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Evaluating Manufacturing Systems Effectiveness Under Random Failures and Quality Disturbances

Amel Hajji
RIFTSI Laboratory, ENSIT, University of Tunis, Tunis, Tunisia
Industrial Engineering Department, ENIT, University of Tunis El Manar, Tunis, Tunisia
amel.hajji.12@gmail.com

Karem Dhouib
RIFTSI Laboratory, ENSIT, University of Tunis, Tunis, Tunisia
karemdhouib@yahoo.fr

Ali Gharbi
C2SP Laboratory, École de Technologies Supérieure (ÉTS), Montréal, Canada
Ali.Gharbi@etsmtl.ca.

Abstract

This paper evaluates the effectiveness of manufacturing systems operating under random failures and quality disturbances. Each manufactured part was inspected to be good or non-conforming. The non-conforming parts can be scrapped or reworked, considering its implications on system effectiveness. Three quality strategies are considered depending on specific industrial contexts: 1- reworking non-conforming parts until they meet specifications, 2- reworking parts with the possibility of scrapping them, and 3- scrapping parts even when they could be reworked. To analyze and evaluate the dynamic and stochastic behavior of these manufacturing systems, the paper presents analytical formulations based on a Markov chain approach. Simulation models replicating the real dynamic and stochastic behavior of these production systems were developed to validate the accuracy of the proposed analytical formulations. Finally, comparative studies, based on system effectiveness and economic aspects, were carried out between these considered quality strategies.

Keywords
System effectiveness, Random failure, Scrap-Rework, Markov chain, Simulation modeling.

1. Introduction
Given that the manufacturing ecosystem has become increasingly competitive over the past ten years, numerous corporations must adopt Industry 4.0 technologies, that involve AI, IoT, simulation, flexible manufacturing systems (FMS) with autonomous robots, AGVs, AS/RS, and Additive Manufacturing machines, in an effort to enhance their productivity and the quality of their goods (Abdullah et al. 2022; Ghobakhloo 2018; Dhouib and Ait-Kadi 1994; Wang et al. 2016). In this context, achieving high manufacturing effectiveness is crucial for meeting market demands and maintaining competitiveness. However, inherent imperfections in production processes, such as non-conforming parts, pose significant challenges (Soares et al., 2021). Once detected, these non-conforming parts require critical decisions: either they are rejected as scrap or reworked to meet required standards. To address these challenges, companies need strategies that not only resolve immediate issues but also optimize resources, reduce waste, and ensure long-term sustainability.

While rework can enhance yield and reduce waste (Jia et al. 2023), some companies prefer to reject non-conforming parts due to the perception that rework adds costs without increasing product value (Mona, 2022). This decision-making process becomes even more complex in highly regulated industries such as aerospace, pharmaceuticals, and food production, where strict quality and safety requirements must be met (Raza and Turiac 2016). In such contexts, it becomes imperative to evaluate the impact of rework and scrap strategies on overall system performance. This study examines strategies that balance effectiveness and quality management, focusing on the decision to rework or scrap parts to improve overall system performance.

1.1 Objectives

The main objective of this paper is to explore quality strategies and their impact on manufacturing systems effectiveness, particularly in the context of decisions related to reworking or scrapping non-conforming parts to enhance overall system performance. The specific objectives of this study are:

- Develop a Markovian analytical model to assess the impact of rejection of non-conforming parts on the overall effectiveness of manufacturing systems.
- Develop simulation models replicating the real stochastic behavior of these production systems to validate the accuracy of the proposed analytical formulations.
- Compare the proposed model's performance with existing models, including those that incorporate rework, highlighting their advantages in addressing quality-related challenges.
- Identify the best strategies for managing non-conforming parts, balancing effectiveness and quality across diverse manufacturing contexts.

The remainder of this paper is organized as follows: Section 2 presents a literature review for evaluating the performance of manufacturing systems considering quality issues. Section 3 describes the characteristics of the manufacturing system. Section 4 presents existing approaches and the proposed method for assessing effectiveness. Section 5 introduces the simulation model. Finally, Section 6 presents numerical and simulation results, and compares the proposed quality strategy to existing approaches.

2. Literature Review

Performance measurement of manufacturing systems is a critical issue from the managerial viewpoint. Manufacturing effectiveness is widely recognized as a critical performance metric in most manufacturing systems. In fact, it allows to assess several main Key Performance Indicators such as the system's throughput (Dhouib et al. 2008, 2009, 2010). The production system effectiveness is not only affected by its operational availability but it is significantly influenced by quality management decisions, such as rejecting non-conforming parts as scrap or reworking them to restore compliance, thereby reducing production costs.

In the literature, numerous studies focus on modeling manufacturing systems while considering quality issues (Bouti et al. 1994; Nourelfath et al. 2016; Ait-El-Cadi et al. 2021; Bouabid et al. 2024-a). Some research has examined systems that incorporate rework processes (Pillai and Chandrasekharan 2008; Hadjinicola 2010; Chao et al. 2022; Zhou and Zha 2023), where reworked parts may undergo either a single rework (Davis and Kennedy 1987; Pillai and Chandrasekharan 2008; Biller et al. 2010; Ni et al. 2021; Jia et al. 2023) or an infinite number of rework attempts (Kimbler et al. 1989; Hadjinicola 2010). Conversely, other studies have focused on modeling manufacturing systems that address only scrap, completely overlooking rework processes (De Ron and Rooda 2005; Ahmad et al. 2018; Ait-El-Cadi et al. 2024; Bouabid et al. 2024-b).

Although significant research has been conducted to evaluate the performance of manufacturing systems addressing quality issues, most existing models are based on approximate techniques (De Ron and Rooda 2005 & 2006; Pillai and Chandrasekharan 2008; Biller et al. 2010; Ni et al. 2021). Additionally, these studies often overlook the impact of system failures. Moreover, while several studies focus on rework and its benefits for enhancing yield and reducing waste (Jia et al. 2023), some companies still prefer to reject non-conforming parts, even when rework is feasible. This choice is frequently motivated by concerns over increased lead times and higher costs associated with rework, which may exceed the cost of rejection.

These perceptions highlight the need to choose a quality strategy that fits the system's goals and constraints. The next section describes the studied systems and present approaches to evaluate their effectiveness, considering both quality issues and system failures.

3. Problem description

3.1 System description and notations

This study examines a system including an automated production machine that produces a single product type, with each component being checked for conformance (Figure 1).

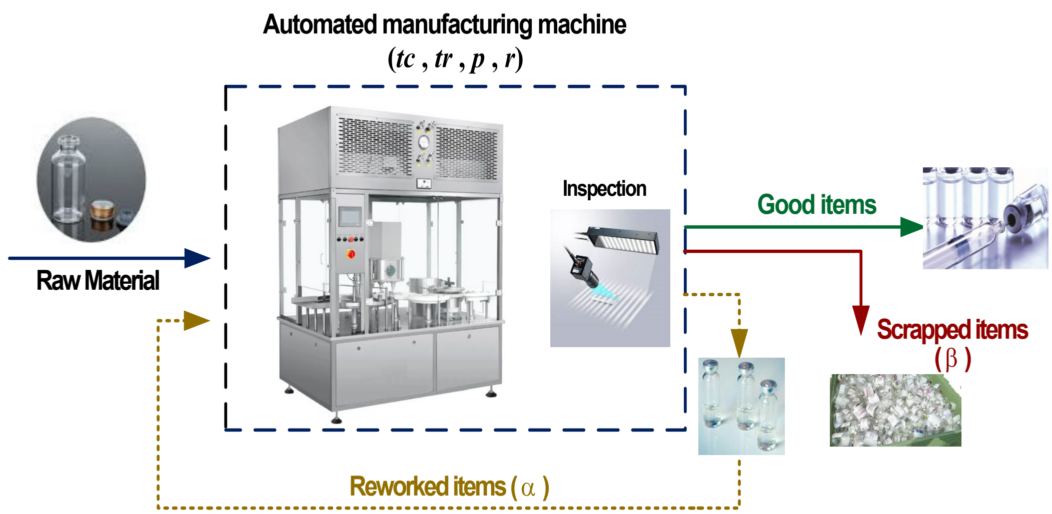

Figure 1. Manufacturing system description.

All parts require the same amount of processing time, including inspection delay, which is designated as the cycle time (tc). The final product might be classified as satisfactory, trashed with probability β, or reworked with probability α. The production system is prone to sporadic breakdowns and repairs. With corresponding probabilities p and r, the operational uptimes and repair times have geometric distributions. When the system is operating, it performs at its peak efficiency.

3.2 Manufacturing effectiveness

Manufacturing effectiveness, denoted as E, is a key performance indicator that represents the proportion of time a system produces conforming parts. This metric is often referred to Overall Equipment Effectiveness (OEE), which combines three critical factors: availability, performance, and quality rates (SEMI E79-1106). Therefore, effectiveness is commonly expressed by equation 1.

$$E = UTR \cdot PR \cdot QR \tag{1}$$

In this equation, UTR represents the Up Time Ratio, corresponding to the proportion of time the system is operational. PR denotes the Performance Ratio, which measures the system's operational efficiency relative to its maximum potential. Finally, QR refers to the Quality Ratio, which quantifies the proportion of good parts produced relative to the total number of parts. For automated manufacturing systems, as considered in this study, the Performance Ratio (PR) is often assumed to be 100%, indicating that the machine operates at its optimal performance level when running.

Thus, the manufacturing system effectiveness is influenced by quality management decisions, such as rejecting non-compliant parts or reworking them. In the next section we will explore quality decisions and their impact on system effectiveness by considering different quality strategies.

4. Modeling effectiveness considering quality issues

In this section, we present analytical models to evaluate the effectiveness of production systems that integrate both quality issues and system failures. We examine three quality strategies related to some specific industrial contexts: 1- Reworking non-conforming parts until they meet specifications (Strat. 1), 2- Reworking parts with the possibility of scrapping them (Strat. 2), and 3- Scrapping parts even when they could be reworked (Strat. 3).

4.1 Reworking non-compliant parts

The first quality strategy explores production systems affected by machine failures and quality issues, where non-conforming parts are subject to rework actions (Strat. 1). The model used for this scenario is based on the approach proposed by Hajji et al. (2024), where parts can undergo an infinite number of reworks attempts to be rectified and converted into good parts. The resulting system effectiveness is expressed by equation 2.

$$E = \frac{r}{p+r}(1-\alpha) \tag{2}$$

4.2 Reworking or scrapping non-compliant parts

The second strategy consider the combined effects of machine failures and reworking or scrapping non-conforming parts on the manufacturing system effectiveness (Strat. 2). The model used here is based on the approach proposed by Hajji et al. (2025), which makes the assumption that there would be an infinite number of rework actions. The effectiveness is then expressed by equation 3.

$$E = \frac{r}{p+r}(1-\alpha)(1-\beta) \tag{3}$$

4.3 Scrapping non-compliant parts even they can be reworked

In this paper, we propose an analytical model to evaluate the performance measures of a manufacturing machine rejecting non-compliant parts even though they could potentially undergo rework (Strat. 3). The stochastic-dynamic behavior of such manufacturing machines can be modelled by the Markov chain diagram presented in Figure 2.

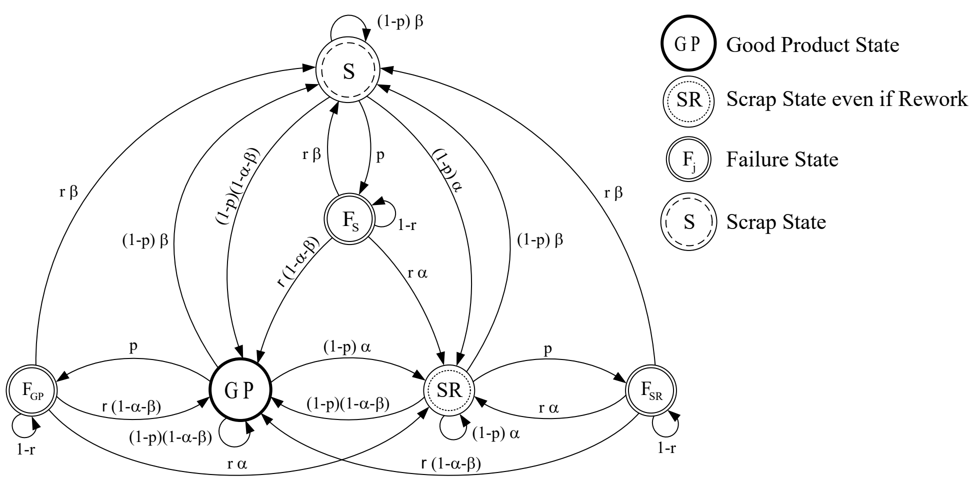

Figure 2. Markov chain model of the manufacturing system operating under the quality strategy 3

Thus, the manufacturing machine can be in one of the following 6 states : state GP if after inspection the product is found to be good, scrap state S if the product is found non-conforming and must be scrapped, scrap state SR if the product is found non-conforming and will be scrapped even it can be reworked, and failure states F_{GP}, F_S, and F_{SR} associated to states GP, S, and SR, respectively.

The machine begins operating at state GP by manufacturing a new item. Once the production cycle is achieved, the item is inspected to be:

- good and the system remains in state GP,
- reworked and the system transits to scrap state SR, even it can be reworked (with probability α), or
- scrapped and the system transits to state S (with probability β).

If a failure occurs while the machine is in state GP, S, or SR, it transits to the respective failure state F_{GP}, F_S, or F_{SR} where it remains in this state until maintenance activities are achieved.
According to the Markov model of figure 2, the effectiveness can be evaluated by resolving the 6 Chapman-Kolmogorov equations (4).

$$\begin{aligned}
P_{GP} &= (1-p)(1-\alpha-\beta)P_{GP} + r(1-\alpha-\beta)P_{F_{GP}} + (1-p)(1-\alpha-\beta)P_{SR} + \\
&\quad r(1-\alpha-\beta)P_{F_{SR}} + (1-p)(1-\alpha-\beta)P_S + r(1-\alpha-\beta)P_{F_S} \\
P_{F_{GP}} &= pP_{GP} + (1-r)P_{F_{GP}} \\
P_{SR} &= (1-p)\alpha P_{GP} + r\alpha P_{F_{GP}} + (1-p)\alpha P_{SR} + r\alpha P_{F_{SR}} + (1-p)\alpha P_S + r\alpha P_{F_S} \\
P_{F_{SR}} &= pP_{SR} + (1-r)P_{F_{SR}} \\
P_S &= (1-p)\beta P_{GP} + r\beta P_{F_{GP}} + (1-p)\beta P_{SR} + r\beta P_{F_{SR}} + (1-p)\beta P_S + r\beta P_{F_S} \\
P_{F_S} &= pP_S + (1-r)P_{F_S}
\end{aligned} \tag{4}$$

The resolution of these state transition equations gives the stationary probabilities of the different states (Eq. 5).

$$\begin{aligned}
P_{GP} &= \frac{r}{p+r}(1-\alpha-\beta) \\
P_{F_{GP}} &= \frac{p}{p+r}(1-\alpha-\beta) \\
P_{SR} &= \frac{r}{p+r}\alpha \\
P_{F_{SR}} &= \frac{p}{p+r}\alpha \\
P_S &= \frac{r}{p+r}\beta \\
P_{F_S} &= \frac{p}{p+r}\beta
\end{aligned} \tag{5}$$

Based on the steady-state probabilities (Eq. 5), the manufacturing machine effectiveness can be evaluated, which is equal to the probability that the system is in the GP state while producing good parts (Eq. 6).

$$E = \frac{r}{p+r}(1-\alpha-\beta) \tag{6}$$

The availability is determined by equation (7) excluding states during which it is in a failure mode (F_j with j = GP, S, and SR).

$$UTR = 1 - \left(\sum_j P_{F_j}\right) = \frac{r}{p+r} \tag{7}$$

5. Simulation model

A simulation model was developed using the ARENA software to study the stochastic and dynamic behavior of the manufacturing system under study (Figure 3) (Kelton et al. 2015). Multiple experiments were conducted by varying system parameters, including UTR, p, r, α, and β. Each simulation was run for 10,000,000 time units, with an initial warm-up period of 100,000 time units to ensure stable performance metrics. A total of five replications were carried out for each machine configuration.

The flowchart comprises five primary modules:

a. The INITIALIZATION module defines the system parameters such as UTR, p, r, α, and β for each experiment.
b. The PRODUCTION module runs the flow of parts within the machine.

c. The INSPECTION module checks the final product quality (good, scrap, rework).
d. The FAILURE & REPAIR module simulates machine breakdowns and repair durations.
e. The UPDATE PERFORMANCE module tracks the quantities of good parts, scrapped items, and rework activities throughout the simulation, enabling the assessment of production effectiveness.

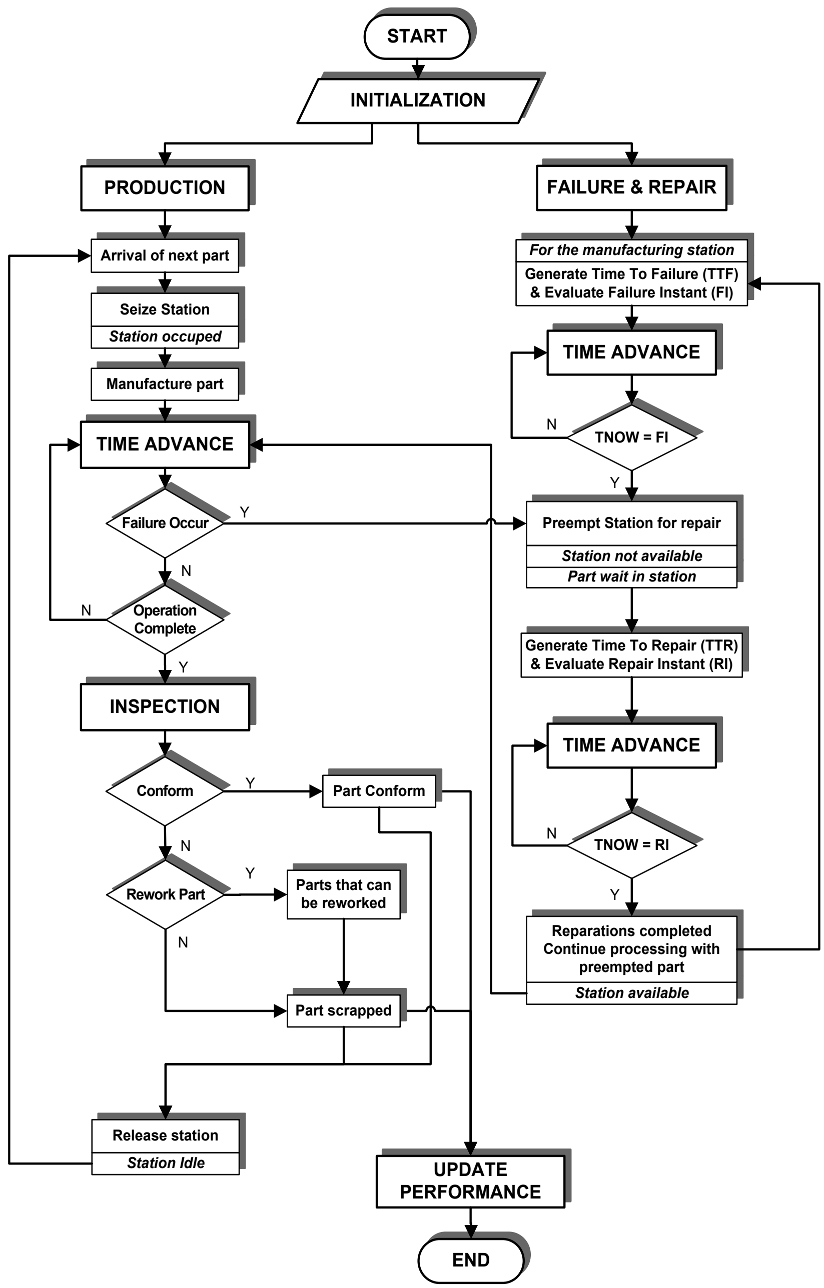

Figure 3. Simulation model flow chart for the manufacturing system operating under the quality strategy 3.

6. Results and Discussion

6.1 Simulation versus analytical results

To validate the various formulations explored in this study, hundreds of experiments were conducted across different configurations. For each configuration, we considered a range of operational, reliability, and quality parameters specific to the manufacturing system. Table 1 presents, for a manufacturing system operating under quality strategy 3, 10 randomly generated configurations each with varying reliability and quality parameters (p, r, α and β).

Compared to simulation results, Table 1 shows that the mean relative errors (Eq. 8) generated by analytical formulations of the manufacturing system effectiveness are negligible, which implies that the analytical results align with the simulation results.

$$\varepsilon(\%) = \frac{E_{sim} - E_{anal}}{E_{sim}}.100 \tag{8}$$

where E_{sim} and E_{anal} represent the simulated and the analytical value of the system effectiveness.

Table 1. Analytical and simulation results

	System parameters				***KPIs* (%)**			
Case	***p***	***r***	α	β	***UTR***	E_{anal}	E_{sim}	$\mathcal{E}$ **(%)**
Base	0.005	0.12	0.1	0.05	96	81.60	81.69	0.1100
1	0.003	0.147	0	0	98	98.00	97.95	-0.0500
2	0.007	0.133	0.1	0	95	85.50	85.41	-0.1000
3	0.008	0.192	0	0.1	96	86.40	86.47	0.0830
4	0.01	0.19	0.1	0.2	95	66.50	66.57	0.1060
5	0.006	0.094	0.2	0.1	94	65.80	65.80	0.0060
6	0.1	0.45	0.1	0.05	75	63.75	63.70	-0.0720
7	0.01	0.04	0.1	0.05	80	68.00	68.06	0.0813
8	0.005	0.03	0.05	0.1	87.5	74.38	74.45	0.1063
9	0.01	0.023	0.05	0.1	70	59.50	59.49	-0.0087
10	0.01	0.09	0.05	0.1	90	76.50	76.57	0.0957

6.2 Comparative study

In this section, we compare the proposed model presented in Section 3.3 with those presented in Sections 3.1 and 3.2. The comparison is conducted using the same reliability and maintainability parameters as those defined in the base case shown in Table 1, while varying quality probabilities α and β. Table 2 provides a detailed comparison between the three considered quality strategies.

Table 2. Manufacturing effectiveness considering quality issues

System parameters				**Effectiveness (%)**		
p	***r***	α	β	**Strat. 1**	**Strat. 2**	**Strat. 3**
0.005	0.12	0.1	0.1	86.4	77.76	76.8
0.005	0.12	**0.05**	0.1	91.2	82.08	81.6
0.005	0.12	**0.15**	0.1	81.6	73.44	72.0
0.005	0.12	**0.2**	0.1	76.8	69.12	67.2
0.005	0.12	0.1	**0.05**	86.4	82.08	81.6
0.005	0.12	0.1	**0.15**	86.4	73.44	72.0
0.005	0.12	0.1	**0.2**	86.4	69.12	67.2

Figure 4 also illustrates the effectiveness evolution of the manufacturing system, under each one of the three studied quality strategies, when varying quality parameters α and β. The analysis of Figure 4 and Table 2 yields the following key insights:

1. The effectiveness of the manufacturing machine, when considering Strat. 1, rework strategy converting a non-conforming product into a good one, is higher than when rejecting non-conforming parts, regardless of the values of quality parameters.
2. However, it is observed that the manufacturing system operating under Strat. 3, scrap a non-conforming product even it can be reworked, almost achieves the same level of effectiveness as if it is operated under Strat. 2, involving reworking or scraping non-conforming products.

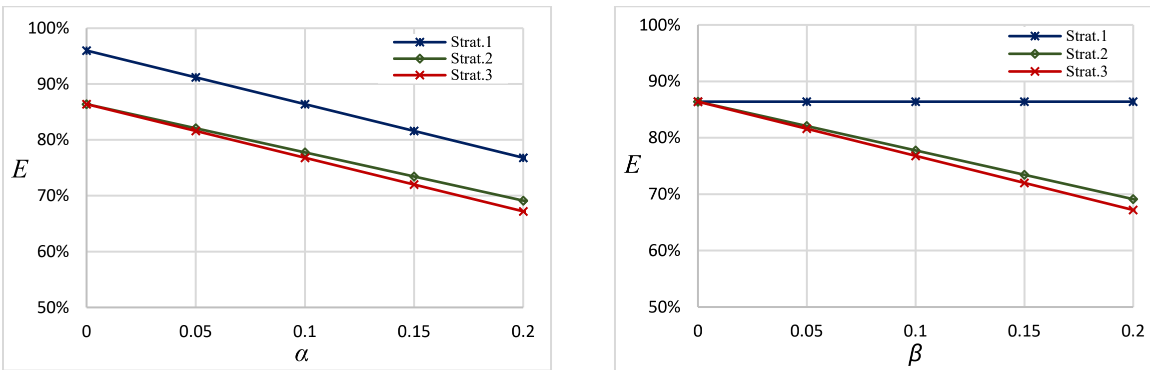

Figure 4. Manufacturing effectiveness evolution considering quality issues

In conclusion, these results show that the rework strategy yields better than the other ones. This indicates that reworking parts is often preferable to rejecting them in terms of effectiveness. However, the decision to rework or to reject a part depends on other factors beyond efficiency, mainly the production deadlines, the safety standard requirements, and the incurred costs. The following section focuses on the impact of the incurred costs, including raw material, operating, and reworking costs, on managers' decisions.

6.3 Managerial insight

While rework activities can improve effectiveness and enhance yield, they generally incur additional costs. These costs, such as those related to indirect costs associated with defect management, can influence managers' decisions. In this section, we illustrate this problem in the context of a pharmaceutical industry where the additional costs associated with rework directly impact the strategy chosen to manage defects and maintain the best operational performance.

The system being studied here is a medical ampule filling machine. The machine operates with a cycle time of 2 minutes. The mean time to failure is 10 minutes, and the failure probability is 0.05. The machine is subject to an inspection process where 5% of non-conforming parts are rejected, while 10% are reworked. The raw material costs \$2/unit, the operating cost of the filling machine is \$1.5/minute, and the non-recoverable tooling costs \$0.20/unit. Given these data, the average cycle time equals 2.5 minutes ($Tp = 2 + 0.05 \times 10$). Thus, the corresponding effectiveness without considering scrap and rework is 0.8.

Considering the scrap strategy (Strat. 3), the effectiveness is adjusted to 0.68. Then, the cost of a good part equals \$7 and is given by equation 9, considering that 10% of the parts are rejected even if they can be reworked.

$$Cpc = \frac{1}{0.85}\left(\$2 + \$1.5 \times 2.5 + \$0.2\right) = \$7/\text{unit} \tag{9}$$

These non-compliant parts can be reworked again and transformed into good ones via an extra operation at a cost (C_{rew}) of \$5 each. Then, the cost of a good part becomes \$6.45, and is given by the equation 10.

$$Cpc = \$2 + \$1.5 \times 2.5 + \$0.2 + 5 \times 0.1 = \$6.45/\text{unit} \tag{10}$$

Thus, the lowest cost per conforming part is obtained through the rework. However, if the rework cost increases, for example C_{rew} is \$12, the cost of a good part will be \$ 7.15/unit. Therefore, the decision to scrap the 10% of the non-compliant parts that can be reworked seems preferable in this case unless additional units are required to meet demand.

It is important to note that although rework may offer theoretical advantages in terms of effectiveness, it involves additional costs that could exceed the costs of rejecting non-compliant parts. To observe the impact of C_{rew} on the decision making, Figure 5 illustrates the variation of the cost of a good part according to different rework cost values.

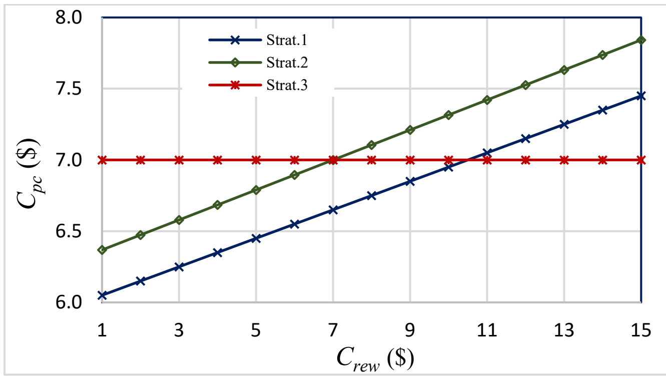

Figure 5. Evolution of the cost of a good part depending on C_{rew}

We can observe that the unit cost of a produced part remains constant under the rejection model (Strat.3), whereas it increases linearly with C_{rew} in the rework models (Strat.1 and Strat.2). It is also important to note that the costs of a good part for Strat.1 and Strat.2 are balanced and intersect with Strat.3 at specific break-even points. These break-even points correspond to specific values of C_{rew}, which is \$7 for Strat.2 and \$10.5 for Strat.1. If the rework cost exceeds these values, opting for Start. 3 becomes more cost-effective.

However, in several industrial contexts, the decision to rework or scrap parts is not only based on the rework cost of non-compliant parts. For example, when raw material prices rise due to supply chain disruptions, reworking may be more cost-effective than scrapping. On the other hand, if demand suddenly drops, scrapping the defective parts and producing new ones might be a better option to avoid unnecessary rework costs and minimize the risk of excess inventory.

To analyze the impact of rework and scrap parameters (α and β) on the unit cost of a produced good part, consider the case where the rework cost is \$11. Figure 6 shows that Strat. 2, which involves both reworking and rejecting non-compliant parts, always results in the highest unit cost, regardless of the values of α and β. Comparing Strat. 1 and 3, Figure 6 also indicates that for large values of α or low values of β (in this case, $\alpha > 8\%$ and $\beta < 4\%$), Strat. 3, which rejects non-compliant parts, results in a lower unit cost than Strat. 1, which includes only rework.

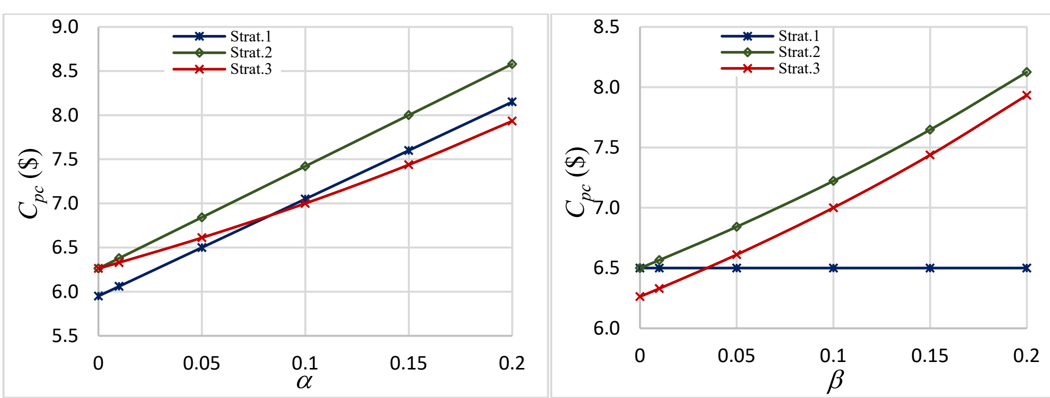

Figure 6. Evolution of the cost of a good part depending on quality parameters

This analysis supports strategic decision-making by comparing unit costs and effectiveness while considering quality and cost parameters. For example, in additive manufacturing or process molding, reworking a defective part is cost-effective when the defect is small and can be easily fixed, such as in the case of surface polishing. However, for larger defects, like a crack in an engine part or a misalignment in a mold (Figure 7), reworking may require expensive procedures like welding and testing. In such cases, rejecting the part and making a new one is often cheaper.

Figure 7. Mold alignment defect

7. Conclusion

This study evaluated the effectiveness of unreliable manufacturing systems by examining different approaches considering quality issues, including rework and scrap. A new Markov chain model was proposed to assess the system effectiveness where non-conforming parts are scrapped even when rework is possible. This model was validated through comparison with simulation results. The proposed approach is also compared against strategies that prioritize rework.

The results reveal that systems employing rework consistently outperform those relying solely on scrap in terms of effectiveness, regardless of the quality parameters α and β. Interestingly, under certain conditions, the rework-with-scrap approach exhibited effectiveness levels comparable to the scrap-only strategy.

Although rework theoretically offers significant advantages in terms of effectiveness, it also incurs additional costs that, in some cases, may exceed the costs associated with rejection of non-compliant products.

These findings highlight the need to align the chosen approach with the specific objectives of the manufacturing system, whether it is to maximize effectiveness or optimize costs. Future research could delve deeper into the cost implications of these strategies and expand the models to address more complex production environments, including multi-products, multi-machines, and buffer stocks. Adding environmental considerations could further enhance the models by addressing sustainability challenges, balancing resource use and material consumption, and reducing emissions. This aligns global sustainability goals and promotes eco-efficient manufacturing systems.

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Biographies

Amel HAJJI is an Assistant Professor at the 'École Supérieure PRivée d'Ingénierie et de Technologie' (Esprit), Tunisia. She is actually following a Ph.D. program in Industrial Engineering at the 'École Nationale d'Ingénieurs de Tunis' (ENIT), Tunisia. She is a member of the Laboratory of Intelligent Robotics, Reliability, and Signal & Image Processing (RIFTSI) at the 'École Nationale Supérieure d'Ingénieurs de Tunis' (ENSIT), Tunisia. His current research interests include cellular manufacturing, ERP, stochastic modelling, KPIs assessment, and production system performance improvement.

Karem DHOUIB, Ph.D. is an Associate Professor and Director of the Mechanical and Production Engineering Department at the 'École Nationale Supérieure d'Ingénieurs de Tunis' (ENSIT), Tunisia. He is also the Director of the Laboratory of Intelligent Robotics, Reliability, and Signal & Image Processing (RIFTSI) at the 'École Nationale Supérieure d'Ingénieurs de Tunis' (ENSIT), Tunisia. He teaches courses on Operations Management, Inventory Management, Optimization, Performance Modeling of Manufacturing Systems, and Simulation. He has worked in Tunisia, in Saudi Arabia, as well as in Canada. His research has been published in reputed journals like JMS, IJAMT, IJPR, OMEGA, and IJPE. Dr. Dhouib received the Habilitation Degree in Mechanical and Production Engineering from the 'École Nationale Supérieure d'Ingénieurs de Tunis' (ENSIT), Tunisia, a Ph.D. and a M.Sc.A. in Mechanical Engineering from Laval University, Canada, and B.Sc. in Mechanical and Production Engineering from University of Québec, Canada. His current research interests include Production planning and control, cellular manufacturing, Operations and Production Management, stochastic modelling, KPIs assessment, Simulation modelling, and Production system performance improvement.

Ali GHARBI, Ph.D. is a Full Professor in the Department of Systems Engineering at 'École de Technologie Supérieure' (ÉTS), Montréal, Canada. He is a leading expert in industrial engineering with significant contributions to optimizing unreliable manufacturing systems. His work has advanced the field by developing stochastic feedback control policies for manufacturing and remanufacturing systems, particularly in dynamic, unreliable environments. Over the past thirty years, Prof. Gharbi and his team have developed and refined a methodology based on the integration of optimal stochastic control theory with simulation-based optimization models. This methodology has made it possible to solve many complex problems related to the integration of production and maintenance strategies to handle machine failures, random demand variations, and product quality and perishability issues. His research has been widely recognized, earning over 6,000 citations and an h-index of 47. Prof. Gharbi has also supervised numerous postdoctoral researchers and doctoral and master's students, many of whom now hold prestigious academic and industrial positions. His collaboration with scholars and industries across various domains has resulted in over 130 high-impact publications in top-tier journals. He continues to innovate by developing policies that balance economic and environmental concerns.