Mora, M., Tang, P., Toledo, M. (2025). Towards enabling sustainability-aware operations in housing manufacturing with AI-driven Value Stream Mapping: A Review. In O. Seppänen, L. Koskela, & K. Murata (Eds.), *Proceedings of the 33rd Annual Conference of the International Group for Lean Construction* (IGLC33) (pp. 976-986)..https://doi.org/10.24928/2025/0266

TOWARDS ENABLING SUSTAINABILITY-AWARE OPERATIONS IN HOUSING MANUFACTURING WITH AI-DRIVEN VALUE STREAM MAPPING: A REVIEW

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ABSTRACT

The construction industry is a major contributor to global CO2 emissions, with housing construction playing a significant role. Lean and technological approaches offer promising solutions for reducing emissions in housing, since Value Stream Mapping (VSM) enhances process analysis, and Artificial Intelligence (AI) can optimize complex systems. This paper aims to identify the state-of-the-art and drivers of current approaches that combine AI and VSM to integrate sustainability analysis in manufacturing. The main objective is to gather insights from the manufacturing industry to develop an AI-driven VSM for sustainability-aware operations in housing manufacturing.

Based on a literature review based on the PRISMA methodology, the authors identified that Internet of Things (IoT) approaches enable AI-driven VSM by integrating real-time data collection. Specifically, IoT enables real-time data collection, and AI enables dynamic process analysis for monitoring, optimizing, and controlling. Additionally, defining sustainability goals and assessing information quality is critical before integrating sustainability variables in AI-driven VSM approaches. This paper presents the research background, findings, recommendations, and future research guidelines to deliver an AI-driven VSM approach for reducing CO2 emissions in housing manufacturing.

KEYWORDS

Value Stream Mapping, Artificial Intelligence, IoT, Housing Manufacturing, Sustainability

INTRODUCTION

The construction industry is one of the main ones responsible for global CO2 emissions (United Nations Environment Programme, 2022). Specifically, housing construction in 2023 accounted for 41% of the total investment in construction (Oxford Economics, 2023). Thus, there is an opportunity to adopt sustainable practices in housing construction to reduce industry CO2 emissions. These practices include technological implementation and prefabricating elements through industrialized and manufacturing means (Mckinsey Global Institute, 2017; United Nations Environment Programme, 2022). Moreover, industrialization and manufacturing are promising practices to reduce CO2 emissions because of the nature of the housing mass-

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production (ARUP, 2018). Their successful implementation of CO2 emissions reduction relies on considering CO2 emissions variables and traditional production objectives during production (Chen et al., 2017). Moreover, housing has mass-customization requirements that decision-makers address during the definition of the production schedule by allocating resources to produce the products within the defined goals (Giret et al., 2015; Kundakcı & Kulak, 2016; Trentesaux and Prabhu, 2014).

Several methodologies can help users to integrate sustainable manufacturing principles into processes. This research focuses on Lean Manufacturing, which aims to reduce waste in manufacturing processes (Brown et al., 2014; Dües et al., 2013). Over the years, the Lean Manufacturing definition has evolved among Lean researchers and practitioners, and today, two main currents are recognized: a philosophical and a practical (Bhamu & Singh Sangwan, 2014; Čiarnienė & Vienažindienė, 2012; Pettersen, 2009; Shah & Ward, 2007). Focusing on the practical side, Value Stream Mapping (VSM), a process-value visualization methodology for mapping tasks, material, and information flows, is the most applied Lean methodology (Jasti & Kodali, 2015; Rewers et al., 2016; Sundar et al., 2014). Moreover, the VSM can integrate environmental variables. For example, Rosenbaum et al. (2014) used VSM to track environmental waste in construction projects.

The VSM methodology defines two scenarios: the current state as the process's baseline to identify waste and the process's future state with the process's optimization and waste elimination (Pereira Librelato et al., 2014). Thus, it delivers a static system optimization that does not consider real-time data. However, the housing industry's dynamic nature makes static production scheduling obsolete when new orders arrive in the system. Therefore, users need dynamic assessment tools to make proactive decisions and propose new production schedules with up-to-date information. Additionally, most of the research on CO2 emissions reduction in manufacturing focuses on order assessment based on historical data (Cao & Li, 2014; Chung & Caldas, 2024; G. Liu et al., 2020; Mao et al., 2018; Tao et al., 2018; Tuo et al., 2019). Therefore, there is a gap in delivering real-time CO2 emissions data for decision-makers who want to proactively and dynamically improve their processes towards minimizing the CO2 emissions of their operations (Cao & Li, 2014; Cassettari et al., 2017; Chung & Caldas, 2024; G. Liu et al., 2020; Q. Liu et al., 2018; Mao et al., 2018; Tao et al., 2018; Tuo et al., 2019).

Since dynamic analysis requires managing more variables, there is a potential for integrating Artificial Intelligence (AI) approaches to support users in dynamic assessments. For example, there are several AI approaches to support the production scheduling problem (Hassanchokami et al., 2022; Kundakcı and Kulak, 2016; Mohan et al., 2019; Popper et al., 2021; Salido et al., 2017; Wang and Chen, 2024). These AI approaches can have economic, environmental, and social objectives defined by the users and enable real-time and dynamic analysis because they can manage more variables and scenarios faster than humans (Çaliş & Bulkan, 2015; Jarrahi, 2018). Nonetheless, applying existing AI approaches from one industry to another is not straightforward since domain- and problem-specific requirements exist (Hassija et al., 2024).

This research studies the potential for integrating VSM and AI approaches to enable dynamic sustainability-aware assessments in housing manufacturing operations. However, since different industries have specific requirements, this study aims to identify the state-of-the-art and enablers of AI-driven VSM approaches to integrate sustainability variables in manufacturing. The authors aim to gather insights from these approaches to develop and implement an AI-driven VSM approach for housing manufacturing operations. Then, this research addresses the following research question: *What is the state-of-the-art AI-driven VSM for sustainable manufacturing, and what enables AI-driven VSM dynamic assessments on sustainable manufacturing?*

The following sections of this paper first explain the background of the relevant topics to this research. The following sections present the research approach, findings, and discussion to finalize the study with the conclusions and future research proposals.

LITERATURE REVIEW

This section presents the background of this research. First, the authors explore the concept of sustainable manufacturing. Then, they present the definition of VSM and existing approaches to support sustainability-aware operations. Finally, they present existing AI approaches to support integrating sustainable practices in manufacturing.

SUSTAINABLE MANUFACTURING

Sustainable manufacturing is a manufacturing approach that adopts innovative technical and organizational strategies to prevent resource scarcity and environmental concerns (Garetti et al., 2012; Giret et al., 2015). Moreover, in 2015, the Environmental Protection Agency of the United States (EPA) defined sustainable manufacturing as "the creation of manufactured products through economically-sound processes that minimize negative environmental impacts while conserving energy and natural resources" (US EPA, 2015). Then, sustainable manufacturing integrates social, environmental, and economic sustainable practices within manufacturing processes. This sustainable manufacturing concept aims to develop and implement new manufacturing methods, practices, and technologies at strategic and operational levels to reduce negative and maximize positive sustainability impacts (Garetti et al., 2012; Giret et al., 2015; Rosen and Kishawy, 2012).

VALUE STREAM MAPPING TO SUPPORT SUSTAINABLE MANUFACTURING

As discussed, Value Stream Mapping is the Lean methodology most studied in research papers about Lean between 1988 and 2011 (Jasti and Kodali, 2015). VSM is a visualization methodology for process mapping that helps users to identify waste and the relationships between tasks, people, information, and elements in the process (Biazzo, 2002). The VSM methodology considers the complete system instead of a particular process in the manufacturing process (Pereira Librelato et al., 2014). Thus, as a process mapping methodology, VSM allows identifying how a particular organization executes a process (White and Cicmil, 2016).

Traditional VSM approaches focus on the seven wastes identified by Ohno in 1988 (Faulkner and Badurdeen, 2014) However, recent approaches in the literature aim to integrate sustainable features into VSM. For example, by analyzing several manufacturing case studies in Brazil, the Helleno et al. (2017) study aimed to integrate social and environmental sustainability variables within VSM (Helleno et al., 2017). Another approach is the SUS-VSM methodology developed in the Faulkner and Badurdeen (2014) study. As in traditional VSM, the SUS-VSM approach integrates the makespan of the manufacturing process, but also integrates the GHG emissions by assessing the energy consumption of the manufacturing process (Faulkner & Badurdeen, 2014). The Faulkner and Badurdeen (2014) study also integrated operator (or user) indexes for social assessment. Further studies have successfully tested the methodology of SUS-VSM on a manufacturing process with product customization requirements (Brown et al., 2014).

AI TO SUPPORT SUSTAINABLE MANUFACTURING

AI scheduling approaches can support users in managing manufacturing, mainly when many tasks and variables must be analyzed to define a production schedule. There are precise and approximate AI models where methodologies, such as Artificial Neural Networks, Genetic Algorithms, and Ant Colony optimization, are identified within the approximate AI models (Mohan et al., 2019). These approximate models cannot find the best-optimizing solution.

Nevertheless, they are suitable for real-life optimization problems because they can propose a solution in an acceptable time and with minimal machine resource consumption (Mohan et al., 2019). In this study, AI algorithms to support sustainable manufacturing consider at least one environmental variable in their objective function. The final environmental impacts of these AI methodologies rely on the analyzed variable, such as energy savings, total process noise, and carbon footprint. (Hassanchokami et al. 2022). For example, the Zhang et al. (2015) study aimed to integrate energy and CO2 emission variables in the production scheduling optimization process (Zhang et al., 2015). This study considered that manufacturing processes can produce CO2 emissions through processes, auxiliary materials, tools, and internal transport (Zhang et al., 2015). Based on this assumption, they apply a hybrid algorithm to estimate the CO2 emissions of the processes through a relationship between energy consumption, material removal rate, and specific machinery coefficients (Zhang et al., 2015).

Thus, AI methodologies can help users analyze more variables simultaneously and integrate them into an analysis of sustainable manufacturing. On the other hand, VSM allows users to represent sustainable variables within a process in static representations. Therefore, integrating AI within VSM can move VSM from static to dynamic analysis. This AI+VSM integration can allow the analysis and representation of sustainable variables to enable sustainability-aware operations in manufacturing. The objective is to gather insights to further develop an AI-driven VSM approach for housing manufacturing. Because an AI-driven VSM approach could support decision-making towards a sustainability-aware operations framework for housing manufacturing.

RESEARCH METHODOLOGY

To address this research, the researchers present a systematic literature classification and synthesis of Value Stream Mapping with AI implementations. This literature review uses the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) methodology, a methodology from the healthcare field intended to guide, define inclusion criteria from different domains, and report systematic reviews ("PRISMA 2020 flow diagram", 2024). Thus, since there are several manufacturing domains, PRISMA is suitable to identify the state-of-the-art and drivers of AI-driven VSM.

To identify the most relevant studies, the researchers used the Google Scholar database and applied the PRISMA methodology to sort, filter, and identify the most relevant studies. The authors performed the following initial query to identify the studies: ("value stream mapping" OR "VSM") AND ("AI" or "Artificial Intelligence"). This search query presented 8,580 results, and the researchers sorted the results using the Google Scholar relevance sorting option. The researchers screened the first 40 most relevant records from this search, finding 36 research articles to review. Then, the research team only selected literature in English and reviewed the articles' abstracts. This initial article review excluded research papers where VSM stood for Vehicle Scanning Methods and Virtual Shared Models or other meanings unrelated to Value Stream Mapping. After applying this inclusion criterion, the research team selected 10 articles eligible for this systematic review. The following sections present this systematic review's analysis, findings, discussion, and conclusions.

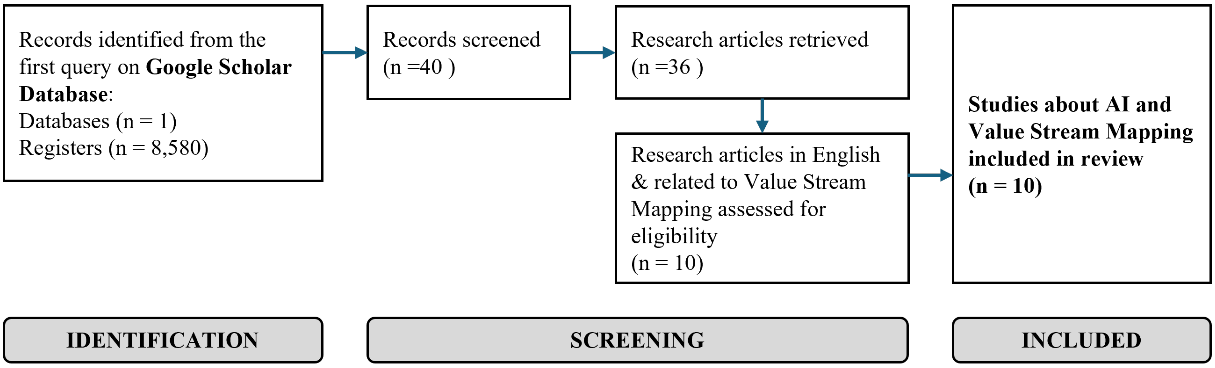

Figure 1: Systematic literature review methodology based on PRISMA methodology

RESULTS AND FINDINGS

This section summarizes the results and findings from the analyzed article. The 10 analyzed articles ranged from 2019 to 2024, most from 2024 (4). Seven articles presented VSM approaches, three articles are literature reviews (Table 1), nine articles are from the manufacturing industry, and one is from education. Furthermore, several approaches exist to integrate AI and VSM into manufacturing, but they require IoT approaches to support simulation, monitoring, and controlling material flows and labor in manufacturing environments.

Table 1: State-of-the-art AI-driven VSM literature from review studies

Article	Literature review approach	Identified Enablers
(Hansen & Bøgh, 2021)	To identify the application of IoT and AI approaches in Small and Medium Enterprises (SMEs)	Identified that IoT and AI are enablers of Dynamic Value Stream Mapping in manufacturing. Identified IoT layers definition: Sensors, communication protocols, databases
(Shahin et al., 2024)	To identify how AI can enhance Lean principles and methodologies (6S, VSM, and Total Productive Maintenance)	Identified the potential integration of IoT for real-time data collection to enable AI-assisted waste and loss analysis
(Endrigo Sordan et al., 2024)	To identify how Industry 4.0, AI, and Augmented Reality (AR) approaches can support Lean and Six Sigma implementations	Identified that Industry 4.0 approaches, such as IoT, AI, simulation, and Virtual Reality, can leverage VSM capabilities towards digitalization and automation

The authors present a summary of the reviewed articles in Table 2. Based on the analysis of these results, the authors identified six articles where IoT approaches are enablers of AI-driven VSM. IoT enables real-time data collection to optimize VSM future state maps in these approaches. However, the Busert & Fay (2019) study identified that practitioners must perform an information quality assessment before implementing IoT and AI approaches into VSM. This information quality assessment can help users identify if the AI and IoT implementation is suitable for solving the user's identified problem. Also, two studies focused on Small and Medium Enterprises (SMEs), specifically on analysing how Industry 4.0 and AI can leverage their flexibility capabilities in the current manufacturing industry. Both studies identified that companies must estimate, through simulation, how to address IoT layers for capabilities improvement assessment of their current manufacturing scenario before investing in technology implementation.

Table 2: State-of-the-art AI-driven VSM approaches from specific studies

Article	Research driver	Research AI-approach	AI-approach Enabler	Proposed model or finding
(Busert and Fay, 2019)	Standardize the information quality from Industry 4.0 for production planning and control based on VSM	To standardize the information flows between the physical environment, data acquisition, and data analysis to implement VSM and supporting technologies	Information quality requirements from Industry 4.0	Extended VSM methodology with granularity, frequency, and accuracy considerations for information quality assessment
(Huang et al., 2019)	Traditional VSM cannot handle dynamic manufacturing variables	AI's multi-agent system approach with model simulation and Radio Frequency Identification (RFID)	Simulation for scenario analysis and RFID for data acquisition	Dynamic Value Stream Mapping to integrate real-time data from materials flows into VSM
(Ferreira et al., 2022)	VSM for assessing the implementation of Industry 4.0 approaches	Discrete-event simulation and Agent-based modeling and simulations to assist Industry 4.0 approaches embedded with VSM	Simulation for future state scenario analysis	Hybrid Simulation (Discrete-event simulation + Agent-based modeling and simulation) VSM framework approach
(Manimuthu et al., 2022)	To identify IoT and Machine Learning approaches for real-time monitoring with volatility, uncertainty, complexity, and ambiguity	IoT for data collection and Machine Learning (ML) algorithms for analysis	IoT sensors available in the manufacturing area, and Support Vector Machine Learning	Identified that IoT and AI approaches can support Value Mapping in Vehicle Assembly factories
(Geisthardt et al., 2023)	An AI-assisted educational approach to teach value stream analysis	An AI-assisted game to complete a given activity	CRISP gamification framework	An AI-assisted gamification model with a graphical interface to interact with the user
(Batwara et al., 2024)	To identify technology, approaches, and metrics that can enable Smart and sustainable practices in manufacturing	To identify AI and IoT approaches to assist and leverage Small and Medium Enterprises (SMEs) capabilities in industrial environments, enabling smart and sustainable practices	Smart technology and IoT for real-time monitoring, simulation, and visualization	Smart Sustainable (SS-VSM) for SMEs integrating sustainable practices with technological tools, such as AI and IoT, with 11 indexes and 20 approaches
(Shatiry et al., 2024)	To monitor and track productivity during component prefabrication with digital video and AI	To automate and track labor occupancy times with digital cameras	Digital images from cameras	Digital Value Stream Mapping using IoT and AI to monitor labor productivity and safety

For sustainability integration in VSM, two studies identified that AI and IoT approaches can support integrating sustainability variables in manufacturing. These studies identified that to implement sustainability approaches successfully, practitioners must first define the sustainability objectives. Then, they can define and implement a suitable IoT and/or AI-driven VSM approach to support the identified problem. As the Batwara et al. (2024) study identified, several sustainability approaches and indexes are available, and they aim to support different industry problems. Therefore, the AI and/or IoT implementation must integrate specific users and the organization's sustainability goals to select the most appropriate indexes and approaches for the given manufacturing context (Busert & Fay, 2019).

DISCUSSION

The literature classification and synthesis identified that AI implementation in VSM is tied to IoT approaches. This is because IoT enables real-time data collection for dynamic process monitoring. Moreover, real-time data can support dynamic control and decision-making in the manufacturing system. Thus, the researchers identified IoT as an enabler of AI-based VSM approaches.

Additionally, the studies recognize that Industry 4.0 approaches can leverage the capabilities of the manufacturing industry by integrating simulation, monitoring, and controlling material flows and labor in manufacturing. However, Hansen & Bøgh (2021) and Batwara et al (2024) studies identify that SMEs must be aware of the implementation costs. The leveraged capabilities may not match the investment and requirements. Thus, before implementing AI and IoT approaches encompassed in Industry 4.0, the users must clearly define requirements (data acquisition, communication layers), objectives, and investment.

The same principle applies to integrating sustainability variables with AI-based VSM. Although they can provide real-time monitoring and dynamic decision-making capabilities, users must clearly define their sustainability objectives before implementation. As identified, current approaches aim at different objectives, and there is no one-size-fits-all AI-based VSM approach.

Based on the findings and discussion, to deliver a suitable AI-based VSM approach for supporting practitioners in reducing CO2 emissions in housing manufacturing, the following steps must be taken:

- Define the implementation objectives for reducing CO2 emissions
- Identify IoT approaches that can support and enable CO2 real-time data collection
- Perform an information quality assessment to identify whether the IoT and AI-based VSM approach can communicate adequately and produce reliable results to support the user's problem
- Assess the implementation costs

These steps can help practitioners define their AI-based VSM or Industry 4.0 implementation objective. They can also help users define their implementation path according to their requirements and investment capabilities.

CONCLUSIONS

The housing manufacturing industry faces the challenge of implementing sustainability practices to reduce its negative environmental impact. Previous researchers have identified that AI approaches and Lean methodologies, specifically VSM, can support users in implementing sustainable manufacturing practices. Since housing manufacturing applies manufacturing principles, this research explored manufacturing's AI-based VSM to gather insights for housing manufacturing.

To do so, the researchers performed a literature review to identify current AI-driven VSM approaches. From this literature review, the authors identified that IoT is an enabler of implementing AI-driven VSM approaches. Moreover, the authors identified that practitioners must define their sustainability goals and indexes before developing and implementing AI or Industry 4.0 approaches. Because several approaches exist, selected approaches may not support the users' identified problem, despite their implementation and investment requirements.

Further studies must work on defining specific sustainability practices and indexes to guide practitioners' implementation. They also must study how practitioners understand AI capabilities to enhance the VSM application. Additionally, and also focusing on practitioners, future research must understand housing manufacturing-specific users and organizational requirements to define the appropriate AI and IoT approaches. Moreover, researchers must define a specific IoT to support users in integrating sustainability variables, such as CO2 emissions. Thus, researchers must identify specific workflows and information requirements to support sustainability-aware operations in housing manufacturing.

REFERENCES

Batwara, A., Sharma, V., Makkar, M., & Giallanza, A. (2024). Impact of smart sustainable value stream mapping – Fuzzy PSI decision-making framework. *Sustainable Futures*, *7*, 100201. https://doi.org/10.1016/j.sftr.2024.100201

Bhamu, J., & Singh Sangwan, K. (2014). Lean manufacturing: Literature review and research issues. *International Journal of Operations & Production Management*, *34*(7), 876–940. https://doi.org/10.1108/IJOPM-08-2012-0315

Biazzo, S. (2002). Process mapping techniques and organisational analysis: Lessons from sociotechnical system theory. *Business Process Management Journal*, *8*(1), 42–52. https://doi.org/10.1108/14637150210418629

Brown, A., Amundson, J., & Badurdeen, F. (2014). Sustainable value stream mapping (Sus-VSM) in different manufacturing system configurations: Application case studies. *Journal of Cleaner Production*, *85*, 164–179. https://doi.org/10.1016/j.jclepro.2014.05.101

Busert, T., & Fay, A. (2019). Extended Value Stream Mapping Method: Harmonizing Information Flows for the Control of Production Processes. *IFAC-PapersOnLine*, *52*(13), 54–59. https://doi.org/10.1016/j.ifacol.2019.11.129

Çaliş, B., & Bulkan, S. (2015). A research survey: Review of AI solution strategies of job shop scheduling problem. *Journal of Intelligent Manufacturing*, *26*(5), 961–973. https://doi.org/10.1007/s10845-013-0837-8

Cao, H., & Li, H. (2014). Simulation-based approach to modeling the carbon emissions dynamic characteristics of manufacturing system considering disturbances. *Journal of Cleaner Production*, *64*, 572–580. https://doi.org/10.1016/j.jclepro.2013.10.002

Cassettari, L., Bendato, I., Mosca, M., & Mosca, R. (2017). Energy Resources Intelligent Management using on line real-time simulation: A decision support tool for sustainable manufacturing. *Applied Energy*, *190*, 841–851. https://doi.org/10.1016/j.apenergy.2017.01.009

Chen, X., Luo, Z., & Wang, X. (2017). Impact of efficiency, investment, and competition on low carbon manufacturing. *Journal of Cleaner Production*, *143*, 388–400. https://doi.org/10.1016/j.jclepro.2016.12.095

Chung, I. B., & Caldas, C. H. (2024). A Literature Review of Carbon Emissions Monitoring Practices in Construction Projects. *Construction Research Congress 2024*, 296–304. https://doi.org/10.1061/9780784485279.031

Čiarnienė, R., & Vienažindienė, M. (2012). Lean Manufacturing: Theory and Practice. *Economics and Management*, *17*(2), 726–732. https://doi.org/10.5755/j01.em.17.2.2205

Dües, C. M., Tan, K. H., & Lim, M. (2013). Green as the new Lean: How to use Lean practices as a catalyst to greening your supply chain. *Journal of Cleaner Production*, *40*, 93–100. https://doi.org/10.1016/j.jclepro.2011.12.023

Endrigo Sordan, J., Andersson, R., Antony, J., Lopes Pimenta, M., & Oprime, P. C. (2024). How Industry 4.0, artificial intelligence and augmented reality can boost Digital Lean Six

Sigma. *Total Quality Management & Business Excellence*, *35*(13–14), 1542–1566. https://doi.org/10.1080/14783363.2024.2375299

Faulkner, W., & Badurdeen, F. (2014). Sustainable Value Stream Mapping (Sus-VSM): Methodology to visualize and assess manufacturing sustainability performance. *Journal of Cleaner Production*, *85*, 8–18. https://doi.org/10.1016/j.jclepro.2014.05.042

Ferreira, W. D. P., Armellini, F., Santa-Eulalia, L. A. D., & Thomasset-Laperrière, V. (2022). Extending the lean value stream mapping to the context of Industry 4.0: An agent-based technology approach. *Journal of Manufacturing Systems*, *63*, 1–14. https://doi.org/10.1016/j.jmsy.2022.02.002

Garetti, M., Mummolo, G., & Taisch, M. (2012). Special issue on "sustainable manufacturing." *Production Planning & Control*, *23*(2–3), 79–82. https://doi.org/10.1080/09537287.2011.591617

Geisthardt, M., Engel, L., & Schnegelberger, M. (2023). *Simulation Game Concept For AI-Enhanced Teaching Of Advanced Value Stream Analysis and Design*. https://doi.org/10.15488/15262

Giret, A., Trentesaux, D., & Prabhu, V. (2015). Sustainability in manufacturing operations scheduling: A state of the art review. *Journal of Manufacturing Systems*, *37*, 126–140. https://doi.org/10.1016/j.jmsy.2015.08.002

Hansen, E. B., & Bøgh, S. (2021). Artificial intelligence and internet of things in small and medium-sized enterprises: A survey. *Journal of Manufacturing Systems*, *58*, 362–372. https://doi.org/10.1016/j.jmsy.2020.08.009

Hassanchokami, M., Vital-Soto, A., & Olivares-Aguila, J. (2022). The Role of Environmental Factors in the Flexible Job-Shop Scheduling Problem: A Literature Review. *IFAC-PapersOnLine*, *55*(10), 175–180. https://doi.org/10.1016/j.ifacol.2022.09.386

Hassija, V., Chamola, V., Mahapatra, A., Singal, A., Goel, D., Huang, K., Scardapane, S., Spinelli, I., Mahmud, M., & Hussain, A. (2024). Interpreting Black-Box Models: A Review on Explainable Artificial Intelligence. *Cognitive Computation*, *16*(1), 45–74. https://doi.org/10.1007/s12559-023-10179-8

Helleno, A. L., De Moraes, A. J. I., & Simon, A. T. (2017). Integrating sustainability indicators and Lean Manufacturing to assess manufacturing processes: Application case studies in Brazilian industry. *Journal of Cleaner Production*, *153*, 405–416. https://doi.org/10.1016/j.jclepro.2016.12.072

Huang, Z., Kim, J., Sadri, A., Dowey, S., & Dargusch, M. S. (2019). Industry 4.0: Development of a multi-agent system for dynamic value stream mapping in SMEs. *Journal of Manufacturing Systems*, *52*, 1–12. https://doi.org/10.1016/j.jmsy.2019.05.001

Jarrahi, M. H. (2018). Artificial intelligence and the future of work: Human-AI symbiosis in organizational decision making. *Business Horizons*, *61*(4), 577–586. https://doi.org/10.1016/j.bushor.2018.03.007

Jasti, N. V. K., & Kodali, R. (2015). Lean production: Literature review and trends. *International Journal of Production Research*, *53*(3), 867–885. https://doi.org/10.1080/00207543.2014.937508

Kundakcı, N., & Kulak, O. (2016). Hybrid genetic algorithms for minimizing makespan in dynamic job shop scheduling problem. *Computers & Industrial Engineering*, *96*, 31–51. https://doi.org/10.1016/j.cie.2016.03.011

Liu, G., Chen, R., Xu, P., Fu, Y., Mao, C., & Hong, J. (2020). Real-time carbon emission monitoring in prefabricated construction. *Automation in Construction*, *110*, 102945. https://doi.org/10.1016/j.autcon.2019.102945

Liu, Q., Tian, Y., Wang, C., Chekem, F. O., & Sutherland, J. W. (2018). Flexible Job-Shop Scheduling for Reduced Manufacturing Carbon Footprint. *Journal of Manufacturing Science and Engineering*, *140*(6), 061006. https://doi.org/10.1115/1.4037710

Manimuthu, A., Venkatesh, V. G., Raja Sreedharan, V., & Mani, V. (2022). Modelling and analysis of artificial intelligence for commercial vehicle assembly process in VUCA world: A case study. *International Journal of Production Research*, *60*(14), 4529–4547. https://doi.org/10.1080/00207543.2021.1910361

Mao, C., Tao, X., Yang, H., Chen, R., & Liu, G. (2018). Real-Time Carbon Emissions Monitoring Tool for Prefabricated Construction: An IoT-Based System Framework. *ICCREM 2018*, 121–127. https://doi.org/10.1061/9780784481738.015

Mckinsey Global Institute. (2017). *Reinventing construction: A route to higher productivity*. www.mckinsey.com/mgi

Mohan, J., Lanka, K., & Rao, A. N. (2019). A Review of Dynamic Job Shop Scheduling Techniques. *Procedia Manufacturing*, *30*, 34–39. https://doi.org/10.1016/j.promfg.2019.02.006

Oxford Economics. (2023). *Chartbook: Global Construction Outlook Q3 2023*. Oxford Economics. https://www.oxfordeconomics.com/resource/chartbook-global-construction-outlook-q3-2023/

Pereira Librelato, T., Pacheco Lacerda, D., Henrique Rodrigues, L., & Rafael Veit, D. (2014). A process improvement approach based on the Value Stream Mapping and the Theory of Constraints Thinking Process. *Business Process Management Journal*, *20*(6), 922–949. https://doi.org/10.1108/BPMJ-07-2013-0098

Pettersen, J. (2009). Defining lean production: Some conceptual and practical issues. *The TQM Journal*, *21*(2), 127–142. https://doi.org/10.1108/17542730910938137

Popper, J., Motsch, W., David, A., Petzsche, T., & Ruskowski, M. (2021). Utilizing Multi-Agent Deep Reinforcement Learning For Flexible Job Shop Scheduling Under Sustainable Viewpoints. *2021 International Conference on Electrical, Computer, Communications and Mechatronics Engineering (ICECCME)*, 1–6. https://doi.org/10.1109/ICECCME52200.2021.9590925

Rewers, P., Trojanowska, J., & Chabowski, P. (2016). Tools and methods of Lean Manufacturing—A literature review. *Proceedings of 7th International Technical Conference Technological Forum 2016*, 135–139.

Rosen, M. A., & Kishawy, H. A. (2012). Sustainable Manufacturing and Design: Concepts, Practices and Needs. *Sustainability*, *4*(2), 154–174. https://doi.org/10.3390/su4020154

Rosenbaum, S., Toledo, M., & Gonzalez, V. (2014). Green-Lean Approach for Assessing Environmental and Production Waste in Construction. *Proceedings of the Annual Conference of the IGLC20*. https://iglc.net/Papers/Details/830

Salido, M. A., Escamilla, J., Barber, F., & Giret, A. (2017). Rescheduling in job-shop problems for sustainable manufacturing systems. *Journal of Cleaner Production*, *162*, S121–S132. https://doi.org/10.1016/j.jclepro.2016.11.002

Shah, R., & Ward, P. T. (2007). Defining and developing measures of lean production. *Journal of Operations Management*, *25*(4), 785–805. https://doi.org/10.1016/j.jom.2007.01.019

Shahin, M., Maghanaki, M., Hosseinzadeh, A., & Chen, F. F. (2024). Improving operations through a lean AI paradigm: A view to an AI-aided lean manufacturing via versatile convolutional neural network. *The International Journal of Advanced Manufacturing Technology*, *133*(11–12), 5343–5419. https://doi.org/10.1007/s00170-024-13874-4

Shatiry, M. S. A., Abd Rahim, Z., Ros, I. M., Matlan, M. N., Mazny, F. S. M., & Chelliah, N. (2024). Artificial Intelligence HSE Monitoring & Digital Value Stream Mapping for Prefabrication Yard. *International Journal of Integrated Engineering*, *16*(8), 134–142. https://penerbit.uthm.edu.my/ojs/index.php/ijie/article/view/19013

Sundar, R., Balaji, A. N., & Kumar, R. M. S. (2014). A Review on Lean Manufacturing Implementation Techniques. *Procedia Engineering*, *97*, 1875–1885. https://doi.org/10.1016/j.proeng.2014.12.341

Tao, X., Mao, C., Xie, F., Liu, G., & Xu, P. (2018). Greenhouse gas emission monitoring system for manufacturing prefabricated components. *Automation in Construction*, *93*, 361–374. https://doi.org/10.1016/j.autcon.2018.05.015

Trentesaux, D., & Prabhu, V. (2014). Sustainability in Manufacturing Operations Scheduling: Stakes, Approaches and Trends. In E. Bayro-Corrochano & E. Hancock (Eds.), *Progress in Pattern Recognition, Image Analysis, Computer Vision, and Applications* (Vol. 8827, pp. 106–113). Springer International Publishing. https://doi.org/10.1007/978-3-662-44736-9_13

Tuo, J., Liu, P., & Liu, F. (2019). Dynamic Acquisition and Real-Time Distribution of Carbon Emission for Machining Through Mining Energy Data. *IEEE Access*, *7*, 78963–78975. https://doi.org/10.1109/ACCESS.2019.2919564

United Nations Environment Programme. (2022). *2022 Global Status Report for Buildings and Construction: Towards a Zero-emission, Efficient and Resilient Buildings and Construction Sector*. www.globalabc.org

US EPA, O. (2015, July 30). *Sustainable Manufacturing* [Overviews and Factsheets]. https://www.epa.gov/sustainability/sustainable-manufacturing

Wang, Y.-C., & Chen, T. (2024). Adapted techniques of explainable artificial intelligence for explaining genetic algorithms on the example of job scheduling. *Expert Systems with Applications*, *237*, 121369. https://doi.org/10.1016/j.eswa.2023.121369

White, G. R. T., & Cicmil, S. (2016). Knowledge acquisition through process mapping: Factors affecting the performance of work-based activity. *International Journal of Productivity and Performance Management*, *65*(3), 302–323. https://doi.org/10.1108/IJPPM-01-2014-0007