Procedia CIRP 90 (2020) 209–214

Contents lists available at ScienceDirect

Procedia CIRP

journal homepage: www.elsevier.com/locate/procir

Assessing the environmental and economic sustainability of autonomous systems: A case study in the agricultural industry

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ARTICLE INFO

Article history:
Received 29 June 2019
Revised 16 January 2020

Keywords:
Sustainable automation
Autonomous systems
Environmental sustainability performance
Comparative life cycle assessment
Case study

ABSTRACT

While autonomous machines are considered as a new opportunity to augment safety, reliability, productivity, and efficiency, the actual environmental and economic sustainability performances of many autonomous systems remain yet to be quantified. The present research aims to fill part of this gap by evaluating the life cycle impact and cost of autonomous solutions in the agricultural industry. Comparative life cycle assessment (LCA) and life cycle costing (LCC) are carried out on a real-world case study putting in parallel a robotic electric lawn mower (autonomous solution) and conventional – gasoline- and electricity-powered – pushing mowers (human-operated counterparts). Results are interpreted in terms of global warming potential and total cost of ownership. While the autonomous system already appears to be a promising sustainable alternative, discussions and quantitative insights are also provided on the conditions that would lead to further environmental savings and economic profit for this autonomous solution.

1. Introduction

1.1. Context and motivation

The uptake of autonomous systems – such as robots, autonomous tractors or self-driving cars – is rising and seems increasingly promising in diverse industrial and home applications (Melo et al., 2019). Autonomy is defined here as a state in which a robot or piece of equipment operates independently, without explicit instructions from a human (SAE International, 2016).

As such, autonomous solutions are increasingly viewed as a promising opportunity to augment the safety, reliability and productivity of human-operated tasks. Yet, the actual environmental and economic performances for most of these systems remain to be evaluated, in comparison to conventional ones (Nouzil et al., 2017).

In this line, life cycle engineering researchers and designers can help (i) to actually quantify and inform on the real impact of these new and advanced autonomous systems, in order (ii) to improve and control their performance in terms of sustainability, so as (iii) to figure out how to exploit the full potential of such systems to contribute in the United Nations 2030 sustainable development goals.

For instance, the experimentation and deployment of autonomous systems in the automotive industry are gaining traction, and first life cycle analysis on driverless cars are being released (Gawron et al., 2018). Meanwhile, there are other industries that also are also wondering whether autonomous systems make sense environmentally and/or economically, as well as how to extract the most value from these emerging autonomous solutions from a sustainability standpoint. The agricultural industry is one of these industries that appears to be an interesting case to investigate, including numerous farming and gardening equipment doing repetitive and tedious tasks.

In fact, the stakes are high as agriculture in the United States is a $200 billion industry, and $19 billion for the State of Illinois (Arp, 2018). Before, engines and widespread electricity access have helped to improve production efficiency in farms. Now, automation and autonomous systems – among other solutions – could help increase the agricultural yields.

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https://doi.org/10.1016/j.procir.2020.02.123

Technology underpinning autonomous tractors is relatively advanced and has been developed by the major tractor manufacturers. Similarly, electric robotic lawn mowers can be a relevant solution to both freed landowners from time-consuming lawn care tasks, and potentially replace the gasoline pushing and riding mowers releasing greenhouse gases and toxic pollutants directly on the ground and into the atmosphere (Banks and McConnell, 2015). According to the Environmental Protection Agency, around 30 million tons of pollutants are indeed emitted by gasoline-powered lawn and garden equipment (GLGE) every year in the U.S., accounting for more than a quarter of all nonroad gasoline emissions. And lawn mowers represent 40% of the population of the GLGE (Banks and McConnell, 2015).

With this background, the present study aims to evaluate the environmental and economic sustainability of a robotic lawn mower, in comparison with conventional pushing mowers. On this basis, a key challenge is then to find out under what conditions – including possible design improvements and suitable use modes – a future generation of autonomous robotic mower could lead to an environmental-friendlier as well as a more economically sustainable solution.

1.2. Objectives of the project and scope of the present study

The present study is part of a wider project aiming to assess the sustainability of autonomous machines in the agriculture industry, including farming and gardening equipment. This project is conducted in collaboration with a major original equipment manufacturer (OEM) of agricultural equipment interested in the environmental footprint and economic profitability of their autonomy-to-automation (A2A) solutions.

Through the analysis of existing literature on this topic, plus industrial case studies, the project aims to provide new quantitative insights on how sustainable are A2A systems compared to human-operated counterparts. A recent literature survey on this topic has notably shown a lack of life cycle assessment (LCA) and life cycle costing (LCC) applied to automation processes and autonomous systems (Nouzil et al., 2017). As such, this project seeks to fill out part of this gap by investigating the sustainability of A2A solutions in the agricultural sector.

In this paper, the first results on a real-world case study comparing a current version of a robotic lawn mower with usual pushing lawn mowers are revealed. These preliminary results will serve as a relevant basis to improve the next generation of autonomous. Particularly, incorporating the uncertainties related to the usage of such autonomous systems, as well as the expected performance improvement in the next few years, quantitative insights are provided on the features – including potential design enhancements and use modes modifications – that would lead to further environmental savings and economic profit for the autonomous solution.

In the meantime, this project seeks also to analyze if we have the right methods, tools, and indicators to make a sound comparison between autonomous systems with traditional counterparts from a sustainability perspective. Throughout these case studies and the deployment of LCA methodology on autonomous systems, discussions are expected to be made on: (i) suitable function unit to make sound comparison between autonomous machines and human-operated counterparts; (ii) appropriate system boundaries, to prevent impact transfers; (iii) relevant environmental indicators and complementary performance-based metrics, to satisfactorily evaluate possible trade-offs between conventional machines and autonomous alternatives.

2. Materials and methods

2.1. Life cycle assessment (LCA) and costing (LCC)

The environmental impact is evaluated by using the life cycle assessment (LCA) methodology. LCA is a standardized approach to quantify the potential environmental impacts of a product, process, or activity, all along its life cycle, i.e., from materials acquisition to manufacturing, use, and end-of-life. According to the ISO standard 14040:2006 (ISO 14040:2006, 2006), an LCA comprises four major steps: goal and scope definition; life cycle inventory (LCI); life cycle impact assessment (LCIA); and interpretation of results. Importantly, the outcomes of the LCI and LCIA stages are interpreted in order to find environmental hotspots and compare alternative scenarios. Life cycle costing (LCC) is the equivalent of LCA for the economic assessment, by considering as well, the pre-life, usage, and end-of-life phases, and all associated costs (Kloepffer, 2008). Combining LCA and LCC is particularly relevant as it allows tradeoff analysis between product alternatives.

Here, to conduct a sound comparison between these autonomous lawn mowers and conventional pushing or riding mowers, we want to emphasize the importance of defining a relevant and well-justified functional unit (FU). The FU is defined as a "quantified performance of a product system for use as a reference unit" (ISO 14040:2006, 2006). A clearly and measurable FU is the key to determine the benefits and tradeoffs between two or more comparable products. Indeed, a well-defined FU enables scientifically sound (i.e. consistent and unbiased) comparison between different product systems and scenarios.

Although no further guideline exists in the ISO standards to define a FU, numerous authors have proposed elements to structure and define properly FUs (Cooper, 2003). To reduce the variability and uncertainty around the choice of a FU, Cluzel et al. (2013) have proposed a structured and unified framework (Cluzel et al., 2013), in accordance with the guidelines from the Joint Research Center (European Commission, 2010). Five key elements have to be included in the definition and structure of a sound FU: (i) verb (functional analysis); (ii) what (form of the output); (iii) how much (magnitude); (iv) how well (performance); (v) for how long (duration, time horizon of the analysis).

This framework is used in the next sub-section to define the FU of our case study in order to compare adequately the sustainable performance of a human-operated equipment with its autonomous alternative, having a similar overall function, but with non-negligible differences in terms of features (e.g., random vs. optimal path planning), constraints (e.g., boundary wire, battery) or freedom of operation (e.g., a possible non-stop 24-h time window for the autonomous system).

2.2. Comparative LCA and LCC on lawn mowers

2.2.1. Context and system description

Autonomous mowers are currently mostly utilized in the European market. Residential properties in Europe are appropriate for autonomous vehicle implementation because their average size is much smaller than a residential property in the United States. Actually, in the U.S. the average lawn size is 0.25 acre (i.e. 1000 square meters) (Home Advisor, 2019). Interestingly, the use case for comparative LCA and LCC developed in this paper, aims to capture the average residential lawn for the untapped U.S. market. The autonomous solution considered here is expected to enter into the U.S. market in 2020–2021. And as autonomous mowers become more capable of cutting larger areas, it is estimated this market will grow. The autonomous lawn mower under consideration here, in its current version, is already available on the European market (mainly in Germany, France, and UK) at a premium of $2665.

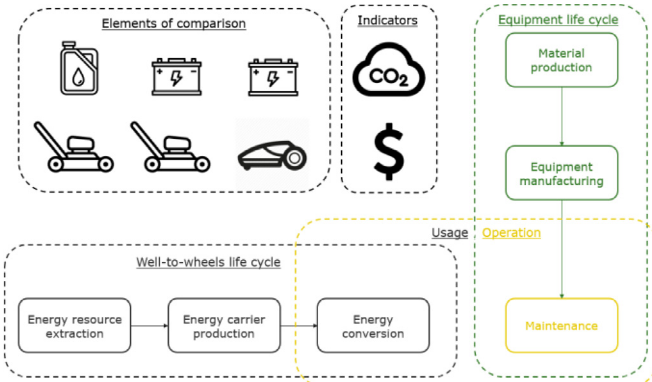

Fig. 1. Scope and system boundaries of the LCA and LCC.

This autonomous solution is a relatively small robotic mower (compared to pushing or riding mowers) which constantly maintains a lawn according to a user-defined schedule and a mowing zone that is delimitated by a buried boundary wire. It has also the ability to find its own docking station (considered as well in the scope of the LCA) and automatically recharges itself. Yet, the movement or walk of this robotic mower is currently dictated by bouncing off the boundary wire at a random angle. This random walk is further analyzed and discussed in the results section, as it has both a significant impact on the use phase and a large room for improvement.

2.2.2. Goal and scope definition

The purpose of the study is to assess and compare the environmental and economic performances of the autonomous robotic mower described below with generic walk-behind or pushing mowers already available on the U.S. market.

The scope and interest of the first use case developed in this study is for the automated solution to replace the traditional walk-behind lawn mower for a residential yard.

More precisely, the lawn mower systems being compared through LCA and LCC, are the following:

- 1 generic gasoline pushing (walk-behind) mower;
- 1 generic electric pushing (walk-behind) mower;
- 1 autonomous robotic mower (with its current features, with improved features, and with ideal path planning).

The lawn mowers being compared, the system boundaries and the environmental and economic indicators used for the comparative LCA and LCC are illustrated through Fig. 1, and are further described in the next sub-sections.

2.2.3. Functional unit (FU)

The functional unit (FU) has to be tied directly to the goal of the analysis and to the capabilities of the systems being studied (Caffrey and Veal, 2013). As aforementioned, the objective of the present study is to evaluate the life cycle environmental impact and economic performance of an autonomous robotic mower compared to human-operated mowers.

On this basis, the performance and constraints of the autonomous mower compared to the conventional mower have to been analyzed in order to define an appropriate FU. According to technical experts developing the robotic mower, three specific main constraints have to be considered, namely: a boundary wire constraint, a battery constraint, and a time-window constraint. Calculations related to these constraints (not detailed in this paper for reasons of space) were made to evaluate the workable area of the autonomous solution and thus to come up with realistic and feasible use cases by deploying whether one robotic mower or a fleet of robotic mowers to accomplish the task defined through the FU.

With all this background and in accordance with the framework mentioned in Section 2.1, the FU for the residential yard use case, in order to compare these mowers on a technically equivalent basis, is defined as it follows: “Maintaining the lawn of a 0.25-acre yard (average U.S. residential yard, Home Advisor, 2019) under a height of 2.5 in. (6.35 cm), 26 weeks a year (average mowing season in the U.S, Sivaraman and Lindner, 2004), for 10 years (lifespan)”.

2.2.4. Life cycle impact assessment (LCIA)

On the one hand, for the quantification of the environmental impacts associated with the manufacturing – including materials impact and processing impact – and the maintenance of the equipment, the SimaPro software (version 8), developed by PRé (Product Ecology Consultants), has been used. Within SimaPro 8, the database Ecoinvent Unit (version 3), and the method ReCiPe Midpoint (H) have particularly been exploited to perform the environmental assessment.

On the other hand, for the quantification of the environmental impacts attributed to the use phase, datasets from the GREET model (Argonne National Laboratory, 2018), developed by the Argonne National Laboratory, has been exploited. Interestingly, as illustrated in Fig. 1, the well-to-wheels analysis given by the GREET model, considers both the production of fuel or electricity required to run the mower and the energy conversion (including associated emissions) during the use phase. The GREET model provides global warming potential (GWP) (expressed in kg CO_2 eq.) scores for a wide range of commodities produced in the United States. To ensure consistency, the GWP indicator is also used to quantify the impact of greenhouse gases (GHGs) induced by the manufacturing and maintenance phases.

On the economic front, the total cost of ownership (TCO) is the indicator used to compare the economic sustainability of the equipment from a user perspective, including the initial buying price of the equipment, the cost of spare parts for the maintenance, and the cost of the fuel or electricity.

2.2.5. Life cycle inventory (LCI)

For the manufacturing impact of mowers, the actual and complete bill of materials (BoM) given by the OEM was used for the autonomous robotic solution (35 kg including the charging station, 12-in. cutting deck, 2.6-A 25-V lithium-ion battery). For the electric-powered pushing mower (27 kg with battery, 20 in., 5.0-A 40-V lithium-ion battery) and the gasoline one (30 kg, 21 in., 2.5 hp engine) generic BoMs were used according to the information given by the OEM.

Regarding the maintenance of the robotic mower, two items might need to be replaced over the 10-year lifetime according to the usage intensity of the machine: (i) the lithium-ion battery, after 1000 charge cycles; (ii) the cutting blades, after every 500 h of mowing. Appropriate maintenance operations and parts replacement for the conventional mowers (especially the engine oil, spark plug and air filter for the gas-powered mower) over their lifetimes are also taken into consideration but not further detailed here for space considerations (available on demand, if needed).

Regarding the use phase, E10 gasoline (i.e. with 10% ethanol content) is the fuel used for the gas-powered solution at a consumption rate of 0.5 gal per hour, and at an average cost of $2.6 per gallon in the United States. For the electric-powered mowers (both for the robotic and pushing ones), the U.S. electricity mix has been used, based on the GREET model, and at an average cost of $0.12 per kWh.

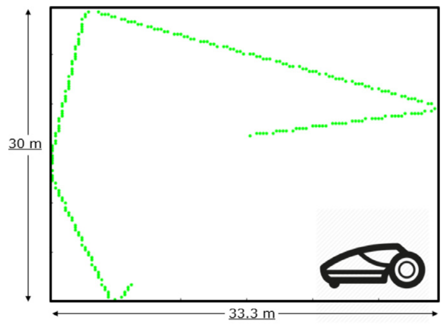

Fig. 2. Simulations to estimate the mowing time for 0.25 acre, random walk.

3. Results and discussion: comparative LCA and LCC

The comparative LCA and LCC results revealed in this section put in parallel three lawn mowing solutions: one walk-behind gasoline-powered mower, one walk-behind electricity-powered mower, one autonomous robotic mower. Note that three different environmental and economic performance evaluations are provided for the autonomous solution, namely: (i) results for the current version, (ii) results for a possible upcoming generation with incremental design improvement (e.g., higher speed, larger cutting blades), (iii) results if optimal path planning (instead of random navigation) is implemented.

In addition to the sustainability performance assessment of the actual version, these two complementary analyses allow us to quantify the potential environmental and economic benefits offered by an augmented or smart version of the autonomous solution. In fact, such improvement features would lead to a reduction of mowing time, which is non-negligible for the autonomous solution has further detailed in the next Section 3.1.

In Sections 3.2 and 3.3, results are given and interpreted respectively in terms of global warming potential for the environmental footprint, and total cost of ownership for the economic perspective.

3.1. Required mowing time to respect the FU

As the current version of the autonomous solution is operated on a random walk, as described in Section 2.2.1, Matlab simulations have been run to estimate the time it needs to cover a 0.25-acre yard, as defined in the functional unit.

Given the default speed (33 cm/s) and the length of the cutting blades (12 in.) of the robotic mower, 20 h (of actual mowing time) are required to properly cover a 0.25-acre rectangular field, as represented in Fig. 2.

Note that using an optimal path planning (as a human would naturally mow the field), it would take 4 h a week to completely mow this 0.25-acre yard, including a first 1h30 of mowing time; 1h30 to recharge the battery, and a final 1 h of mowing activity.

In comparison, the time required to mow a 0.25-acre yard with a human-operated pushing mower is estimated to 1 h.

3.2. Global warming potential (GWP)

The absolute greenhouse gas emissions associated with the manufacturing, usage, and maintenance phases for each mowing solution are compared in Fig. 3.

In terms of relative CO_2 eq. impact savings, the current version of the autonomous robotic mower is 23% greener than conventional gasoline pushing mower. The environmental savings could be significantly higher (lower electricity consumption, and fewer battery replacements) by improving the efficiency of the autonomous solution. For instance, the emissions of 0.5 metric ton

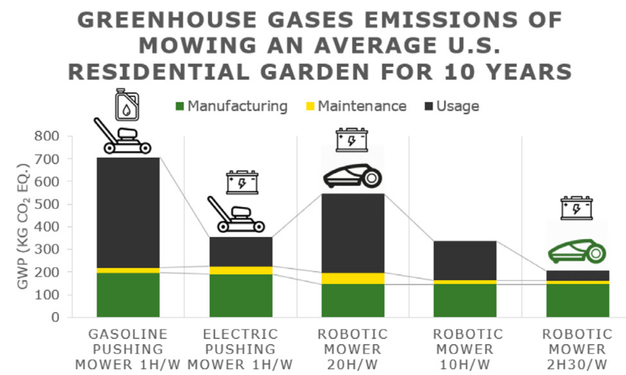

Fig. 3. Quantitative results of the LCA: bar charts, with icons.

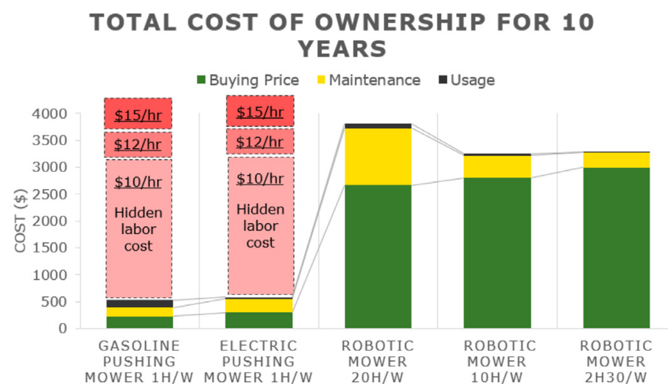

Fig. 4. Quantitative results of the LCC: bar charts, hidden cost in dotted line.

of CO_2 could be avoided by replacing one gasoline pushing mower with a robotic mower having optimal path planning. One can argue this value is non-negligible as it represents 10% of the annual emissions of an average U.S. car. In fact, according to the Environmental Protection Agency, a typical passenger U.S. vehicle emits about 4.6 metric tons of carbon dioxide per year (EPA. Emissions from passenger vehicle in the U.S, 2019).

3.3. Total cost of ownership (TCO)

The TCO – including buying price, usage and maintenance costs – for each mowing solution is compared in Fig. 4.

Currently on the market, the initial buying price of the autonomous robotic mower is much higher than the traditional pushing mowers.

When integrating hidden cost – i.e. labor cost or how much money one value his/her time to perform the mowing task, as illustrated in dotted line through Fig. 4 – the autonomous mower, which is a time-saving solution for the owned, can be a more cost-effective alternative than human-operated mowing services from a lifecycle perspective.

In this line, this residential use case is further split into three main situations, and their sub-variations as illustrated in Fig. 5:

- One situation where the owner is using the autonomous solution (with its three different efficiency scenarios);
- One situation in which the owner has whether a gasoline- or electricity- powered case and hires an independent worker on an average rate of $12 per hour;
- One situation where the mowing activity is outsourced to a private lawn care company (PLC) at a cost of $37 per operation for a 0.25-acre yard.

Considering the 10-year time frame of the functional unit, the initial extra buying cost of the autonomous solution would ulti-

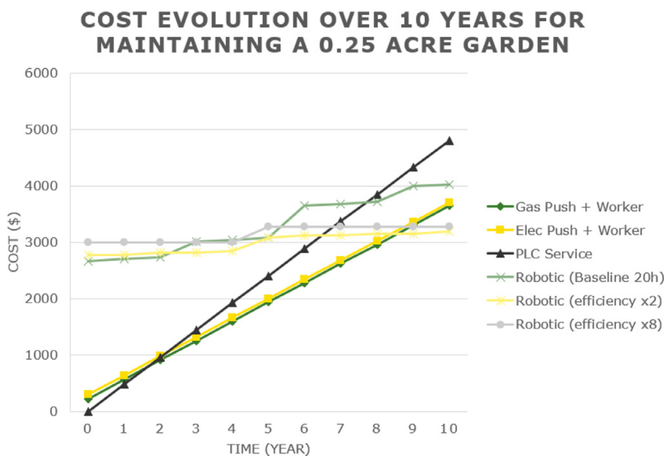

Fig. 5. Total cost for the owner, year by year.

mately balance with the other conventional mowing service solutions.

4. Conclusion and perspectives

The future of agriculture, including farming and gardening tasks, will increasingly rely on autonomous systems. While it is assumed that smart systems could reduce the ecological footprint of farming and gardening activities, as well as make it more profitable for the owner (Walter et al., 2017), such agricultural or mowing robots are only in the prototype or early stage commercial trial phase (IDTechEx, 2018), and their environmental sustainability performance needs to be tested and quantified in comparison with traditional human-operated systems.

A screening of the literature and of industrial or marketing reports that questioned how autonomous systems will transform the agricultural sector has shown a lack of numerical analysis through the lens of environmental sustainability. To contribute into filling part of this gap, a real-world case study has been performed on an autonomous robotic mowing solution. Through comparative LCA and LCC with conventional equipment, quantitative insights have been provided to the question if the automation of lawn mowing services is making environmental sense, and under which conditions it could provide further sustainable benefits.

It has been found that the robotic mower is a non-negligible greener alternative to gasoline pushing mower (lower environmental footprint in terms of global warming potential). Also, when considering the hidden cost for the user, the autonomous could even become a cheaper alternative than human-operated mowing services. The first results exposed in this paper – including the limitations of the present study that are further discussed in the next sub-sections – could serve as a relevant and sound basis to open up on promising perspectives and future work, for the life cycle engineering research community, on the sustainable impacts of upcoming autonomous systems.

4.1. Potential design improvements for augmented, smarter and greener autonomous solutions

An interesting line for future research includes investigating more closely, case by case, the impact of possible and realistic design improvements – including the length of the cutting deck, the battery duration, or the speed of the robotic mower – to complement the analysis doing here on the overall efficiency of the autonomous solution. To do so, sensitivity analysis can be performed to search for significant improvement direction, e.g., for each case by increasing one or several design parameters – such as blade lifespan, blade width, battery duration, speed – by different percentages.

Additionally, in terms of potential environmental savings, there is a major room for improvement related to the navigation mode of current autonomous solutions. In fact, solutions currently available on the market (e.g., John Deere Tango, Honda Miimo, Worx Lamdroid, Robomow, Husqvarna Automower) operate on a random navigation mode. Based on the LCA results, one of the key recommendations, to achieve higher environmental sustainability, is thus to work on the spatial awareness and topological understanding of the yard for the next generations of robotic mowers. Some OEMs are already working in this direction and are trying to implement path-planning capabilities. Notably, an OEM recently mentioned using a high-precision (accuracy of 2–3 cm) navigation system to control the robotic mower.

4.2. Scaling-up the comparative LCA and LCC to larger agricultural equipment

The adoption of electric-powered robotic mowers, in replacement of conventional gasoline pushing mowers, could contribute to the mitigation the environmental impact generated by garden equipment (Banks and McConnell, 2015). To go further in this direction, another use case relevant to be considered and quantified from a sustainability standpoint is the deployment of a fleet of small autonomous robotic mowers to replace gasoline riding mower used for larger and/or uneven gardens.

Also, supplementary LCA and LCC analyses should be conducted on wider agricultural equipment such as autonomous tractors. Indeed, driverless tractors required additional equipment that could increase the environmental footprint of the overall system, including: cameras and machine vision systems, GPS for navigation, IoT connectivity to enable remote monitoring, plus radar for object detection and avoidance. In this case, by integrating as well as the interaction with the farmer, who will have more time to perform other tasks in parallel, the definition of a functional unit and the extension of the system boundaries for a sound comparative LCA with traditional farmer-operated tractors might be challenging and interesting to discuss.

Then, in future work, in addition to the GWP indicator, complementary environmental indicators such as human health, ecotoxicity, eutrophication should also be quantified in order to get a more comprehensive and accurate picture, especially regarding possible impact transfers.

4.3. Autonomous systems in a circular economy perspective

Last but not least, note that the end-of-life impacts of the different mowers were out of scope for the present study, due to lack of data and high uncertainty related to the fate of such equipment, especially for the autonomous solution which is only available on the market since a few years. In future research, to anticipate a sustainable take-back and end-of-life recovery of autonomous equipment, it appears relevant to consider the next generations in a circular economy perspective (Saidani et al., 2019) – including e.g., design for easy-disassembly or remanufacturing. Concretely, as some agricultural equipment are already operating in a shared mode, it might be relevant to consider possible product-as-a-service scenarios (Kjaer et al., 2018) for these new autonomous systems, in order to facilitate the traceability and maintenance during the use phase, as well as the recovery at the end-of-life of the equipment.

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