Towards Eco-Efficient Production Planning: Stochastic Models Incorporating Quality Uncertainty and Environmental Impact

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Abstract. In industrial production, balancing demand volatility and customer lead times remains a critical challenge. Traditional production planning often assumes all manufactured products meet quality standards; however, defective parts detected during production can disrupt delivery schedules, leading to increased shipments to meet customer expectations. This not only affects customer satisfaction but also results in higher CO_2 emissions due to urgent premium transportation. This study addresses these challenges by integrating quality defect rates into daily production planning and transitioning from deterministic to stochastic approaches. The objective is to improve planning accuracy, mitigate the environmental impact of expedited shipments, and maintain high customer satisfaction. The methodology starts with a literature review of existing solutions, followed by a real-world automotive industry case study. Results highlight the effectiveness of the proposed model, providing decision-makers with multiple scenarios evaluated via a multi-criteria function to select the optimal plan, thus reducing premium shipments and supporting sustainable, customer focused production.

1 Introduction

The aim of this study is to present a new perspective on carbon footprint reduction by linking it to the use of premium shipments, which are often triggered to preserve customer satisfaction when planned output levels are not achieved due to quality defects. Specifically, the research focuses on integrating the defect rate into daily production planning and transitioning from a deterministic to a stochastic model. This approach seeks to reduce CO_2 emissions by minimizing the reliance on urgent transportation solutions caused by quality-related shortfalls.

Many manufacturing companies face challenges in meeting their output targets, frequently due to poor product quality. When defective parts are identified during production, the number of acceptable products decreases, directly disrupting delivery plans. These non-quality issues can lead to rework, production delays, and operational inefficiencies factors often overlooked in traditional planning methods, which assume that all outputs will be

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compliant. To maintain customer satisfaction in such situations, companies often resort to last-minute production efforts or premium transport, leading to increased costs and environmental impact.

In many industrial contexts, particularly those involving high production volumes and product diversity, achieving planned outputs remains difficult due to quality-related disruptions. While advanced technologies like machine learning, digital twins, and predictive analytics have shown promise in reducing defects and improving yield (Jun, Chang, et Jun 2020) (Qi et Tao 2018), their real-time integration into planning systems is still limited. Some research has attempted to incorporate inspection strategies into lot-sizing and scheduling (Bettayeb, Brahimi, et Lemoine 2018), yet most planning systems continue to operate under ideal conditions, failing to account for actual defect variability or its logistical consequences. Despite the progress in predictive maintenance and quality forecasting, a significant gap remains in how quality variability is incorporated into planning models especially in terms of environmental consequences. Traditional models largely ignore the link between quality-related shortfalls and the increased carbon footprint associated with premium shipments. Recent studies do support the use of stochastic programming to improve planning under uncertainty (Li et al. 2021) (Ben-Ammar, Bettayeb, et Dolgui 2020), but few have explicitly connected quality defects, environmental impact, and customer satisfaction within a unified, dynamic framework.

The added value of this paper lies in the use of historical defect data per workstation as an input for a stochastic planning model. The initial database covers six months of quality data, and the model is designed to dynamically update the defect prediction rate with each new planning cycle. This allows decision-makers to anticipate potential production shortfalls due to quality issues and proactively adjust plans to avoid unnecessary expedited shipments and related CO2 emissions.

This paper is structured as follows: it begins with a literature review presenting the existing solutions related to production planning, quality integration, and sustainability. This is followed by a real-world case study from the automotive industry to apply and validate the proposed approach. Finally, the results are presented and discussed, highlighting the positive impact of the model. Multiple scenarios are generated and evaluated using a multi-criteria decision-making function to support managers in selecting the most efficient and sustainable plan. The paper concludes by outlining future research directions.

2 Case study

2.1 Literature review

This literature review synthesizes a wide range of studies on the integration of production planning, scheduling, quality control, and transport optimization, within the evolving context of Industry 4.0 and the human centric and sustainable vision of Industry 5.0. A foundational distinction is drawn between interrelated and fully integrated models in production environments, especially those aiming to unify planning, maintenance, and quality functions (Hadidi, Turki, et Rahim 2012). Recent advances in digital twin systems and big data analytics have made it possible to design smart production environments that simulate, monitor, and optimize operations in real time, with demonstrated applications in high-complexity settings like satellite assembly (Zhuang, Liu, et Xiong 2018). Complementing this, Quality 4.0 initiatives have employed sensor networks, anomaly detection, and AI algorithms to predict defects and improve yield, even under constraints of limited or imperfect data (Md et al. 2022) (Jun et al. 2020). However, digital transformation remains

hindered by inaccurate or manually entered data, often linked to human error and organizational issues, underlining the need for better frameworks and tools to support the transition toward smart PPC (Lindström et al. 2023). Machine learning has become a powerful enabler for predictive planning and adaptive control, but its practical use is still limited by issues of data quality, model generalizability, and insufficient attention to real-time logistics, sustainability, and workforce adaptability (Usuga Cadavid et al. 2020).

In parallel, stochastic programming approaches have addressed the challenge of uncertainty in production inputs and process variability. Notably, these have been applied to optimize refinery operations under fluctuating crude oil qualities, yet limitations in scalability and computational intensity remain (Li et al. 2021) (Li et Grossmann 2021). Similarly, several studies integrate quality assurance into lot-sizing and inspection planning, supporting cost-effective compliance with quality standards, but many models still rely on simplifying assumptions, such as deterministic lead times and fixed inspection costs, which reduce their robustness (Bettayeb et al. 2018) (Ben-Ammar et al. 2020) (Galetto et al. 2020). Agent-based simulations and hybrid simulation-optimization models have demonstrated performance improvements up to 30% over traditional planning approaches (Nazabadi, Najafi, et Rasinojehdehi 2024), though their effectiveness may degrade in complex, multi-machine, or high-variability systems. Comparative research on big data and digital twin systems also reveals that their synergies can enhance smart manufacturing across the product lifecycle, but widespread implementation continues to be limited by infrastructure readiness and system integration challenges (Qi et Tao 2018) .

To further connect production with transport operations, various studies have proposed integrated approaches that align scheduling, inventory, and logistics decisions. For example, agent technologies combined with mathematical optimization have been proposed as a promising method to support decisions in production–transport systems (Holmgren, 2010). Heuristic methods have also been successfully applied to synchronize production and transport flows in multi-product industries such as bottled water (Zhong et al., 2013), while other work presents analytical models to optimize planning across manufacturing, reconditioning, and transport activities by considering ordering, transport costs, and capacity constraints (Abassi et al., 2023). Additionally, the optimization of transport direction tasks has been explored to minimize reconfiguration costs and improve raw material flows in production systems (Lesnikova et al., 2019). These contributions point to the growing importance of linking production and transport strategies, particularly as organizations adopt Industry 5.0 paradigms that emphasize flexibility, human-centric decision-making, and environmental sustainability. Quality 5.0, as a complement to this movement, calls for a rethinking of quality control systems by embedding intelligence, personalization, and resilience into every layer of the production and logistics network.

Overall, the reviewed literature indicates strong momentum toward integrating production, transport, and quality systems, supported by technologies from both Industry 4.0 and Industry 5.0. Nevertheless, significant challenges remain regarding data reliability, cross-system communication, and model adaptability to real-world uncertainties. Future research should prioritize hybrid approaches that bridge analytical optimization with intelligent systems and human centred design, to ensure robust, scalable, and sustainable production and logistics planning across dynamic industrial environments.

2.2 Stochastic model parameters

- EDI: Customer demand

- S: Number of scenarios
- T: Number of production shifts
- R: Number of references
- p: Man-hour difference – difference of the needed time for the production of 2 units
- D: Similarity matrix based on components and design of the product
- Threshold: Similarity threshold
- CAPchaine: Production line capacity
- m: Minimum number of good units to produce
- meancapacity: Mean capacity
- stddev capacity: Capacity standard deviation
- tauxdefaut: Defect rate
- i, j: Reference indices
- t: Shift index
- s: Scenario index
- Rework rate (α): the recoverability rate of defective parts (i.e., the fraction of defects that can be repaired or reprocessed)

2.3 Model variables

- x [i, j,s,t]: Binary variable indicating whether reference i is produced at position j during shift t in scenario s.
- $x_{i,j,s,t} = \begin{cases} 1 & \text{if reference } i \text{ is produced at position } j \text{ during shift } t, \text{scenario } s \\ 0 & \text{otherwise} \end{cases}$

- q[i,s,t]: Quantity of reference i produced during shift t for scenario s
- shortage [s, i]: Shortage quantity for scenario s and reference i

2.4 Objective function

The objective is to minimize the total cost, which includes:

- Labor cost due to the difference between consecutively produced references (weighted by the penalty matrix p[i][j])

- Shortage penalty, applied to unmet demand quantities.

Minimize $\sum s\in S \sum t\in T \sum i,j\in R$ p[i][j] × x[i,j,s,t] + penalite_de_penurie × $\sum s\in S \sum i\in R$ pénurie[s,i] [E]

2.5 Production constraints

- Demand Satisfaction [E1]:

For each scenario and reference, the quantity produced (considering rework and defects), plus any shortage, must cover the demand:
$\sum i\in R$ q [s, i, t] × (1 − tauxdefaut[s][i]) + α × q [s, i, t] × tauxdefaut[s][i] + penurie [s, i] ≥ EDI[i]

- q × (1 - tauxdefaut): Good pieces directly produced
- q × tauxdefaut × α
- shortage: Unmet quantity (e.g covered by stock or delay)

- Capacity Constraint [E2]:

The total load (including rework overhead) must not exceed available capacity:
$\sum i \in R\ q\ [s, i, t] \times (1 + \beta \times \alpha \times tauxdefaut[s][i]) \leq CAPchaine[s][t]$
β: Overload factor for rework (e.g a reworked unit "uses" more capacity)

- Sequencing Constraints [E3]:

One reference per position per period: $\sum i \in R\ x\ [i, j, s, t] = 1$

- [E4]:

Each reference has only one position: $\sum j \in J\ x\ [i, j, s, t] = 1$

- Similarity Constraint [E5]:

Encourage similar products to be produced in adjacent positions, to limit abrupt changes (e.g setup, tooling):
$D[i][k] \times x\ [i, j, t, t] \times x\ [s, k, j + 1, t] \leq seuil, \forall s \in S, \forall t \in T, \forall i, k \in R,$
$\forall j \in J\ [: -1]$
D[i][k]: similarity between references i and k
Threshold: Max dissimilarity allowed between successive references

- Shift Variation Constraint [E6]:

Limit variation of production quantity of reference i across shifts t_1 and t_2 (same scenario s):
$|q\ [s, i, t1] - q\ [s, i, t2]\ | \leq b \quad \forall s \in S, \forall i \in R, \forall t1, t2 \in T, t1 \neq t2$

- Minimum Production Constraint [E7]:

If a reference i is scheduled in a shift, the quantity produced must ensure at least m good units:
$q\ [s, i, t] \geq m / (1 - tauxdefaut\ [s, i]) \times \sum j \in R\ x\ [i, j, t]$

2.6 Multi criteria analysis

- Total Cost [E8]:

Global cost includes production and shortage penalties:
$\sum s \in S\ \sum i \in R\ \sum t \in T\ q\ [s, i, t] \times solution\_value + \sum s \in S\ \sum i \in R\ penurie\ [s, i] \times solution\_value \times 1000$
-1000: High penalty for each unit of unmet demand

- Demand Satisfaction Rate [E9]:

Measures how much of the demand is covered, accounting for repaired defects.
$(\sum s,t,i\ q\ [s, i, t] \times solution\_value \times [(1 - tauxdefaut[s][i]) + \alpha \times tauxdefaut[s][i]]) / \sum EDI$

- Capacity Utilization [E10]:

$(\sum s \in S\ \sum i \in R\ \sum t \in T\ (q\ [s, i, t] + \beta \times q\ [s, i, t] \times tauxdefaut) \times solution\_value) / \sum EDI$

Evaluates capacity consumption relative to customer demand.

- Production Stability [E11]:

Calculation of the average production variation between all shifts
Stability = 100 − (∑variations) / (nombre de variations)
variation = $|\sum i \in R\ q\ [s, i, t1] - \sum i \in R\ q\ [s, i, t2]\ |$

- Total Shortages [E12]:

Calculation of the total shortage quantities across all scenarios:
$\sum s \in S \sum i \in R$ penurie [s, i] × solution_value

3 Results and discussion

3.1 Simulation of planning code

The inputs of the stochastic model consist of several key parameters that feed into the mathematical formulation and influence the optimization results. All the parameters used are presented in the table below.

Table 1: Inputs of stochastic model

Parameters	Values
Scenarios	3
Shifts	3
EDI	[60, 45, 45, 55, 40, 50, 52, 58, 40, 42]
P : ManHour difference	[[0, 0.20, 0.30, 0.15, 0.25, 0.35, 0.12, 0.22, 0.32, 0.18], [0.20, 0, 0.40, 0.25, 0.35, 0.45, 0.22, 0.32, 0.42, 0.28], [0.30, 0.40, 0, 0.35, 0.45, 0.55, 0.32, 0.42, 0.52, 0.38], [0.15, 0.25, 0.35, 0, 0.30, 0.40, 0.17, 0.27, 0.37, 0.23], [0.25, 0.35, 0.45, 0.30, 0, 0.50, 0.27, 0.37, 0.47, 0.33], [0.35, 0.45, 0.55, 0.40, 0.50, 0, 0.37, 0.47, 0.57, 0.43], [0.12, 0.22, 0.32, 0.17, 0.27, 0.37, 0, 0.24, 0.34, 0.20], [0.22, 0.32, 0.42, 0.27, 0.37, 0.47, 0.24, 0, 0.44, 0.30], [0.32, 0.42, 0.52, 0.37, 0.47, 0.57, 0.34, 0.44, 0, 0.40], [0.18, 0.28, 0.38, 0.23, 0.33, 0.43, 0.20, 0.30, 0.40, 0]]
D : Similarity matrix	[[1.0, 0.2, 0.4, 0.3, 0.1, 0.5, 0.2, 0.3, 0.4, 0.1], [0.2, 1.0, 0.6, 0.4, 0.3, 0.2, 0.5, 0.4, 0.3, 0.6], [0.4, 0.6, 1.0, 0.5, 0.4, 0.3, 0.6, 0.5, 0.2, 0.7], [0.3, 0.4, 0.5, 1.0, 0.6, 0.4, 0.3, 0.7, 0.5, 0.4], [0.1, 0.3, 0.4, 0.6, 1.0, 0.5, 0.4, 0.6, 0.7, 0.3], [0.5, 0.2, 0.3, 0.4, 0.5, 1.0, 0.3, 0.2, 0.4, 0.6], [0.2, 0.5, 0.6, 0.3, 0.4, 0.3, 1.0, 0.5, 0.3, 0.7], [0.3, 0.4, 0.5, 0.7, 0.6, 0.2, 0.5, 1.0, 0.4, 0.5], [0.4, 0.3, 0.2, 0.5, 0.7, 0.4, 0.3, 0.4, 1.0, 0.6], [0.1, 0.6, 0.7, 0.4, 0.3, 0.6, 0.7, 0.5, 0.6, 1.0]]
m : nombre min d'unités à produire	5
Alpha_rework	0.8
Beta	1.2

Similarity threshold	0.95
b : maximum GAP between 2 shifts	10
Unit price of production	20 €
Penalty penurie	1000 €
Random variables of stochastic model	
mean_capacity	163/Shift
std_capacity : écart type de la capacité	10
mean_defaut : α rework	0.04
std_defaut : écart type du taux de défaut	0.01
Weight of the multi-criteria analysis	
Cost_ weight	0.25
Satisfaction_ weight	0.30
Utilization_ weight	0.20
Stability_ weight	0.15
Shortage_weight	0.10

3.2 Results of the stochastic model

The resolution was done using python, the results are as follow:

Scenario 1:
Total available capacity: 501.4
Rework rate per reference:
REF_01: 4.5% | REF_02: 3.9% | REF_03: 4.6% | REF_04: 5.5% | REF_05: 3.8%
REF_06: 3.8% | REF_07: 5.6% | REF_08: 4.8% | REF_09: 3.5% | REF_10: 4.5%

Shift 1:
Available capacity: 157.0
Production order: REF_02 → REF_07 → REF_01 → REF_09 → REF_06 → REF_08 → REF_10 → REF_03 → REF_05 → REF_04

Shift 2:
Available capacity: 181.5
Production order: REF_10 → REF_07 → REF_04 → REF_01 → REF_02 → REF_06 → REF_09 → REF_08 → REF_03 → REF_05

Shift 3:
Available capacity: 162.9
Production order: REF_02 → REF_06 → REF_09 → REF_10 → REF_04 → REF_01 → REF_05 → REF_08 → REF_03 → REF_07

Quantities produced for the different references under Scenario 1 across the 3 shifts:

Table 2: the quantities produced per shift

Reference	Quantities produced by shift1	Quantities produced by shift2	Quantities produced by shift3
1	20.9	34.6	5
2	5	35.3	5
3	5	5	35.3
4	5.1	5.1	45.5
5	19.4	5	15.9
6	5	4.3	5
7	5.1	5.1	26.9
8	48.5	5	5
9	30.2	5	5
10	5	32.3	5

GLOBAL KPIs – SCENARIO 1:

- Total demand: 487
- Total effective production: 471.6
- Total shortages: 15.4
- Overall satisfaction: 96.8%
- Capacity utilization: 100.0%
- Production cost: € 9517
- Shortage cost: € 15,414
- Total cost: € 24,931

Scenario 2:
Total available capacity: 474.4
Rework rate per reference:
REF_01: 3.5% | REF_02: 3.5% | REF_03: 4.2% | REF_04: 2.1% | REF_05: 2.3%
REF_06: 3.4% | REF_07: 3.0% | REF_08: 4.3% | REF_09: 3.1% | REF_10: 2.6%

Shift 1:
Available capacity: 152.4
Execution order: REF_10 → REF_06 → REF_07 → REF_01 → REF_04 → REF_08 → REF_03 → REF_09 → REF_02 → REF_05

Shift 2:
Available capacity: 171.2
Execution order: REF_01 → REF_02 → REF_03 → REF_10 → REF_08 → REF_07 → REF_04 → REF_05 → REF_06 → REF_09

Shift 3:
Available capacity: 150.8
Execution order REF_03 → REF_06 → REF_09 → REF_07 → REF_08 → REF_04 → REF_01 → REF_05 → REF_02 → REF_10

Quantities produced for the different references under Scenario 1 across the 3 shifts:

Table 3: the quantities produced per shift

Reference	Quantities produced by shift1	Quantities produced by shift2	Quantities produced by shift3
1	5	5	50.4
2	5	5	35.2
3	14	17.8	13.6
4	5	45.2	5
5	5	30.1	5
6	40.3	5	5
7	5	42.3	5
8	5	5	153
9	30.2	5	5
10	32.2	5	5

GLOBAL KPIs – SCENARIO 2:

- Total demand: 487
- Total effective production: 454.2
- Total shortages: 32.8
- Overall satisfaction: 93.3%
- Capacity utilization: 100.0%
- Production cost: € 9142
- Shortage cost: € 32,801
- Total cost: € 41,943

Scenario 3:
Total available capacity: 474.4
Rework rate per reference:
REF_01: 5.5% | REF_02: 3.8% | REF_03: 4.1% | REF_04: 2.6% | REF_05: 3.5%
REF_06: 4.1% | REF_07: 2.8% | REF_08: 4.4% | REF_09: 3.4% | REF_10: 3.7%

Shift 1:
Available capacity: 165.1
Execution order: REF_02 → REF_03 → REF_06 → REF_05 → REF_08 → REF_07 → REF_04 → REF_01 → REF_09 → REF_10

Shift 2:
Available capacity: 143.4
Execution order: REF_07 → REF_10 → REF_01 → REF_03 → REF_09 → REF_06 → REF_08 → REF_02 → REF_05 → REF_04

Shift 3:
Available capacity: 143.4
Execution order: REF_07 → REF_10 → REF_01 → REF_03 → REF_09 → REF_06 → REF_08 → REF_02 → REF_05 → REF_04
Quantities produced for the different references under Scenario 1 across the 3 shifts:

Table 4: the quantities produced per shift

Reference	Quantities produced by shift1	Quantities produced by shift2	Quantities produced by shift3
1	5.1	5.1	5.1
2	5	35.5	5
3	5	35.3	5
4	45.2	5	5
5	5	30	5
6	35.4	5	10
7	5	5	42.2
8	42.2	5	5
9	5	5	30.2
10	5	6	31.1

GLOBAL KPIs – SCENARIO 3:

- Total demand: 487
- Total effective production: 435.8
- Total shortages:51.2
- Overall satisfaction: 89.5%
- Capacity utilization: 100.0%
- Production cost: € 8780
- Shortage cost: € 51,175
- Total cost: € 59,956

Analysis of the results:

To compare the different production configurations in an uncertain context, a multi-criteria dashboard was developed to evaluate and distinguish the planning scenarios proposed by the stochastic model.

This dashboard aims to visually and quantitatively analyze the performance of the simulated scenarios based on several key dimensions: total cost, demand satisfaction, production stability, shortage rate, capacity utilization, and sensitivity to parameters.

This multi-criteria analysis thus helps identify the scenario that offers the best overall trade-off, based on industrial objectives.

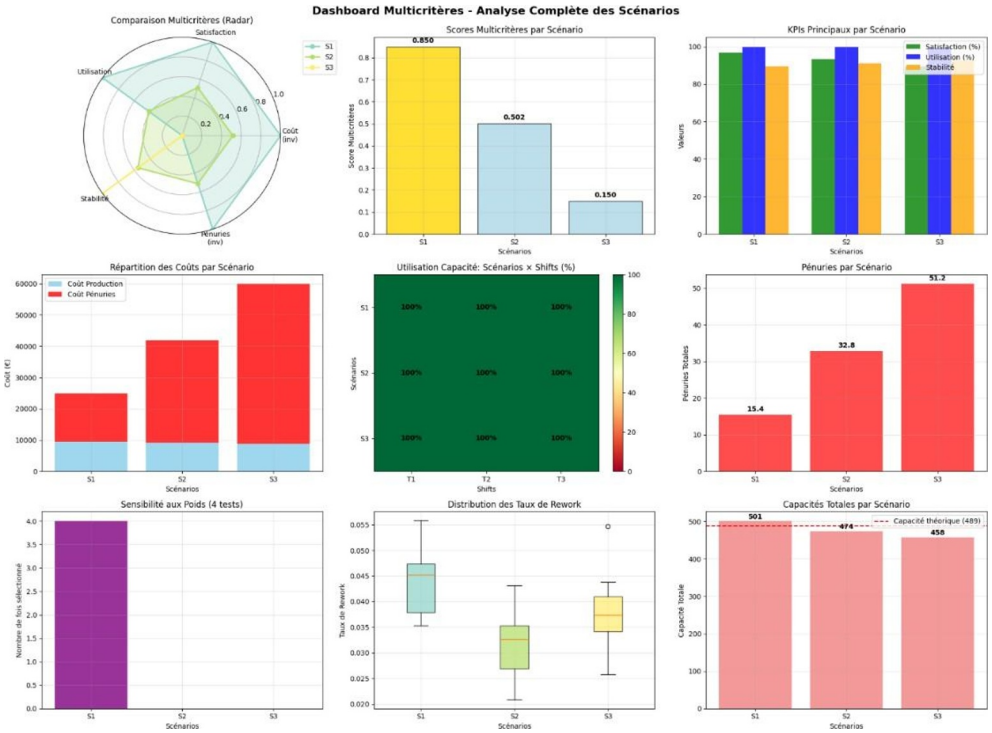

Figure 1: multi-criteria dashbord

- Multi-Criteria Radar: Provides a visual comparison of the five main criteria (satisfaction, utilization, stability, shortages, cost).

Scenario1 (S1) clearly stands out, with balanced and strong performance across all dimensions.

- Multi-Criteria Scores per Scenario: Displays a weighted overall score for each scenario, enabling direct comparison.

S1 achieves the best score (0.850), followed by S2, with S3 trailing far behind.

- Key KPIs per Scenario: Shows normalized values for demand satisfaction, capacity utilization, and stability. All three scenarios exhibit high-capacity utilization, but S1 is the most stable and best meets the demand.
- Cost Breakdown per Scenario: Differentiates between production cost (blue) and shortage cost (red).

S3 has a very high total cost, mainly due to shortages. S1 is the most economical.

- Capacity Utilization per Scenario and Shift: Shows consistent 100% capacity usage across all shifts and scenarios, indicating a planned saturation of resources.
- Shortages per Scenario: Displays the total shortages per scenario.

S1 performs very well with only 15.4 units missing, whereas S3 exceeds 50 units, which is critical.

- Sensitivity to Weights: Measures the robustness of the scenario ranking against variations in multi-criteria weights.

S1 remains the top performer in all tests, confirming its robustness.

- Rework Rate Distribution: Illustrates the variability of rework rates per scenario.

S1 has higher average rates but with a tighter distribution, which may explain its effective planning management.

- Total Capacities per Scenario: Compares the total realized capacity in each scenario to a target theoretical capacity (dashed red line).

S1 is the only scenario that exceeds the target capacity, ensuring better demand coverage.

As part of this phase, a prediction model was implemented to estimate defect rates based on historical production data. The goal is to feed the stochastic planning model with more reliable and scenario-specific input data. Using predicted rework rates enhances the accuracy and robustness of planning decisions under uncertainty. The practical integration of these predictions into the decision-making process will be addressed in the next phase.

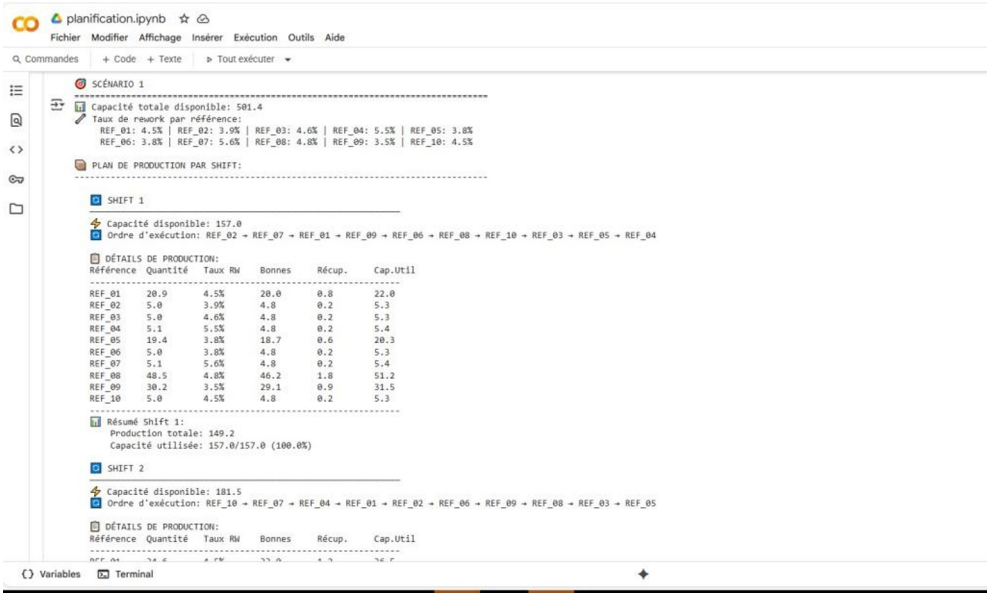

Figure 2: The results displayed in python

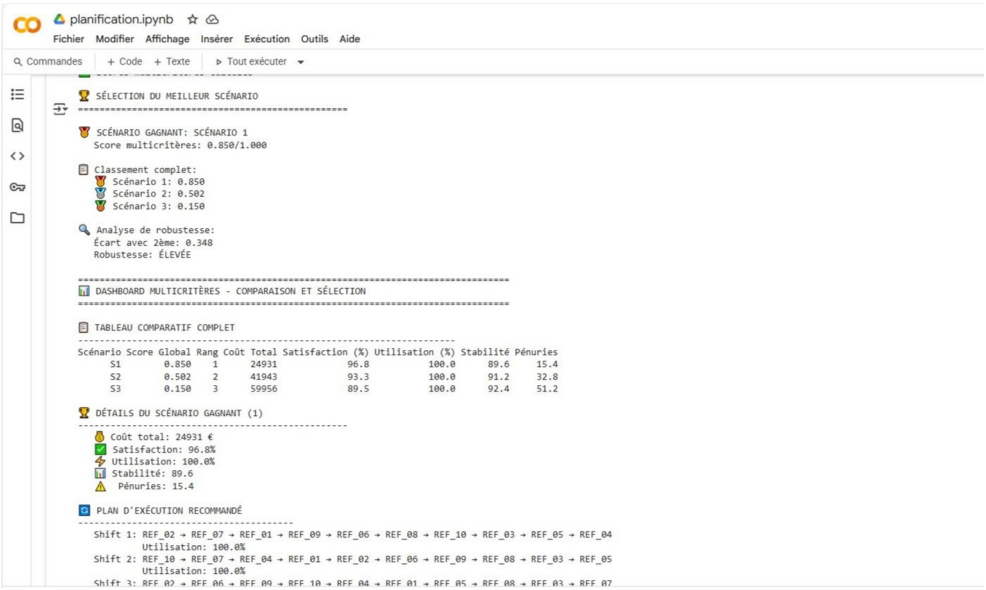

Figure 3: The multi-criteria analysis in Python

4 Conclusion and perspectives

This study demonstrates the benefits of integrating quality defect rates into production planning to move from a deterministic to a stochastic model. By accounting for non-quality issues, the proposed approach enhances planning reliability, reduces the need for premium shipments, and supports both environmental sustainability and customer satisfaction. The automotive case study confirms the model's ability to generate practical, optimized scenarios for real-world application.

Looking ahead, future research will focus on expanding this approach to multi-site operations and incorporating real-time quality data for more responsive planning. Additionally, refining the decision-making process through IA advanced optimization techniques and predictive analytics will further strengthen the model's effectiveness in complex manufacturing environments.

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