83	9.21	10.48	9.69
5	10.34	10.52	10.90	10.05
Mean	10.40	10.00	10.22	10.07
Standard Deviation	0.29	0.71	0.48	0.29
Standard Error	0.13	0.32	0.21	0.13

Standard deviations and standard errors were calculated from the data in Table 3 to assess the variability and precision of the data. The low standard deviations (ranging from 0.29 to 0.71 seconds) indicate minimal variability in cycle times for each process, further confirming the balanced nature of the production line. Similarly, the small standard errors (ranging from 0.13 to 0.32 seconds) suggest that the sample means are precise estimates of the population means, reinforcing the reliability of the data. The mean process cycle times for each process were calculated to plot the line balancing graph, as illustrated in Figure 9.

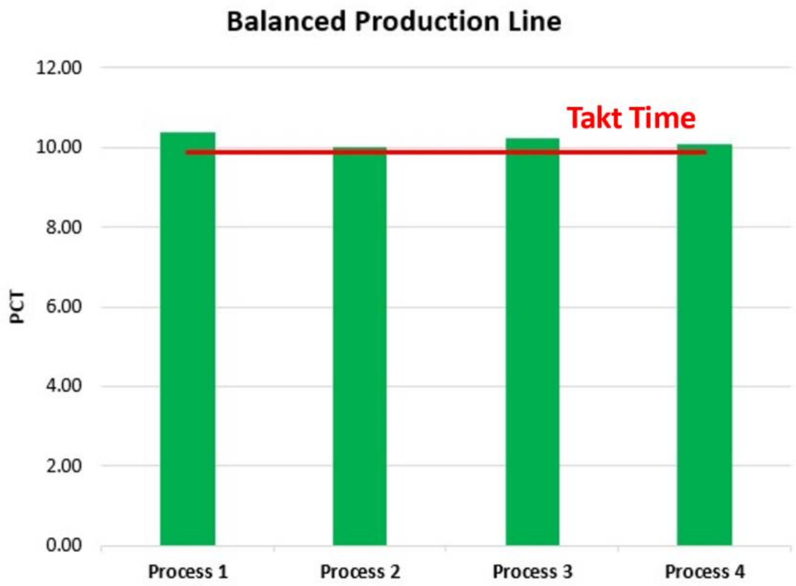

Fig. 9. Graph of takt time and process cycle time for Case Study 1

Figure 9's-line balancing graph reveals that the mean cycle times across all processes exhibit a consistent pattern, closely aligning with the calculated takt time of 10.25 seconds. Process 1 boasts an average Processing Cycle Time (PCT) of 10.40 seconds, while Process 2, Process 3 and Process 4 report mean PCTs of 10.00, 10.22 and 10.07 seconds, respectively. This alignment between the mean cycle times and the takt time underscores the well-tuned equilibrium of the production line, signifying that the processes operate at a pace that consistently meets the intended rhythm of production. Such alignment with the takt time not only underscores the efficiency of the system but also suggests that the production line is finely tuned to meet the demands of the production target. In summary, Case Study 1 demonstrates how the well-balanced production line effectively maintains consistent and efficient cycle times in its processes, with only a minor deviation from the takt time, thereby facilitating the achievement of production targets while reducing variability and uncertainty.

5.2 Un-Balanced Production Line

Table 4 presents the results for Case Study 2, which represents an un-balanced production line simulation. In this scenario, the research aimed to emulate a manufacturing environment where processes exhibit varying cycle times, potentially leading to bottlenecks and inefficiencies. The table provides data for PCT across four different processes (Process 1 to Process 4) over five samples.

Table 4
Results for Case Study 2: Un-balanced production line

Sample	Process Cycle Time (PCT)			
	Process 1 (s)	Process 2 (s)	Process 3(s)	Process 4 (s)
1	10.86	8.07	13.58	8.21
2	10.73	13.88	16.00	6.29
3	9.94	11.72	17.11	8.34
4	9.16	11.62	14.28	7.31
5	9.84	10.72	12.00	7.38
Mean	10.11	11.20	14.59	7.51
Standard Deviation	0.70	2.10	2.01	0.83
Standard Error	0.31	0.94	0.90	0.37

The standard deviations and standard errors calculated from the data in Table 4 emphasize significant variability among the processes. Process 2 and Process 3 exhibit the highest standard deviations (2.10 and 2.01 seconds) and standard errors (0.94 and 0.90 seconds), indicating substantial variations in cycle times. These findings suggest that the un-balanced production line may struggle to meet production targets efficiently and could experience potential bottlenecks in certain processes. Additionally, from the mean data presented in Table 4, a line balancing graph was plotted, as shown in Figure 10.

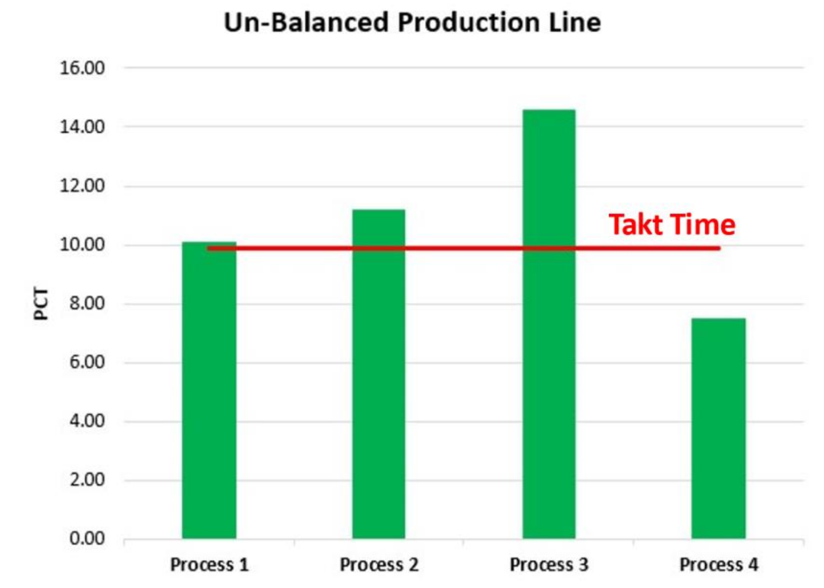

Fig. 10. Graph of takt time and process cycle time for Case Study 2

Figure 10's graph illustrates that Process 1 has a mean Processing Cycle Time (PCT) of 10.11 seconds, Process 2 at 11.20 seconds, Process 3 at 14.59 seconds and Process 4 at 7.51 seconds. Notably, these PCT values reveal significant differences in cycle times across these processes, some of which exceed the calculated takt time of 10.25 seconds. These disparities indicate an unbalanced production line where some processes operate significantly faster or slower than others. The presence of PCT values above the takt time suggests that certain processes may need optimization or workload redistribution to achieve better balance and efficiency. In summary, these findings underscore the clear need for adjustments to address the imbalances within the production line.

5.3 Production Line with Machine Downtime

Table 5 presents the results for Case Study 3, which simulates a production line with machine downtime. In this scenario, the research aimed to replicate a manufacturing environment where one of the processes (Process 3) experiences extended downtime, potentially causing disruptions and inefficiencies in the production line. The table provides data for PCT across four different processes (Process 1 to Process 4) over five samples.

Table 5
Results for Case Study 3: Production line with machine downtime

Sample	Process Cycle Time (PCT)			
	Process 1 (s)	Process 2 (s)	Process 3(s)	Process 4 (s)
1	9.28	10.46	10.87	10.60
2	9.52	9.84	9.36	10.93
3	10.27	10.87	386.83	10.21
4	10.41	9.24	9.22	10.30
5	10.28	10.26	10.17	10.98
Mean	9.95	10.13	85.29	10.60
Standard Deviation	0.51	0.62	168.57	0.35
Standard Error	0.23	0.28	75.39	0.16

The standard deviations and standard errors calculated from the data in Table 5 reveal significant variations, particularly in Process 3, where the standard deviation is notably high (168.57 seconds), indicating a wide range of cycle times. Additionally, the standard error for Process 3 is 75.39 seconds, suggesting a substantial level of variability in the sample means. These findings underscore the impact of machine downtime on the production line's performance, as evidenced by the erratic cycle times in Process 3. Furthermore, the mean data for all processes indicate that Process 3 has a significantly higher mean PCT (85.29 seconds) compared to the other processes, which is also evident in the line balancing graph of Figure 11.

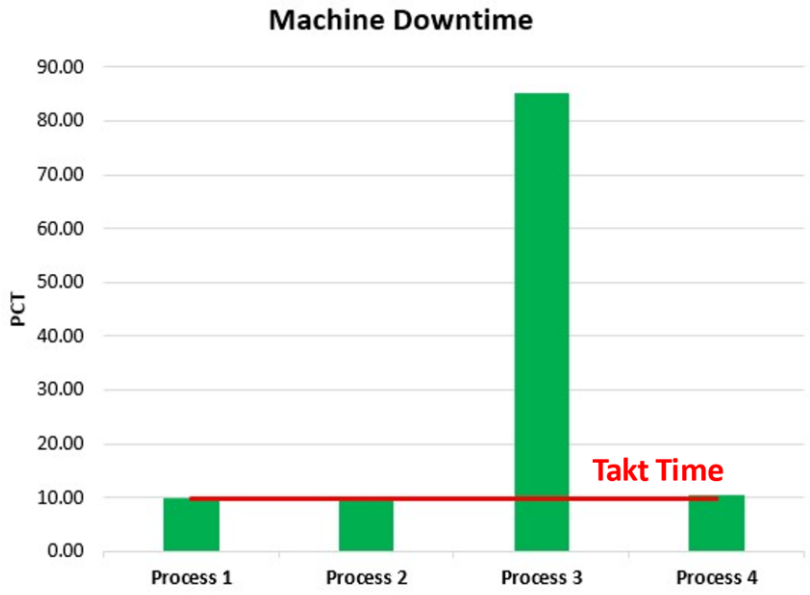

Fig. 11. Graph of takt time and process cycle time for Case Study 3

From Figure 11, a noticeable spike in cycle time at Process 3 is evident, underscoring the disruptive impact of machine downtime on production efficiency. Machine downtime significantly extends the cycle time, affecting the overall production process. In Case Study 3, this issue is prominent and it highlights the challenges posed by machine downtime within a production line. The increased cycle times and interruptions in the production process are directly related to inefficient production line performance caused by machine downtime. These findings emphasize the critical importance of addressing and minimizing machine downtime to maintain production line efficiency, ensuring the production targets are met.

4. Conclusions

In conclusion, this research has successfully developed an approach to process cycle time measurement systems with sensor applications for production line monitoring. The proposed system, equipped with infrared sensors and microcontrollers, enables real-time measurement of process cycle times and facilitates data analysis. Three distinct case studies, encompassing balanced production lines, unbalanced production lines and production lines with machine downtime, were conducted to assess production line performance and efficiency. The results of the case studies indicate that the proposed system accurately captures process cycle times according to the specific setup conditions, as evident from the analysis of the exported Excel data. However, there is room for future improvements for the proposed system, including the analysis of line balancing graphs within the LabVIEW GUI system for users to view the production situation in real-time. Moreover, there is potential for the integration of human data in future, such as heart rate and brain activity, to evaluate worker performance, safety and health status, which can typically affect the process cycle time of production. As part of this integration, a feedback mechanism can be included to promptly alert if any issues arise in the production process, enhancing the intelligence of the monitoring system.

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