



Designing Energy-Efficient Industrial Machines Based on Parametrised Life Cycle Assessment

Anastasiia Timofeeva¹(✉), Giampaolo Campana², Gregory Peters³,
and Maurizio Fiorini¹

¹ Department of Civil, Chemical, Environmental and Materials Engineering, University of Bologna, Via U. Terracini 28, 40131 Bologna, Italy

anastasiia.timofeev2@unibo.it

² Department of Industrial Engineering, University of Bologna, Viale del Risorgimento 2, 40136 Bologna, Italy

³ Division of Environmental Systems Analysis, Department of Technology Management and Economics, Chalmers University of Technology, Chalmersplatsen 4, 41296 Gothenburg, Sweden

Abstract. This paper addresses the lack of data on the total energy demand of industrial washing processes. It presents an approach to designing energy-efficient industrial automated machines based on a parametrised Life Cycle Assessment (LCA) as a key analytical tool. In particular, the environmental performance of an industrial washing machine designed for the pharmaceutical sector is evaluated throughout its LCA performed in a cradle-to-grave boundary using the ReCiPe 2016 midpoint calculation method. Parametrisation in LCA enables modelling of different energy consumption scenarios based on various factors of the machine's washing cycle and usage mode. This method allows manufacturers to compare energy-saving designs, operational improvements and sustainable energy strategies without rebuilding the entire LCA model. Furthermore, a Total Estimated Energy Consumption (TEEC) framework, including operational states, has been applied to achieve a more comprehensive energy demand. Indeed, determining energy parameters for different operating states allows for a more detailed environmental impact evaluation.

This work supports the development of sustainable industrial machines, aligning with circular economy principles and eco-design strategy. The findings revealed that the use phase contributes the most to environmental impact, mainly due to energy consumption. The analyses allowed for the identification of critical components for their improvement. Besides, optimisation scenarios are proposed to enhance the machine energy efficiency.

Keywords: Sustainable Manufacturing · Life Cycle Assessment · Industrial Washing Machines · Energy Efficiency · Eco-Design

1 Introduction

Life Cycle Assessment (LCA) is today a fundamental approach for evaluating the environmental impacts caused by materials, products and processes over their whole life cycles. This necessitates the estimation of material and energy flows, which may mean

consulting databases, such as the Ecoinvent, Sphera and Agri-footprint databases. Additionally, parametrised LCA is an approach that estimates variable parameters in the foreground systems to assess environmental impacts under varying conditions.

Although LCA is commonly used to assess environmental performance, its implementation for specific industrial machines remains limited, especially in the context of operational data from automated systems, which constrains the potential for detailed sustainability assessment at a professional level. Indeed, industrial automated machines are complex systems designed to perform specific manufacturing or processing tasks with minimal human intervention by integrating mechanical, electrical, and digital components. These machines are commonly used in various sectors such as pharmaceuticals, automotive, electronics, and food production, where they execute functions like assembly, material handling, packaging, or cleaning with high precision and consistency. The primary advantages of industrial automation include increased productivity, improved product quality, reduced operational costs, and enhanced workplace safety. In the pharmaceutical sector, automated washing machines ensure sterilisation and product safety, preventing contamination and meeting regulatory standards [3]. However, they have significant environmental impacts due to high energy consumption during the use stage.

Many researchers have focused on developing energy consumption models by associating them with different process parameters. Zeulner et al. presented an Extended Energy Modeling Approach, that has been developed for the machining process of vertical pick-up turning machines. This approach allows for the use of a single measurement campaign to model the energy demand of process variations on the machine tool, thereby reducing the need for further measurements [4]. Kibira et al. developed a systematic approach for identifying and applying Key Performance Indicators (KPIs) aimed at evaluating, monitoring, and enhancing the environmental performance of manufacturing processes [5, 6]. The Consumption Performance Sustainability Index (CPSI), a dimensionless index developed originally for additive manufacturing, has been adapted for CNC (Computerised Numerical Control) machining to serve as a complementary tool to LCA, incorporating process-specific parameters often excluded from conventional assessments [7].

The ISO 14955 standards provide a specialised methodological framework for assessing and enhancing the energy efficiency of machine tools by considering their operational behaviour, design parameters, and energy flows. It not only enables the calculation of total energy consumption but also allows for a detailed breakdown of energy use across different machine tool functions and subsystems. This functional decomposition makes it possible to identify specific components or operational states responsible for the highest energy demand [8]. Since ISO 14955 is specifically designed for machine tools that operate across multiple functions and distinct operational states, its methodological approach is particularly suited for analysing energy flows at the scale of industrial systems. Therefore, it is reasonable to consider extending the model to industrial automated equipment, which similarly performs diverse operations and exhibits variable energy consumption patterns depending on the operating state.

This study aims to quantify the environmental impacts of automatic industrial washing machines associated with life cycle stages, thereby identifying critical areas for improvement. For this purpose, a design efficiency approach, mainly based on a

parametrised LCA, has been implemented on a washing machine for the pharmaceutical sector with the aim of identifying critical areas that can be the object of improvements.

2 Methodology

The implemented LCA adopts cradle-to-grave system boundaries, which include the extraction and production of raw materials, machine assembly, transportation, usage, and end-of-life stages. Primary data was collected from the manufacturer, accessible datasheets, and the Ecoinvent v3.10 database, which provides the background data. The system was modelled with SimaPro v9.6 using the ReCiPe 2016 Midpoint (H) impact assessment method. The Functional Unit (FU) was defined as the washing process of mechanical parts.

The designing for energy-efficient machines has been implemented according to ISO 14955, adapted and applied to an industrial automatic washing machine [8]. The average performance of the machine tool represents the estimated amount of energy supplied according to the time shares of defined operating states of the machine. These shares are determined based on a single production year.

The assessment of the time share of operating states is based on the individual distribution of machine states, which reflects the machine's actual usage scenario. It includes both active and inactive periods of machine and divided into following states that will be sub-indexed as: "Off", "Standby", "Setup", "Ready", "Processing" and "Emergency Stop". For instance, the "Emergency Stop" state means that the operator has stopped the machine for safety reason. In the following paragraphs it will be sub-indexed as "Estop". If individual time shares are unavailable, the default state distribution provided in ISO 14955 shall be applied [8].

To define the operating state shares, the manufacturer provided data describing a full-year reference working scenario. It includes the durations of both active and inactive periods and measured values of power and time for the "Off" and "Processing" operating states. Data for the remaining operating states were determined using default ISO values, supplemented by empirical modelling of the power consumption, based on values from the scientific literature review (Table 1) [9]. Based on the measured power values and the real-time shares, the estimated annual energy supply of the machine is calculated according to Eq. 1 [8]:

$$E_{\text{year}} = (S_{\text{off}} \times P_{\text{off}} + S_{\text{standby}} \times P_{\text{standby}} + S_{\text{setup}} \times P_{\text{setup}} + S_{\text{ready}} \times P_{\text{ready}} + S_{\text{processing}} \times P_{\text{processing}} + S_{\text{estop}} \times P_{\text{estop}}) \times (365 \times 24) \quad (1)$$

where "S" is for the share value of machine operating states per year, and "P" is the average power during machine operating states. The calculated annual energy demand E_{year} for each operating state identifies which are energetically significant. This allows for the Functional-Oriented Analysis (FOA) to be conducted in accordance with [8].

Furthermore, the obtained annual energy demand of the machine was scaled to the lifetime of the equipment using Eq. (2–4), see Sect. 3.2, and subsequently integrated into the use stage of the LCA model. This enables a quantitative assessment of the energy-related environmental burden for a specific production case, which is particularly relevant

when comparing technological alternatives. This approach ensures the integration of real operational performance into the LCA, rather than relying on generic or average data approximations.

To assess energy consumption during the industrial washing process, a parametrised LCA was conducted based on two energy scenarios. The first, baseline scenario considered only the energy consumed by the equipment during active operational phases, such as washing, rinsing, and drying. In contrast, the second, extended scenario included energy consumption encompassing all operational states. This approach allowed for a more accurate estimate of the Total Estimated Energy Consumption (TEEC) during use stage and, consequently, a more comprehensive evaluation of the environmental impact.

LCA was further parametrised using the TEEC data obtained from the extended operational analysis. To evaluate the influence of the electricity source on environmental performance, three distinct electricity mixtures were incorporated into the model. Each mix reflects a different energy profile based on regional supply characteristics: Mix_1 combines electricity from natural gas and alpine reservoir hydropower; Mix_2 is dominated by hydropower; and Mix_3 primarily relies on natural gas. This parametrisation allows for a more detailed assessment of the environmental impacts associated with electricity consumption, highlighting the sensitivity of LCA results to the energy mix composition, particularly in terms of greenhouse gas emissions.

3 Results and Discussion

3.1 Identification of Share Values for Each Operation State

To accurately estimate the operational energy behaviour of a machine within its annual production context, a detailed time allocation analysis was performed based on a representative industrial scenario. The modelled production schedule assumes 250 active production days per year with 16 h of daily operation, of which 11.16 h are dedicated to the processing state. The remaining 8 h of each working day are categorised as non-operative – “Off” state, and an additional 115 non-working days per year are considered entirely inactive, as 24 h/day in “Off” state. Based on this structure, the total yearly duration, equal to 8760 h, was decomposed into the mentioned operating states (Table 1). Time shares for non-processing states were distributed proportionally according to ISO 14955 default values, enabling the derivation of empirical annual hour distributions per state.

The resulting share of each operating state over one year is shown in Table 1. It reveals the dominance of the “Off” state, which accounts for approximately 56.1% of total time, due to both scheduled downtimes and production breaks. The “Processing” state contributes 31.9%, reflecting the core value-generating activity. Other states represent minor shares: “Standby” (5.2%), “Setup” (3.5%), “Ready” (1.7%), and “Emergency Stop” (1.7%). These time-based distributions are critical for calculating annual energy consumption per operational mode and serve as the basis for FOA of energy performance.

The average power consumption was determined across operating states using a hybrid data acquisition strategy, combining measured data with literature-derived estimations (when measurements are unavailable). Specifically, the average power values for the “Off” and “Processing” states were obtained directly from the washing machine

Table 1. Parameters for the calculation of supplied energy for the share of operating states

	Off	Standby	Setup	Ready	Processing	Emergency stop
Share per year (%)	56.1	5.2	3.5	1.7	31.9	1.7
Share value per year, S	0.561	0.052	0.035	0.017	0.319	0.017
Average power P , kW	0.02	3.945	2.63	1.35	15.78	1.35

manufacturer, based on standardised operating conditions. These values provide a high-confidence baseline for the most energetically dominant states within the annual cycle. In contrast, for states such as “Standby”, “Setup”, “Ready”, and “Emergency Stop”, no direct measurements were available. Therefore, average power values for these states were modelled based on empirical data from published studies [9, 10], including prior implementations of ISO 14955 and related energy performance analyses of comparable machines. This approach ensures methodological consistency while acknowledging data availability limitations, thereby enabling a complete estimation of the machine’s annual energy profile.

3.2 Total Estimated Energy Consumption Over the Lifetime of the Machine

The estimated energy supplied by a machine for one production year under the given circumstances is defined as the sum of the power consumed during a given time and can be expressed mathematically based on Eq. 1 and Table 1, the result of which is presented in Eq. 2.

$$E_{year} = 4.72 \times 10^4 kWh \quad (2)$$

When multiplied by its expected lifetime, a machine’s annual total energy demand yields a cumulative value representing TEEC over the entire use stage (Eq. 3–4):

$$E_{total} = E_{year}(kWh) \times t_{lifetime}(year) \quad (3)$$

$$E_{total} = 4.72 \times 10^4 * 20 = 9.44 \times 10^5 kWh \quad (4)$$

E_{total} can be directly integrated into an LCA model as a quantitative input for the use stage. Incorporating lifetime energy demand allows a more accurate estimation of environmental impacts, particularly in categories such as global warming potential (GWP) and resource scarcity.

3.3 Parametrised Life Cycle Assessment

The results of LCA demonstrate that the use phase is the dominant contributor across many environmental impact categories. The results indicate that impact categories such as freshwater eutrophication (99.9%) and stratospheric ozone depletion (98.7%) are probably driven by using detergent during the operational phase. Similarly, water consumption (98.4%) can be attributed to the intensive use of water during the washing

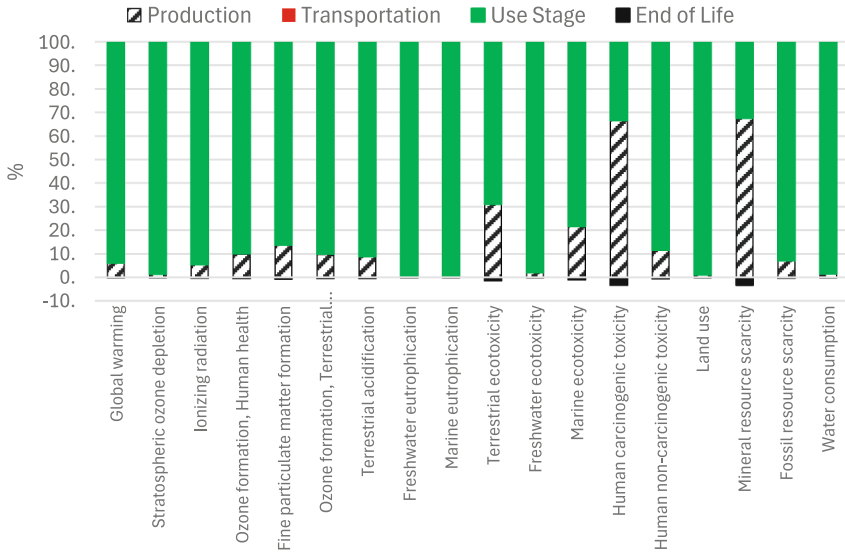


Fig. 1. LCA of an automated machine within cradle-to-grave system boundaries.

process. Furthermore, the high contribution to GWP (93.9%) is primarily associated with elevated electricity consumption during equipment operation (Fig. 1).

Conversely, impact categories such as human carcinogenic toxicity and mineral resource scarcity show a relatively minor contribution at the use stage, indicating that materials extraction and production processes also represent significant environmental hotspots. The transportation stage makes the most minor contribution, and its impact is negligible. On the other hand, the disposal stage recovers the environmental impact through a high rate of recycling of the metal materials, which are the dominant components in the production stage. These findings underscore the critical importance of operational efficiency and energy optimisation during the use stage to reduce the overall environmental footprint of the machine.

The comparative analysis of LCA at the use stage, Fig. 2, reveals that modelling with estimated annual energy supply results in notably higher environmental impacts across all damage categories that are most relevant for the impact assessment of energy, compared to the baseline scenario.

These differences emphasise the crucial significance of including total estimated energy consumption of machine during the use stage in the LCA. Neglecting this parameter leads to an underestimation of impact and reduces the accuracy of sustainability assessments, especially for energy-intensive systems operating over a long lifetime.

The comparative evaluation of the electricity mixtures reveals significant differences in their environmental performance. Mix_3 exhibits the highest impact across nearly all categories, particularly for GWP, ozone formation, toxicity, and resource depletion, indicating a high reliance on carbon-intensive or polluting energy sources (Fig. 3).

In contrast, Mix_2 demonstrates the lowest overall impact, suggesting a more significant share of renewable energy sources in its composition. Mix_1 shows intermediate

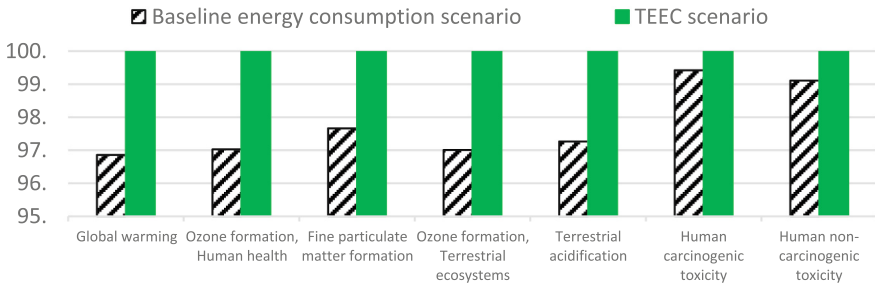


Fig. 2. Use stage comparison of annual energy demand.

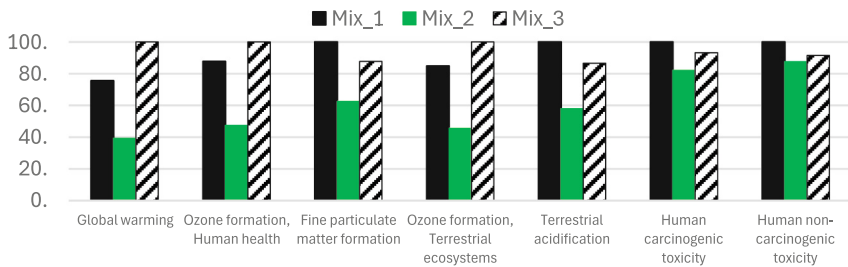


Fig. 3. LCA comparison based on energy sources.

results, with notable impacts in particulate matter formation and toxicity. These findings underline the crucial necessity of LCA parameterisation, especially for energy-intensive systems, and emphasise that integrating renewable energy sources can substantially mitigate life cycle environmental damage.

4 Conclusion

The analysis demonstrates that the use stage is the primary driver of environmental impact in the life cycle of the industrial automatic machine under investigation, primarily due to its high energy consumption. This result confirms what is generally expected for production machines.

Accurate modelling of operational time shares and energy demand is essential for reliable LCA outcomes. Precise measurements are necessary to acquire the needed data for this analysis. Alternatively, when some data cannot be directly measured, models can be considered in order to evaluate the missing data. This analysis is a first step to identify operational stages that need attention and can be considered to reduce energy consumption.

To identify possible scenarios related to relevant aspects, for example, the energy mix, a parametrised LCA has been implemented. The choice of electricity mix significantly

affects impact results, with renewable-rich mixes substantially reducing environmental burdens. These findings underscore the importance of energy efficiency measurements and the integration of cleaner energy sources to minimise the machine's life cycle footprint.

Acknowledgements. This research was supported by the Ministry of Universities and Research (MUR), and funded by the European Union - Next Generation EU, Mission 4, Component 2, Investment 3.3 (Ministerial Decree 117/2023) CUP J33C22001470009.

References

1. ISO 14044:2006 - Environmental management - Life cycle assessment - Requirements and guidelines
2. ISO 14040:2006 - Environmental management - Life cycle assessment - Principles and framework
3. Sammut Bartolo, N., Azzopardi, L.M., Serracino-Inglott, A.: Pharmaceuticals and the environment. *Early Human Dev.* **155**, 105218 (2021)
4. Zeulner, J., Zeller, V., Schebek, L.: Parameterized modeling of the energy demand of machining processes as a basis for reusable life cycle inventory datasets. *Energies* **16**(16), 6011 (2023)
5. Kibira, D., et al.: Procedure for selecting key performance indicators for sustainable manufacturing. *Proc. ASME MSEC* **2017**, 1–8 (2017)
6. Kibira, D., et al.: Procedure for selecting key performance indicators for sustainable manufacturing. *J. Manuf. Sci. Eng.* **140**(011005), 1–7 (2018)
7. De Bernardes, L., et al.: A proposal for an extension of the consumption performance sustainability index to machining processes. In: *LNME*, pp. 721–729, Springer, Cham (2025)
8. ISO 14955 Machine tools — Environmental evaluation of machine tools
9. Zhou, L., et al.: Energy consumption model and energy efficiency of machine tools: a comprehensive literature review. *J. Clean. Prod.* **112**, 3721–3734 (2016)
10. Loffredo, A., Frigerio, N., Matta, A.: Energy efficiency improvement of industrial parts washers using state control. *J. Manuf. Lett.* **35**, 1303–1311 (2023)
11. Dybinski, O., et al.: Modeling industrial scale washing machine process using artificial neural networks. *J. Environ. Integr.* **9**(4), 1933–1946 (2024)

Open Access This chapter is licensed under the terms of the Creative Commons Attribution-NonCommercial-NoDerivatives 4.0 International License (<http://creativecommons.org/licenses/by-nc-nd/4.0/>), which permits any noncommercial use, sharing, distribution and reproduction in any medium or format, as long as you give appropriate credit to the original author(s) and the source, provide a link to the Creative Commons license and indicate if you modified the licensed material. You do not have permission under this license to share adapted material derived from this chapter or parts of it.

The images or other third party material in this chapter are included in the chapter's Creative Commons license, unless indicated otherwise in a credit line to the material. If material is not included in the chapter's Creative Commons license and your intended use is not permitted by statutory regulation or exceeds the permitted use, you will need to obtain permission directly from the copyright holder.

