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A Centralized IOT-Based Process Cycle Time Monitoring System for Line Balancing Study

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ABSTRACT

This study proposes a Centralized IoT-based Process Cycle Time Monitoring System (CTMS) to improve the efficiency and accuracy of line balancing studies in a production line with a conveyor system. The traditional approach of measuring cycle time, typically done by manual observation and recording, can be prone to errors due to human factors such as fatigue or inaccuracies in manual recording. The proposed CTMS utilizes a combination of cutting-edge technologies such as a cloud database, android application, LABVIEW GUI, analogue infrared (IR) sensors, and appropriate controllers to improve the reliability of cycle time measurements. The system continuously monitors the production line and provides real-time data on cycle time, downtime, and other relevant metrics, allowing production engineers to quickly identify bottlenecks and areas for improvement. The results of the study demonstrate the potential of the CTMS to be applied and expanded to actual production lines with conveyor systems, providing a valuable tool for production engineers to develop strategies to reduce cycle time and ensure it is kept in check. The proposed CTMS is expected to have a positive impact on the efficiency and profitability of the production line by reducing downtime and increasing productivity.

1. Introduction

Internet of things (IoT) technology has become well known due to the introduction of Industry 4.0, where everything is now connected to the internet. Integrating the monitoring system with IoT made an impression on the manufacturing industry because the system had many advantages over the manual monitoring system [1-3]. The common drawback of manual monitoring systems is due to human error during manually inserting data into the system, manipulating data by the person in charge and no real-time data collecting, resulting in a delay in management-level planning [4,5]. As for the future of conveyor type production line monitoring systems, a long-range wireless type

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monitoring system is rapidly being explored to ease some tasks such as cycle time measurement which refers to the amount of time it takes for a product to complete the entire production process, from start to finish [6,7].

In this paper, the Process Cycle Time Monitoring System (CTMS) for line balancing study is presented. The proposed CTMS utilizes LabVIEW Graphical User Interface (GUI) and IoT technology (including mobile apps) for monitoring purposes. Infrared (IR) sensors were employed on the production line conveyor system to capture the process time (in and out). The cycle time of each process was determined and transferred to the cloud database, where five data samples were collected through actual testing on the assembly line.

2. Cycle Time

Cycle time is a crucial metric in manufacturing as it measures the efficiency of a production line process. By identifying bottlenecks and areas for improvement, manufacturers can optimize their processes to reduce downtime and increase productivity [8,9]. Cycle time can also be used to calculate the production rate and schedule production runs. However, traditional methods of measuring cycle time, such as manual observation and recording, can be prone to errors due to human factors like fatigue or inaccuracies in manual recording. To overcome this, some companies use automated systems, like sensors or machine learning algorithms, to provide more accurate and consistent cycle time measurements. Figure 1 illustrates the components of cycle time measurement, including product in, process (time measurement), and product out. The cycle time is calculated as the sum of production time divided by the quantity of produced units, as shown in the Eq. (1) [10].

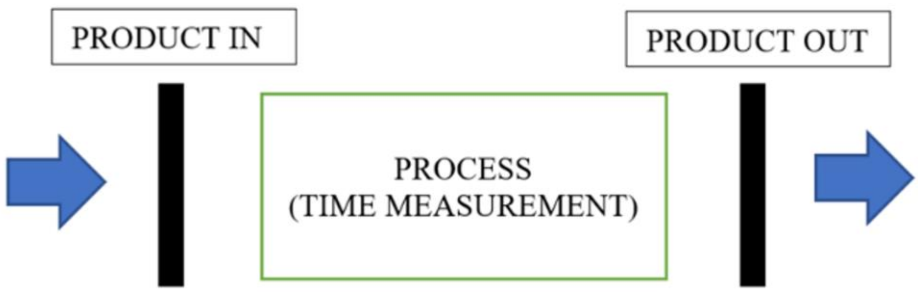

Fig. 1. Cycle time concept

$$Cycle\ Time = \frac{Net\ Production\ Time}{No.\ Units\ Produced} \tag{1}$$

3. An Overview of LabVIEW and IOT Based Applications

LabVIEW, a popular software for developing automated research, validation, and production test systems, has a wide range of applications in a variety of sectors. In this section, we will look at how LabVIEW and IoT-based real-time monitoring systems are used in diverse fields such as automotive, health, manufacturing, and agricultural. Table 1 compares prior studies in various disciplines, highlighting the components and software employed, as well as the technology and providing a brief synopsis of the studies.

Based on Table 1, real-time monitoring via remotely has been applied in a variety of fields such as healthcare [11], environment [12], automotive industries [13] and manufacturing [6,14]. Microcontrollers are utilized as the primary component of embedded systems for real-time monitoring. Several different types of microcontrollers, including Arduino [12,14] and Raspberry Pi

[6], have been found to be used in earlier studies. Moreover, sensors are necessary for real-time monitoring in which it detects and measures the input and converts it into electrical, then processes into data. Different types of sensors are employed, and their selection is influenced by the intended purpose and the input measurements such as blood pressure and pressure sensors are use in health monitoring system [11] and seawater pressure monitoring system respectively [12].

Table 1
Comparison of previous search

Applications	Electronic Parts	Software	Category	Findings/outcomes
Healthcare application [11]	- DAQ Device - RFID card - Sensors: Blood pressure, pulse oximeter and temperature	LabVIEW	Health	Real-time Patients' health monitoring via remotely
Environment monitoring [12]	- Microcontroller - Pressure sensor - Wi-Fi module	Arduino IDE	Environment	Real-time seawater pressure monitors via remotely
Automotive industries [13]	- STM32 - LCD display - OBD2	-	Automotive	Real-time car damage monitoring via remotely
Production line monitoring [14]	- Arduino Uno - High Temperature Thermal couple - Node Wi-Fi module - IR distance sensor	Arduino IDE and LabVIEW	Manufacturing (non-conveyor type)	Real-time production line monitoring via remotely
Process cycle-time measurement [6]	- Raspberry Pie - RFID card	MATLAB	Manufacturing (non-conveyor type)	Real-time cycle time monitoring via remotely

4. Methodology

4.1 General Block Diagram

The main input for the CTMS is Infrared (IR) sensors, which detect the presence of products on a moving conveyor. For the purpose of this study, 4 processes were simulated, each equipped with two IR sensors. These sensors are placed at the entrance and exit of each process to monitor the time the product enters and exits. The acquired time data is then accumulated in LabVIEW software. Figure 2 illustrates the overall system operation and function.

The time data captured by the IR sensors is acquired by LabVIEW through the Arduino hardware (LINX serial communication) [15-16] via a Virtual Serial Port. The cycle time for each process is then calculated and displayed in the LabVIEW GUI. The data is also transferred to a cloud database for storage and mobile application use (Google Firebase) [17] via internet connection. The Representational State Transfer Application Programming Interface (REST API) method is used for database and GUI connectivity, allowing hypertext transfer protocol (HTTP) requests to access the data via an internet connection.

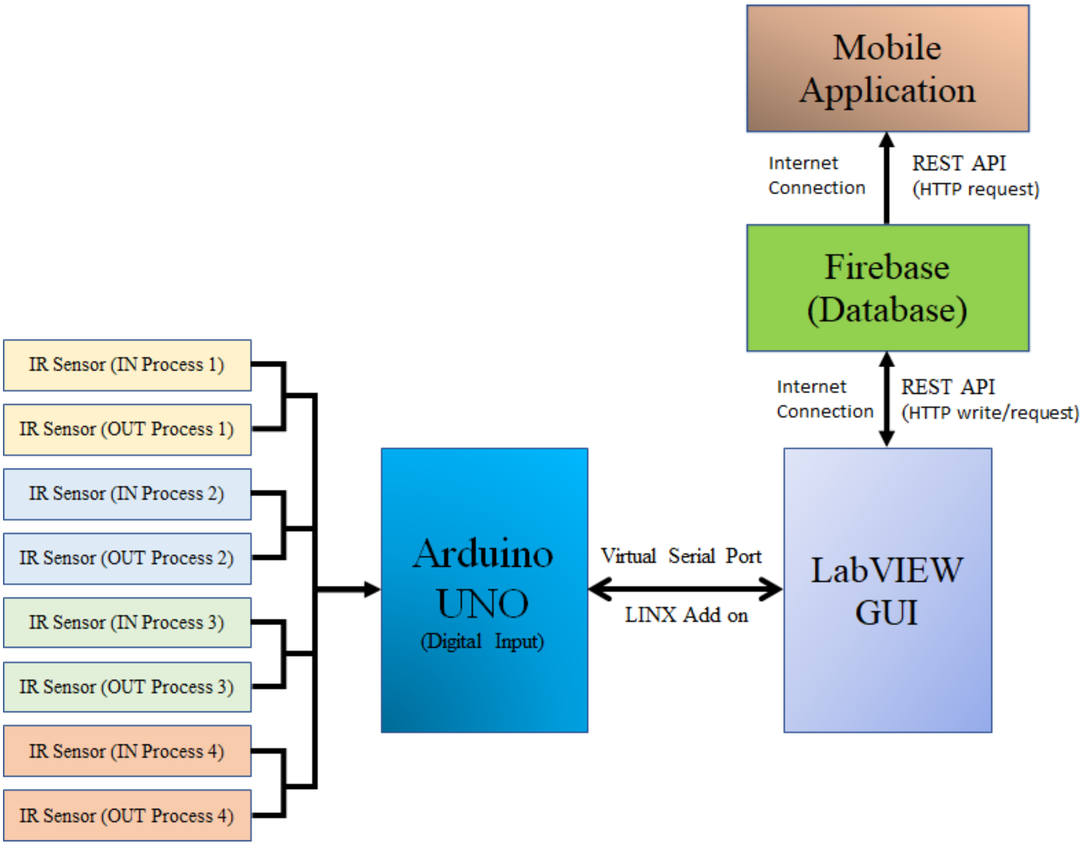

Fig. 2. Centralized IoT-based Process Cycle Time Monitoring System (CTMS) general block diagram

4.2 Cycle Time Measurement Method

Figure 3 displays the method used to acquire and calculate the cycle times for each process. The IR sensors (2 units) are positioned at the side-edge of the conveyor to detect products as they move in and out of each process. Once the sensor detects that a product has entered the process, a timestamp is saved and added to the LabVIEW array function, indicating the start of the process. When the production process is complete, the product is returned to the conveyor and the sensor detects its movement as it exits the station. The signal is then sent to the LabVIEW system to capture the output time data. Both the input and output time data are added to LabVIEW array functions, and the cycle time is calculated from Eq. (2) using a mathematical operation in the LabVIEW program. The results are then displayed on the GUI and transferred to the Firebase cloud database [18].

$$System\ Cycle\ Time = Output\ Timestamp - Input\ Timestamp \tag{2}$$

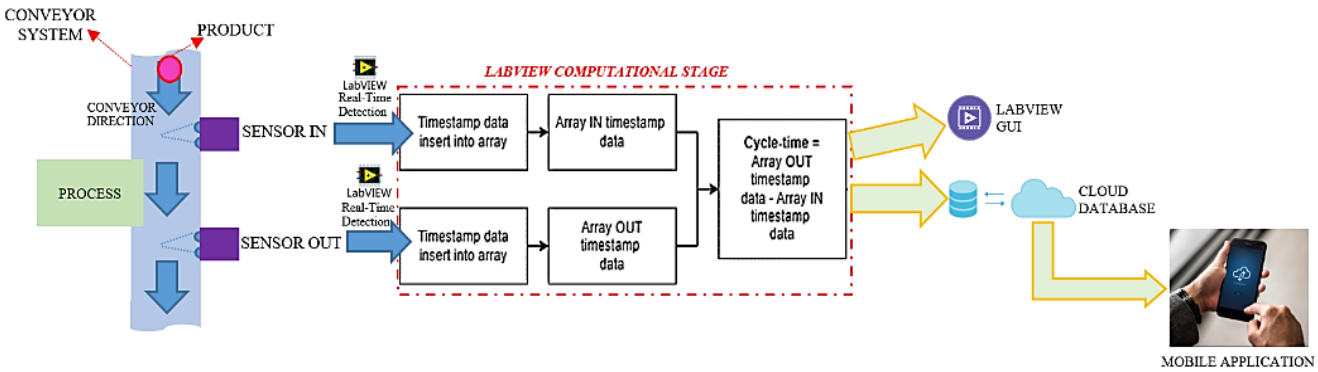

Fig. 3. Cycle time measurement method

4.3 Process Simulation

The research system was simulated on an assembly line layout, as shown in Figure 4. The assembly line consisted of four processes needed to complete a product. The O-shaped conveyor moved the product through each station and process. The first process was "Insert Shaft", where operators inserted a metal shaft into the device's body securely. The next process was "Insert Spring", where operators inserted a high-tension spring into the device with care and precision. The third process was "Insert Top Cover", where operators inserted the top cover, ensuring proper alignment and secure retention.

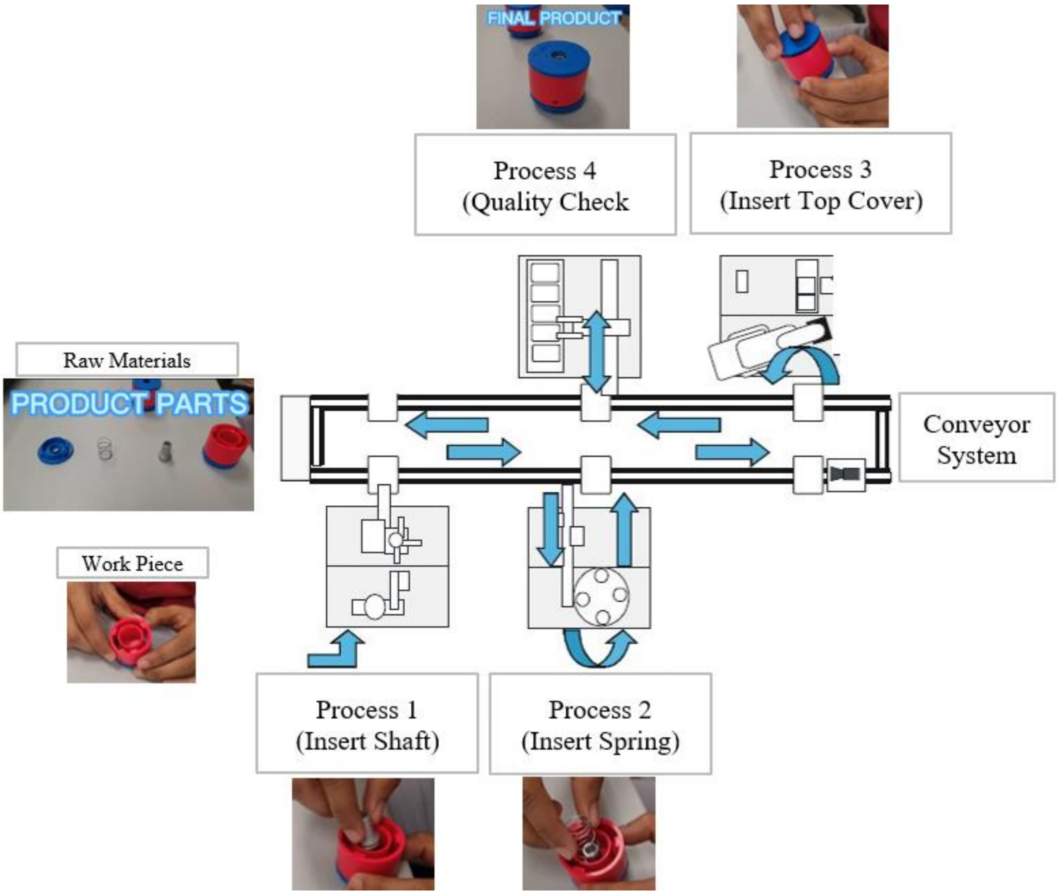

Fig. 4. Assembly line layout

The final process was "Quality Check", where operators checked each final product for appearance quality. IR sensors were attached at the input and output of each process, as shown in Figure 5.

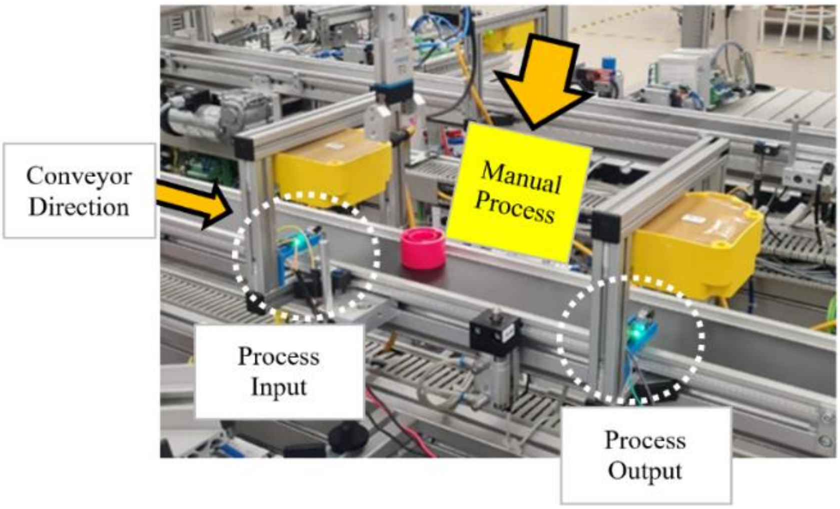

Fig. 5. Sensor attachment for each process station

5. Result and Discussions

5.1 LabVIEW GUI

Figure 6 displays the GUI for the monitoring system, showcasing the cycle time data for all four processes.

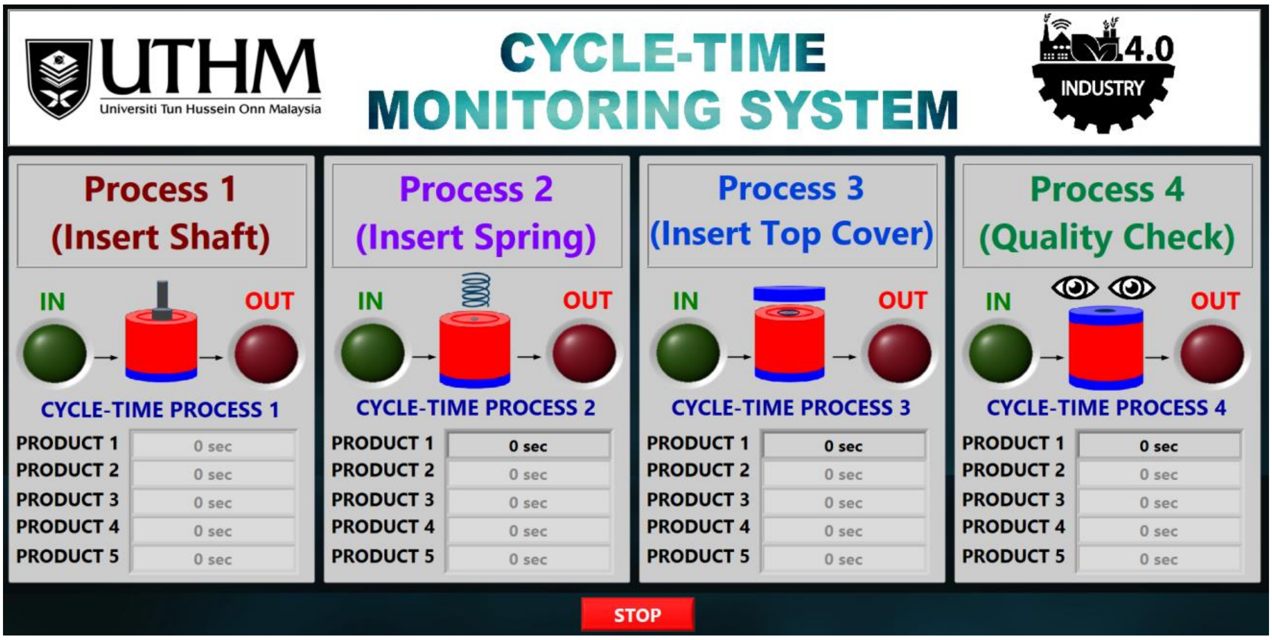

Fig. 6. LabVIEW GUI for CTMS

The interface includes data for processes such as "insert shaft", "insert spring", "insert top cover" and "quality check". Lights indicator displays are also included to enable users to monitor the status of up to 5 products continuously as they move and are processed. The lights indicate the product's entry (IN) and exit (OUT) for each process. The cycle time for each process is also displayed, making it easy for users to understand the performance of the production line by clearly showing the amount of time each product takes to complete each process. The data is also stored in the cloud, accessible from any device with internet access, such as computers or smartphones, providing users with the ability to track and analyse data anytime, anywhere and in real-time through a mobile application.

5.2 Analysis and Discussions

A test was conducted to compare the results of CTMS with those obtained using the manual stopwatch method. The cycle time of 5 continuous product samples was recorded and analysed. The data for these five samples are presented in Table 2.

Table 2
The general time for 5 data continues sample (in seconds)

		Sample 1	Sample 2	Sample 3	Sample 4	Sample 5	Mean	Standard Deviation
Process 1	CTMS	15.45	13.08	15.29	14.19	11.59	14.08	1.32
	Stopwatch	15.47	13.11	15.35	14.29	11.55	14.09	0.16
	Difference	+0.02	+0.03	+0.06	+0.10	-0.04		
Process 2	CTMS	4.67	4.46	4.10	3.90	4.80	4.44	0.22
	Stopwatch	4.77	4.49	4.10	4.00	4.90	4.46	0.23
	Difference	+0.10	+0.03	0.00	+0.10	+0.10		
Process 3	CTMS	5.97	5.53	5.12	5.11	5.46	5.34	0.32
	Stopwatch	6.15	5.42	5.25	5.25	5.46	5.39	0.27
	Difference	+0.18	-0.11	+0.13	+0.14	0.00		
Process 4	CTMS	7.38	7.64	7.67	7.27	7.07	7.38	0.23
	Stopwatch	7.58	7.69	7.75	7.38	7.14	7.52	0.15
	Difference	+0.20	+0.05	+0.08	+0.11	+0.07		

Based on the results, the mean difference between CTMS and stopwatch data is generally small, which indicates a consistent reading between those two approaches. Further statistical analysis was performed to determine the standard deviation of the data. The Eq. (3) was used for the calculation [19]

$$Standard\ Deviation = \sqrt{\frac{\sum(x\text{-}mean)^2}{n\text{-}1}} \quad (3)$$

where x is each data point, mean is the mean of the data, and n is the number of data points.

It is found that the standard deviation of the CTMS data and stopwatch data does not always match across the four processes. This can be seen in process 1, where the standard deviation of the CTMS data is greater than the stopwatch data, while in process 4, the standard deviation of the CTMS data is lower than the stopwatch data. The difference in standard deviation can be attributed to measurement error, variability in the production processes or differences in the way the CTMS and stopwatch measurements were taken.

The result also shows that CTMS times are often between -0.44% and -1.71% slightly faster than the stopwatch times. The performance of the CTMS system in general might not be significantly impacted by these changes, which are rather minor. Furthermore, to evaluate the correlation between the CTMS data and stopwatch data for each of the four production line processes, the correlation coefficient (r) is computed. The correlation coefficient is a statistical measure that indicates the strength and direction of the relationship between two variables. It ranges from -1 to

1, where a positive correlation is indicated by a value close to 1, a negative correlation by a value close to -1 and no correlation by a value close to 0.

The Pearson's correlation coefficient (r) formula can be used to find the correlation coefficient between the CTMS and stopwatch data for each process. The Eq. (4) was used to calculate Pearson's correlation coefficient [20]

$$r = \frac{n\sum(xy) - \sum x \sum y}{\sqrt{[n\sum x^2 - (\sum x)^2][n\sum y^2 - (\sum y)^2]}} \tag{4}$$

where x_d is CTMS time data, y_d is the stopwatch time data, n_o is the number of observations. The results are shown in Table 3.

Table 3
Pearson correlation coefficient result

Correlation Coefficient (r)	Sample 1	Sample 2	Sample 3	Sample 4	Sample 5
Process 1	0.9997	0.9997	0.9997	0.9997	0.9997
Process 2	0.9935	0.9935	0.9935	0.9935	0.9935
Process3	0.9465	0.9465	0.9465	0.9465	0.9465
Process 4	0.9726	0.9726	0.9726	0.9726	0.9726

Based on Table 3, it is clear that there is a strong positive correlation between the CTMS measurements and the stopwatch measurements for all processes and samples. The correlation coefficient for all the samples is close to 1, specifically between 0.9465 to 0.9997 which indicates that as the CTMS measurements increase, the stopwatch measurements also increase, and vice versa. This suggests that the CTMS measurements are highly correlated with the stopwatch measurements, meaning that they are measuring the same thing and measuring in the same way, which is a good indication that the CTMS system is producing accurate results. Process 3 has the lowest correlation coefficient among all the processes, which indicates that the correlation between CTMS and stopwatch measurements is slightly weaker than the other processes. This could be due to measurement errors, technical issues or human errors that affect the CTMS measurements in this process specifically.

5.3 Mobile Application Monitoring

The system can also be monitored by cell phones in addition to being accessible through a computer. The outcome of CTMS monitoring using a mobile application is shown in Figure 7. The mobile application uses a user-friendly interface to present the cycle-time statistics from the Firebase real-time database. Users can easily grasp the production line's flow because of the data's presentation, which follows the order of the processes from process one to process four. Users can easily read and see the cycle times for each process and product, quickly and easily access the data when they need it using the mobile application's intuitive interface and simple navigation. This makes it an effective tool for tracking the performance of production lines since it enables users to rapidly spot areas that could require improvement and to take data-driven decisions to streamline the manufacturing process.

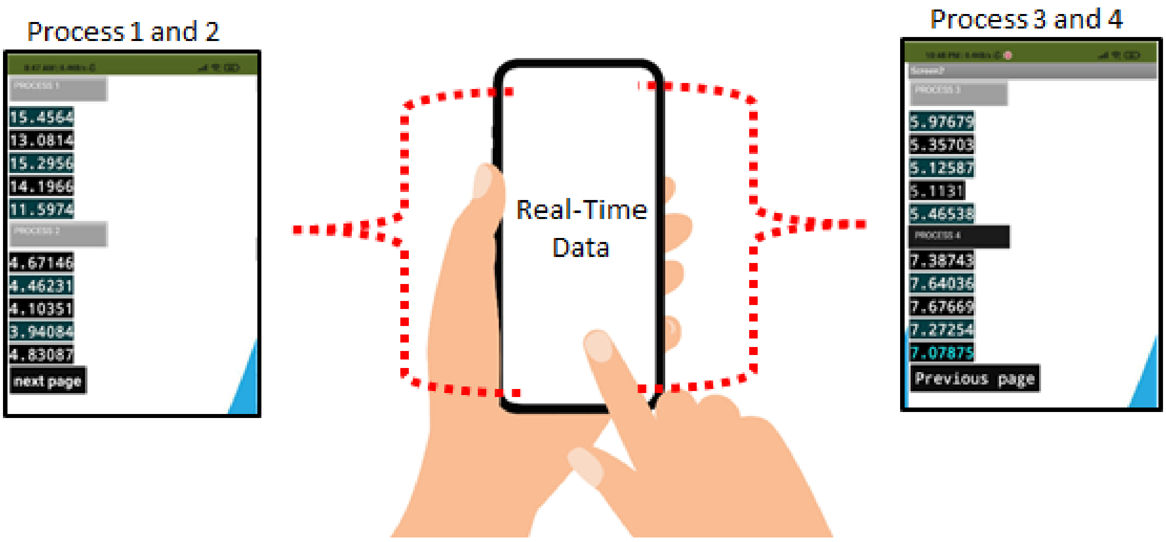

Fig. 7. The CTMS monitored through the mobile application

6. Conclusions

In conclusion, this study introduces a revolutionary CTMS system that is expected to transform how companies manage and improve their production lines. The system has four processes in the production line and eight IR sensors in total. It uses an infrared (IR) sensor to identify the presence of the product as it moves through the conveyor. The system processes and analyses the data, and it is then saved in the Google Firebase cloud database, enabling remote access and monitoring via online platforms like desktops or smartphones. This enables companies to monitor the operation of their manufacturing lines in real-time and take data-driven decisions to streamline the procedure. Companies are able to pinpoint problem areas, identify bottlenecks, and shorten total cycle times thanks to the systems thorough reports, which correctly evaluate progress. In order to increase performance, firms can now recognize inefficiencies in their manufacturing process and implement the necessary modifications. The system is also user-friendly, enabling users to obtain the data quickly and conveniently whenever they need it, making it a potent tool for assessing the effectiveness of production lines. It's important to note, though, that the system can only monitor; it cannot interfere with the work being done by the process. Therefore, the process in the system can be optimized by including the work's interference in the cycle time measurement in the future. Overall, the CTMS system provides a valuable tool for monitoring production line performance and optimizing the production process, and it has the potential to transform the way businesses operate and compete in the market.

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