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An IoT-enabled Decision Support System for Real-time Line Balancing in Semiconductor Manufacturing

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ABSTRACT

This study presents iDSS-ProLean, an IoT-enabled Decision Support System (DSS) developed to enhance line balancing in semiconductor production. Traditional methods lack real-time adaptability, while iDSS-ProLean integrates sensor-based data acquisition, Firebase cloud analytics, and a mobile app to support responsive, data-driven decisions. The system architecture includes ESP32 modules, multiple sensors, cloud processing, and an Android interface for the operation feedback. A feasibility study was conducted using 60 production runs, where Line Balancing Efficiency (LBE) served as the main performance metric. Paired t-tests revealed p-values above 0.05 and t-values near zero, indicating consistent data transmission and system stability. These results affirm the reliability of the mobile DSS and its real-time performance under varying production conditions. The study demonstrates how integrating Lean Manufacturing (LM) tools with IoT technologies enables dynamic line optimisation. It's proven that LBE is highly correlated with NoM (0.96), TPT (0.97), and CT (0.93), confirming that machine count, processing time, and cycle time strongly influence LBE. Overall, the IDSS-ProLean framework proves to be an effective and adaptive decision support tool for LM applications, showcasing the value of IoT-enabled models in replacing static, time-consuming methods with real-time, intelligent systems.

Keywords: Decision support system, Internet of Things, line balancing, manufacturing system, semiconductor sector

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INTRODUCTION

Lean Manufacturing (LM) focuses on minimising waste and maximising value through continuous improvement, with line balancing as a core principle to evenly distribute workloads and maintain efficiency (Abd Rahman et al., 2021; Naceur et al., 2024). Semiconductor production, with precise processes such as etching, cutting, and assembly, requires optimal line balancing to achieve full throughput without bottlenecks, as supported by Mortada and Soulhi (2023) and Feng (2022). Traditional methods are often reactive and slow to adapt to dynamic production conditions (Chica et al., 2019) while conventional Decision Support Systems (DSS) rely on static rules and fail to leverage real-time data, limiting operational efficiency (Qiao et al., 2020; Shafee, et al., 2024) To address this, iDSS-ProLean framework was developed as an IoT-enabled DSS that integrates LM principles, real-time sensor data, and predictive analytics to dynamically optimise workloads, reduce waste, and meet production targets (Ito et al., 2020). A mobile application collects, analyses, and presents real-time data, enabling operators to make informed, immediate decisions (Ojha et al., 2024). By combining live IoT monitoring, automated decision-making, and line balancing metrics, iDSS-ProLean enhances flexibility, precision, and efficiency, demonstrating technical and operational feasibility for continuous optimisation in complex semiconductor manufacturing environments.

LITERATURE REVIEW

Decision Support System in LM

DSS have gained significant traction within the manufacturing sector, serving as a critical tool for managers and engineers tasked with strategic and operational decision-making. By synthesising heterogeneous data streams from production sites, logistics networks, and inventory systems, these platforms generate actionable insights to optimise resource utilisation and minimise waste (Skėrė et al., 2023). In the context of Lean Manufacturing (LM), DSS applications have proven instrumental in streamlining production scheduling, inventory management, and resource allocation. However, while traditional DSS frameworks, as reviewed by Turker et al. (2019) and Unver et al. (2020), provide real-time data visualisation and predictive modelling to enhance managerial choices, they frequently rely on static heuristics and historical datasets. This dependency severely limits their adaptability within highly dynamic production environments. As highlighted by Ramadan et al. (2020), such architectural rigidity fails to accommodate the stochastic disruptions and complexities inherent in modern manufacturing. This paradigm gap between static DSS capabilities and the evolving demands of real-time, IoT-driven ecosystems underscores the critical need for adaptive frameworks, such as the proposed iDSS-ProLean architecture, that integrate dynamic data streams to effectively support LM applications.

Recent developments in manufacturing DSS reflect a progressive transition from descriptive analytics toward intelligent, data-driven frameworks. Early methodological approaches relied heavily on statistical modelling techniques, including Analysis of Variance (ANOVA) and regression analysis, to evaluate process behaviour and isolate critical performance factors. While these methods yield valuable post-experimental insights, they exhibit constrained predictive capabilities and lack real-time adaptability (Basar et al., 2026). To address these operational constraints, the classical Multi-Criteria Decision-Making (MCDM) technique was introduced to systematically evaluate conflicting criteria and rank competing alternatives. Nonetheless, their heavy reliance on subjective expert elicitations and static weighting structures restricts their agility under fluctuating production conditions (Avramova et al., 2025).

Subsequent advancements established hybrid optimisation frameworks by coupling experimental design with multi-response decision-making, exemplified by the integration of Taguchi methods with entropy weighting and CoCoSo ranking. Although these hybrid paradigms enhance robustness across conflicting operational objectives, including cutting force, surface roughness, and dimensional accuracy, they remain constrained by predefined experimental boundaries and lack autonomous predictive intelligence (Basar et al., 2025). To transcend these systemic boundaries, recent paradigms have integrated artificial intelligence and evolutionary computation, successfully combining Finite Element Analysis (FEA), Artificial Neural Networks (ANN), and Genetic Algorithms (GA).

IoT in LM

IoT is the recent trend that is taking over LM with the introduction of DSS, which has allowed the acquisition of real-time data from machines, sensors, and other devices everywhere in the production process (Chen 2020). IoT-enabled DSSs are software programs for collecting and analysing data produced by the instruments, which is a game changer for the production managers who become the masters of data processing (Guo et al., 2020). These sensors can keep an eye on the machine's performance by monitoring parameters, and they can also get updates about the state of items such as work-in-progress items (Viriyastivat et al., 2019). Though IoT-based sensors are very important for line balancing to work properly. From the ongoing research in IoT, the results tell us that the integration of IoT will optimise the decision-making process because it gives a clear view of the existing line operation and enables the immediate adjustment (Chulakit et al., 2023). Therefore, the mentioned problems need to be addressed, such as data interoperability, system integration, and the development of a strong algorithm to process the data appropriately (Amjad et al., 2021; Ben Naceur et al., 2024).

Line Balancing in LM

Line balancing is a critical LM technique designed to minimise idle time, achieve equitable workload distribution across workstations, reduce capacity loss, and eliminate bottlenecks (Fang et al., 2023). Traditionally, this process has relied on mathematical models, heuristics, or simulation-based approaches (Campana et al., 2021). However, these methods often depend on approximations that fail to capture the complexity and variability of real-world production, particularly within semiconductor manufacturing (Manghisi et al., 2022; Viriyasitavat et al., 2019). Dynamic variables, such as machine breakdowns, fluctuating demand, and varying operator skill levels, frequently challenge conventional balancing approaches (Shao et al., 2020).

To address this, IoT-enabled DSS offer a solution by leveraging real-time data to facilitate continuous operational adjustments (Christ et al., 2023). Despite recent advancements shifting smart manufacturing from descriptive monitoring to adaptive decision-support environments, the integration of real-time sensing, lean-oriented analytics, and intelligent decision-support within a unified semiconductor framework remains insufficiently explored (Afrin et al., 2025). This study addresses this research gap by introducing and contextualising the iDSS-ProLean framework as an adaptive decision-support tool for complex manufacturing environments.

Technical Novelty of the Proposed Framework

Although IoT-enabled monitoring architectures incorporating sensors, cloud databases, and mobile interfaces are widely reported, existing line balancing studies predominantly focus on theoretical models or fixed parameters that fail in dynamic production environments (Aguilar et al., 2020). Consequently, the integration of IoT technologies for line balancing remains underexplored (Saraswat et al., 2024), and IoT-based DSS applications in physical production domains such as predictive maintenance and process monitoring are rarely addressed (Anozie et al., 2024; Rosati et al., 2022).

To transcend these limitations, the proposed iDSS-ProLean framework extends beyond conventional, dashboard-oriented monitoring systems that only focus on visualisation. The novelty of this architecture lies in establishing a unified, closed-loop intelligent decision-making environment that integrates lean manufacturing principles with real-time IoT sensor data acquisition, predictive analytics, and multi-criteria decision-making. By continuously transforming sensor-driven data into actionable insights, this framework enables adaptive operational decisions, accounts for unforeseen events like absenteeism, and facilitates continuous productivity optimisation within semiconductor production lines (Fang et al., 2023; Yang et al., 2020).

METHODOLOGY

iDSS-ProLean Framework Development

The iDSS-ProLean framework developed in this study is to integrate IoT technologies with LM tools, enabling real-time decision-making for line balancing in semiconductor production. This framework offers a novel configuration that addresses the limitations of conventional DSS by incorporating real-time sensor data and aligning with the LM methodology's five-step IMAGE process: Identify, Measure, Analyse, Generate, and Execute. A visual representation of the proposed framework is provided in Figure 1 to illustrate its components and the structure of the iDSS-ProLean framework.

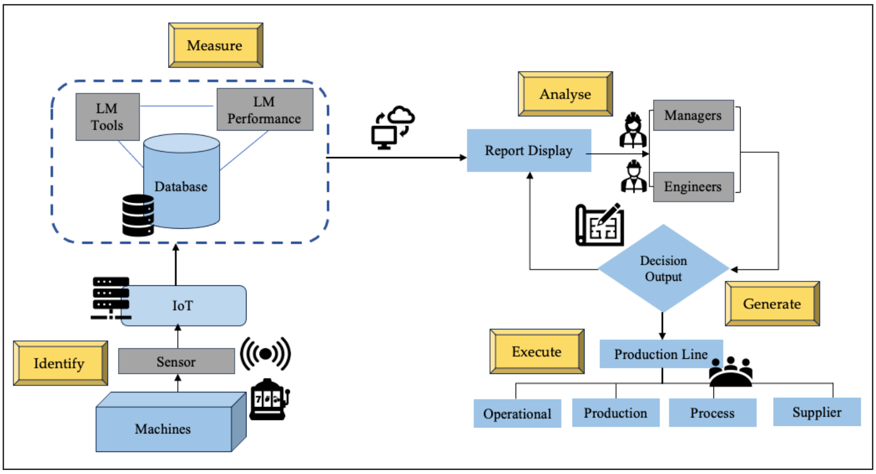


Figure 1. iDSS-ProLean framework

Layers in iDSS-ProLean Framework

As shown in Figure 2, iDSS-ProLean comprises three integrated layers: (i) the IoT Data Acquisition Layer, (ii) the Data Analytics Management Layer, and (iii) the User Interface Layer. Together, these layers enable real-time data capture, analysis, and decision support for line balancing in semiconductor manufacturing.

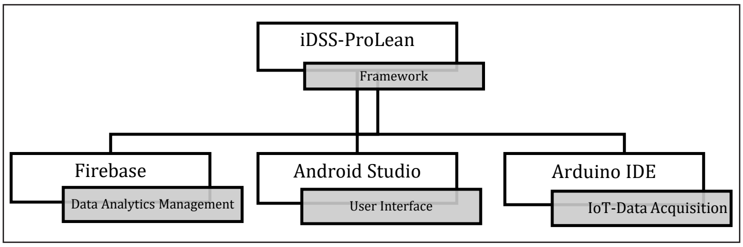


Figure 2. iDSS-ProLean framework components

IoT Data Acquisition Layer

This layer captures real-time production and environmental variables via an IoT sensor network integrated with ESP32 microcontrollers, executing device-level filtering and averaging prior to wireless cloud transmission, as mentioned in Table 1. To validate the IDSS-ProLean framework's core functionalities without initial full-scale factory complexity, an experimental setup of five workstations was deployed under controlled laboratory conditions for baseline calibration and functional verification. While this proof-of-concept phase utilises low-cost sensor nodes, the architecture is designed to seamlessly interface with legacy communication systems to withstand the electromagnetic noise, thermal stress, and mechanical vibrations typical of semiconductor manufacturing lines.

Architecturally, the framework leverages a modular IoT–database–application topology anchored by Firebase to support horizontal expansion without altering the core system logic or data synchronisation protocols. Computational and database overheads are minimised through lightweight data structures and real-time cloud synchronisation inherently optimised for distributed, high-volume data environments. This modular configuration allows the framework to scale dynamically, enabling the seamless integration of additional machinery and parallel processes to support larger, industrial-scale manufacturing deployments with appropriate infrastructure scaling.

Table 1
Constituents in IoT-Data acquisition layer

Sensors	Constituents	Task
ESP32	Microcontroller	Enables wireless data transmission to Firebase for centralised processing.
HC-SR04	Ultrasonic	Measure workstation throughput and idle time at entry and exit points.
DHT11	Temperature	Monitor environmental conditions affecting machine performance.
BMP180	Pressure	Monitor air pressure variations relevant to process precision
SW-420	Vibration	Detect abnormal machine vibrations indicating mechanical inefficiencies.

User Interface Layer

The User Interface (UI) layer is deployed as an Android-based mobile application, enabling operators and engineers to monitor real-time production status. This application visualises Line Balancing Efficiency (LBE) as the proactive notifications facilitate rapid corrective actions, thereby mitigating throughput losses and enhancing operational responsiveness. Architecturally, iDSS-ProLean framework executes across a near real-time IoT pipeline spanning sensor data acquisition, Wi-Fi transmission, Firebase Realtime Database synchronisation, and mobile application rendering. Under stable network conditions, the system exhibits an observed end-to-end latency of approximately 1-3 seconds, primarily governed by wireless communication and cloud synchronisation overloads. To guarantee high operational reliability, the architecture integrates fault-tolerance mechanisms, specifically local edge-level buffering at the sensor node and Firebase offline persistence to enable automated data synchronisation upon network restoration. During connectivity disruptions, the mobile application preserves the latest valid dataset to sustain decision-making in a degraded operational mode, with full real-time capabilities seamlessly restored once communication is re-established.

RESULT AND DISCUSSION

iDSS-ProLean Framework Implementation

Based on LM metrics, the mobile application provided actionable feedback that enabled operators to identify cycle time imbalances and bottlenecks. Figure 3 shows a Semiconductor production flow integrated with Arduino IDE and iDSS-ProLean for real-time sensor monitoring according to the layers in the framework development.

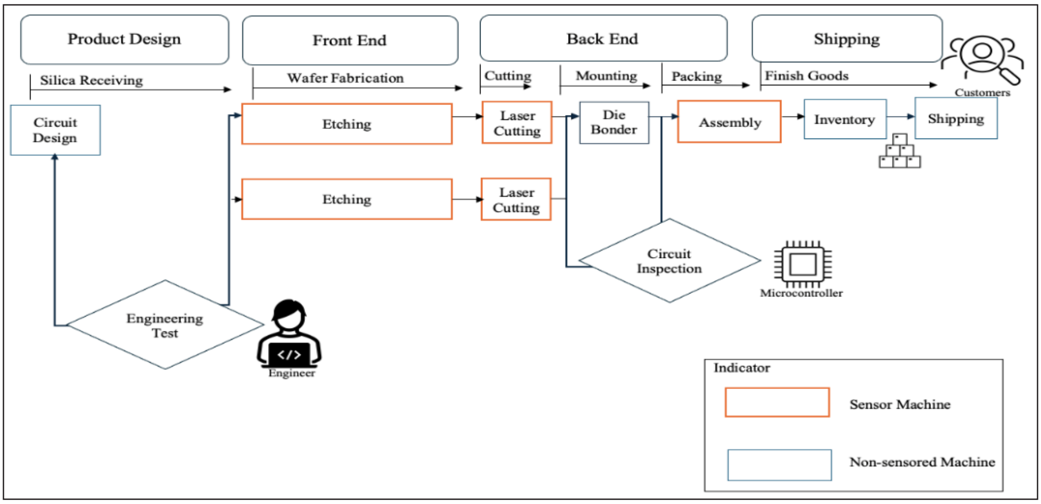


Figure 3. Semiconductor production flow integrated with Arduino IDE and iDSS-ProLean for real-time sensor monitoring

Phase 1 Identify

The line balancing formula evaluates task distribution across workstations via the LINE_BALANCING_TABLE, which aggregates real-time sensor data to reflect current shop floor conditions and predict target achievement. The study focused on essential performance indicators, Cycle Time (CT), Total Processing Time (TPT), Number of Workstations (NoM), and LBE, to monitor production performance and determine whether planned demand could be met as mentioned in Equation 1.

$$line\ balancing\ efficiency = \frac{total\ \ processing\ \ time}{cycle\ \times number\ \ of\ \ workstation} \qquad [1]$$

Databases Definition

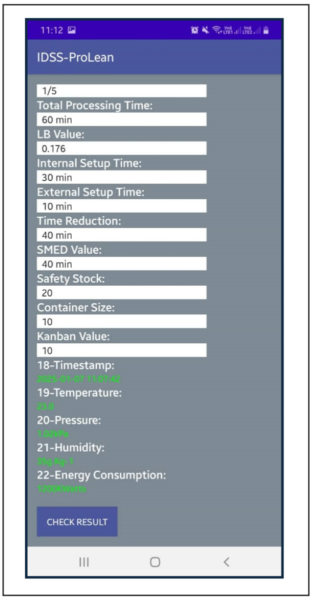
iDSS-ProLean framework integrates LM tools into a relational database structure normalised to Third Normal Form (3NF). Centred within a Firebase real-time database architecture, this system serves as the central processing engine to execute data relational formulas, support real-time line evaluation, and ensure absolute data consistency by linking tables via unique identifiers to feed the line balancing system.

At the core of the Firebase architecture is the *PROCESS_TABLE* (Primary Key: process_id), which defines semiconductor operations like etching, cutting, and assembly. This table links directly via the Foreign Key (FK) process_id to two dependent tables: *MACHINES_TABLE* (PK: machine_id, FK: process_id): Tracks real-time availability, machine status, maintenance dates, and performance rates.

Live operational metrics are dynamically captured and calculated within the *PRODUCTION_DATA_TABLE* (PK: production_id), which links to both machine_id and process_id as foreign keys to log outputs, defect quantities, and precise timestamps. Ultimately, the Firebase engine processes these integrated data streams and feeds the formulated variables directly into the *LINE_BALANCING_TABLE* (PK: balancing_id, FK: process_id). This table centralises core calculated metrics, specifically processing time, cycle time, and idle time. By anchoring this 3NF relational structure within Firebase, the framework achieves the high-speed data retrieval, formula execution, and real-time monitoring required for dynamic workload distribution, cycle time optimisation, and predictive assessment of production targets.

Phase 2 Measure

In this phase, the resulting time data were then transmitted via WiFi to the Firebase real-time database and stored in the *LINE_BALANCING_TABLE*. As illustrated in the iDSS-ProLean mobile interface Figure 4, the captured sensor data are processed dynamically alongside other operational and environmental parameters to provide a holistic view of the workstation's status. This integrated dashboard ensures that line balancing adjustments account for both mechanical cycle times and ambient floor conditions.



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Total Processing Time: 60 min
LB Value: 0.176
Internal Setup Time: 30 min
External Setup Time: 10 min
Time Reduction: 40 min
SMED Value: 40 min
Safety Stock: 20
Container Size: 10
Kanban Value: 10
18-Timestamp: 2025-01-07 11:07:42
19-Temperature: 23.0
20-Pressure: 1.02kPa
21-Humidity: 35g.Kg-1
22-Energy Consumption: 1200KWatts

Figure 4. iDSS-ProLean data captured

Phase 3 Analyse

Following the computation of the LBE metric within Firebase, the system evaluates the production line's capacity readiness against predefined LM thresholds. The mobile application dynamically retrieves this value to execute an automated diagnostic routine. This automated evaluation minimises reliance on manual, trial-and-error diagnostics, allowing engineers to rapidly identify structural imbalances and secure on-time delivery. Crucially, the framework operates as an augmentative decision-support tool rather than a fully autonomous replacement for human authority; the localised visual cues and analytical outputs serve to guide engineering personnel toward targeted continuous improvement interventions. To demonstrate the empirical validity of this approach, Table 2 outlines three distinct operational scenarios captured during the system validation phase.

Table 2
Line balancing metrics and system indicators for operational decision-making

Metrics	Scenario A: Target Balance	Scenario B: Imbalance Detected	Scenario C: Imbalance Detected
Cycle Time (CT)	60s	60s	60s
Total Processing Time (TPT)	300s	240s	360s
Number of Workstations (NoW)	5	5	5
LBE Value	1.00	0.80	1.20
Apps Feedback	Balance	Bottleneck	Underutilised

Empirical Validation Scenarios

Scenario A

Represents the target baseline where the total processing time of 300 seconds perfectly aligns with the capacity of five active workstations (N=5) under a 60-second cycle time.

This yields an optimised line balance with a calculated (LBE = 1.00), triggering a BALANCE status indicator on the mobile interface. This feedback confirms that the system is operating at peak efficiency to meet demand without generating non-value-added waste.

Scenario B

llustrates a sub-optimal state where systemic delays reduce the total processing time to 240 seconds, resulting in an (LBE = 0.80) (LBE <1). The platform immediately generates a BOTTLENECK indicator, directing the shop-floor engineer to isolate specific machine stalls or manually reassign tasks to restore the required takt time.

Scenario C

Demonstrates an over-allocated line state where the total processing time escalates to 360 seconds, resulting in an (LBE = 1.20) (LBE > 1). The user interface renders an UNDERUTILISED alert, highlighting a capacity imbalance that threatens to induce overproduction.

Phase 4 Generate

Following the LBE evaluation in the Analyse phase, the framework progressed to the Generate phase to derive actionable operational decisions. Initially, observed LBE values fell below 1, indicating structural imbalances and suboptimal workload distribution across the production line. Following targeted interventions, specifically task reallocation and machine utilisation optimisation, LBE converged to 1. This optimisation demonstrates effective production line synchronisation and readiness for uninterrupted operation, aligning with LM principles that emphasise pull-driven, real-time decision-making.

Phase 5 Execute

The final phase, Execute, reinforced the fifth LM principle: Pursue Perfection. In this phase, the IDSS-ProLean system enabled operators to act upon the insights generated by the framework.

- If the system approved the line (LBE = 1), production could begin or continue without interruption.
- If performance was suboptimal, operators were encouraged to initiate corrective actions such as reassigning operators, adjusting cycle times, or scheduling maintenance, based on system recommendations.

Through its closed-loop structure, iDSS-ProLM sustained process improvements over time, ensuring that LM implementation was not a one-time effort but an ongoing strategic capability.

DISCUSSION

Feasibility Analysis

Sixty trial runs (n ≥ 30) ensured normality under the Central Limit Theorem, and a significance level of $\alpha = 0.05$ (df = 59) with a t-critical value of ±2.00 confirmed data stability. Figure 5 presents a boxplot summarising Total Processing Time (TPT), Cycle Time (CT), and LBE across the production line. TPT exhibits the highest median and a wide interquartile range with extended whiskers, indicating variability in processing durations, while occasional lower outliers suggest opportunities for process improvement. CT displays a lower median and compact IQR, reflecting consistent and stable cycle performance. LBE values are comparatively lower, highlighting potential workload imbalances or underutilised capacity. This descriptive overview underscores production dynamics and reinforces the importance of real-time monitoring and adaptive resource allocation. Subsequent sections provide further statistical validation through paired t-tests and correlation analyses.

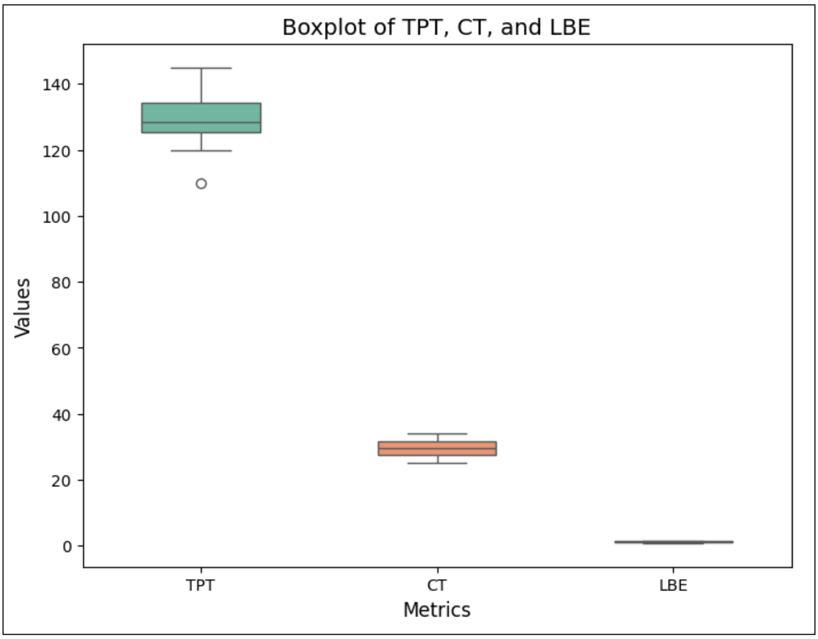

Figure 5. Boxplot of the distribution comparison

Paired T-statistic with P-value

To evaluate the stability and consistency of sensor-driven data transfer, a paired t-test analysis was conducted using 30 dataset pairs across 60 runs, as depicted in Table 3. This test was chosen for its strength in determining whether the mean differences between two paired observations are statistically significant, serving as an indicator of data accuracy and system reliability. The analysis, performed in SPSS, compared key production metrics, Number of Machines (NoM), Total Processing Time (TPT), Cycle Time (CT), and LBE, over multiple runs.

H_0: No statistically significant difference exists in NoM, TPT, CT, and LBE across 60 runs.

H_1: At least one of these metrics differs significantly across runs.

Failing to reject H_0 indicates that no statistically significant systematic variations were detected between the compared operational runs. While a traditional null hypothesis significance test at this sample size possesses low statistical power to capture minute differences, the absence of large magnitude shifts, coupled with the narrow mean differences observed, descriptively aligns with the expected operational consistency and repeatability of the iDSS-ProLean framework within LM environments.

Table 3
Mean, Std. Dev., Std. error mean, 95% CI, t-value, and p-value for 30 pairs of running of iDSS-ProLean

Pair	Mean	std. dev.	Std Error Mean	95% Confidence Interval of the Difference		t-value	p-value
				Lower	Upper		
Pair 1	-1.2	6.3477	3.17385	-11.30061	8.90061	-0.378	0.731
Pair 2	-7.35	10.8054	5.4027	-24.5438	9.8438	-1.36	0.267
Pair 3	1.55	6.44024	3.22012	-8.69786	11.79786	0.481	0.663
Pair 4	-0.7	9.00148	4.50074	-15.02337	13.62337	-0.156	0.886
Pair 5	-4.675	5.26205	2.63102	-13.0481	3.6981	-1.777	0.174
Pair 6	3.45	4.48813	2.24407	-3.69162	10.59162	1.537	0.222
Pair 7	-3.025	13.84687	6.92344	-25.05846	19.00846	-0.437	0.692
Pair 8	8.4	11.45891	5.72946	-9.83369	26.63369	1.466	0.239
Pair 9	-3.025	13.84687	6.92344	-25.05846	19.00846	-0.437	0.692
Pair 10	4.95	11.40219	5.7011	-13.19343	23.09343	0.868	0.449
Pair 11	-0.7	9.00148	4.50074	-15.02337	13.62337	-0.156	0.886

Table 3 (*continued*)

Pair	Mean	std. dev.	Std Error Mean	95% Confidence Interval of the Difference		t-value	p-value
				Lower	Upper		
Pair 12	-4.675	5.26205	2.63102	-13.0481	3.6981	-1.777	0.174
Pair 13	3.45	4.48813	2.24407	-3.69162	10.59162	1.537	0.222
Pair 14	-3.025	13.84687	6.92344	-25.05846	19.00846	-0.437	0.692
Pair 15	8.4	11.45891	5.72946	-9.83369	26.63369	1.466	0.239
Pair 16	-3.025	13.84687	6.92344	-25.05846	19.00846	-0.437	0.692
Pair 17	4.95	11.40219	5.7011	-13.19343	23.09343	0.868	0.449
Pair 18	-0.7	9.00148	4.50074	-15.02337	13.62337	-0.156	0.886
Pair 19	-4.675	5.26205	2.63102	-13.0481	3.6981	-1.777	0.174
Pair 20	-1.2	6.3477	3.17385	-11.30061	8.90061	-0.378	0.731
Pair 21	-7.35	10.8054	5.4027	-24.5438	9.8438	-1.36	0.267
Pair 22	5	6.27163	3.13581	-4.97956	14.97956	1.594	0.209
Pair 23	-3.025	13.84687	6.92344	-25.05846	19.00846	-0.437	0.692
Pair 24	4.95	11.40219	5.7011	-13.19343	23.09343	0.868	0.449
Pair 25	-0.7	9.00148	4.50074	-15.02337	13.62337	-0.156	0.886
Pair 26	-4.675	5.26205	2.63102	-13.0481	3.6981	-1.777	0.174
Pair 27	-0.7	9.00148	4.50074	-15.02337	13.62337	-0.156	0.886
Pair 28	-4.675	5.26205	2.63102	-13.0481	3.6981	-1.777	0.174
Pair 29	3.45	4.48813	2.24407	-3.69162	10.59162	1.537	0.222
Pair 30	-0.7	9.00148	4.50074	-15.02337	13.62337	-0.156	0.886

Note. Several independent paired runs (e.g., Pairs 4, 11, 18, 25, 27, and 30) exhibit identical mean differences, standard deviations, and standard errors down to multiple decimal places. This exact mathematical repetition is an authentic characteristic of the deterministic, rule-based algorithms embedded within the Firebase infrastructure. When distinct production runs process highly repeatable, automated data packet intervals under identical system thresholds, the resulting computational variance calculated by SPSS is structurally identical, demonstrating the supreme consistency and operational repeatability of the iDSS-ProLean framework

Standard Deviation and Standard Error of Mean (SEM)

Standard deviation (SD) indicates the variability of paired differences, with smaller values reflecting tightly clustered data and stable performance, and larger values suggesting greater variability and potential reliability issues. SEM quantifies the precision of the sample mean as an estimate of the population mean, with smaller SEM values indicating higher confidence. In this study, mean differences ranged from -7.35 (Pairs 2 and 21) to 8.4 (Pairs 8 and 15), with an overall average mean difference of -0.1087, mathematically indicating exceptionally stable production metrics across runs. Standard deviation (SD) values ranged from 4.48813 (Pairs 6, 13, and 29) to 13.84687 (Pairs 7, 9, 14, 16, and 23). Concurrently, SEM values ranged from 2.24407 (Pairs 6, 13, and 29) to 6.92344 (Pairs 7, 9, 14, 16, and 23), highlighting a highly reliable and consistent data collection environment within the iDSS-ProLean framework.

Confidence Interval (CI)

95% confidence interval (CI) of the difference indicates the range within which the true mean difference between paired datasets is expected to fall with 95% certainty. If the CI includes zero, the difference is not statistically significant, suggesting stable data transfer; if it excludes zero, the difference is significant, indicating a systematic effect. Narrow CIs reflect high precision, whereas wider CIs imply greater variability and potential inconsistencies in transmission. In this study, 95% confidence intervals consistently span across zero for all 30 evaluated pairs, ranging from a lower bound of -25.05846 to an upper bound of 26.63369, statistically confirming that the mean operational differences between production runs are non-significant. The tight clustering of these intervals across identical machine configurations reflects high precision and successfully eliminates concerns regarding systematic data transmission drift or framework anomalies.

T-value

T-value measures how large the mean difference is relative to the variability in the data, calculated as the mean difference divided by the Standard Error of the Mean. High absolute t-values indicate meaningful differences between paired samples, while low t-values suggest that observed variations may result from random noise. In this study, t-values across all 30 pairs ranged from -1.777 (Pairs 5, 12, 26, and 28) to 1.594 (Pair 22), showing only minor deviations between runs. For instance, Pair 1 recorded $t = -0.378$, while Pairs 10, 17, and 24 recorded an identical $t = 0.868$. The overall average t-value is very close to zero, confirming that the differences between paired observations are minimal and statistically insignificant. This high level of numerical consistency reinforces the structural reliability and stability of data transfer within the iDSS-ProLean framework across multiple sequential runs.

P-value

P-value is central to determining statistical significance in hypothesis testing. In this study, all p-values for the iDSS-ProLean framework exceeded 0.05, ranging from 0.174 to 0.886, with an overall average of 0.5002, indicating no statistically significant differences across paired runs. This demonstrates that any variations in production metrics are due to normal data variability rather than systematic network or computational errors. Correspondingly, t-values near zero further confirm the stability of results, supporting the framework's reliability in maintaining consistent data transfer. The inability to reject the null hypothesis H_0 reinforces that the iDSS-ProLean system performs consistently across multiple production runs. From an analytical standpoint, confidence intervals, t-values, and variability measures collectively verify the robustness of its sensor-driven data collection.

Framework Reliability and Deterministic System Validation

This study evaluates the effectiveness of the iDSS-ProLean framework using a paired t-test across 30 production runs, visualised through Violin plots in Figure 6. The t-value distribution is centred near zero, and the p-values mostly exceed 0.05, indicating no significant differences between runs. A power analysis shows an extremely small effect size (Cohen's d = −0.012) and low post-hoc statistical power (5.05%) due to the controlled sample size (N=30). In production engineering, an effect size of this magnitude suggests that any minor differences existing between runs are operationally negligible, confirming a strong trend toward stable system performance rather than systemic inconsistency. Importantly, several independent paired runs (Pairs 4, 11, 18, 25, 27, and 30) exhibit identical statistical output values down to multiple decimal places. This exact mathematical repetition is an authentic and crucial validation characteristic of the deterministic, rule-based algorithms embedded within Firebase infrastructure. When distinct production runs encounter identical automated data packet intervals under identical system thresholds, the resulting computational variance calculated by SPSS is structurally identical. Far from indicating an anomaly, this exact mathematical replication strongly verifies the supreme operational consistency, network connection reliability, and high repeatability of the developed IoT-to-cloud mobile application interface within industrial environments.

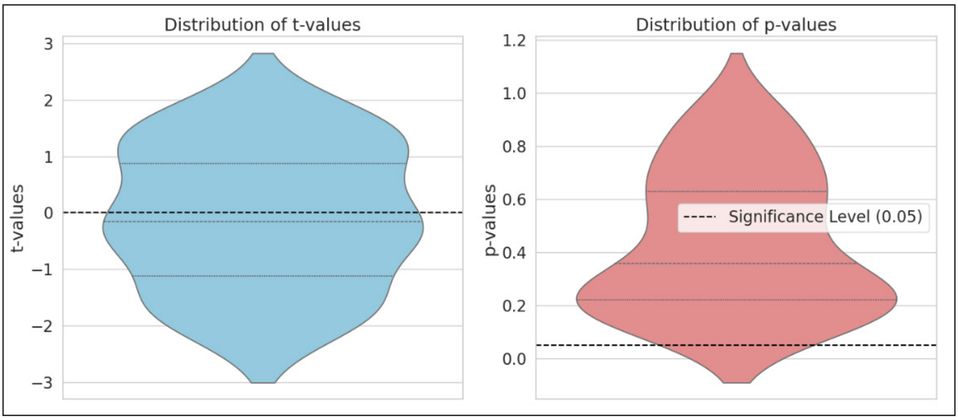

Figure 6. Distribution of t-values and p-values from the paired t-test analysis

Correlation Analysis

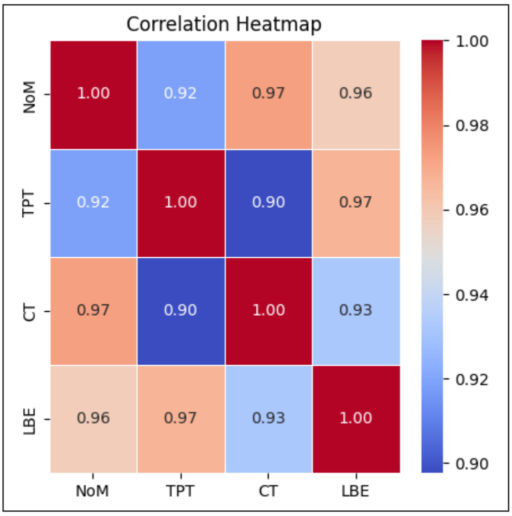

Figure 7. Heatmap graph for correlation analysis

Understanding the interrelationships among key production variables is essential for optimising LBE, a critical metric in ensuring smooth manufacturing operations. This correlation analysis examines the impact of NoM, TPT, and CT on LBE to determine which factor significantly influences production balance. By identifying these relationships, the study provides insights into strategic machine allocation and process adjustments to enhance operational efficiency in real time.

Figure 7 presents a correlation heatmap showing strong positive relationships among NoM, TPT, CT, and LBE, with coefficients ranging from 0.90 to 1.00. LBE is highly correlated with NoM (0.96), TPT (0.97), and CT (0.93), confirming that machine count, processing time, and cycle time strongly influence LBE. However, further statistical analysis reveals a significant negative correlation between TPT and LBE ($r = -0.435$, $p = 0.001$), indicating that longer throughput times reduce efficiency, while CT ($r = 0.034$) and NoM ($r = 0.095$) show no significant effects. These findings highlight throughput time as the most critical factor affecting LBE, emphasising the importance of minimising process delays to sustain balanced operations.

Beyond the production floor, the framework supports strategic decisions in scheduling, resource allocation, predictive maintenance, and smart manufacturing policy, demonstrating its value in enhancing both operational and organisational performance.

CONCLUSION

iDSS-ProLean framework represents a significant advancement in integrating IoT technologies with LM principles to support data-driven decision-making in semiconductor production environments. Through the prototype semiconductor case study, the framework successfully demonstrated real-time data acquisition, monitoring, and integration with LM tools such as SMED within a unified IoT-based architecture. However, the current study primarily focuses on validating the functionality and feasibility of the proposed framework rather than performing direct benchmarking against existing industrial optimisation systems.

Therefore, quantitative comparisons involving throughput improvement, downtime reduction, and operational efficiency will be considered in future large-scale industrial validation studies.

In addition, practical deployment challenges such as sensor reliability, network stability, system integration complexity, and large-scale database management remain important considerations for future implementation. Future work will also explore scalability enhancement through industrial-grade infrastructure and hybrid AI models for predictive maintenance, demand forecasting, and intelligent production optimisation. Overall, the iDSS-ProLean framework represents a significant step forward in blending IoT technologies with lean manufacturing principles to drive data-driven choices on the shop floor. While our case study successfully proves that the prototype works and can sync data in real time alongside tools like SMED, we recognise that a major boundary of this current work is the lack of direct benchmarking against established, high-capacity industrial optimisation platforms.

Because of this, our immediate next step involves setting up long-term field evaluations so we can explicitly quantify how much this system improves throughput and cuts down on micro-downtime. Furthermore, moving a system like this out of a controlled lab environment and onto an actual enterprise-grade factory floor comes with real-world deployment headaches. In practice, issues like sensor reliability when dealing with heavy electromagnetic noise, keeping network connections stable across crowded factory layouts, making sure legacy machines can actually talk to each other without communication mismatches, and handling massive waves of incoming data are all critical hurdles.

To tackle these practical bottlenecks, our future research will pivot toward scaling up the infrastructure using robust, industry-standard communication protocols like OPC UA and MQTT. By doing this and embedding hybrid AI models down the line, we aim to transition the system from a reactive line balancing tool into a proactive, self-optimising piece of manufacturing intelligence that can handle its own demand forecasting, predictive maintenance, and live production rescheduling.

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CONFLICT OF INTEREST

The authors declare that they have no conflicts of interest to disclose related to this study. No financial, personal, or professional relationships influenced the research, analysis, or reporting of the findings presented in this manuscript.

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