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Research Article

Quantifying the Operational Impact of Missed Defective Units in ML-Based Quality Inspection

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Industrial manufacturing uses a variety of Key Performance Indicators (KPIs) to measure and manage the quality of their products. These indicators evaluate different aspects and help to identify losses related to quality issues, and thus to pinpoint areas for improvement. For instance, Overall Equipment Effectiveness (OEE) and first pass yield are widely used metrics in industry, they determine the ability of a process to produce good products by measuring the proportion of detected defects. With the growing utilization of machine learning in defect detection, additional indicators have emerged, this time connected to the behaviour of the used algorithms. Among these, Recall plays an operational role, it indicates how effectively defective units were identified and removed from the production flow. With a low Recall, there is a risk that some defective items go unnoticed, which leads to various losses because those units continue to consume time and resources. This case referred to as late defect detection; because, instead of being detected early, defective units go down the production system and are discovered later at stages where the lost is significantly higher. Hence, in this work, we point out the importance to consider the impact of late defect detection on multi-stage production system by investigating how variations in Recall shape process performances. We introduce two key performance indicators, the first one helps to quantify value-added time wasted due to late defect detection, while the second one allows to determine the impact of this loss on each production process. We have implemented a simulation using Arena software and we have declared our proposed metrics via Record module. The results showed that the impact of late defect detection on processes varies depending on whether a process have a reserve capacity or not.

Keywords: Defect detection, Process Performance Machine learning, OEE, Recall, First pass yield, Lean management, Arena simulation.

INTRODUCTION

Quality control is a paramount concern for industries; it helps to ensure that products meet customer expectations and specified standards. Recently, particular focus was directed toward the use of machine learning techniques to enhance the efficiency of defect detection (Chaabi & Hamlich, 2022). (Ma et al., 2023) Proposed an end-to-end defect detection network to inspect quality of metallic surfaces, while (Kim et al., 2021) explored the use of deep learning model for Printed Circuit Board (PBC) defect detection, they evaluate also the impact of data quality and image contamination on results. (Zeng et al., 2022) examined tiny defect of PBC through the application of ATROUS spatial pyramid pooling-balanced-feature pyramid network (ABFPN). The challenge of collecting enough data to train machine learning models has led some researchers to explore one-class classification (Czimmermann et al., 2020), the key tenet of this approach is elaborating models that are trained basically on defect free class (Chaabi et al., 2023).

To improve industrial decision-making, recent works have proposed automated algorithm selection frameworks using meta-modeling and data characterization (Garouani et al., 2023), as well as reinforcement learning-based coordination strategies tailored for dynamic and uncertain environments (Hamed & Hamlich, 2021, 2024) . These advances support the development of smarter inspection and control systems that adapt to production variability and enhance fault detection in real time. Moreover, anomaly detection techniques in multi-robot systems have proven beneficial for industrial monitoring and predictive maintenance, contributing to robust production quality (Khatib et al., 2024).

Regardless of various methodologies or fields of application, all these research works have the same purpose to elaborate an efficient quality inspection system that detects all defected units (Ren et al., 2021), which can prevent the spread of this items throughout production system. This early defect inspection guarantee that detection is made at the nearest point to the source of defect (Hauck et al., 2022). This takes us to JIDOKA (M. Soliman, 2016), this Lean pillar aim extends beyond quality inspection, striving to built-in quality and prevent defective items from being created, by first, ensuring that the machine can detect irregularities and once an anomaly is identified, the production stops immediately (M. H. A. Soliman, 2020). Human also holds an important position among the key elements in JIDOKA framework (Escott, 2024). (Sordan & Chiabert, 2025) examined the evolutionary pathway that has led to JIDOKA 4.0; advanced technologies of Industry 4.0 such as Internet of things and machine learning, have shaped JIDOKA into a more automated and data driven model; JIDOKA 4.0 could anticipate potential issues thereby enhancing the principal of built-in quality. (Crespo Montoya et al., 2023) proposed a JIDOKA implementation, they monitor process variations that can lead to defects. While built-in quality or robust quality inspection methods are essential for identifying defective units, it is equally important to evaluate the impact of these defects on performance of production processes. Over time, multiples Key performance indicators (KPIs) have been introduced in order to quantify losses associated to quality issues.

Total Productive Maintenance (TPM) approach has introduced a powerful key performance: overall equipment effectiveness (OEE); this metric measures the performance of production equipment based on three components: Availability(A), Performance(P) and Quality (Q)(Dobra & Jósvai, 2023). OEE metric is computed as:

$$OEE = A \times P \times Q \quad (1)$$

each component highlights a different type of productivity loss as it explained in Figure 1.

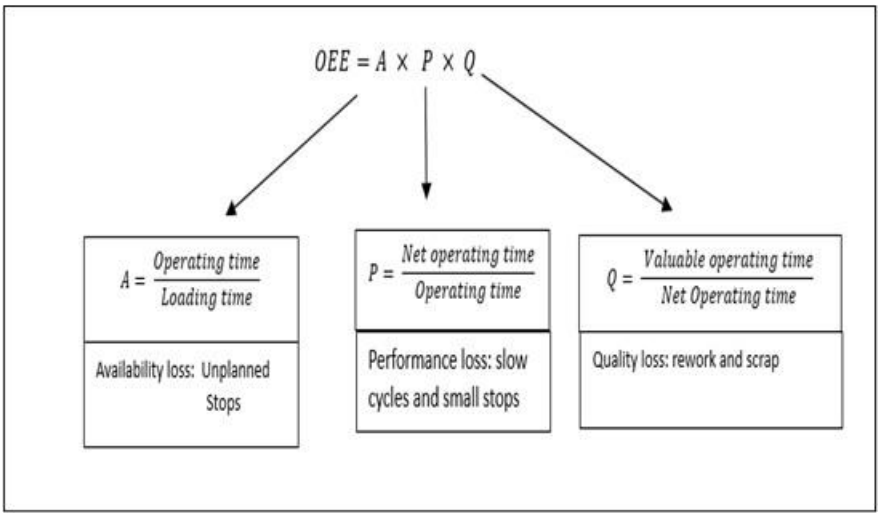

Figure 1: Explanation of OEE components

First pass yield is also a widely metric used to evaluate quality loss (Broz & Humphrey, 2021). It is similar to OEE quality component, it indicates quality parts that successfully pass through the manufacturing process without requiring any rework as a percentage of the total units that entered the process.

The use of machine learning algorithms for automated defect detection have brought to the surface an important metric: the recall (Naidu et al., 2023). It is computed as:

$$\text{Recall} = \frac{TP}{TP+FN} \quad (2)$$

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Where TP: is the number of units correctly detected by the ML algorithm as defective.

FN: is the number of units incorrectly detected by the ML algorithm as non-defective.

The Recall determines how many defects the inspection system can catch, therefore when defective items go unnoticed, they affect the performances of downstream processes.

Although these indicators help to capture inefficiencies within the process and highlight waste related to quality problems, however they fall short of providing a clear picture of loss related to late defect detection. Thus, the intent of this work is to go beyond the value of recall itself and aim a better understanding of its impact on multi-stage production system. To do that, we propose two metrics that evaluate the impact of letting defective units pass through further steps of production process.

This article consists of 4 sections. Section 1 provides an introduction and examines related works. Section 2 presents in details the proposed metrics. In Section 3, an implementation on Arena software is detailed. Section 3 covers also the results and discussion. Finally, conclusion regarding the results obtained and perspective of this work are presented in Section 4.

METHODOLOGY

The problem of late defect detection in multi-stage production system revolves around letting defective units move through the production process, which means that we continue to add value to a defective product.

Figure 2 illustrates a multi-stage production system with several inspections points that based on machine learning algorithms. If one of the inspection points operates with low recall, which means that it fails to accurately detect all defective units, those units will proceed further along the production line, resulting in a various loss. Hence, this work stems from the need of a clear indicator that measure the impact of the late defect detection on production process.

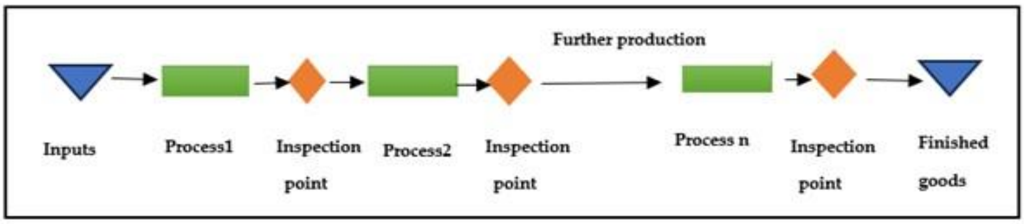

Figure 2: multi-stage production system with several inspection points

We seek answers to the following questions: if a defective unit is not detected early, near the process where the defect occurred, how much value-added time was wasted? and to what extent does this affect the production system?

In order to address this issue, we need to take a step further than OEE and first pass yield. Since it is not enough just to determine the defective unit, we must analyze its root cause. To this aim, a root cause analysis process should be established using tools such as current reality tree (da Costa et al., 2019) and fishbone diagram (Durroh et al., 2023).

VALUE ADDED TIME LOSS

The value-added time is the time devoted to production steps that add value to the final product based on customer's perspective; therefore, it is a crucial factor in Lean approach (Palange & Dhatrak, 2021).

We consider a multi-stage production system consisting of n processes, and each process is followed by an inspection point before proceeding to the next production step. The key performance indicator proposed in equation helps to pinpoint the value-added time loss (V.A.T Loss) due to late defect detection:

$$\mathrm{V.A.T\ Loss} = \sum_{i=2}^{n} \sum_{j=1}^{i} D_{ji} \left(\sum_{k=j+1}^{i} t_k \right) \tag{3}$$

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Where: Dji: if j ≠ i, Dji is the number of defected units detected at inspection point i limited to those that occurred at process j,

Otherwise Dji=0.

t_k is the value-added time of process k per unit.

IMPACT OF LATE DEFECT DETECTION ON EACH PROCESS

The V.A.T loss indicator can't capture the full scope of the impact of late defect detection on processes. For instance, this wasted time would have a severe impact on a bottleneck process. Owing to the fact that bottleneck operate at full capacity (Siregar, 2019). Moreover, each unit of time lost at this process constraint results in an equivalent loss for the entire system (Dawande et al., 2021).

The reserve capacity refers to the unused portion of available capacity of a production process. The fact that bottleneck has no reserve capacity, makes the impact of wasted value-added time different for this process compared to other production stages. Whereas the same amount of V.A.T loss does not necessarily affect all process in the same manner. For a production process that lacks reserve capacity, any waste will directly lead to delays and extended lead times. This goes back to the fact that this process has no additional capacity that can be used to catch up on defective units, which at least prevents negative impact on logistic service rate. This rate refers to the percentage of customer orders delivered on time and in full (Bower, 2021). Thus, we propose to assess the extent of late defect detection on each production process by evaluating the impact on reserve capacity:

$$\text{Impact on reserve capacity of process i} = \textit{reserve capacity of process}\ \mathrm{i} - \frac{D_{ji} \times t_i}{} \quad (4)$$

Where: t_i is the value-added time of process i per unit.

And reserve capacity of process is defined as:

$$\text{Reserve capacity} = 1 - \frac{\textit{busy capacity}}{\textit{scheduled capacity}} \quad (5)$$

If the impact on reserve capacity of process i is >0;

Then the process can at least catch up on the wasted product under normal operating conditions.

Otherwise, the value-added time loss for process i can lead to delays and it will impact the flow of the entire system.

QUALITY OF PROPOSED KEY PERFORMANCE INDICATORS

To assess the relevance of the proposed metrics, we have considered the SMART criteria (Sagala, 2022). SMART refers to an acronym for specific, measurable, achievable, relevant and time-bound. It is a widely used framework to ensure that KPIs are well-defined and effective (Efkarpidis et al., 2022).

Table 1 provides a summary of the conducted analysis based on SMART criteria.

Table 1: SMART analysis of proposed indicators.

SMART / KPIs	V.A.T loss	Impact on reserve capacity
Specific	It is focused on the impact of late defect detection on value-added time	It targets a specific loss related to the capacity of a process.
Measurable	It can be quantified	It can easily be tracked

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Achievable	Targets can be set based on factors such as the accuracy of the quality inspection system	We can define targets based on historical data.
Relevant	It reflects the impact on an important Lean factor: Value-added time	It's crucial since process capacity impact the production flow
Time-bound	It can be set in a clear time frame	It can be tracked in a clear time frame

SIMULATION AND RESULTS

IMPLEMENTATION

We used Arena, Siman based simulation software, to model a multi-stage production system. Figure 3 shows the structure of the system; it consists of 3 production process with an inspection process across the production flow.

We used the bloc Create to define the inputs of the production system, and to model each production stage. Process module allows to declare resources and capacities. Block Decide was used to model the inspection points; we defined a variable to declare the quality rate, which is calculated as the ratio of good detected products over the total produced units. The use of variables enables us to later compare the initially declared quality rates and those obtained after analyzing the impact of late defect detection.

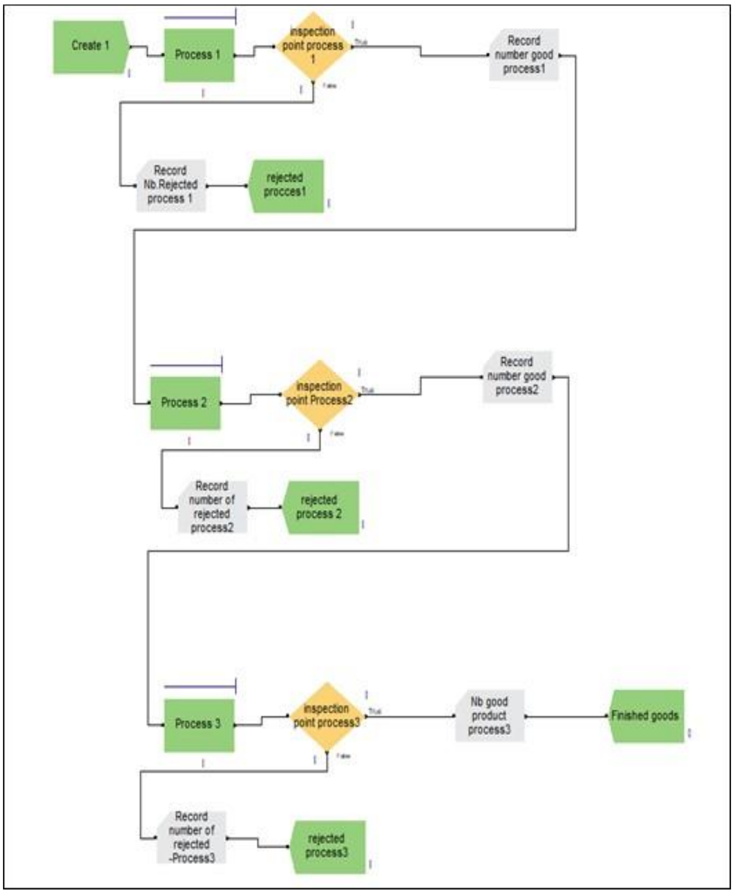

Figure 3: the implemented system

Table 2 lists the data input entered in each Arena module.

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Table 2 Arena modules parameters

Arena module	Parameters
Create	Time between arrivals: 6.5 minutes
Process 1	Delay type: Normal (3,1) (min)
Quality rate 1	98%
Process 2	Delay type: Normal (4,1) (min)
Quality rate 2	98%
Process 3	Delay type: Normal (7,2) (min)
Quality rate 3	96%

To count the number of good products and rejected ones, we used Record module, and to compute our proposed metrics, we defined the Key performance indicators through Record module, more precisely, trough the option 'Expression'.

We consider, after defect root analysis, that 15 defects that were detected at third inspection point, were actually occurred in earlier production stages as depicted in Table 3.

Table 3: defect root analysis

Number of defects	Detected at inspection point number	Occurred in process number
5	3	1
10	3	2

RESULTS AND DISCUSSION

We ran the simulation for one working week, assuming 16 working hours per day, 5 days per week, and using 10 replications. As shown in Table 4, the proposed metric V.A.T loss determine that 2.08 h was wasted on adding value to a defected product. The KPI of impact on reserve capacity shows that process 2 can make up for the defective units without causing any delays. In contrast, process 3 which is the bottleneck has lost due to late defect detection a capacity of production that is not recoverable under normal operating conditions. Furthermore, this analyze leads us to reconsider the effectiveness of the inspection systems used, and the impact of low recall on downstream processes. it can be a starting point to an improvement project of the ML based inspection system by analyzing why defects were not identified earlier.

Table 4: simulation results

Name	Average Of Replication Averages
good products process1	705,8
Rejected products process 1	14,1
good products process2	691
Rejected products process 2	14,9
good products process3	641,9
Rejected products process 3	25,9

V.A.T. loss (h)	**2,08**
reserve capacity process1(%)	0,5398
reserve capacity process2(%)	0,3953
reserve capacity process3(%)	0,00
Impact of missed defect on reserve capacity process 2 (%)	**0.3911**
Impact of missed defect on reserve capacity process 3 (%)	**-1,87**

To illustrate the importance of this analysis, we compared the initial quality rates to those that would have been obtained if defects were detected earlier to the nearest point where they have been occurred, so we can estimate the potential process improvement if the inspection system had operated with higher recall.

We used Arena tool Process Analyzer, and we varied the quality rate according to each scenario by the variable we had already identified in the block Decide. As shown in Figure 4, if defects were detected earlier, it would have prevented the decrease in the system output rate, since the bottleneck is controlling the output flow.

	Scenario Properties				Controls			Response
	S	Name	Program File	Reps	Q.rate process 1	Q.rate process2	Q.rate process 3	NB.good product process 3
1		Scenario 1	1 : model pape	10	98.0000	98.0000	96.0000	642
2		Scenario : if defects were detected earlier	1 : model pape	10	97.3000	96.5000	98.3000	657

Figure 4: Process Analyzer results

CONCLUSION

The current paper highlights that the indicator Recall of ML based inspection quality system is a key driver of process outcomes. We proposed practical key performance indicators to quantify the impact of late defect detection on multi-stage production system. The suggested metrics evaluate the value-added time wasted and the impact on reserve capacity. The motivation behind this work is that the indicators evaluating quality related loss such as OEE or first pass yield can be misleading and do not truly reflect process performances if we only consider the number of defects detected, without analyzing the root cause of these defects and whether we have managed to detect them as early as possible.

We simulated a multi-stage production system using Arena. We declared our proposed metrics in Record Block. The results showed the value-added time wasted, and that the impact of this loss on each process varies depending on the capability of a process to catch up the defects units under normal operating conditions.

As a future work, we plan to conduct a detailed study on a multi-stage production system, by first evaluating the impact of late defect detection on production system using our proposed KPIS, then setting an objective to improve these metrics by analyzing the root cause of a low Recall.

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