

From Fragmentation to Integration: Automating Cross-Functional Planning Workflows for Proactive Production Management

Douiri Rokaya, Taraa Chaymae, Dadda Afaf, Elmoussami Haj and Ezzine Latifa

Research Team: Modeling and Optimization of Industrial Systems

ENSAM School, Moulay Ismail University

P.O. Box 15290, Al Mansour, Meknes 50000, Morocco

r.douiri@edu.umi.ac.ma, taraa.chaymae@gmail.com, afaf_dadda@yahoo.fr,

h.elmoussami@umi.ac.ma, latifae@yahoo.com

Abstract

Contemporary manufacturing systems suffer from misalignment between production planning and operational execution due to fragmented processes and the separation of quality and planning functions. This paper introduces an integrated operational decision support application that unifies quality and production planning within a continuous workflow, enabling proactive capacity management and real-time alignment between planned and actual production. By embedding quality-induced capacity deviations directly into planning activities, the system improves decision consistency, resource utilization, and schedule reliability. The proposed framework supports human expertise by automating routine coordination tasks and allowing greater focus on value-adding activities. Its effectiveness is demonstrated through an industrial case study, highlighting improved agility and operational performance in line with Industry 5.0 principles.

Keywords

Quality–production integration, Workflow automation, Capacity management, Operational excellence, Human-centric manufacturing

1. Introduction

Production planning stands as a cornerstone of manufacturing competitiveness, yet contemporary research reveals persistent misalignment between planning systems and operational reality. A comprehensive analysis of production planning approaches in Industry 4.0 contexts identifies five critical dimensions—planning activities, planning horizon, data sources, company size considerations, and solution approaches—that shape how organizations manage their production workflows (S. Daniel Bird 1997). Furthermore, research demonstrates that optimal resource allocation in high-mix, low-volume manufacturing requires integrated bottleneck analysis and multi-objective optimization [2,3] (Virginia Fani et al 2023; May et al., n.d.), and decision aid frameworks for Aggregate Production Planning reveal that strategy selection demands comprehensive evaluation across multiple demand scenarios (Tariq et al. 2021). Recent innovations in manufacturing automation offer promising pathways toward integration: human-robot collaborative scheduling demonstrates how proactive planning combined with reactive adjustments can optimize performance when task durations deviate from predictions (Tóth et al. 2023). Integrated frameworks combining digital twins with dynamic scheduling enable adaptive execution in collaborative environments (Tchane Djogdom et al. 2024), and sustainable digital transformation methodologies show that combining collaborative robotics with artificial intelligence and lean principles can simultaneously improve flexibility and reduce coordination complexity (Hémono et al. 2024). However, despite these technological advances, manufacturing environments continue to suffer from fragmented processes, information silos, and the functional separation of quality management and production planning

(Daniel et al., 1997; Virginia et al., 2023). The root cause lies in systemic disconnecting quality management systems operate independently from production planning workflows, creating information islands where insights from quality control remain disconnected from capacity allocation decisions (Bento et al. 2020; Hirunyawipada et al. 2010), perpetuating reactive decision-making where organizations respond to problems after they occur rather than anticipating and preventing them. Beyond technological barriers, organizational factors compound this challenge. Cross-functional integration requires transforming individual tacit knowledge into collective organizational knowledge through structured socialization (Abraham and Reddy 2010), yet inter-departmental coordination often reveals significant gaps in communication and information sharing (Wettre et al. 2019). Advances in visual communication and systemic team coaching show promise for breaking organizational silos (Orkamo et al. 2025), yet these interventions remain ad hoc rather than embedded in operational systems. The shift toward Industry 5.0 principles emphasizing human-centric, value-driven collaboration between humans, artificial intelligence, and innovative technologies (Soleimani and Sari 2026) demands that planning systems transcend technology-centric approaches and integrate human expertise as a core component rather than a peripheral consideration. This work addresses the persistent gap between planning intent and operational reality by proposing an operational decision support application that consolidates quality and production planning functions into a unified, continuous workflow. Rather than replacing human coordination, the system automates routine planning tasks and facilitates cross-functional interactions, enabling operators to focus on value-adding and improvement-oriented activities. This approach directly advances operational excellence (Zhang et al. 2025) by enabling proactive capacity management and reducing the redundancies that characterize fragmented planning. Grounded in Industry 5.0 principles (Soleimani and Sari 2026), the proposed framework demonstrates through a representative industrial case study addressing rework-related capacity deviations how integrated planning workflows can enhance agility, efficiency, and human-centric manufacturing practices.

1.1 Objectives

The aim of this article is to integrate operational decision support application that unifies quality and production planning within a continuous workflow, enabling proactive capacity management and real-time alignment between planned and actual production.

2. Literature Review

Production planning is a critical capability in modern manufacturing, encompassing five key dimensions: planning activities, planning horizons, data sources, target company size, and solution approaches (S. Daniel Bird, 1997). However, a significant gap persists between academic research and industrial implementation, with 74% of reviewed studies failing to validate their models in real-world contexts, particularly for small and medium-sized enterprises (SMEs) (S. Daniel Bird 1997). This fragmentation stems from persistent misalignment between production planning and operational reality, compounded by the functional separation of quality management from production planning activities.

Traditional quality management has relied on reactive control mechanisms, yet contemporary research emphasizes a paradigm shift toward proactive quality management through intelligent support technologies. This transition requires comprehensive frameworks integrating quality function deployment (QFD) and decision support systems as essential prerequisites for cross-functional quality management (Bento et al. 2020). The technological infrastructure supporting planning compounds this fragmentation, as legacy systems remain the most frequently cited data source (27% of reviewed applications), while cyber-physical systems are utilized in only 23% of applications (S. Daniel Bird 1997). This infrastructure gap perpetuates information silos—termed "information islands"—where isolated enterprise systems with heterogeneous protocols prevent seamless integration and efficient cross-system information flow (Hirunyawipada et al. 2010).

Recent advances demonstrate significant potential for addressing these challenges. A framework combining Association Rule Mining (ARM) and Discrete Event Simulation (DES) enables organizations to identify production bottlenecks and evaluate improvement actions (Tariq et al. 2021). For specific planning challenges, decision aid frameworks for Aggregate Production Planning (APP) evaluate performance of basic strategies (chase, level, overtime, and subcontracting) across various demand scenarios (Maya et al., 2025.). Simulation-based decision support systems incorporating bottleneck analysis and multi-objective optimization with meta-learning have

demonstrated substantial improvements in high-mix, low-volume environments, with the NSGA-II-ML algorithm achieving 24% improvement in throughput compared to current performance (Maya et al.,2025.).

Beyond technological barriers, organizational factors significantly impact planning effectiveness. Cross-functional integration requires transforming tacit knowledge into collective organizational knowledge through structured socialization (Abraham and Reddy 2010). However, qualitative research has identified three major coordination obstacles: ineffective inter-departmental interactions, ineffective information handoffs, and unintended consequences of information technologies (Wettre et al. 2019). Innovative workshops combining giga mapping and systemic team coaching have improved cross-functional collaboration through visual communication (Orkamo et al. 2025), with 41% of empirical applications reporting successful silo bridging with positive outcomes (Maya et al.,2025.).

Leadership plays a critical role in enabling integrated planning systems. Systematic reviews examining leadership behaviors in digital transformation have identified four performance dimensions: effective leadership, digital acceptance, digital competence, and digital innovation . Task-oriented leadership positively relates to digital competence, while relation-oriented behaviors support digital acceptance and innovation . Emotional intelligence emerges as a critical moderator for balancing contradictory leadership behaviors and adapting to organizational context (Laouenan et al. 2022).

The evolution toward Industry 5.0 represents a fundamental shift from Industry 4.0's technology-centric approach to a human-centric, value-driven model. The industry 5.0 Collaboration Architecture (I5arc) integrates humans, artificial intelligence, and innovative technologies, emphasizing resilience, sustainability, and human empowerment (Soleimani and Sari 2026). Within this context, human-robot collaborative (HRC) environments present specific challenges, with research proposing two-level scheduling approaches combining offline proactive planning with online reactive adjustments (Valencia et al., n.d.). An integrated framework combining digital twins (DTs), dynamic scheduling, and automatically generated behavior trees (BTs) demonstrates a 28.57% reduction in maximum operator workload while maintaining minimal execution impact (Tchane Djogdom et al. 2024). For SMEs, the "Flexibilization 4.0" framework combines collaborative robotics, artificial intelligence, and vision systems with lean manufacturing principles, achieving key performance targets including mobile collaborative robots capable of station changes in under 6 minutes (Hémono et al. 2024).

Mathematical optimization approaches enhance system efficiency through comprehensive frameworks. A two-stage framework integrating Pre-Digital Twin and full-scale Digital Twin technologies demonstrates 100% elimination of machine failure impact through job reallocation, 33% reduction in aisle congestion delays, and 37% decrease in buffer overflow delays (Azab and Pourvaziri 2025). Complex assembly line balancing with multi-criteria optimization achieved cost savings of 10.6% reduction (€1.36 million over three years), 43.4% space reduction, and 3.06% production volume increase (Schäfer et al. 2025).

Quality control remains critical for integrated production planning. Comprehensive reviews of quality control in robot-based manufacturing machine vision as the most widely studied inspection method, leveraging deep learning and AI . Digital twin technology shows promise for predictive maintenance and real-time quality monitoring (Papavasileiou et al. 2025). Machine learning approaches provide additional tools for predictive decision-making, with neural networks ranking highest in usage (21 articles), followed by decision support systems (20 articles) in reviewed AI literature . Five key driving forces enable operational excellence through AI adoption: improved computing abilities, data-based AI development, deep learning advancements, cloud computing, and data management capabilities . However, four major barriers persist: cultural constraints, fear of the unknown, lack of skills, and lack of strategic planning (Zhang et al. 2025).

As manufacturing becomes increasingly automated, safety frameworks are critical. A unified safety framework integrating ISO 26262 (functional safety), ISO 21448/SOTIF (Safety of the Intended Functionality), and UL 4600 (autonomy safety) combines System-Theoretic Process Analysis (STPA) with Hazard Analysis and Risk Assessment (HARA) to systematically address both fault-based and performance-based risks (Trentesaux and Thomas 2012).

Intelligent enterprise system integration solutions address data isolation challenges. A knowledge graph-based approach combining graph theory with visual workflow orchestration demonstrates 80% reduction in cross-system development cost, 60% improvement in process arrangement efficiency, and 75% reduction in problem location time (Hirunyawipada et al. 2010). An emerging paradigm, Product-Driven Control (PDC), shifts from centralized

hierarchical architectures to distributed intelligent systems where products become active agents, achieving 4% reduction in lead time and 6% reduction in Work-in-Progress (Basharat et al. 2025).

Despite progress in individual planning components, significant gaps persist in achieving comprehensive cross-functional integration. The fragmentation between quality management and production planning, persistent organizational silos, and limited industrial validation remain critical challenges. Future work must focus on integrating these components into operationally viable systems maintaining human-centric principles while advancing Industry 5.0 objectives of resilience, sustainability, and collaborative human-AI manufacturing. Addressing these limitations requires integrated decision support applications that explicitly connect quality defect prediction with production planning, transforming quality information from reactive control into proactive planning drivers and enabling systems to account for expected capacity losses from quality defects when generating production plans.

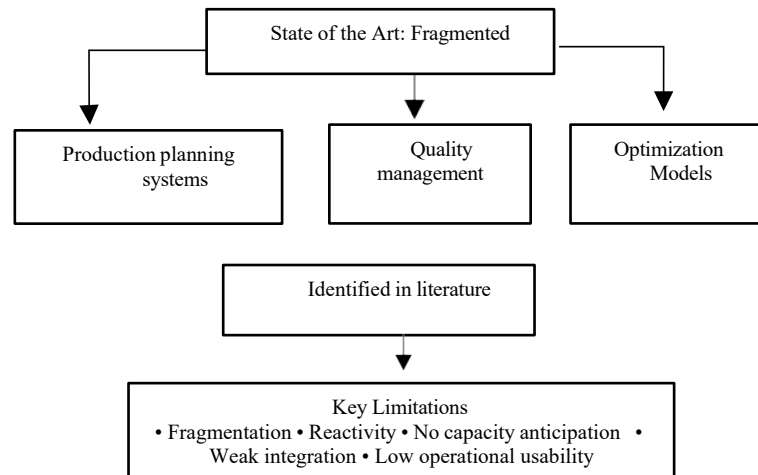
3. Methods

This work builds upon a research trajectory spanning two previous scientific communications. The first (Douiri et al 2025) focused on predicting quality defects using statistical models, revealing significant limitations regarding non-normal error distributions and the difficulty of selecting a single global model. Consequently, machine learning models were optimized separately for each workstation using mean squared error (MSE) as the performance criterion. The second communication (Tarra et al 2025) extended this work by integrating defect prediction into production planning through a stochastic mathematical model, treating production.

line capacity and rework rate as random variables to account for various influencing factors and prediction uncertainty.

The present work establishes a direct link between these developed models and an operational decision support application. Stochastic outputs are exploited through scenario generation, enabling planners to evaluate alternative capacity configurations and rework-related deviations. Rather than introducing an additional standalone optimization model, the application orchestrates existing data, predictive models, and planning routines into an operationally meaningful decision- support system, designed as a modular yet unified planning framework that consolidates quality and production planning activities into a single, continuous workflow.

The approach consists of four interconnected layers. First, historical quality defect data is ingested through a standardized Excel interface, ensuring compatibility with legacy industrial systems while minimizing implementation barriers. Second, machine learning models trained on historical data predict expected defects and rework rates over the planning horizon, providing forward-looking estimations rather than reactive detection. Third, predicted defect rates are translated into expected rework workloads and explicitly incorporated into capacity calculations, enabling estimation of effective production capacity. Finally, scenario-based production planning generates multiple feasible and optimal planning scenarios, allowing decision-makers to evaluate trade-offs between demand satisfaction, shift requirements, and resource utilization, thereby supporting informed planning decisions (Figure 1- Figure 3).



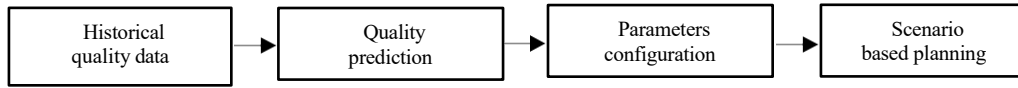


Figure 1. Bridging Planning Gaps toward Integrated Systems

4. Data Collection

Two complementary datasets were collected from an automotive manufacturing facility to support the proposed framework. The first dataset consists of historical quality records used to train the defect prediction model. Each observation captures the production day of the week and the daily production volume as input variables, along with the corresponding number of quality defects recorded enabling the model to learn temporal and volumetric patterns in defect occurrence across the production cycle.

The second dataset targets a critical production line within the same facility and is specifically designed to support production planning under uncertainty. This dataset characterizes the set of references manufactured on the line, and for each reference it documents: the number of defects historically generated, the line's production capacity, the number of shifts operated, a man-hour matrix reflecting the labor resources allocated per reference, a similarity matrix between references capturing their degree of commonality in terms of process requirements and changeover compatibility, the minimum gap between consecutive shifts expressed in number of references produced, and the minimum lot size per reference. Together, these variables provide a comprehensive operational picture of the line's constraints and behavioral dynamics, forming the foundation for the stochastic scenario generation model and the subsequent multi-criteria decision analysis.

5. Results and Discussion

This case study illustrates the industrial application of the proposed integrated decision support framework. Following two previous conference communications that introduced the conceptual and methodological foundations of the approach, the present work focuses on its application in a real production environment affected by quality-related rework and capacity variability. The objective is to assess how predictive quality information can be embedded into production planning to enable proactive and human-centric decision-making.

The development of the application required selecting tools suitable for the project's functional, technical, and industrial requirements. The choice of technologies was based on several criteria: ease of integration, development speed, compatibility with existing models, code readability, accessibility for end users, and capabilities for advanced data visualization (Table 1).

Python was chosen for several reasons:

- Its extensive data processing libraries (pandas, numpy)
- Compatibility with predictive modeling libraries (scikit-learn, xgboost, etc.)
- Clear and readable syntax, facilitating collaboration and code maintenance

A rich ecosystem for visualization and interactive tool development

Streamlit was selected for the user interface development because:

- It allows rapid creation of interactive web interfaces without deep web development knowledge
- It integrates seamlessly with Python scripts
- It is lightweight, fast to deploy, and well-suited for industrial prototypes or internal decision-support tools
- It provides graphical components (filters, sliders, tables, buttons) that are simple to implement. Principal used libraries

Table 1. Principal used libraries

	Library
pandas	Processing and manipulation of tabular data
numpy	Mathematical and statistical computations
scikit-learn	Training and application of the predictive model (ML)
matplotlib/plotly	Visualization of results (charts, histograms, etc.)
streamlit	Creation of the interactive web interface

The developed application is based on a modular architecture that clearly separates the different business functions, including data import, prediction, computation, planning, and visualization. This structure enhances code readability, facilitates scalability, and simplifies maintenance

Module 1: Data Import and Processing Loading data files, Data cleaning and validation, Format transformation, Data caching. Module 2: Rework Rate Prediction using Neural Networks, Gradient Boosting algorithms, Decision trees, ensemble learning, and cross-validation.

Module 3: Weighted Computation and Aggregation Weighting computations, Aggregation at the production line level, Parameter optimization, Metric consolidation

Module 4: Input Interface Interactive Streamlit widgets , Input forms , Input validation, Parameter management
Module 5: Stochastic Planning Two-stage stochastic programming , Branch-and-Cut algorithm , Optimization under uncertainty , Scenario-based decomposition
Module 6: Dashboard and Scenario Chart generation , Interactive dashboards , Scenario visualization

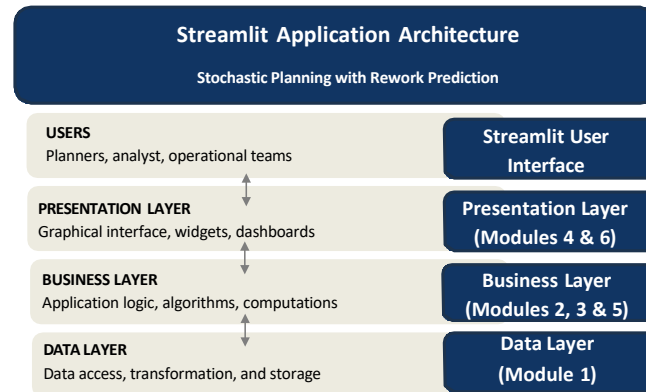


Figure 2. Streamlit application architecture

5.1 Numerical Results

The configuration stage reflects a human-centric design philosophy in which users retain full responsibility for critical operational choices, including resource allocation, shift configuration, and capacity and demand definition for each product. Users also define deviation ranges for random variables, allowing them to explicitly express uncertainty based on experience and contextual constraints, and assign relative weights to evaluation criteria in the multi-criteria analysis to prioritize objectives according to operational priorities. By integrating expert judgment directly into configuration while providing structured support without enforcing rigid automated rules, the application augments rather than replaces human decision-making, reinforcing human control, transparency, and adaptability in production planning

Following the configuration of operational parameters, the stochastic planning model is executed to generate planning

outcomes that explicitly account for uncertainty in production capacity and rework rates. The results provide a set of feasible production plans reflecting different scenarios derived from the defined random variables and their associated deviation ranges. This approach enables the evaluation of planning robustness under varying operational conditions rather than relying on a single deterministic solution.

The generated plans highlight the impact of predicted quality defects and rework on effective capacity utilization, shift allocation, and demand satisfaction for each product reference. By comparing scenario-based outcomes through a multi-criteria evaluation, the model supports informed decision-making by identifying plans that achieve an optimal trade-off between capacity efficiency, service level, and operational risk. These results demonstrate the added value of stochastic planning in improving alignment between planned and actual production while enhancing the reliability of short-term operational decisions (Table 2).

Table 2. Scenario generated

Scenario	Global score	Total cost	Satisfaction	Utilization	Stability	Shortage
S1	0.954	9519	100.0	99.5	99.2	0.0
S2	0.840	9520	100.0	99.5	92.6	0.0
S3	0.650	9520	100.0	97.8	90.5	0.0
S4	0.325	20679	97.6	100.0	97.7	11.4

In Table 3 below we have the execution plan by shift 1 for the first generated scenario

Table 3. Scenario generated

Reference	Gross quantity	useful production	Defect rate
REF_01	5	5	2.2%
REF_02	5	5	1.8%
REF_03	35	35	1.8%
REF_04	5	5	2.0%
REF_05	5	5	1.9%
REF_06	40	40	2.2%
REF_07	38	38	2.0%
REF_08	5	5	1.9%
REF_09	5	5	2.5%
REF_10	17	17	2.1%

The execution production order is presented

REF_02 → REF_04 → REF_09 → REF_08 → REF_06 → REF_07
→ REF_10 → REF_01 → REF_05 → REF_03

Shift Metrics:

Capacity Used :165/165 Utilization Rate :100.0%

Active References :10

An illustrative example of a production plan generated for a single shift under a given scenario is presented to demonstrate the functioning of the proposed approach. This example is representative of the planning mechanism implemented in the application. The same procedure is systematically applied to all remaining shifts and across the full set of generated scenarios, ensuring consistency in plan generation and comparability of results. Consequently, the decision-maker

has access to a comprehensive portfolio of shift-level production plans reflecting different uncertainty configurations, from which the most appropriate solution can be selected based on operational priorities.

5.2 Graphical Results

Particular attention was given to usability and accessibility, with the objective of enabling rapid adoption by industrial practitioners without requiring advanced technical expertise. The application offers an intuitive interface, simplified data inputs, and automated processing sequences that guide users through the decision-making process. This ease of use allows planners and quality engineers to focus on analysis and improvement actions rather than tool manipulation or data preparation. As a result, the application acts not only as an automation enabler, but also as a human-centric support system, bridging the gap between advanced analytical methods and day-to-day operational decision-making. At this stage, the application operates on historical production data uploaded by the user, capturing the daily variation of defect quantities in relation to production volume. This dataset provides a structured representation of quality fluctuations over time and constitutes the primary input for the predictive module. By analyzing these variations, the system identifies recurrent patterns and deviations that affect operational performance and planning reliability.

In addition to the initial prediction based on production volume, a second predictive layer is introduced by incorporating the day of the week and the observed defect quantities as explanatory variables. This enriched modeling approach enables the application to account for temporal effects and operational rhythms that are not captured by volume-based analysis alone. The combination of both prediction levels enhances the robustness of defect estimation and improves the relevance of downstream planning decisions, particularly in the generation of realistic rework scenarios and capacity adjustments.

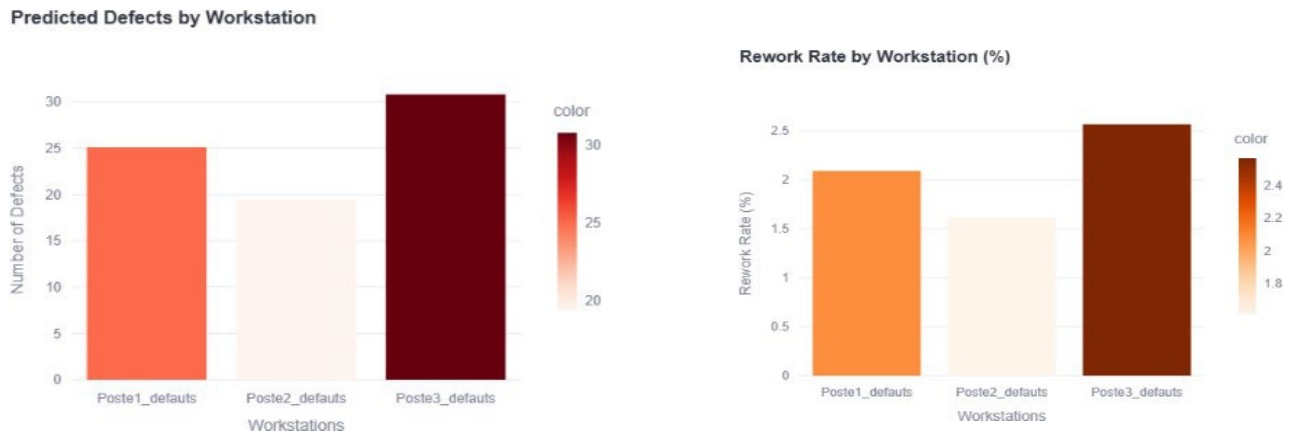


Figure 3. Predicted defects by workstation and rework rate calculated

6. Conclusion

This work addresses the misalignment between production planning intent and operational reality through an integrated decision support application that consolidates quality management and production planning into a unified workflow. The primary contribution is a human-centric design that automates routine tasks while leveraging operator expertise for proactive decision-making and management of production deviations. By incorporating stochastic modeling and multi-criteria evaluation, the framework produces robust plans accounting for uncertainty in capacity and demand. The industrial case study demonstrates that integrating quality insights improves lead time, resource utilization, and schedule reliability while enhancing human-machine collaboration. Future research should explore adaptation to diverse manufacturing contexts, real-time dynamic rescheduling, and formalization of human expertise into adaptive heuristics. Overall, the proposed application demonstrates that combining automation, predictive analytics, and human expertise in a collaborative framework significantly enhances agility and operational excellence, providing a practical pathway toward Industry 5.0 principles.

References

Abraham, J. and Reddy, M.C., Challenges to Inter-Departmental Coordination of Patient Transfers: A Workflow Perspective, *International Journal of Medical Informatics*, vol. 79, no. 2, pp. 112-122, 2010, <https://doi.org/10.1016/j.ijmedinf.2009.11.001>

- Arshad Abbasi, U.B., Zhang, W., Mahroof, S., Han, C., Li, S. and Khan, S.H., Optimizing Machine Learning Methods for Groundwater Quality Prediction: Case Study in District Bagh, Azad Kashmir, Pakistan, *Ecotoxicology and Environmental Safety*, 2025.
- Azabab, A. and Pourvaziri, H., Scheduling in Industry 4.0: A Digital Twin-Based Approach for Scheduling and Smart Material-Handling Considerations, *NAMRC 53*, 2025.
- Bento, F., Tagliabue, M. and Lorenzo, F., Organizational Silos: A Scoping Review Informed by a Behavioral Perspective on Systems and Networks, *Societies*, vol. 10, no. 3, p. 56, 2020, <https://doi.org/10.3390/soc10030056>
- Bird, S.D., Intelligent Decision Support for Quality Function Deployment, *Manufacturing Decision Support Systems*, 1997.
- Chaymae, T., Rokaya, D., Ezzine, L. and Elmoussami, H., Towards Eco-Efficient Production Planning: Stochastic Models Incorporating Quality Uncertainty and Environmental Impact, 2025, <https://doi.org/10.1051/e3sconf/202568000032>
- Fani, V., Antomarioni, S., Bandinelli, R. and Bevilacqua, M., Data-Driven Decision Support Tool for Production Planning: A Framework Combining Association Rules and Simulation, *Computers in Industry*, 2023.
- Hemono, P., Nait Chabane, A. and Sahnoun, M., Leveraging Digital Twin and Dynamic Scheduling for Enhanced Human-Robot Collaboration, *Preprint, SSRN*, 2024, <https://doi.org/10.2139/ssrn.5065955>
- Hirunyawipada, T., Beyerlein, M. and Blankson, C., Cross-Functional Integration as a Knowledge Transformation Mechanism: Implications for New Product Development, *Industrial Marketing Management*, vol. 39, no. 4, pp. 650-660, 2010, <https://doi.org/10.1016/j.indmarman.2009.06.003>
- Laouenan, G., Dossou, P.-E. and Delahousse, J., Flexibilization 4.0 for Production Manufacturing Optimization, *Procedia Computer Science*, vol. 200, pp. 348-357, 2022, <https://doi.org/10.1016/j.procs.2022.01.233>
- Mahmoodi, E., Fathi, M., Tavana, M., Ghobakhloo, M. and Ng, A.H.C., Data-Driven Simulation-Based Decision Support System for Resource Allocation in Industry 4.0 and Smart Manufacturing, *Journal of Manufacturing Systems*, vol. 72, pp. 287-307, February 2024, <https://doi.org/10.1016/j.jmsy.2023.11.019>
- May, M.C., Hart, C. and Duffie, N., A Decision Aid for Aggregate Production Planning (APP) Strategies, 2025.
- Orkamo, M., Ukko, J., Rantala, T. and Saunila, M., Leadership Behaviours to Promote Organisational Performance in Private Sector Digital Transformation - A Systematic Literature Review, *Digital Business*, 2025.
- Papavasileiou, A., Michalos, G. and Makris, S., Quality Control in Manufacturing - Review and Challenges on Robotic Applications, *International Journal of Integrated Manufacturing*, 2024.
- Rokaya, D., Taraa, C., Ezzine, L. and Elmoussami, H., Data-Driven Quality Assurance Defect Prediction to Reduce Carbon Footprint in Manufacturing Logistics, 2025, <https://doi.org/10.1051/e3sconf/202568000037>
- Schafer, L., Tse, S., May, M.C. and Lanza, G., Assisted Production System Planning by Means of Complex Robotic Assembly Line Balancing, *Journal of Manufacturing Systems*, 2025.
- Soleimani, M. and Sari, A.A., A Unified Safety Framework for Automated Vehicle Development: Integrating ISO 26262, SOTIF, and UL 4600, *Transportation Research Interdisciplinary Perspectives*, 2026.
- Tariq, M.U., Poulin, M. and Abonamah, A.A., Achieving Operational Excellence Through Artificial Intelligence: Driving Forces and Barriers, *Frontiers in Psychology*, vol. 12, p. 686624, July 2021, <https://doi.org/10.3389/fpsyg.2021.686624>
- Tchane Djogdom, G.V., Meziane, R. and Otis, M.J.-D., Robust Dynamic Robot Scheduling for Collaborating with Humans in Manufacturing Operations, *Robotics and Computer-Integrated Manufacturing*, vol. 88, p. 102734, August 2024, <https://doi.org/10.1016/j.rcim.2024.102734>
- Toth, A., Nagy, L., Kennedy, R., Bohus, B., Abonyi, J. and Ruppert, T., The Human-Centric Industry 5.0 Collaboration Architecture, *MethodsX*, vol. 11, p. 102260, December 2023, <https://doi.org/10.1016/j.mex.2023.102260>
- Trentesaux, D. and Thomas, A., Product-Driven Control: A State of the Art and Future Trends, *Proceedings of the 14th IFAC Symposium on Information Control Problems in Manufacturing*, Bucharest, Romania, 2012.
- Valencia, E.T., Lamouri, S., Pellerin, R., Forget, P. and Moeuf, A., Planification de la production et Industrie 4.0: Revue de la litterature, *13eme Conference internationale CIGI QUALITA*, Montreal, Canada, 2020, <https://hal.science/hal-02475847v1>
- Wettre, A., Sevaldson, B. and Dudani, P., Bridging Silos: A New Workshop Method for Bridging Silos, *OCAD University Open Research Repository*, 2019.
- Zhang, L., Chen, J. and Liu, W., Research on Enterprise Workflow Engine Optimization Based on Knowledge Graph Algorithm, *Procedia Computer Science*, vol. 262, pp. 244-251, 2025, <https://doi.org/10.1016/j.procs.2025.05.050>

Biographies

Douiri Rokaya is a first-year PhD student, member of team research Modeling and Optimization of Industrial Systems. She received her Engineering degree in Industrial and Productive Engineering in 2025 from ENSAM School (Ecole Nationale Supérieure d'Arts et Métiers de Meknès), Moulay Ismaïl University, Morocco. Her current research focuses on Artificial Intelligence, Transition Toward Industry 5.0, Production Planification and Quality Defect Prediction.

Taraa Chaymae is an Operational Research Engineer. She received her Engineering Degree in Operational Research Engineering in 2019 from the INSEA School (National Institute of Statistic & Applied Economy). Her research interests include modeling, optimization, supply chain management & continuous improvement, member of team research Modeling and Optimization of Industrial Systems.

Dadda Afaf is a Professor at the Department of Industrial Engineering, ENSAM School (Ecole Nationale Supérieure d'Arts et Métiers de Meknès), Moulay Ismaïl University, Morocco and. She obtained her Ph.D. Degree in 2016 from ENSAM, Moulay Ismaïl University, Morocco. Member of team research Modeling and Optimization of Industrial Systems. Her current research focuses on Inverse Optimization, Multi Criteria Decision Making, .

Elmoussami Haj is a Professor at the Department of Mechanical conception, ENSAM School (Ecole Nationale Supérieure d'Arts et Métiers de Meknès), Moulay Ismaïl University, Morocco and. He obtained his Ph.D. Degree in 2003 from ENSAM, Bordeaux, France. Member of team research Modeling and Optimization of Industrial Systems. His current research focuses on 3D printing, control systems, and mechanical conception.

Ezzine Latifa is a Professor at the Department of Industrial Engineering, ENSAM School (Ecole Nationale Supérieure d'Arts et Métiers de Meknès), Moulay Ismaïl University, Morocco and. She obtained her Ph.D. Degree in 2010 from the Faculty of Sciences, Moulay Ismaïl University, Morocco Team director student in r Modeling and Optimization of Industrial Systems. Her current research focuses on statistics and artificial intelligence, modeling and optimization, control systems, and telecommunications.