Proceedings of the 11th North American International Conference on Industrial Engineering and Operations Management, Milwaukee, Wisconsin, USA, June 9-11, 2026

Proceedings of the International Conference on Industrial Engineering and Operations Management

Publisher: IEOM Society International, USA DOI: 10.46254/NA11.20260060
Published: June 9, 2026

Integrating Production and Repair Operations Through Data Driven Defect Flow Analytics for Yield and Resource Optimization in PCBA Manufacturing

Ali Tahmasebi, Yingge Zhou and Daryl Santos
Systems Science and Industrial Engineering Department
Watson Institute for Systems Excellence (WISE)
Thomas J. Watson College of Engineering and Applied Science
The State University of New York at Binghamton
Binghamton, NY 13902, USA
atahmasebi1@binghamton.edu, yzhou@binghamton.edu, santos@binghamton.edu

Sai Srikanth Reddy Kolli and Edward Wong
Foxconn Industrial Internet
Mount Pleasant, WI 53177, USA
sai.kolli@fii-usa.com, edward.wong@fii-na.com

Abstract

In Printed Circuit Board Assembly (PCBA) manufacturing, maintaining a closed loop connection between production and repair operations is critical to improving product quality and operational efficiency. However, in the manufacturing environment that motivated this work, production and repair data are often managed separately, and repair findings are not systematically fed back to production teams, limiting visibility into defect routing patterns and repair workload drivers. This study developed a data-driven framework that integrates production and repair data streams to analyze defect flow and support repair resource planning. The framework applies descriptive statistics, cross tabulations of repair inflow by product/project and repair stage, and temporal trend analysis to characterize in-line repair demand and downstream transfers to the offline repair/disposition area, referred to as the Not Good Warehouse (NGWH). Using historical production output and repair records, the analysis quantifies the proportion of boards entering in-line repair and the proportion transferred to NGWH, providing actionable feedback for prioritizing improvement efforts and informing planning for in-line benches, material handling (e.g., transport carts), and staffing. Results demonstrate that structured defect flow analytics can identify products and operational areas that contribute disproportionately to repair workload and downstream transfers, patterns that may be overlooked when relying on yield metrics alone. The proposed approach supports data-informed decision making for defect reduction, yield improvement, and production repair synchronization, aligning with Industry 4.0 initiatives for smart and connected manufacturing systems.

Keywords
Data Analytics, PCBA Manufacturing, Defect Flow Analysis, Repair Operations, Digital Transformation

1. Introduction
Printed Circuit Board Assembly (PCBA) manufacturing is a high volume, multi-stage process in modern electronics production, supporting a wide range of products across computing, communications, industrial systems, and consumer electronics. PCBA manufacturing environments are typically characterized by high product complexity, tight production schedules, frequent model or project changes, and strict quality requirements. Under these conditions, even

relatively small defect rates can create significant operational impacts through yield loss, rework demand, delayed throughput, and increased resource utilization. As a result, improving the visibility and management of defects is not only a quality concern but also an operations management priority.

In the PCBA manufacturing facility studied in this paper, defective boards identified during production do not follow a single repair path. Instead, a two-stage repair structure is used. Boards with relatively straightforward issues may be handled in in-line repair (Stage 1) and then returned to production flow. Boards that cannot be resolved in in-line repair due to defect complexity, diagnostic requirements, repeated failures, or limited in-line capacity are transferred downstream to the Not Good Warehouse (NGWH) (Stage 2), the central repair/disposition area where deeper debugging and disposition activities are performed. This structure is operationally practical, but it creates a multi-stage defect routing process that can be difficult to quantify systematically using standard production and yield reporting. As boards move between production, in-line repair, and NGWH, information about failure mechanisms, recurring patterns, and repair workload can become fragmented across teams and data systems.

A key challenge in practice is that production and repair operations are closely connected physically and operationally, but the corresponding data streams are often managed separately. Production teams frequently monitor metrics such as output volume, yield, and line performance, while repair teams track incoming failures, troubleshooting activity, and repair completion (Escobar et al. 2021; Balaha et al. 2025; Hafid et al. 2025). When these datasets remain disconnected, organizations lose the ability to clearly see how failures route from production into different repair stages, which products generate disproportionate repair burden, and how repair outcomes can inform upstream production improvements. In effect, the manufacturing system may have a repair process that restores units, but it lacks a sufficiently structured feedback mechanism that translates repair findings into production focused learning and planning.

In electronics manufacturing environments characterized by production variability, shifting product mix, and resource constraints, the downstream repair/disposition function serves not only as troubleshooting support but also as a leading indicator of upstream process health. When repair data are not systematically analyzed and communicated back to production, recurring defect patterns can persist longer than necessary and targeted root cause investigation may be delayed. Operationally, this gap is reflected in measurable outcomes such as reduced first pass yield (FPY), increased rework/repair labor hours, higher accumulation of WIP in downstream queues (e.g., NGWH inventory), longer turnaround time from test failure to disposition, and increased operational costs associated with troubleshooting, material handling, and schedule disruption. These impacts also translate into planning challenges: without visibility into defect routing and downstream workload, decisions about in-line bench capacity, transport resources (e.g., carts), and staffing are often reactive rather than evidence-based.

These challenges motivate the need for a practical framework that strengthens the production repair feedback loop using routine operational records. In many facilities, production and repair functions are tightly coupled operationally but remain analytically disconnected, with production output tracked in separate reporting artifacts and repair activity tracked in action level logs. As a result, defect routing behavior across stages and the drivers of repair workload are not consistently represented in a unified analytical view, limiting the ability of manufacturing teams to (i) identify products/projects and operational areas that contribute disproportionately to downstream workload, (ii) detect changes in routing behavior early, and (iii) plan repair resources using historical demand patterns. This study addresses that process gap by developing a data-driven framework that integrates production output and repair records to quantify defect routing between in-line repair (Stage 1) and the downstream repair/disposition area, the Not Good Warehouse (NGWH) (Stage 2). The framework is designed to support defect flow visibility by product/project, repair workload characterization, and planning decisions related to in-line benches, material handling, and staffing, thereby enabling data informed decisions for yield improvement and production repair synchronization.

To address this problem, this paper develops a data-driven framework for integrating production and repair data in a PCBA manufacturing environment and analyzing the routing of failed boards (defect routing) across operational stages. The framework is designed to support practical use cases including defect visibility by product, repair workload characterization, and planning decisions related to in-line repair benches, transport carts, and personnel allocation. By focusing on the connection between production and repair rather than treating them as isolated functions, the study aims to provide a more complete operational perspective on defect routing behavior and repair demand in support of yield improvement and production repair synchronization.

1.1 Objectives
The objective of this research is to develop and apply a practical data-driven framework that integrates production and repair data in a PCBA manufacturing environment to improve defect flow visibility, strengthen feedback from repair to production, and support repair capacity planning. The study focuses on the movement of boards through in-line repair and the NGWH and uses historical operational data to characterize defect routing behavior across products and repair stages.

The specific objectives of this study are as follows:
1. Develop an integrated defect flow dataset by linking production output with inline repair routing and downstream transfer to NGWH for PCBA products.
2. Quantify and characterize defect flow behavior across repair stages and over time to identify products that contribute disproportionately to repair volume and NGWH workload.
3. Translate defect flow insights into operational guidance that supports production repair feedback for continuous improvement and informs repair capacity planning (in-line benches, transport carts, and staffing).

This study makes three primary contributions:
1. It proposes an integrated view of production and repair data that are often managed separately in PCBA manufacturing environments.
2. It introduces a defect routing analytics perspective that captures routing behavior and repair workload implications across in-line repair and NGWH stages.
3. It presents an implementable analytical approach based on descriptive statistics, cross tabulations, and time series trend analysis to support data informed decision making in an Industry 4.0 aligned manufacturing context.

2. Literature Review
2.1 PCBA defect detection and inspection
PCBA manufacturing quality depends heavily on early detection of assembly defects such as solder bridges, insufficient solder, opens, misalignment, and missing components. Automated Optical Inspection (AOI) is widely used because it provides fast, repeatable inspection at production scale. Recent research has advanced AOI defect detection using integrated pipelines that combine localization and classification of solder related defects, improving consistency relative to manual inspection (Dai 2020). Broader surveys of PCB inspection methods describe the progression from traditional image processing toward machine learning and deep learning approaches, while emphasizing deployment challenges such as false calls, dataset limitations, and manufacturing variability (Fonseca et al. 2024; Zhou et al. 2023). In addition, process focused studies highlight that upstream stages particularly stencil printing and printing related parameters can strongly influence downstream defect rates and yield, motivating the need to connect process outcomes with defect handling and repair observations (Fung et al. 2020; Khader et al. 2021). While this literature strengthens defect detection and process monitoring, most work is focused on inspection accuracy or stage level process control rather than analyzing how failed boards route through multiple repair stages and what those routing patterns imply for repair workload and resource planning.

2.2 Repair, rework operations and repair workload planning
Rework and repair are essential in electronics manufacturing because not all defects can be corrected within line takt time. Industry guidance formalizes repair and rework procedures, tools, and decision contexts, and distinguishes "rework" (reprocessing to meet specifications) from "repair" (restoring functional capability without necessarily meeting the original drawings/specifications) (IPC 2017). Industry recommendations also discuss opportunities and risks associated with rework/repair processes and emphasize consistent process design to protect product reliability (ZVEI 2017). From an operations perspective, repair organizations face fluctuating demand driven by production yield, product mix, and defect complexity. Recent work has addressed predicting repair department workload in electronics manufacturing by using historical and production-related signals to forecast upcoming repair volumes (Górecki et al. 2025). However, despite the importance of repair to throughput and shipment performance, the literature provides limited practical frameworks that connect production output with Stage 1 repair outcomes (e.g., in-line repair) and downstream escalation to a central repair facility into a unified defect flow view that supports planning decisions such as benches, carts/material handling, and staffing.

2.3 Data integration for Quality 4.0 and Industry 4.0 decision support

Industry 4.0 and Quality 4.0 research emphasizes that value comes not only from collecting data but from integrating it across functions to enable actionable decision support. Surveys of Industry 4.0 analytics highlight the role of data analytics in converting large scale operational data into insights that support smart manufacturing decisions (Duan et al. 2021). Quality 4.0 literature similarly frames manufacturing quality as increasingly data-driven, where analytics and connected systems support improved monitoring and improvement cycles (Bousdekis et al. 2023). Related work on manufacturing quality assessment in the Industry 4.0 era emphasizes the shift toward information quality, integration of multiple data sources, and the use of analytics enabled systems for decision making (Markatos et al. 2023). Despite these advances, a recurring challenge in practice is that production and downstream functions often remain siloed, limiting feedback loops and reducing the operational value of repair findings for upstream improvement and capacity planning. Recent review work on data quality in smart manufacturing further highlights that heterogeneous, multi-source manufacturing data require stronger quality assessment practices if analytics outputs are to remain reliable and decision-useful (Peixoto et al. 2025).

2.4 Summary and gap addressed by this study

Across the reviewed domains, prior research strongly supports improved defect detection and inspection technologies and recognizes the growing importance of data-driven quality and integration under Industry 4.0/Quality 4.0. Meanwhile, repair and rework standards, emerging forecasting studies demonstrate the operational need for structured repair processes and workload planning. However, there is limited published work that addresses all of the following in an integrated way:

1. Links production output with Stage 1 in-line repair and downstream Stage 2 (NGWH) repair/disposition outcomes.
2. Quantifies defect routing as a multi-stage process (production → in-line repair → NGWH transfer) rather than a single aggregated yield metric.
3. Translates routing behavior into practical planning guidance for repair capacity and production–repair feedback.

This study addresses that gap by integrating production and repair records to characterize defect routing across stages and support resource planning and continuous improvement decisions.

3. Methods

This study applies a data-driven analytics approach to quantify defect routing between production, in-line repair, and the NGWH in a PCBA manufacturing environment. The approach is designed to be implementable using routine operational records and to support two practical objectives: strengthening production repair feedback and informing repair capacity planning. Analysis was conducted using standard data tools (e.g., spreadsheet-based pivoting and scripting for record processing) to produce repeatable board level metrics and trend summaries.

3.1 Repair routing structure

Boards that fail production testing are first routed to in-line repair, where some are corrected and returned to production flow. Boards not resolved during in-line repair are transferred to NGWH for deeper debugging and disposition. This routing is summarized in Figure 1

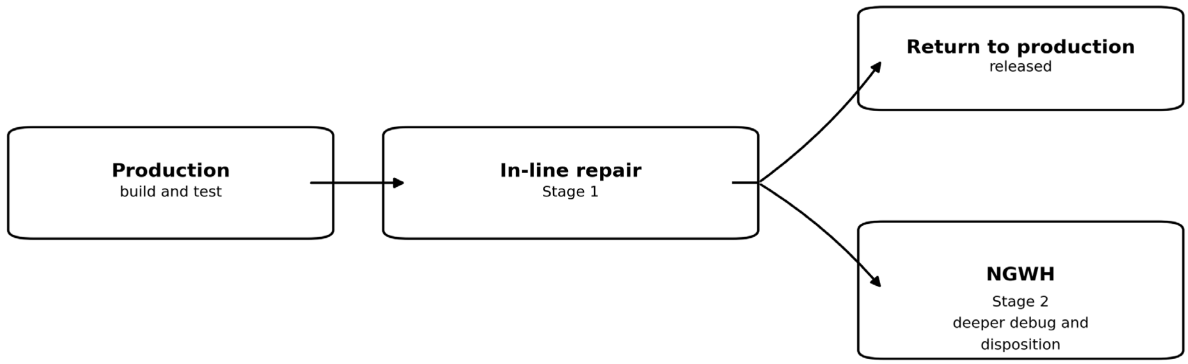

Figure 1. Repair routing structure for the two-stage repair pipeline

Figure 1. Boards failing production testing enter in-line repair (Stage 1); boards resolved in-line are released back to production, while unresolved boards (or those constrained by in-line capacity) are transferred to NGWH (Stage 2) for deeper debugging and disposition.

4. Data Collection

This study was conducted at a U.S. based PCBA manufacturing company operating a two-stage repair pipeline (in-line repair followed by NGWH as the downstream repair/disposition stage). The analysis uses three operational datasets collected over an approximately two-month window in early 2026 and aggregated to the facility's weekly operational reporting intervals.

- Production output (weekly production reports)
    - Source: internal weekly production reporting.
    - Grain: work-order level (summarized weekly).
    - Key variables used: reporting interval, work order, product/project label, packed output ("Total Pack" or equivalent packed quantity).
    - Purpose: provides the denominator for normalizing repair inflows (e.g., in-line entry rate).
- In-line repair records (Stage 1)
    - Source: repair tracking system export for the in-line repair stream.
    - Grain: action level repair logs (multiple rows per board) with supporting board-level summaries.
    - Key identifiers used: serial number, work order, repair ID (when applicable), production line/station fields, timestamps.
    - Purpose: quantifies stage 1 inflow and supports calculation of in-line entry rate and workload by product/project and week.
- NGWH records (Stage 2)
    - Source: repair tracking system export for the NGWH stream.
    - Grain: action level repair logs (multiple rows per board) with supporting board level summaries.
    - Key identifiers used: serial number, work order, repair ID (when applicable), production line/station fields, timestamps.
    - Purpose: quantifies downstream transfer to NGWH and supports calculation of NGWH transfer rate and downstream workload patterns.

Dataset summary:

- Study window: approximately two months in early 2026 (aggregated to weekly operational reporting intervals; 8 weeks).
- Production: packed output totals 184,926 units across the study window.
- In-line repair (Stage 1): 15,788 unique boards (distinct serial numbers) observed.
- NGWH (Stage 2): 4,124 unique boards observed.
- Repair logs are action level; therefore, inflows are computed using unique serial numbers per stream per interval to avoid double counting.

4.1 Dataset integration and preparation

Production output and repair records were integrated at the board level using serial number and work order, supported by product labels and timestamps. Because repair exports contain action level detail (multiple rows per board), repair inflow and workload measures were computed using unique serial numbers within each repair stream and aggregation interval.

Data preparation steps included:

1. Product standardization: product/project attribution was standardized using Work Order as the linking key between production reports and repair summaries.
2. Timestamp alignment: timestamps were converted to a consistent format and used to align records to the study window and weekly reporting intervals.
3. De-duplication: duplicate administrative entries (e.g., repeated scans or repeated action entries for the same serial number) were removed to avoid double counting boards within a stream.
4. Aggregation: board level counts and rates were computed by reporting intervals and product to enable consistent comparison across production output, in-line repair inflow, and NGWH inflow.

4.2 Defect flow metrics and statistical summaries

Defect flow behavior was quantified using descriptive statistics and cross tabulations by product and repair stream (in-line repair versus NGWH). Board level measures were computed using unique serial numbers. The primary measures include:

- Production volume: weekly packed output by product/project from production reports.
- In-line repair inflow: number of unique serial numbers appearing in in-line repair records within the aggregation interval.
- NGWH inflow: number of unique serial numbers appearing in NGWH records within the aggregation interval.
- In-line repair entry rate: in-line repair inflow normalized by production volume.
- NGWH transfer rate: NGWH inflow normalized by in-line repair inflow .
- Workload concentration: cross tabulations of in-line and NGWH board counts by product to identify products contributing disproportionately to overall repair burden.

These measures support two comparisons: (i) across products/projects to identify high burden contributors and (ii) over time to examine changes in repair demand and transfer behavior. Where applicable, overlap of serial numbers between in-line and NGWH records was used as a consistency check of the two-stage routing structure.

4.3 Trend analysis

Repair demand and transfer behavior were evaluated over time using weekly aggregation aligned to operational reporting intervals. Time series were generated for production output, in-line inflow, NGWH inflow, and NGWH transfer rate trends to identify periods of elevated downstream workload and shifts in routing behavior.

4.4 Decision support outputs

Results were structured to support production prioritization and repair capacity planning. Product level summaries were used to identify high burden products for targeted improvement, while repair stage volumes and temporal trends were used to inform planning discussions related to in-line benches, transport carts/material handling, and staffing needs.

4.5 Statistical

To strengthen inference beyond descriptive reporting, statistical tests were conducted to evaluate whether defect routing behavior varies over time and across production lines. Two proportion based outcomes were analyzed: (i) the in-line repair entry rate (in-line inflow normalized by packed output) and (ii) the NGWH transfer rate (NGWH inflow normalized by in-line inflow). Week to week differences in these rates were evaluated using chi-square tests of homogeneity on the corresponding success/failure counts ($\alpha = 0.05$). In addition, the likelihood that an in-line board subsequently appears in NGWH records during the study window (transfer indicator) was modeled using a binomial logistic regression with production line and weekly interval as predictors to quantify line level effects while controlling analysis for temporal variation. Effect sizes are reported using odds ratios (OR) with 95% confidence intervals.

5. Results and Discussion

This section reports overall defect flow volumes and rates, followed by statistical comparisons across weeks and production lines.

5.1 Numerical Results

Table 1 summarizes overall production output and repair stage inflows across the approximately two-month study window. Production output is reported as a packed output (units). Repair stage inflows are computed as the number of unique serial numbers observed in each repair stream during the study window. Across the study period, packed output totaled 184,926 units, with 15,788 unique (distinct serial numbers) boards entering in-line repair and 4,124 unique boards appearing in NGWH records. This corresponds to an overall in-line entry rate of 8.5% and an overall NGWH transfer rate of 26.1%.

Table 1. Overall production output and repair stage inflows

Packed output (units)	In-line inflow (unique boards)	NGWH inflow (unique boards)	In-line entry rate (%)	NGWH transfer rate (%)
184926	15788	4124	8.5	26.1

Figure 1 shows weekly in-line entry rate and NGWH transfer rate across the eight operational reporting intervals. The in-line entry rate varies from 7.2% to 12.7% across weekly intervals, and the NGWH transfer rate varies from 8.9% to 40.0%, indicating substantial temporal variability in both first stage repair inflow and downstream transfer behavior. To evaluate whether the observed week-to-week variability reflects statistically significant differences rather than random fluctuation, we applied a chi-square test of homogeneity to the underlying count data. In this test, χ^2 denotes the chi-square test statistic and the value in parentheses denotes the degrees of freedom (df). The p-value reports the probability of observing differences at least as large as those measured under the null hypothesis that the rates are equal across intervals; $p < 0.05$ indicates statistically significant differences. Statistical tests confirm that these week to week differences are not attributable to random variation alone: the in-line entry rate differs significantly across weekly intervals ($\chi^2(df = 7) = 597.8$, $p < 0.001$), and the NGWH transfer rate also differs significantly across weekly intervals ($\chi^2(df = 7) = 955.8$, $p < 0.001$).

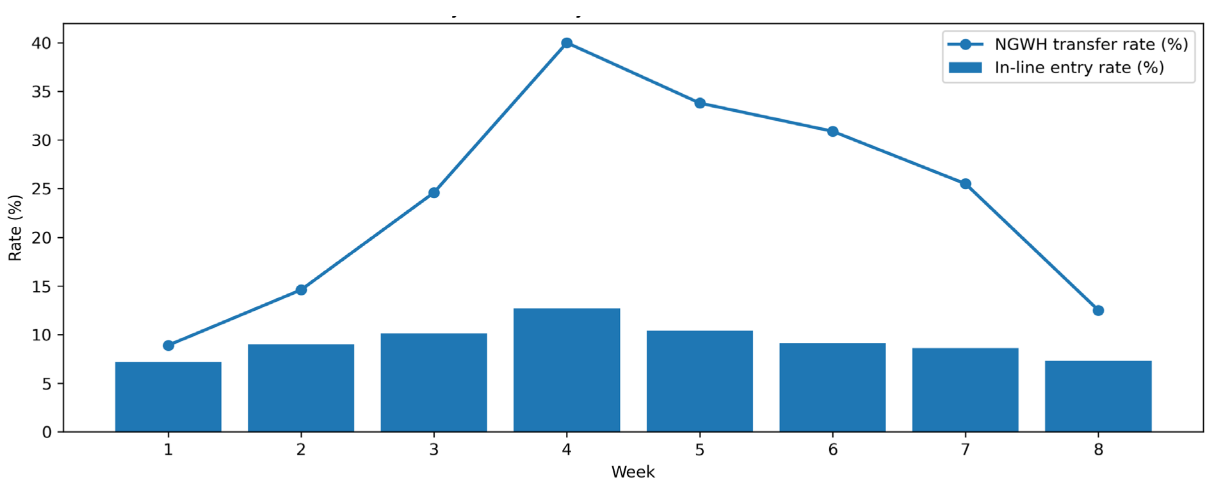

Figure 1. Weekly in-line entry rate and NGWH transfer rate

To evaluate whether downstream transfer behavior differs across production lines after accounting for temporal variation, a logistic regression model was fit to in-line boards using a binary transfer indicator (whether an in-line board appears in NGWH records during the study window). Both production line and weekly interval effects are statistically significant based on likelihood-ratio tests (line effect: $\chi^2(7) = 102.1$, $p < 0.001$; weekly interval effect: $\chi^2(7) = 836.0$, $p < 0.001$), indicating that NGWH transfer likelihood varies systematically across the operation. Table 2 reports line-level transfer rates and odds ratios relative to the reference line. Notably, Line 9 shows a significantly higher transfer likelihood (OR = 1.43, 95% CI 1.22–1.68, $p < 0.001$), while Line 5 shows a significantly lower transfer likelihood (OR = 0.64, 95% CI 0.54–0.75, $p < 0.001$). These results support the interpretation that downstream NGWH workload is influenced not only by overall repair volume but also by line-specific routing behavior and week-to-week variation. A plausible operational explanation for the observed line- and week-level differences is that the NGWH transfer decision reflects a combination of defect complexity, in-line diagnostic capability, and capacity constraints that vary by line and over time. Lines running different products (or different process/test conditions) may experience failures that are less recoverable within in-line takt time (target time per unit to meet demand) and therefore require deeper debugging or disposition in NGWH. The week effect is also unlikely to be driven by packed output alone because the downstream metric is expressed as a transfer rate (normalized by in-line inflow); instead, shifts in product mix, priority pressure, and variation in in-line bench staffing/availability can change transfer thresholds and increase downstream transfers even when overall production output is similar. These mechanisms are consistent with the statistically significant line and weekly interval effects, suggesting downstream workload is driven by both structural differences across lines and short-term operational conditions rather than production volume alone.

Table 2. NGWH transfer likelihood by production line

Line	In-line boards (unique)	Transferred to NGWH	Transfer rate (%)	Odds ratio vs Line 2	OR 95% CI	OR p-value
2	2509	706	28.1	1.000000	1.00 (ref)	—
3	2590	638	24.6	0.821919	0.72–0.93	2.75e-03
4	1781	377	21.2	0.741303	0.64–0.86	8.54e-05
5	1406	279	19.8	0.635344	0.54–0.75	3.97e-08
6	3089	879	28.5	1.007421	0.89–1.14	9.05e-01
7	2583	689	26.7	0.924521	0.81–1.05	2.25e-01
8	684	158	23.1	0.900394	0.73–1.10	3.13e-01
9	1139	398	34.9	1.432846	1.22–1.68	8.65e-06

5.2 Graphical Results

Figure 2 visualizes production output alongside repair-stage inflows across weekly operational intervals. In-line inflow and NGWH inflow exhibit clear temporal variability relative to packed output, indicating that repair demand is not proportional to production volume alone. Periods with elevated NGWH inflow correspond to intervals with higher downstream workload, which has direct implications for benching, staffing, and transport planning.

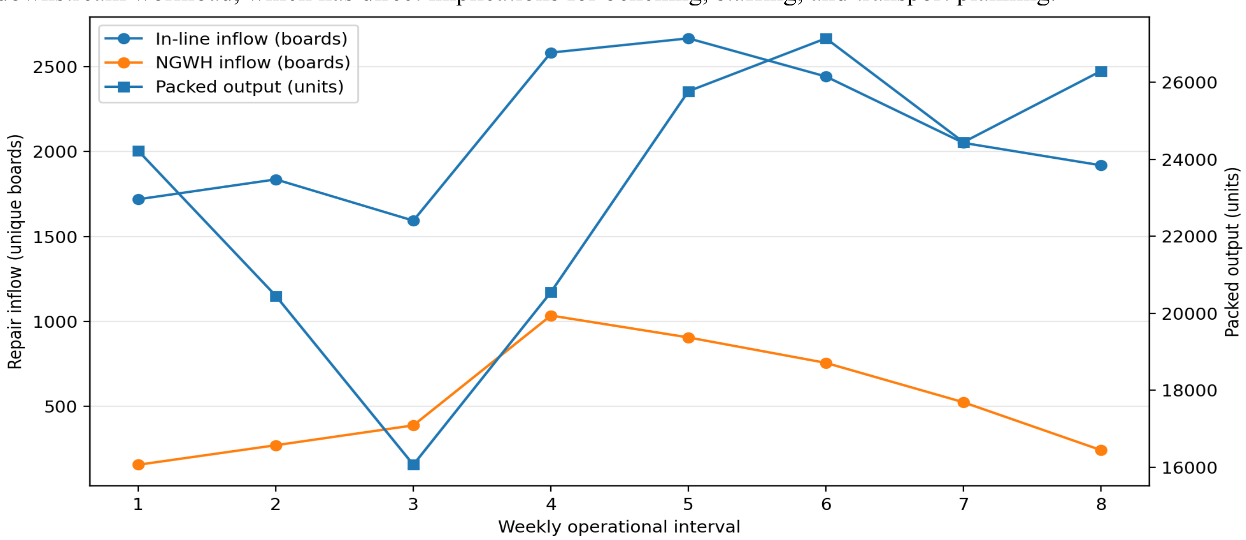

Figure 2. Weekly production output and repair stage inflows

Figure 3 presents the corresponding rate-based view: the in-line entry rate (in-line inflow normalized by packed output) and the NGWH transfer rate (NGWH inflow normalized by in-line inflow). The rate trends highlight intervals where downstream transfer behavior increases even when in-line entry remains moderate, suggesting that transfer behavior is influenced by more than overall repair volume (e.g., defect complexity, troubleshooting constraints, or routing practices).

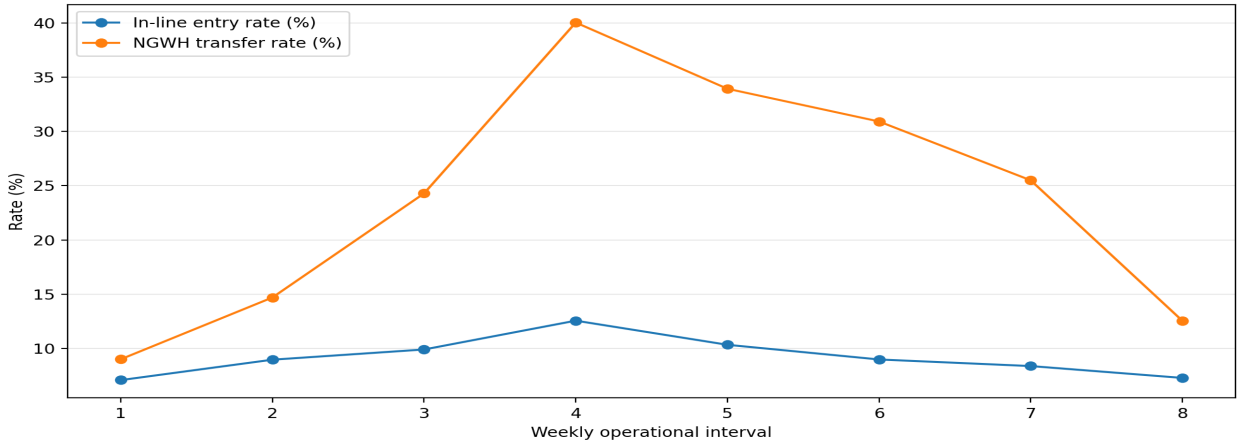

Figure 3. Weekly in-line entry rate and NGWH transfer rate

Figure 4 compares NGWH transfer rates across production lines (top lines by in-line volume). The variation across lines is consistent with the regression results in Section 5.1, indicating systematic differences in downstream transfer likelihood across the operation. This line-level comparison supports prioritizing improvement efforts on lines with both high in-line volume and higher transfer rates, because these lines drive disproportionate downstream NGWH workload. Line to line variation in NGWH transfer rates may reflect differences in product mix and failure complexity, which affect how often issues can be resolved within in-line repair constraints. Differences in in-line capacity and troubleshooting resources can also shift transfer thresholds and increase downstream transfers.

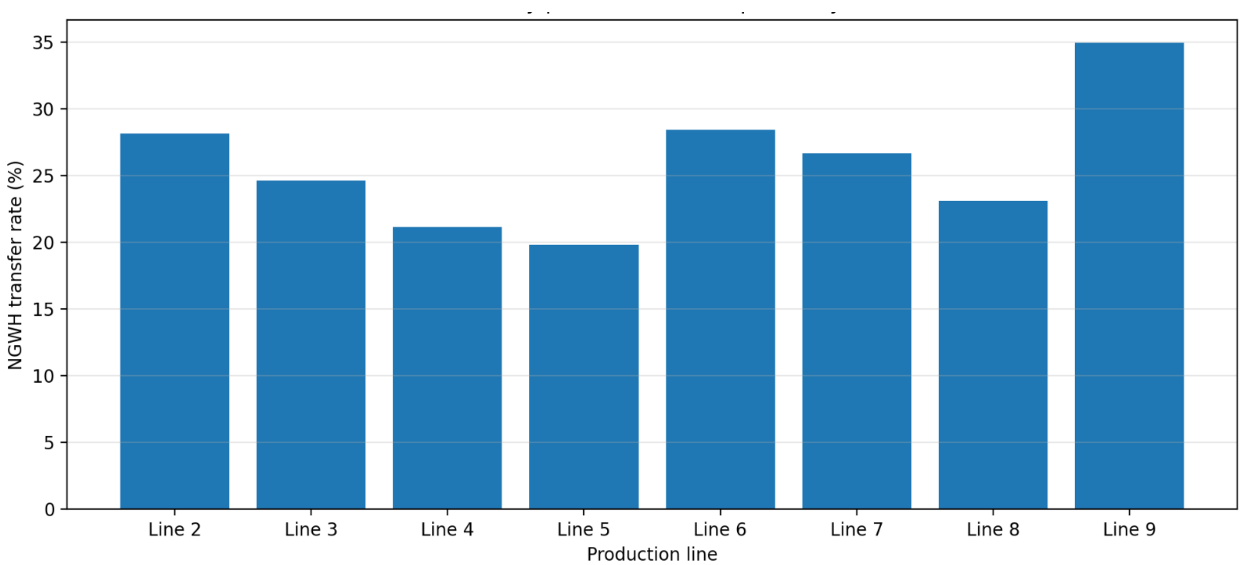

Figure 4. NGWH transfer rate by production line (top 10 by in-line volume)

5.3 Proposed Improvements

The results indicate that both repair inflow and downstream transfer behavior vary substantially across weekly intervals and across production lines. Based on these findings, the following improvements are proposed:

1. Target high transfer production lines for root cause and routing review: Lines with higher NGWH transfer likelihood (as indicated by transfer rate comparisons and regression odds ratios) should be prioritized for focused investigation. This can include reviewing dominant defect categories, verifying standardized in-line troubleshooting steps, and ensuring consistent criteria for transfer to NGWH.
2. Strengthen in-line troubleshooting capability to reduce unnecessary downstream transfers: Because NGWH represents the downstream repair/disposition area, reducing transfers at the in-line stage can directly reduce

downstream workload. Actions may include updating troubleshooting checklists, improving access to diagnostic tools at in-line benches, and clarifying “transfer thresholds”.

3. Use weekly inflow and transfer rate trends to inform capacity planning: The observed week-to-week variability supports moving from reactive planning to a data-driven planning cadence. Weekly forecasts based on historical inflow can be used to adjust the number of in-line benches staffed, prioritize NGWH staffing coverage, and plan transport cart availability during expected high load intervals.
4. Institutionalize a production repair feedback report: A short weekly summary that reports product level inflow counts, NGWH transfer rates, and top contributors can improve visibility and shorten time-to-action for production teams. This report can be used as a standing agenda item between production and repair leadership to accelerate targeted improvement activities.

5.4 Validation

Two validation checks were performed to confirm that the defect routing structure and derived metrics are consistent with system behavior.

First, serial number overlap was evaluated between in-line repair and NGWH records. All NGWH serial numbers observed during the study window also appear in the in-line repair dataset (100% overlap), which is consistent with NGWH representing a downstream subset of in-line boards rather than an independent repair population.

Second, timestamp consistency was assessed using the first record timestamps for overlapping boards. For overlapping serial numbers, 87.6% of boards show NGWH and in-line first record timestamps within ±1 minute, consistent with the system opening the NGWH record at the point of downstream transfer. Together, these checks support the interpretation that NGWH represents a downstream repair/disposition stage and that the computed inflows and transfer rate metrics reflect a two-stage routing process rather than duplicate counting across independent streams.

6. Conclusion

This study developed and applied a data-driven defect flow analytics framework that integrates production output with repair stage records to quantify routing behavior between in-line repair and the downstream Not Good Warehouse (NGWH) repair/disposition area. Using board level identification (unique serial numbers) and weekly operational aggregation, the analysis quantified in-line inflow, NGWH inflow, and two key rates: the in-line entry rate and the NGWH transfer rate. Results demonstrated statistically significant temporal variation in both rates across weekly intervals and statistically significant differences in downstream transfer likelihood across production lines after controlling for time effects via logistic regression. These findings reinforce that NGWH workload is influenced by both overall repair demand and line-specific routing behavior.

Practically, the framework supports production repair feedback and repair capacity planning by identifying when downstream transfer rates increase, which lines contribute disproportionately to NGWH workload, and how repair demand changes over time. Future work can extend this analysis by incorporating defect codes and repair dispositions more explicitly, modeling transfer drivers at the product/project level, and developing lightweight forecasting models to anticipate high load periods for staffing and material handling planning.

References

Balaha, F., Albinali, H., Alrabiah, H., Mohamed, A. and Bahroun, Z., An analytical review of data integration for decision support in smart manufacturing, Decision Analytics Journal, vol. 17, art. 100647, 2025, https://doi.org/10.1016/j.dajour.2025.100647.

Bousdekis, A., Lepenioti, K., Apostolou, D. and Mentzas, G., Data analytics in quality 4.0: literature review and future research directions, International Journal of Computer Integrated Manufacturing, vol. 36, no. 5, pp. 678-701, 2023, https://doi.org/10.1080/0951192X.2022.2128219.

Dai, W., Mujeeb, A., Erdt, M. and Sourin, A., Soldering defect detection in automatic optical inspection, Advanced Engineering Informatics, vol. 43, art. 101004, 2020, https://doi.org/10.1016/j.aei.2019.101004.

Duan, L. and Xu, L. D., Data analytics in industry 4.0: a survey, Information Systems Frontiers, 2021 (online ahead of print), https://doi.org/10.1007/s10796-021-10190-0.

Escobar, C. A., McGovern, M. E. and Morales-Menendez, R., Quality 4.0: a review of big data challenges in manufacturing, Journal of Intelligent Manufacturing, vol. 32, pp. 2319-2334, 2021, https://doi.org/10.1007/s10845-021-01765-4.

Fonseca, L. A. L. O., Iano, Y., Oliveira, G. G. de, Vaz, G. C., Carnielli, G. P., Pereira, J. C. and Arthur, R., Automatic printed circuit board inspection: a comprehensible survey, Discover Artificial Intelligence, vol. 4, art. 10, 2024, https://doi.org/10.1007/s44163-023-00081-5.

Fung, V. W. C. and Yung, K. C., An intelligent approach for improving printed circuit board assembly process performance in smart manufacturing, International Journal of Engineering Business Management, vol. 12, pp. 1-12, 2020, https://doi.org/10.1177/1847979020946189.

Górecki, K., Kowalke, W. and Ptak, P., Methods for predicting the repair stack in an electronics module manufacturing company, Electronics, vol. 14, no. 21, art. 4152, 2025, https://doi.org/10.3390/electronics14214152.

Hafid, A., Sebtaoui, F. E. and Mouchtachi, A., An overview of the transformation towards quality 4.0: technological needs, challenges, and benefits, Engineering Proceedings, vol. 112, no. 1, art. 18, 2025, https://doi.org/10.3390/engproc2025112018.

IPC, IPC-7711/7721C, Rework, Modification and Repair of Electronic Assemblies, IPC—Association Connecting Electronics Industries, 2017.

Khader, N. and Yoon, S. W., Adaptive optimal control of stencil printing process using reinforcement learning, Robotics and Computer-Integrated Manufacturing, vol. 71, art. 102132, 2021, https://doi.org/10.1016/j.rcim.2021.102132.

Markatos, N. G. and Mousavi, A., Manufacturing quality assessment in the industry 4.0 era: a review, Total Quality Management & Business Excellence, vol. 34, no. 13-14, pp. 1655-1681, 2023, https://doi.org/10.1080/14783363.2023.2194524.

Peixoto, T., Oliveira, B., Oliveira, Ó. and Ribeiro, F., Data Quality Assessment in Smart Manufacturing: A Review, Systems, vol. 13, no. 4, art. 243, 2025, https://doi.org/10.3390/systems13040243.

Zhou, Y., Yuan, M., Zhang, J., Ding, G. and Qin, S., Review of vision-based defect detection research and its perspectives for printed circuit board, Journal of Manufacturing Systems, vol. 70, pp. 557-578, 2023, https://doi.org/10.1016/j.jmsy.2023.08.019.

ZVEI, Guidelines Rework of Electronic Assemblies – Qualifiable Processes for Rework, ZVEI—German Electrical and Electronic Manufacturers' Association, 2017. Available: https://www.zvei.org/en/press-media/publications/guidelines-rework-of-electronic-assemblies-qualifiable-processes-for-rework.

Biographies

Ali Tahmasebi is a master's student at Binghamton University – the State University of New York (SUNY) in Industrial and Systems Engineering (ISE). He is a graduate student conducting his work as an Industrial and Manufacturing Engineering research project assistant at Watson Institute for Systems Excellence. Ali earned his bachelor's degree in computer science from Iowa State University of Science and Technology (2025), Ali's research interests include supply chains, optimization, project management, operation research and smart manufacturing.

Yingge Zhou is a SUNY Assistant Professor at Binghamton University. He received his Ph.D. in the Department of Industrial, Manufacturing & Systems Engineering (IMSE) at Texas Tech University in 2020. He earned his B.S. in Mechanical Engineering and Business Administration at Xiangtan University, China, in 2014, and a Master's degree in Industrial Engineering from Texas Tech University in 2016. His most recent work focuses on sacrificial 3D printing tissue scaffold templates and electrospray microparticles for drug delivery applications.

Daryl Santos is a SUNY Distinguished Service Professor at Binghamton University. He has received the SUNY Chancellor's Award for Teaching and the SUNY Chancellor's Award for Scholarship and Creative Activities. Daryl holds a BS degree in Operations Research and Industrial Engineering from Cornell University (1987), an MS degree in Industrial Engineering from the University of Houston (1990), and a PhD degree in Industrial Engineering from the University of Houston (1993). He also holds a Lean Six Sigma Black Belt from Dartmouth College's Thayer School of Engineering. Daryl is the founding managing editor of the Industrial and Systems Engineering Review (ISER) Journal.

Sai Srikanth Reddy Kolli is Project Manager at Foxconn Industrial Internet (Fii). He is also a PhD student at Binghamton University – SUNY, majoring in Industrial and Systems Engineering. He holds a master's degree from Binghamton University, and a bachelor's degree from Mahindra University (École Centrale School of Engineering). His research interests lie in manufacturing, data analytics, Machine Learning, and Artificial Intelligence algorithms application in supply chain management and logistics, process optimization, and automation. He is a member of Alpha

Pi Mu Industrial Engineering Honor Society and serves as a Technical Advisory Committee (TAC) member with SMTAI.

Edward Wong serves as a director of business development and supply chain management at Foxconn Industrial Internet (Fii), USA. He has contributed to major advancements across the diversified Foxconn network. He holds a BS degree in Chemical Engineer from the University of California at Berkeley.