Leveraging Learning Factories to Develop Multi-Site Dashboards for Decentralised Smart Manufacturing in Industry 5.0

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Abstract. With the new focus in Industry 5.0 on human-centric and resilient manufacturing, there is increasing interest in a value chain approach, where enterprises operate across multiple sites or with value chain partners, potentially with decentralised decision-making. However, collaboration across sites presents challenges, as each site often develops its own shopfloor dashboard, leading to inconsistencies in data collection, KPI definitions, and metric displays, preventing a unified cross-site performance view. This paper explores how Learning Factories can be used to develop industry-grade multi-site dashboards, which standardise and consolidate data from diverse systems, enabling a comprehensive perspective for global operations managers. We present a case study of a Learning Factory network spanning three sites with varying products, processes, and protocols. This network was used to develop a multi-site manufacturing dashboard, later deployed regionally to a multinational corporation in high-volume production. The collaboration with the Learning Factory allowed the company to co-innovate a dashboard tailored to their specific needs, improving oversight and optimising decision-making. These dashboards enable more agile real-time drill-down analysis, making it easier to identify underperforming sites and enhance decision-making agility. The collaborative nature of Learning Factories also facilitates the development of multi-enterprise dashboards, addressing challenges such as data privacy, security, and the standardisation of metrics across organisations. Learning Factories are key enablers of innovation in dashboard technology, driving the realisation of distributed smart value chains and supporting companies in their transition to Industry 5.0.

Keywords: Dashboards, Monitoring, Industry 5.0, Multi-site, Multi-enterprise.

1 Introduction

In recent years, the manufacturing sector has increasingly adopted a value chain approach to enhance responsiveness to fluctuating customer demands and market changes. This shift has improved lead times and enabled the delivery of market-specific products, highlighting the strategic importance of integrated value chains over isolated manufacturing systems.

However, decentralised decision-making in value chains presents challenges, particularly in process ownership and governance across diverse stakeholders. It requires harmonising information systems across multiple sites, each with varying scales, capacities, and priorities. The implementation of a shared decision support system (DSS) or dashboard at the value chain level faces complexities in data sharing, with discrepancies in defining and tracking key performance indicators (KPIs) across organisations and countries. Standardisation of KPIs and data collection is essential for effective collaboration in global networks.

This paper presents a case study based on the development of an enterprise-level dashboard for a 3-site Learning Factory (LF) environment. Although the sites were under a single enterprise, they exhibited variations in data structures, metrics, and processes, providing a controlled setting to test collaborative manufacturing concepts. Building on these insights, the study extends the framework to a multinational corporation, where a site-level dashboard has been deployed across 4 out of 6 planned factories, leading to the commitment of a multi-site enterprise dashboard.

This paper proposes advancing research on multi-enterprise dashboards that address cross-enterprise disruptions in value chain setups. Simulating learning factories across a value chain enables exploration of issues such as data privacy, security, and metric standardisation in cross-enterprise collaboration. While manufacturing companies remain cautious about such frameworks due to production constraints, this study highlights the role of collaborative LF networks in driving innovation and proposes a validated multi-site enterprise framework to support the future of interconnected global manufacturing.

2 Background Study

2.1 Literature Review

LFs have emerged as intricate and immersive environments designed to replicate real-world manufacturing systems, offering hands-on experiential learning for participants in various stages of production and value chains. Abele et al. [1] presented a comprehensive review of LFs, detailing their motivations, background, and definitions, emphasising the importance of establishing a network of LFs to meet global demand and supply challenges. Similarly, Suveg V. Iyer [2] addressed the complexities of globalisation and proposed a federated digital twin framework to enhance collaboration in learning factories. Barth [3] integrated Circular Economy principles into LFs through a competency-based learning module developed in collaboration with eight members of the International Association of Learning Factories (IALF). Schuhmacher [4] introduced the "Cross Learning Factory Product Production System" (CLFPPS) to operationalise circular economy concepts across product life cycles using a cross-learning factory network. Wengle [5] highlighted the significance of combining multiple learning factories into a cohesive production network that mirrors real-world value chains. Collectively, these studies highlights the critical role of collaboration between LFs in

fostering innovation and education in global manufacturing, particularly through cross-sector and cross-geography partnerships. Especially in an industry in which trial and testing of research outcomes are a costly endeavour for many enterprises to take on.

In another strand of research, Sorensen [6] explored the role of LFs as experimental spaces for SMEs to engage with Industry 4.0 technologies, helping smaller enterprises avoid the risk of being left behind. Wang [7] discussed the importance of partnerships among industry, academia, and government to ensure LFs remain at the forefront of technological innovation, particularly in AI and Industry 5.0. Both studies underline the value of collaboration between industry and LFs, whereby LFs gain exposure to real-world challenges, while industry benefits from LF-led innovation.

The integration of enterprise systems with DSSs to enable multi-enterprise collaboration is a growing trend in the field. Shafiei and Sundaram [8] demonstrated how the convergence of enterprise resource planning (ERP) and DSSs can maximise intelligence density, improve information visibility, and lay the foundation for effective multi-enterprise collaboration. Andres [9] introduced a DSS that aligns strategies across autonomous partners within collaborative networks, enhancing performance and competitiveness. Allaoui [10] examined collaboration planning in sustainable supply chains, where DSSs helps balance economic, environmental, and social issues through multi-party cooperation. Lau [11] presented a fuzzy multi-criteria decision support (FMCDS) procedure to enhance information delivery in extended enterprise networks, facilitating smoother data exchanges and decision-making across geographically dispersed enterprises. Finally, Vargas [12] proposed a conceptual model for inter-enterprise architecture, applying it to hierarchical production environments to improve decision-making in collaborative production planning. These studies highlight the importance of standardising systems and aligning business objectives with data-sharing frameworks to enhance multi-enterprise collaboration. However, there has been limited recent research on DSS tailored for LF setups.

The literature emphasizes collaboration among LFs to advance multi-site, multi-enterprise manufacturing. While joint research is common, real-world deployment is crucial to address uncontrolled challenges. DDSs standardize processes and align business goals, with LFs serving as testbeds for validating their efficiency, security, and scalability.

2.2 Research Approach

This study adopts a phased approach to developing multi-enterprise dashboards for manufacturing decision support. It begins with an intra-enterprise focus, addressing data integration, KPI standardization, visualization, and role-based customization. Insights from this phase inform the transition to inter-enterprise collaboration, adding complexities in data privacy, access control, and governance across value chain partners. Leveraging real-world Learning Factory case studies, the research tests methodologies for secure, standardized KPI adaptation in multi-site ecosystems. This structured approach ensures practical feasibility and scalability for industry adoption.

3 Multi-site Framework and Architecture for Dashboards

3.1 Learning Factory Use Case

A multi-site DSS dashboard was implemented across three learning factories within a single organisation. Despite each site performing distinct manufacturing processes, a unified narrative was developed to demonstrate how these factories collaboratively meet shared customer demands. This framework allowed us to simulate a value chain where multiple entities work together as part of an ecosystem. The table below presents the structured framework for the use case.

Table 1. Products relevant to use case set-up and corresponding processes.

Site	Product	Machine Processes	Total no. of machines at each site
Site A	Product I	Process 1	25
	Product II	Process 3, 4	
Site B	Product I	Process 1	2
Site C	Product II	Process 5, 6, 7, 8	2

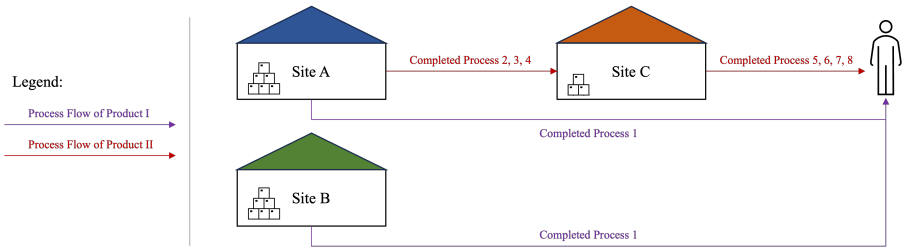


Fig. 1. Collaborative scenario of the 3-site Learning Factory use case.

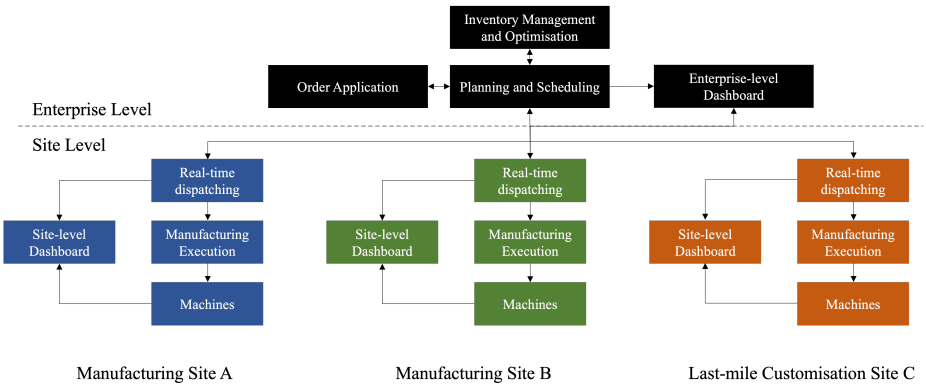


Fig. 2. A system diagram of the 3 site Learning Factory use case set-up consisting of sites A and B that produces similar products (Product I) and different products (Product II) as well as site C that does last mile customisation for Product II manufactured at site A.

Use Case Set-up. To explore multi-site collaboration concepts and new data sources for the DSS, we introduced processes that could be executed at more than one site, as seen in Table 1. Additionally, two distinct products—Product I and Product II—were introduced into the use case. These products followed different manufacturing processes across sites, adding complexity to the scenario. The number of machines at each site was also considered to reflect variations in factory size and capacity, which influenced how KPIs should be represented and aggregated.

The Collaboration Mechanism. The collaboration mechanism between sites was structured to reflect an interconnected production flow. As depicted in Figure 1 and supported by the application architecture in Figure 2, Site A primarily produced Product I and partially processed Product II before transferring it to Site C for final customisation. Meanwhile, Site B provided redundancy for Product I manufacturing, allowing flexibility in resource allocation and production scheduling. The redundancy of Site B ensured that when production volumes were high, the planning and scheduling system could divert some production to another site to fulfill orders. Site C, being a smaller factory with limited space for inventory, played a critical role in the inventory positioning and multi-site material transfer concepts explored in this use case. Data from all sites was centralised via a private cloud network, where a DSS aggregated and visualised the information on an enterprise-level dashboard. This real-time visibility provided key insights into production status across sites and enabled proactive decision-making for operational managers.

Decision Support System & Dashboard Aggregation. The implementation successfully leveraged digital infrastructure for live monitoring across remote sites while highlighting key enterprise-level dashboard design considerations. Limited screen space required careful KPI selection to provide regional managers with the most relevant data. Each KPI was standardized with predefined thresholds to flag critical deviations. Variations in site size, capacity, and complexity necessitated refined data aggregation to prevent larger sites from skewing performance assessments.

The following table presents the key framework components, artifacts, KPIs, and decision levels. Below it is equations used to aggregate the KPIs considering enterprise-level decision making. Weights are assigned to machines or sites when aggregating based on deep domain expertise in manufacturing production and critical processes. This method ensures that the enterprise-level KPIs reflects the performance of machines critical to production, providing management with a more accurate measure of the overall efficiency. Without proper normalisation, the performance of one site could be overshadowed by another, potentially skewing organisational performance assessments. These frameworks and their associated KPIs are critical for evaluating multi-site enterprises. However, additional KPIs relevant to supply chain and shop floor business units exist, which were beyond the scope of this paper.

Table 2. Framework Components, Key Artifacts and KPIs Measured

Framework Component	Key Artifacts	KPIs Measured
Multi-Site Production	Factory Collaboration Model	OEE, Yield Rate, Fulfillment Rate
Inventory Positioning	Material Transfer Strategy	Inventory Turnover, Fill Rate, Inventory Cost

$$Weighted\ OEE = \sum OEE_m \times w_m / \sum w_m \quad (1)$$

$$Weighted\ Yield\ Rate = \sum (Yield_m \times w_m) / \sum w_m \quad (2)$$

$$Fulfillment\ Rate = \sum Orders\ Received\ across\ Sites / \sum Orders\ Fulfilled\ at\ Sites \quad (3)$$

$$Weighted\ Inventory\ Turnover = \sum w_s / \sum (Inventory\ Turnovers \times w_s) \quad (4)$$

$$Enterprise\ Fill\ Rate = \sum Customer\ Orders\ Received / \sum Customer\ Orders\ Fulfilled_s \quad (5)$$

$$Enterprise\ Inventory\ Cost = \sum (Inventory\ Cost\ at\ Sites) \quad (6)$$

The Design Rulebook. A design rulebook was also created to maintain consistency in UI elements across the multi-site dashboard. It defines key principles such as the use of RGB hex colors exclusively for status representation, ensuring no confusion with other UI components. Data placement is organized by categorizing real-time data on one side of the dashboard, while tactical data, aggregated over longer periods, is positioned on the opposite side, defining clear real estate for different goals for DSS users. The dashboard modules follow a two-layer navigation structure: the first layer offers an overview of performance with indicators and statuses to support a 'management by exception' approach, while the second layer allows users to drill down into specific KPIs for root cause analysis of poor performance.

While this use case was limited by its relatively simple setup, single ownership of processes, and a small set of variables, the proposed framework has the potential for expansion. It can be adapted to support more complex and diverse production environments, particularly in networks with multiple enterprise stakeholders and varying levels of data-sharing permissions.

3.2 Industry Use Case

Building on the 3-site LF success, the dashboard architecture was extended to a multinational corporation with high-volume production needs, validating its adaptability to real-world complexities. Initially deployed at a Batam, Indonesia shop floor, the LF team conducted hands-on requirement gathering, guiding implementation from assessment to deployment.

The solution unified shop floor data and KPIs into a single source of truth, integrating modules for waste management, logistics, energy, and production tracking. Its modular design ensured scalability while enhancing reliability through decentralized data sources. Role-based access secured on-premises servers, enabling hierarchical insights for strategic oversight while protecting sensitive data.

Following Batam's success, the corporation expanded the dashboard to five additional sites—Ontario, Klagenfurt, Zhuhai, Varginha, and Drachten—standardizing KPI tracking across locations. The next phase involves developing an enterprise-level dashboard at headquarters, leveraging methodologies from both the LF and site-level deployments to provide a unified, global performance view.

4 Conclusion

The evolution of Decision Support Systems in manufacturing is advancing towards multi-enterprise dashboards that enable seamless data sharing and collaboration across value chain partners. These dashboards provide real-time, comprehensive visibility into operations, necessitating a global approach to standardization. Establishing flexible yet rigorous frameworks for KPI normalization, terminology alignment, and data structuring across sectors, business functions, and regions is crucial. Generative AI can play a transformative role in this process by interpreting the rationale behind multi-site KPIs, thereby assisting in their adaptation and harmonization across diverse manufacturing networks.

5 Next steps

Future development efforts will focus on ensuring that dashboards present customized views based on roles and functions to meet the specific needs of each enterprise. Additionally, key priorities include strengthening data governance through role-based access control and defining clear data ownership guidelines to protect proprietary information. Standardized data models and integration protocols will be essential for bridging internal system disparities, ensuring accurate and reliable data exchange. Advanced security measures, including end-to-end encryption and multi-factor authentication, will be critical in fostering trust among collaborating enterprises.

LFs provide ideal environments for testing and refining multi-enterprise DSS by simulating real-world manufacturing scenarios. These collaborative networks can help address the technical, organizational, and security challenges inherent in inter-enterprise cooperation. Encouraging continuous LF partnerships will drive innovation and knowledge-sharing, supporting the realization of Industry 5.0 and advancing the multi-enterprise framework essential for the future of manufacturing ecosystems.

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References

1. Abele, E., et al.: Learning factories for research, education, and training. Procedia CIRP 32, 1–6 (2015). https://doi.org/10.1016/j.procir.2015.02.187.
2. Iyer, S. V., K. S. Sangwan, and Dhiraj: Evolution of Digital Twin in Manufacturing Application: Definition, Architecture, Applications, and Tools. In: Kumar, A., Kumar, P., Liu, Y. (eds.) Industry 4.0 Driven Manufacturing Technologies, Springer Series in Advanced Manufacturing, Springer, Cham (2024). https://doi.org/10.1007/978-3-031-68271-1_1.
3. Barth, J., et al.: Development of an IALF Overarching Learning Module for Circular Economy. In: Thiede, S., Lutters, E. (eds.) Learning Factories of the Future, Lecture Notes in Networks and Systems, vol. 1059, Springer, Cham (2024). https://doi.org/10.1007/978-3-031-65411-4_43.
4. Schuhmacher, J., et al.: Development of an approach for a "cross learning factory product production system" for circular economy. SSRN Electron. J. (2023). https://doi.org/10.2139/ssrn.4472089.
5. Wengle, M., Dietmüller, T.: "Zukunftsfabrik Bodensee" - A Production Network Combined of Two Different Learning Factories. In: Thiede, S., Lutters, E. (eds.) Learning Factories of the Future, Lecture Notes in Networks and Systems, vol. 1060, Springer, Cham (2024). https://doi.org/10.1007/978-3-031-65400-8_16.
6. Sorensen, D., Lassen, A., Larsen, M., Hansen, A.: Learning Factories for Learning and Experimentation on Industry 4.0 in SMEs. In: Industry 4.0: Revolutionizing Manufacturing, Springer, Cham (2022). https://doi.org/10.1007/978-3-031-15428-7_39.
7. Wang, K., Wang, L., Yu, W., He, F., Ren, S., Gu, P.: Progress and Reflection of Learning Factory. In: Learning Factories: Insights into Future Production Systems, Springer, Cham (2024). https://doi.org/10.1007/978-3-031-65400-8_13.
8. Shafiei, F., Sundaram, D.: Multi-enterprise collaborative enterprise resource planning and decision support systems. In: 37th Annual Hawaii International Conference on System Sciences, Proceedings, pp. 10–. (2004).
9. Andres, B., Poler, R.: A Decision Support System for the Collaborative Selection of Strategies in Enterprise Networks. Decision Support Systems 91, 113–123 (2016). https://doi.org/10.1016/j.asoc.2016.11.034.
10. Allaoui, H., Guo, Y., Sarkis, J.: Decision support for collaboration planning in sustainable supply chains. Journal of Cleaner Production 229, 10–. https://doi.org/10.1016/j.jclepro.2019.04.367.
11. Lau, H.C.W., et al.: A Fuzzy Multi-Criteria Decision Support Procedure for Enhancing Information Delivery in Extended Enterprise Networks. Engineering Applications of Artificial Intelligence 16(1), 1–9 (2003). https://doi.org/10.1016/S0952-1976(03)00020-4.
12. Vargas, A., Boza, A., Patel, S., Patel, D., Cuenca, L., Bas, A.: Inter-enterprise architecture as a tool to empower decision making in hierarchical collaborative production planning. Data & Knowledge Engineering 105, 10–. https://doi.org/10.1016/j.datak.2015.10.002.