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Procedia CIRP 140 (2026) 815–820

www.elsevier.com/locate/procedia

33rd CIRP Conference on Life Cycle Engineering (LCE 2026)

Integrating MaaS and Ex-Ante LCA for Smart and Sustainable Production

Francesco Caraceni[a*], Massimilano Mariani[a], Matteo Cordara[a], Andrea Margheri[a], Carlo Brondi[a], Andrea Ballarino[a]

[a]*Stiima-CNR, via Alfonso Corti 12, Milano 20133, Italy*

* Corresponding author. Tel.: +393336370703; *E-mail address:* francesco.caraceni@stiima.cnr.it

Abstract

The rise of distributed and data-driven manufacturing ecosystems poses a challenge in terms of data tracking and performance assessment. In such manufacturing ecosystems, Manufacturing-as-a-Service (MaaS) platforms offer a solution that shifts from centralized, product-centric production models to agile, service-oriented manufacturing networks. This paper presents a methodological framework for integrating Ex-ante Life Cycle Assessment (LCA) into MaaS architectures to support sustainability-informed decision-making during supply chain configuration and production outsourcing. The proposed approach combines three key aspects, efficiency in production by optimized scheduling, target cost, and environmental footprint, to match customers with the most suitable providers. Suppliers register on the MaaS platform by submitting detailed datasets that cover energy, water and material consumption, working hours, and contextual qualifiers such as electricity mix or water source. These data are then combined with environmental databases in an internal tool to generate predictive sustainability indicators for supplier profiling. Such a process allows for transparent trade-offs between cost, efficiency, and environmental footprint in the matchmaking process. A pillar of this methodology is the integration of Ex-ante LCA as a core service within the MaaS platform. Unlike conventional Ex-post LCA, which relies on finalized product and process data, Ex-ante LCA enables anticipatory assessments of potential environmental impacts under variable manufacturing scenarios. This methodological shift is particularly relevant in MaaS ecosystems, where decisions about outsourcing, remanufacturing, or plant reconfiguration are made before actual production takes place. The preliminary results focus on architecture requirements such as data modeling requirements, system architecture, and computational workflow necessary for implementing Ex-ante LCA in distributed manufacturing environments. Moreover, some challenges emerge about data uncertainty, interoperability, and multi-criteria optimization. The integration of sustainability metrics into service-oriented manufacturing networks can represent a relevant step toward aligning digital manufacturing innovation with environmental objectives, enabling both responsible and adaptive production systems.

Keywords: Life Cycle Assesment; Industrial Matchmaking; Manufacturing Network; Distributed Production;

1. Introduction

The progressive transformation of industrial systems toward more sustainable and intelligent manufacturing practices is being shaped by two converging paradigms: Ex-ante Life Cycle Assessment (EA-LCA) and Manufacturing-as-a-Service (MaaS). These paradigms are not only aligned through their focus on forward-thinking and data-centric methodologies but also synergistic, particularly when applied to technologies characterized by high uncertainty, low maturity, and limited environmental data. EA-LCA represents a complex transformation of traditional Life Cycle Assessment, explicitly developed to assess the future environmental impacts of technologies not yet fully developed or commercialized [1]. It offers a structured framework that encompasses the entire technological trajectory, from early-stage design and research to iterative development and market deployment, thus providing a critical tool for steering innovation toward lower impact [2,3]. Unlike conventional LCA, which operates Ex-post using well-established inventories, Ex-ante LCA relies on

10.1016/j.procir.2026.05.137

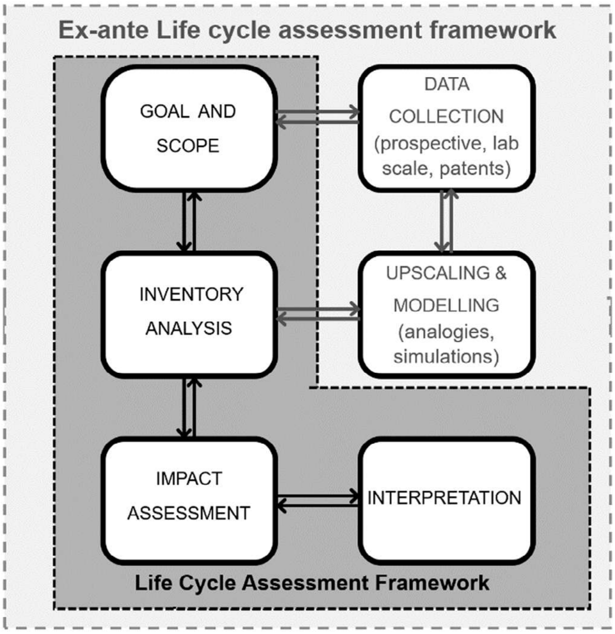

Figure 1, Schematic representation of the difference between traditional and ex-ante LCA framework.

foresight, scenario modeling, and proxy data to estimate the future environmental burdens of products and technologies under development. A major challenge in EA-LCA is the lack of reliable data for emerging systems, especially in early research phases or when technologies exist only as laboratory prototypes. This deficiency is compounded by the uncertainty surrounding future market conditions, process efficiencies, and production volumes [3,4]. To overcome these barriers, researchers are forced to draw upon secondary sources, particularly patent literature, which can provide valuable insights into innovation trajectories, technology readiness levels, and design evolution (Figure 1). Patent analysis not only supports technological forecasting but also enables the development of scenarios for the foreground system modeling [1]. In parallel, the rise of Manufacturing-as-a-Service [MaaS] introduces a paradigm shift in the manufacturing sector, in which traditional product-based production systems are reconfigured into cloud-enabled, service-oriented platforms [5]. Enabled by advances in cloud computing, digital twin technologies, and process virtualization, MaaS facilitates on-demand, modular, and highly flexible production schemes, often arranged across geographically dispersed infrastructures [6–8]. These systems could be particularly advantageous for supporting emerging technologies such as additive manufacturing, where the benefits of local, agile production align well with the distributed logic of MaaS [6,9].

MaaS platforms are designed to emulate the architecture of Software-as-a-Service [SaaS], empowering clients to request production capabilities via networked infrastructure, thereby minimizing capital investment while maximizing configurability [6]. However, successful implementation depends critically on the ability to model, manage, and share product, process, and supply chain data efficiently and securely across platforms. Here, technologies such as Digital Twins play a central role, allowing real-time synchronization between virtual models and physical assets for improved decision support, traceability, and operational performance [7,10].

In both MaaS and EA-LCA, scale-up and data projection methodologies are essential. In EA-LCA, scale-up often relies on a combination of empirical models, engineering estimates, process simulations, and analogies with more mature sectors [11]. For instance, in the ex-ante LCA of commercial-scale cultivated meat, researchers combined lab-scale primary data with industrial-scale analogues and scenario projections to estimate environmental impacts for 2030 [12]. Similar techniques may be required to model the environmental implications of cloud-distributed MaaS infrastructures, especially when evaluating additive manufacturing nodes operating under diverse technical and logistical constraints [9].

Another promising aspect of EA-LCA is the integration of learning effects through learning curves, which are conventionally used in economic modeling but are increasingly being applied to the estimation of environmental impacts [13]. If environmental burdens are driven by variables such as energy efficiency, yield, or material use, parameters subject to improvement with scale and experience, then these impacts may follow predictable patterns. However, learning effects are not uniform across all impact categories, and the extent of improvement often depends on the presence of operational or regulatory incentives aligned with environmental performance goals.

Within the MaaS domain, adaptive decision-making is being enhanced through AI-based optimization tools, particularly deep reinforcement learning, which enables platforms to dynamically allocate resources, accept or reject orders, and manage production workflows in stochastic environments [14]. These methods parallel the scenario analysis approaches in EA-LCA, where a range of technical and organizational assumptions are used to assess robustness and feasibility.

The vision for future MaaS ecosystems includes crowdsourced cyber-manufacturing platforms, where manufacturers of varying sizes and capabilities collaborate through shared digital infrastructure to deliver on-demand services [15,16]. These platforms rely on blockchain-based Cloud MaaS architectures to ensure data provenance, security, and ownership, allowing even small and medium-sized enterprises to participate in distributed production chains [17]. Such decentralized systems intrinsically demand sustainability assessment frameworks capable of handling geographical dispersion, real-time customer interaction, and fluid supply chains, all of which pose challenges for traditional LCA tools but can be addressed through the prospective modeling capabilities of EA-LCA [18].

Beyond environmental performance, both Ex-ante LCA and MaaS are increasingly entwined with risk-informed innovation strategies, such as the Safe by Design approach. This approach emphasizes the integration of life cycle thinking and risk assessment early in product development to identify environmental and human health risks before large-scale implementation [19]. Integrating life cycle thinking and risk assessment is critical in applications involving waste-derived or biomass feedstocks, where upstream decisions can influence downstream sustainability performance and regulatory compliance [20].

Recent bibliometric reviews have highlighted the need to consolidate insights across MaaS research, identifying key technological enablers, deployment models, and open challenges, particularly regarding interoperability, governance, and economic viability [21]. These findings align with the need for methodological integration with EA-LCA, especially when considering distributed and complex production systems that challenge traditional LCA boundaries.

The realization of MaaS within the broader context of Industry 4.0 is underpinned by the development of Cyber-Physical Systems (CPS) and the industrial internet, which support the orchestration of process control systems, intelligent automation, and distributed coordination [22,23]. The integration of CPS with Life Cycle Assessment has already been explored as a way to link real-time production data with environmental performance evaluation, thus enabling more dynamic and predictive sustainability assessments [24]. Foundational knowledge on communication architectures, sensor integration, and automation strategies, such as those comprehensively documented in the Handbook of Automation, are essential for understanding and implementing MaaS environments at scale [25].

Despite the significant progress in both domains, an area requiring attention is the clarification of terminology, particularly in EA-LCA. The distinction between "prospective" and "ex-ante" LCA is frequently blurred in the literature, often leading to inconsistent interpretations. A recent review proposed that temporal positioning and assumptions about technology maturity should guide terminology use, with “ex-ante” implying explicit expectations of maturity progression [26]. A similar effort toward standardization is needed in MaaS to enable data interoperability, shared ontologies, and consistent modeling practices across platforms [6,8]. Finally, the integration of a structured system for assessing the quality of both ex-ante and ex-post LCA results is essential, as it would enable consistent and transparent comparative analyses between retrospective and prospective assessments.

Within the aforementioned context, this paper presents a methodological framework for integrating Ex-ante LCA into MaaS architectures within the scope of the Horizon Europe MEDUSA project, founded by the European Union’s HORIZON-CL4-TWIN-TRANSITION-01 programme [27], to support sustainability-informed decision-making during supply chain configuration and production outsourcing.

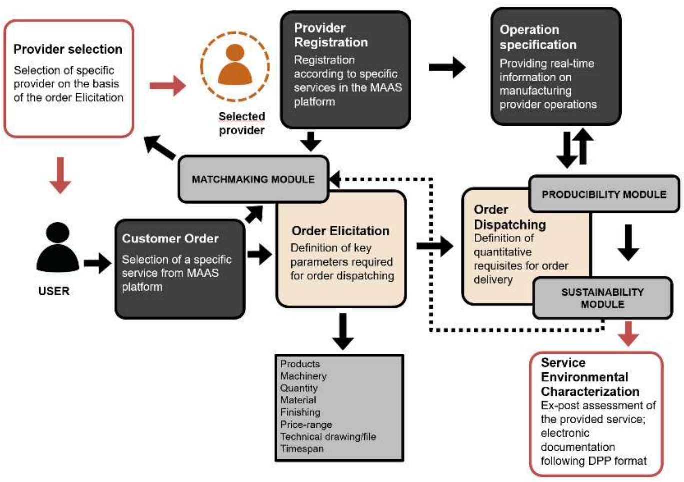

Figure 2. Simplified logic scheme proposed for the provider selection system

2. Materials and methods

2.1. Proposed Architecture

The architecture of the system currently under development is illustrated in Figure 2 and has been conceived to integrate the different decision-making layers required for order management in a distributed manufacturing platform. The proposed operational workflow originates from the reception of a customer order, which is first processed by the matchmaking module. At this stage, the matchmaking module operates iteratively according to a two-step approach: it first triggers a query with the producibility module, where the technical feasibility of the requested product is verified. This verification relies each time on the data provided by potential suppliers during the registration to the platform. During the registration process, the potential suppliers are required to report a detailed and consistent set of information to qualify their production process, including machine availability, specific manufacturing processes that can be performed, and the finishing technologies applicable to the order. Based on this information, the producibility module identifies the set of providers that are capable of performing the requested job within the specified temporal constraints and within the admissible cost range.

Once this filtering process has been completed, the matchmaking module triggers an additional query directed to the sustainability assessment tool. The purpose of this step is to quantify the order-specific environmental implications associated with the providers previously identified as technically and economically feasible. The sustainability module performs the assessment according to the categories recommended by the Environmental Footprint (EF) 3.1 method, generating a dataset of impact values for each provider under consideration. These datasets are then transmitted back to the matchmaking system as a structured response to the original request. In the ensuing decision-making stage, the impact indicators are combined with the estimated production costs and expected delivery times.

The resulting multi-criteria evaluation framework enables the matchmaking system to compare alternative providers not only with respect to traditional performance indicators, such as cost-effectiveness and adherence to deadlines, but also in terms of their relative environmental performance.

The integrated assessment thus supports the selection of the most suitable provider(s), ensuring that the final solution aligns with customer requirements while simultaneously promoting the minimization of environmental impacts.

2.2. Sustainability module

Within the MaaS platform, environmental information is managed through a layered approach that links the intrinsic environmental data of each incoming material or component with the process-specific information generated at every manufacturing step. Materials and components enter the system already characterized by their environmental attributes following a taxonomy that is compliant with Core Data Dictionary structure within Digital Product Passport, while each operation contributes further data such as resource use, energy consumption, waste generation and relevant process conditions. By progressively combining these two information streams, the platform reconstructs a complete and traceable environmental profile for each item or batch, enabling accurate assessment, comparison across providers, and subsequent integration into the product's final digital documentation, including its DPP.

Table 1 summarizes the principal inflows and outflows managed by the sustainability module. This module operates by exploiting annual production data in combination with the specific processing times required for each operation.

Table 1. Proposed Input and Output flows to and from the sustainability module

INPUT from provider registration to the platform	**UoM**
Overall annual production	kg, m^2, unit
Overall electrical energy consumption	kWh
Overall water consumption	m^3
Overall working hours	h
Overall annual material consumption [material_type]$_{1, 2, \dots m}$	kg
Overall annual ancillary consumption [ancillary_type]$_{1, 2, \dots n}$	kg
Renewable energy quota	%
Overall annual fuel consumption [fuel_type]$_{1, 2, \dots f}$	kg, l
Production defectiveness percentage	%
Overall waste generation [waste_type]$_{1, 2, \dots w}$	kg
Overall annual emissions [emission_type]$_{1, 2, \dots k}$	kg
INPUT calculated by the platform data managment	
Transport [transport_type]$_{1, 2, \dots j}$	km
Time needed to complete the MaaS request	h
OUTPUT of the Sustainability Module	
Environmental Impact [Category]$_{1, 2, \dots n}$	Variable
Environmental Impact [Single Score]	Pt

On this basis, it estimates a detailed consumption inventory, obtained by allocating the total annual resource consumption proportionally to the number of effective processing hours. Such an allocation enables the derivation of order-specific consumption profiles, which constitute the fundamental input for subsequent impact assessment.

Once the consumption inventory has been established, it is coupled with a database of unitary impact factors, allowing the implementation of a life-cycle based environmental impact assessment. Through this operation, the module systematically quantifies the potential environmental burdens associated with the manufacturing of the requested order.

The resulting indicators provide a structured representation of the environmental consequences linked to energy use, material consumption, and the use of ancillary consumables.

The final output of this process is a specific set of environmental impact values associated with each provider selected by the producibility module. These values represent

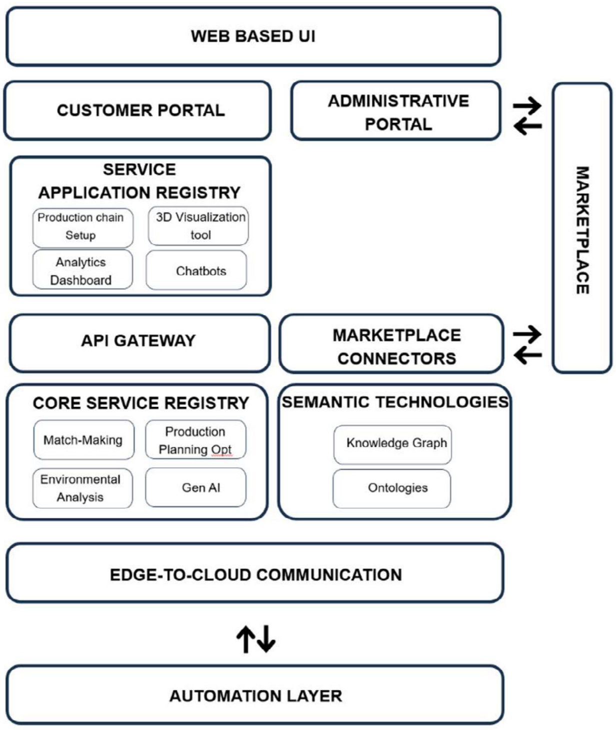

Figure 3 Proposed Architecture of the Medusa platform

the estimated environmental load that would be generated if the order were assigned to a given provider.

3. Discussion

The proposed framework, which originates from the conceptual model developed during the initial phase of the MEDUSA project (Figure 3), has been designed to accommodate the practical constraints associated with the type and level of detail of the data that providers are able and willing to disclose. The project aims to develop a MaaS marketplace that embeds multi-objective optimization algorithms into the platform's matchmaking process. This integration enables sustainability criteria to be directly incorporated into provider–customer matching, supporting informed outsourcing decisions within distributed manufacturing networks.

A critical issue concerns the high degree of granularity required by the system, since the collection of aggregated data such as annual production volumes or total operating hours may lead to both overestimation and underestimation of the associated environmental impacts. However, reducing the temporal scope of the data to a shorter interval, for example a single month, would not necessarily enhance reliability. On the contrary, it would risk incorporating production dynamics that are not representative of the requested order, since biased by exogenous factors (e.g., workload totally different in typology and or in quantity) thereby lowering the accuracy of the results.

Another source of uncertainty arises from the fact that the system refers to the provider's entire production activity, which may encompass multiple production lines dedicated to distinct product categories. In practice, it is not feasible during the registration phase to obtain detailed, line-specific information, since requiring such granularity would impose an excessive burden on providers and discourage their participation in the platform. Furthermore, in cases where several production lines coexist, these may serve different users, and the provider may not be able to allocate energy and material consumptions across them in a manner that accurately reflects operational reality.

Considering these limitations, a top-down approach was deemed more appropriate for data handling and impact allocation. This strategy is based on the assumption that distributing a proportion of the total environmental impacts across orders provides a more consistent approximation than attempting to isolate and quantify arbitrary fractions of production activities. The rationale behind this choice is further reinforced by the nature of the information usually available to the providers, which is generally aggregated at the company level (e.g., utility bills, bulk material purchases, or total recorded working hours). Consequently, a top-down allocation logic not only reduces the complexity of data collection for the providers, but also ensures a higher degree of representativeness and comparability across providers, despite the intrinsic uncertainty associated with such method.

The use case validation of this framework is planned for the coming deployment and testing phase of the MEDUSA project, when the proposed structure and decision-making logic described in this work will be implemented and validated in real industrial contexts. Specifically, the methodology will be tested in two fields: one focused on the mechanical manufacturing of parts, and the other on the production and assembly of printed circuit boards. For both cases, a dedicated marketplace will be developed, tailored to the specific industrial scenario, and tested with a limited number of selected providers.

4. Conclusions

This paper introduced an integrated framework that combines producibility assessment, sustainability evaluation, and decision support within a MaaS-oriented architecture. By implanting Ex-ante LCA into the matchmaking system, the platform allows providers to be selected not only on the basis of cost and lead time but also considering potential environmental impacts. A top-down allocation strategy has been adopted as the most practical solution, as it lessens the data collection effort required from providers while ensuring that calculated impact values remain representative and comparable. Building on the foundations of the MEDUSA project, the proposed structure aims to align MaaS-networks with sustainability objectives and promoting more transparent and informed decision-making in distributed systems. Future research will focus on full deployment of proposed approach, refining data interoperability, reducing uncertainty in impact allocation, and testing the approach in real industrial scenarios, to consolidate its robustness and increase its applicability across multiple manufacturing contexts.

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