Computers and Electronics in Agriculture 193 (2022) 106608

Contents lists available at ScienceDirect

Computers and Electronics in Agriculture

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

Swarm robots in mechanized agricultural operations: A review about challenges for research

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ARTICLE INFO

Keywords:
Agriculture
Operational cost
Electric tractor
Artificial intelligence
Plowing
Forestry
Multi-robot

ABSTRACT

Agricultural mechanization is an area of knowledge that has evolved a lot over the past century, its main actors being agricultural tractors that, in 100 years, have increased their powers by 3,300%. This evolution has resulted in an exponential increase in the field capacity of such machines. However, it has also generated negative results such as excessive consumption of fossil fuel, excessive weight on the soil, very high operating costs, and millionaire acquisition value. The objective of this paper aims at exploring the upcoming challenges of employing swarm robot tractors that together have the same field capacity as a large tractor with an internal combustion engine. A systematic literature review technique is used to survey 32 representative papers that report research about swarm robots in agriculture. These papers are analyzed in an organized manner concerning the operationalization of swarm robots to fulfill agricultural mechanization missions. A comprehensive evaluation is conducted from the aspects of technology readiness level (TRL), configurability, adaptability, dependability, motion ability, perception ability and decision autonomy. Based on the evaluation result, upcoming challenges are detected and summarized, suggesting the development of a roadmap for future research. Another systematic review was done for these challenges by assessing the distance between what is being studied and the needs for a commercial operation of a robotic tractor swarm.

1. Introduction

Agricultural mechanization is the area of knowledge in agribusiness, which has the highest energy expenditure and the highest aggregate cost in agricultural production, reaching 60% of energy consumption (Albiero, 2011). This fact occurs due to the specificities of farming operations that require a lot of mechanical energy (Goering and Hanson, 2004) referring to the different phases of agricultural production: soil preparation, seeding, planting, crop management, harvesting, and conditioning of crop residues. And main energy sources of agriculture is known as agricultural tractors (Goering et al., 2003), which enables the operation of plows, harrows, seeders, harvesters, sprayers, brush cutters, chisels, subsoilers, crushers, conditioners, rakes, terriers, planters, cutters, etc. (Srivastava et al., 2006). Since the appearance of the agricultural tractor at the end of the 19th century and the beginning 20th century, its power and weight tended to increase to improve field capacity in the area (Goering and Hanson, 2004). In 100 years, agricultural tractors have increased their powers by 3,300% (Melo et al., 2019; Goering and Hanson, 2004; Renius, 2020; Vogt, 2018; Vogt et al., 2018; Vogt et al., 2021).

For comparison, at the beginning of the 20th century, the largest tractors had approximately 15 kW of power (Renius, 2020). Today, at the beginning of the 21st century, we have reached a point scale of power for agricultural tractors in the 500 kW range (Goering and Hanson, 2004). There is a consensus in contemporary literature that the power growth curve of these machines is stabilizing and reaching an asymptotic limit.

This trend is approaching a technological limit for parameters that represent three crucial problems: The first is the excessive energy consumption of large tractors that consume a lot of fossil diesel fuel (up to 150 L per hour) (ASABE, 2013); The second refers to the weight of these machines, which increased from about 1,300 kg in 1902 to 25,000 kg in 2019 (Renius, 2020) that generates a very significant degradation of the soil in physical–mechanical terms which is translated into soil compaction. These two problems represent losses in food production; And the third not least is the investment cost of these machines, which reach values of US$ 1,100.00 per kW (Goering et al., 2003; Goering and Hanson, 2004; TractorHouse, 2020).

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https://doi.org/10.1016/j.compag.2021.106608
Received 29 October 2020; Received in revised form 27 October 2021; Accepted 29 November 2021
Available online 15 January 2022
0168-1699/

In this context, an exciting hypothesis is to change the current agricultural mechanization paradigm to increase tractors' field capacity by increasing their power and weight. This paper intends to call the Agricultural Robotics Research Community (ARRC) to propose a roadmap for research in the opposite direction: to decrease the power and weight of the tractors and to increase their number, optimizing the agricultural operations in terms of logistics, operational geometry, and energy efficiency through the science of robotics. Instead of using one gigantic machine of hundreds of kW, the propose uses many robot tractors of tens kW.

However, there is a big problem with this anti-paradigmatic approach. It comes up against the current socio-economic situation of agricultural fields in western nations (Albiero, 2019; Albiero et al., 2019, 2015): Tractor operators are scarce, and their costs (wages, charges, taxes, training, and insurance) are relatively high. Thus, a very suitable solution offered by the science of robotics is operationalizing these small robot tractors as multiple robots operating in a swarm configuration. The European SPARC Committee has set a goal for future studies with broad opportunities to investigate this replacement of large tractors with small multi- robots (SPARC, 2017).

Robots are not new in agriculture; there is much research being developed, some of them very advanced, and already with actual applications in the field, agricultural robotics is an overwhelming trend (Albiero, 2019; Albiero et al., 2020; Fernandes et al., 2021). Hokkaido University, between 1990 and 2018, conducted extensive and very in-depth research on agricultural robotics, covering the entire research area and fully demonstrating the effectiveness of these agricultural robotic systems, and presents recommendations for future studies in addition to essential experiences and lessons to ARRC (Roshanianfard et al., 2020).

Lowenberg-DeBoer et al. (2020) claim there is a need for studies in agricultural robotics that delve deeper into these technologies' economic implications, as most studies estimate the financial implications based on technological parameters from prototypes, which masks the results.

Mao et al. (2021) in an extensive study evaluating environment perception, task allocation, path planning, formation control, and communication about the synergistic technologies of agricultural multi-robots, state that not only does an increase in efficiency occurs, but it also solves problems of decreasing adequate labor supply. On the other hand, they say that much research must be carried out to operationalize these technologies in the field. They conclude that it is realistic to expect automated multi-robot systems in the future.

Ball et al. (2017) affirm that significant advances have occurred in developing robotic technologies applied to agriculture with systems wholly tested in the field. There is an increase in investment for the commercialization of agricultural robots, as demonstrated by the rise of start-ups and companies already consolidated offering products and services. So new robotic technologies can help optimize agricultural operations by reducing human time spent on dangerous and repetitive processes.

The solutions to global food security threats are intelligent technologies, including automation and robotization of agricultural processes. The authors give several examples such as sensing and perception technologies; data collection systems (UAVs, IoT, sensor networks, and emerging robotic platforms); Robotic Cloud technologies to process, store and share information; AI & ML; Swarm Robotics technologies and Control technologies (Grieve et al., 2019).

Agricultural robotics is synonymous with the frontier of knowledge in the agricultural area (Albiero, 2019). Currently, the current work philosophy defined as agriculture 4.0 (Albiero et al., 2020) confirms this, and it clarifies the ever-present interface between IoT (Lima et al., 2020), Connectivity (Simionato et al., 2020), and AI (Megeto et al., 2020) as fundamental research areas for robotics. These areas, combined with advances in computer vision technologies (Fracarolli et al., 2020), sensors (Queiroz et al., 2020), and electric mobility (Weisbach et al., 2020), make up state of art on the subject of swarm agricultural robots.

This paper intends to present the recent literature concerning swarm robots for agriculture and invite the ARRC to launch a roadmap for research to solve the enormous technical and scientific challenges related to this solution.

2. Swarm robots with interface in agricultural applications

2.1. Review agricultural swarm robotics

Wolfert et al. (2017) describe these advances in Agriculture 4.0 called Smart Farming. They explain that intelligent machines and crop sensors on farms have obtained large amounts of agricultural data; the quantity, quality, and scope have grown enormously, making data available to improve processes. In this context, innovations in the field are developing at an accelerated rate. (Bechar and Vigneault, 2016). There are robots for the application of phytosanitary products; for sowing; for diagnosis of soil, plants, water; with computer vision systems; for harvest; with remote steering control systems; with transplant systems; for weed control; for monitoring diseases and pests; for pruning (Bechar and Vigneault, 2017). An exciting innovation in the Smart Farms concept was a robot for irrigating pots in agricultural greenhouses (Araújo Batista et al., 2017).

Guillet et al. (2017) present a control strategy for robot fleets in off-road conditions. Dias and Ollero (2007) affirm that teams of robots working together with humans in complex tasks are an inevitable part of our future. Osaba et al. (2020) state that the success of a robot swarm comes from the efficient use of intelligent sensing, combined with communication and organization of features; all this is linked to the operationalization of inference of knowledge of the environment. Osaba et al. (2020) present the most recent contributions within this paradigm that can be called soft computing. According to Ibrahim (2016), it can be defined as one that deals with the complex problems of real life, where approximate models are solved with tolerance to imprecision, uncertainty, partial truth, and approximations. Soft computing techniques are based on fuzzy logic, genetic algorithms, artificial neural networks, machine learning, and expert systems.

Dornhege et al. (2016) developed a system for multi-robot to observe and cover complex 3D known as OctoMap. Jones et al. (2020) created a distributed situational awareness method to guide the multi-robot project innovatively. Ju and Son (2019) set a control algorithm for a UAV swarm; this algorithm has two layers; the first is a teleoperation layer through a haptic device. Kapoutsis et al. (2019) developed a specialized algorithm for multi-robots that operate in unstructured environments. Xaud et al. (2018) produced an interesting robot for use in bioenergetic crops, De Lemos et al. (2018) present a uni-sensor strategy for navigation between rows of crops for robots, and Oliveira et al. (2018) proposed a methodology to adapt conventional commercial systems to autonomous robotic systems. Davis (2012) described a family of agricultural vehicles that has collective sensing and computational infrastructure. An exciting European research program deeply studies applications of swarm robotics concepts with UAVs used to obtain information on the productivity of beet fields and to generate data on weeds, diseases, and nematodes (Toorn, 2020).

Grimstad and From (2017) have developed an excellent agricultural robot in modular robot mode, with a superb re-configuration capacity, for any weather in any agricultural application. Albani et al. (2019) use UAVs swarm robots to monitor and map weeds in agricultural fields. Albani et al. (2017) presented an exciting roadmap for future studies on swarm robotics for applications in farm monitoring and mapping. Mukherjee et al. (2020) studied the challenges in operationalizing the use of UAVs in swarm robotics configuration. Barrientos et al. (2011) present a team of UAVs able to make georeferenced photos so that they can create a complete forest through mosaic procedures.

Huuskonen and Oksanen (2019) present a system of supervision of a fleet of agricultural multi-robots through augmented reality. Blender et al. (2016) introduced Mobile Agricultural Robot Swarms (MARS) is an approach for autonomous farming operations by a coordinated group of robots and describes an application in seeding. Trianni et al. (2016) described the concept of a set of swarm robots for weed control and defined a roadmap for executing such a project. Minßen et al. (2017) presented conceptual studies for agricultural care in plants considering several swarm robots.

Ayanian (2019) states that although robot hardware has advanced significantly in the last decade, the way to solve problems with multi-robot has not advanced, but when there is the coordination of multi-

Table 1
Summary of agricultural swarm robots technologies.

Name technology	Control architecture	Agricultural swarm innovation	Heterogeneity	Application	Author
Control strategy	Hierarchical	Virtual leader/Lyapunov technique	Yes	Robots in off-road conditions	Guillet et al. (2017)
Multi-robots to 3D environment	Hierarchical	Hierarchical 3D grid	No	To cover complex 3D environment	Dornhenge et al. (2016)
Robot farming system	Centralized	Complete to carry out all the relevant agricultural operations	Yes	For rice, wheat and soybean	Noguchi and Barawid, (2011)
Multi-robot tractors	Distributed	Algorithm to maintain a spatial pattern during the process	No	Agriculture field work	Zhang and Noguchi, (2017)
Multi-robot project	Distributed	Distributed situational awareness	Yes	To capture the environment	Jones et al. (2020)
UAV haptic device	Distributed	Distributed control algorithm	No	Control in two level UAV fly	Ju & Son (2019)
Specialized algorithm multi-robots	Distributed	Cost functions/optimization	No	Operation in unstructured environment	Kapoutsis (2019)
Tanquette bioenergetic robot	Centralized	Semi-autonomous, low-cost, dust and waterproof tankette-type vehicle	No	Agricultural tasks in sugarcane fields	Xaud et al. (2018)
Row of crops	Centralized	Uni-sensor strategy	No	Navigations between row crops	Lemos et al. (2018)
Family vehicles	Distributed	Collective sensing and computational infrastructure	Yes	Applications of robots in field	Davis (2012)
UAV productivity	Distributed	Swarm UAV	No	Obtain information on the productivity	Toorn (2020)
Modular robots	Centralized	Re-configuration capacity	Yes	Work in any farming operation	Grimstad & From (2017)
UAV swarm	Distributed	Collective behaviour for weed monitoring and mapping through of the stochastic coverage and mapping	No	Monitor and map weeds	Albani et al. (2019)
Smart farm UAV	Distributed	Non-trivial control edges	Yes	Heterogeneous aricultural environment	Mukherjee et al. (2020)
Team of UAVs	Distributed	Negotiation algorithm between UAVs	No	Georeferenced photos	Barrientos et al. (2011)
Fleet agricultural Multibots	Hierarchical	Supervision of fleet through Augmented reality	Yes	Agricultural tasks	Husskonen & Oksanen (2019)
MARS	Centralized	Coordinated group of robots	No	Autonomous farming seeding	Blender et al. (2016)
Multi-robots in unstructured environment	Distributed	Skillful policies combined synergistically	Yes	Operation in unstructured environment	Ayanin (2019)
Agricultural robots	Centralized	Navigation with 3D LIDAR	No	Navegation in unstructured environment	Le et al. (2019)
Micro-helicopter for denied GPS	Distributed	Monocular camera and inertial sensor	No	Autonomous navigation	Weiss et al. (2011)
Collaborative robots	Centralized	Centralized Collaborative monocular SLAM	Yes	Autonomous individual navigation with central server	Schmuck & Chli (2019)
Sincronized swarm robots	Hybrid: Centralized + Hierarchical	Dynamic network exchange for voting process	No	Navigation in synchronized map	Sergiyenko (2016)
Agricultural robots	Centralized	GPS navigation with inertial navigation plus stereo vision	No	Navigation in agricultural fields	Ball et al. (2016)
Team multi-vehicles	Hierarchical	Intelligent sensors	Yes	Respond threats in dynamic environment	Butzke et al. (2012)
Foraging robots	Hierarchical	Artificial pheromones	No	Faster navigation paths between obstacles	Campo et al. (2010)
Team robotic tractors	Hierarchical	Team leader (human), robots mimic manual harvesting	No	Harvest peat moss	Johnson et al. (2009)
UAV Spray Swarm	Distributed	Bio-inspired system based on the behaviour of bacteria	No	Spray phytosanitary products	Al-Megren et al. (2018)
Control structure for agricultural robots	Hybrid: Distributed/ Hierarchical	Master-slaves and peer to peer operation	Yes	Control moviments for of agricultural robots	Vougioukas (2012)
Multi-Ground Vehicles	Hierarchical	Platooning algorrithm	Yes	Planning route and speed for vehicle in rough terrain	Shin et al. (2020)
Swarm robots for renewable resources	Distributed	Balanced strategy it remain cohesive swarm collectively behavior	No	Ability to exploit the resources	Miletitch et al. (2018)
Rubber harvesting robot	Hierarchical	Metaheuristic algorithms and soft computing	No	Rubber harvesting system	Gangadharan & Salgaonkar (2020)
Multi-robot navigation	Distributed	Self-clustering algorithm	No	Deploying and navigating multi-robots	Jhang et al. (2020)
Cloud robotics	Distributed	Mandani Fuzzy interference system to cloud robotics	No	Task planning mechanism for decision-making policy	Khan et al. (2020)
Vehicle prediction route	Distributed	Gaussian regression	No	Predict route with minimal energy cost in off-road environment	Quann et al. (2020)

robots in a structured environment is a case of success. However, in an unstructured environment, it is a failure because the problem-solving paradigm is based on simplifying a problem according to premises and then finding an optimized solution for this solution.

Le et al. (2019) proposed a navigation system for an agricultural robot system with a 3D LIDAR and improved its characteristics for an unstructured environment. Weiss et al. (2011) developed an autonomous navigation system for a micro-helicopter suitable for denied-GPS. Schmuck and Chli (2019) present an innovative Centralized Collaborative Monocular Simultaneous Localization and Mapping (CCM-SLAM) for collaboration between robots. Sergiyenko et al. (2016) describe methods to transfer location data to robot swarms through a dynamic network exchange of data for communication based on the voting process.

Ball et al. (2016) present an excellent solution for navigation and obstacle detection for agricultural robots; it is the creative combination of a cheap GPS navigation system with an inertial navigation system and a stereo computer vision system; the results were exciting and promising. Butzke et al. (2012) developed and built a team of robotic multi-vehicles. Campo et al. (2010) describe the development of foraging robots that use artificial pheromones. Johnson et al. (2009) present the evolution of a team of three robotic tractors to harvest peat moss, monitored by a human being (team leader). Al-Megren et al. (2018) present the development of a UAV swarm to spray phytosanitary products on palm trees to combat red palm weevil.

Zhang and Noguchi (2017) they developed a system of multi-robot tractors that maintain a spatial pattern during the process, such as I-pattern, V-pattern, and W-pattern are used in this system. Noguchi and Barawid (2011) developed multiple robots for rice, wheat, and soybean; the system was complete for carrying out all the relevant agricultural operations: planting robot, seeding robot, robot tractor, combine robot harvester, and various implements attached on the robot tractor (Vougioukas, 2012) presents a movement control structure for agricultural robots. Shin et al. (2020) developed and tested a new autonomous platooning algorithm focused on route and speed planning for multi-ground vehicles in rough terrain. Miletitch et al. (2018) proposed a decentralized strategy for a swarm of robots that adapt to the availability of renewable resources. Gangadharan and Salgaonkar (2020) present metaheuristic algorithms for robotic rubber harvesting systems in rubber plantations, ant colony optimization. Jhang et al. (2020) present a new method of deploying and navigating multi-robot through a self-clustering algorithm. W. A. Khan et al. (2020) introduce a new task planning mechanism using Mandani Fuzzy Interference System to operate a Cloud robotics system. Quann et al. (2020) presented an exciting method based on a Gaussian regression and information modeling of a known vehicle to predict a route.

To summarize the analyzed papers, part of the characterization of Multi-robots defined by (Parker, 2008) was used in the following aspects: control architecture, agricultural swarm innovation, heterogeneity, and application, Table 1.

The architecture control of swarm robots can be summarized in centralized, hierarchical, distributed (decentralized), and hybrid. In a centralized architecture, only one control point coordinates the entire team of robots; in hierarchical architecture, the group of robots follows the actions of a small group of robots (leaders). In a distributed architecture, team robots take actions based only on local knowledge of their situation; and the hybrid architecture combines local control with another higher-level control.

Swarm innovation refers to state-of-the-art development that improves or implements a new feature in the agricultural swarm operation. Heterogeneity can be defined in terms of various behaviors, morphologies, quality of performance, size, and cognition that a team of multi-robots can have. Moreover, the application refers to the many applications that a multiple mobile robot system can have in the real agricultural world (see Table 2).

2.2. Evaluation of state-of-art swarm robotics technologies

After presenting these thirty-four Agricultural Swarm Robotics Technologies was evaluated each one of them from seven aspects: technology readiness level (TRL), configurability (Config), adaptability (Adapt), dependability (Depen), motion ability (Mot), perception ability (Perc) and decision autonomy (Decis), according to definitions of (SPARC, 2017).

Technology readiness level (TRL) is the level of development of technology. There are 9 levels: 1-Basic principles; 2-Technology concept formulated; 3-Experimental proof of concept; 3-Technology validated in a laboratory; 5-Technology validated in the relevant environment; 6-Technology demonstrated in the relevant environment; 7-Prototype shown in an operational environment; 8-System completed and qualified; 9-System proven in an operating environment.

Configurability (Config) is the ability of the robot to be configured to perform a task. Already Adaptability (Adapt) is the system to adapt itself to different work scenarios. Dependability (Depen) is the ability of the system to perform the given task without systematic errors. Motion (Mot) ability is the ability of the system to move, which may be highly constrained or unconstrained in different media. Perception (Perc) ability is the ability of the robot to perceive its environment. And decisional (Decis) autonomy is the ability of the robot to act autonomously.

Table 3 was constructed to evaluate the seven aspects of the 32 technologies analyzed, ranked according to a score defined by (Zhai et al., 2020): number three if the aspect is fully considered and described with technical details (best); number two if it is partially mentioned, but without further explanations (medium); and number one if the aspect is not addressed at all (worst).

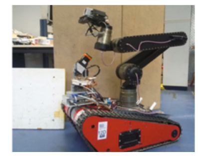
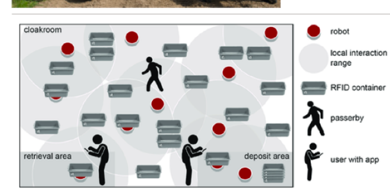
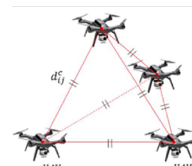
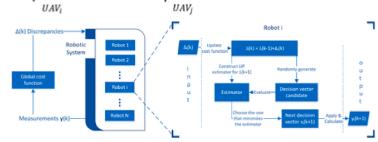
When evaluating the TRL of the technologies presented, it is noticed that only 23.5% of them are in the TRL 7 stage (prototype demonstrated in an operational environment); this indicates that 76.4% of the technologies with the potential to be commercially allocated have not yet reached an availability level. Furthermore, it is vital to note that, according to (SPARC, 2017), a very rough rule moving from one TRL level to the next can cost between 5 and 10 times the cost of the previous step. This fact indicates that technologies are far from significant commercial achievement at level 6 (22%).

Regarding configurability (Config), this criterion is the one with the lowest relative score in Table 3 (73/102); this indicates that this criterion is the one that presents the most significant challenges related to the commercial operation of the agricultural swarm. A possible hypothesis regarding this criterion is that, due to the specificity, that, in general, agricultural swarms are designed for dedicated operations (Albani et al., 2019, 2017) and are specialized for a single operation; they have very little flexibility in modifications to the original settings.

Adaptability (Adapt) is the second criterion with the lowest relative score (76/102). It is consistent with the evaluation of configurability (Config) because if the swarm is dedicated to a specific operation, the robots' self-adaptability is restricted to this operation, with little scope for internal and external adaptations of both the individual and the collective multi-robots. But the dependability and perception ability criteria have a very close and relatively high relative score (86/102) and (88/102), respectively. This fact can be credited to the great emphasis that the robotics research community uses on issues of analysis and resolution of the systematic errors in which the technologies are exposed, both in terms of software/algorithms/processing (Jhang et al., 2020; Quann et al., 2020; Sergiyenko et al., 2016) as in terms of perception of positioning/orientation/mapping/movement/obstacles (Ball et al., 2016; Johnson et al., 2009; Le et al., 2019; Vougioukas, 2012).

The decision autonomy criterion (Decis) has an average relative score (54/102). It indicates that the research community has been paying attention to this critical criterion (Ayanian, 2019; Gangadharan and Salgaonkar, 2020; Jones et al., 2020; Shin et al., 2020), but at the

Table 2
Pictures of agricultural swarm robots technologies.

Name Technology	Author	Picture
Control Strategy	Guillet et al. (2017)	
Multirobots to 3D enviroment	Dornhenge et al. (2016)	
Robot Farming System	Noguchi and Barawid, (2011)	
Multi-robot tractors	Zhang and Noguchi, (2017)	
Multirobot project	Jones et al. (2020)	
UAV haptic device	Ju & Son (2019)	
Specialized algorithm multirobots	Kapoutsis (2019)	
Tanquette Bioenergetic Robot	Xaud et al. (2018)	
Row of crops	De Lemos et al. (2018)	
Family vehicles	Davis (2012)	
UAV productivity	Toorn (2020)	

(continued on next page)

Table 2 (*continued*)

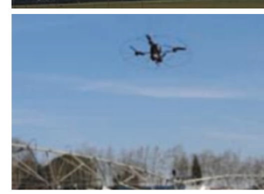
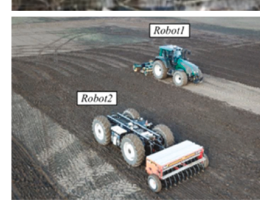
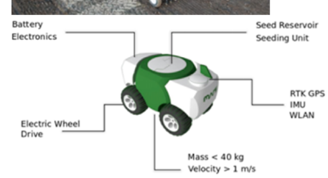
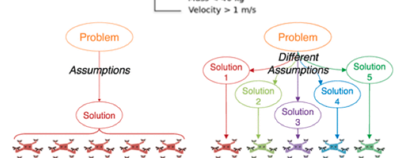
Name Technology	Author	Picture
		
Modular robots	Grimstad & From (2017)	
UAV Swarm	Albani et al. (2019)	
Smart Farm UAV	Mukherjee et al. (2020)	
Team of UAVs	Barrientos et al. (2011)	
Fleet agricultural Multibots	Husskonen & Oksanen (2019)	
MARS	Blender et al. (2016)	
Multirobots in unstructured environment	Ayanin (2019)	
Agricultural robots	Le et al. (2019)	
Micro-helicopter for denied GPS	Weiss et al. (2011)	

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Table 2 (*continued*)

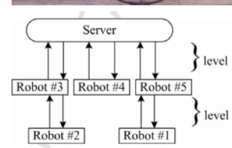
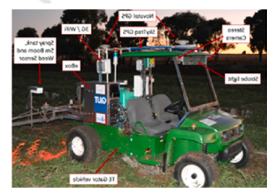
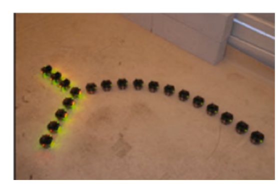
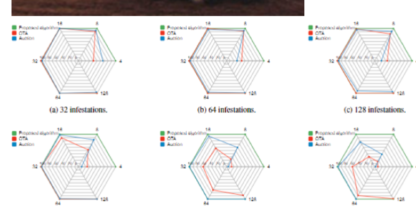
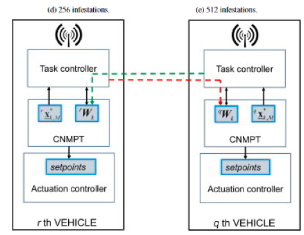
Name Technology	Author	Picture
		
Collaborative robots	Schmuck & Chli (2019)	
Sincronized swarm robots	Sergiyenko (2016)	
Agricultural robots	Ball et al. (2016)	
Team multi-vehicles	Butzke et al. (2012)	
Foraging robots	Campo et al. (2010)	 
Team robotic tractors	Johnson et al. (2009)	
UAV Spray Swarm	Al-Megren et al. (2018)	
Control structure for agricultural robots	Vougioukas (2012)	
Multi-Ground Vehicles	Shin et al. (2020)	

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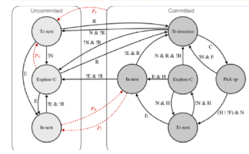
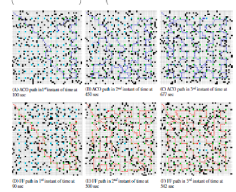
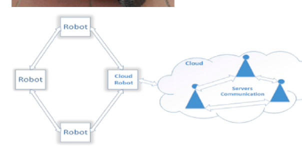
Table 2 (*continued*)

Name Technology	Author	Picture
		
Swarm robots for renewable resources	Miletitch et al. (2018)	
Rubber harvesting robot	Gangadharan & Salgaonkar (2020)	
Multirobot navigation	Jhang et al. (2020)	
Cloud robotics	Khan et al. (2020)	
Vehicle prediction route	Quann et al. (2020)	

same time, it has not been giving the necessary emphasis. The motion ability (Mot) criterion, on the other hand, has the highest relative score (93/102). It is in line with the fact that most of the technologies listed are mainly concerned with the issue of movement in the field or refers to algorithms that aim to optimize this movement (Ayanian, 2019; Guillet et al., 2017; Olcay et al., 2020a; Shin et al., 2020).

Evaluating the overall remark presented in Table 4, perhaps the most representative fact is that it does not necessarily have a high general observation (high score in all evaluation criteria) means that the technology is ready for the market, considering the research question related to the commercial operation of a robot swarm for mechanized agricultural operations. Thus, technologies such as those presented by (Campo et al., 2010; Gangadharan and Salgaonkar, 2020; Jhang et al., 2020; Quann et al., 2020) have overall remarks varying between 94 and 100%, but the TRL varies between 3 and 5. In other words, they are very advanced technologies that encompass all the criteria for a very interesting agricultural swarm but are in a stage of technological development that is still incipient.

The other interesting fact is that 14 technologies have an overall remark below 80% considering the six criteria chosen according to (SPARC, 2017) recommendations, which indicates that practically 40% of state-of-the-art technologies do not fully meet the requirements to operationalize a commercial swarm. This fact can be explained because many of the studied technologies stick to particular objectives, consistent with the analysis carried out in Table 3, considering the adaptability (Adapt) and configurability (Config) criteria, both with the lowest relative scores about the total possible score. This evaluation result summarizes future trends and upcoming challenges in a roadmap suggestion for future research.

3. Challenges in agricultural swarm robot

The European SPARC committee (SPARC, 2017) prepared an excellent Multi-Annual Roadmap, and a Strategic Research Agenda focused on developing studies, projects, and R & D & I priorities for the robotics area with a horizon until 2020. It is a very comprehensive report, detailed and complete, with a chapter dedicated to agriculture. But it is a roadmap for defining R & D & I funding, including near market activities where a research framework is described together with companies. This paper's scope is much less ambitious and much more specific because it intends to present suggestions for particular challenges concerning the operation of swarms in mechanized agricultural operations.

It is perceived that there is a long and challenging path to this demand. It must be initiated in a planned way, always oriented towards the technical–economic viability of such systems for agriculture. In this work, exciting results in this paper were presented in terms of operational costs and field capacity for the deep plowing operation. Because of these positive results, an Electric Robot Swarm Tractor was proposed. Plowing is the agricultural mechanization operation that demands the most energy, but it is not the most expensive. There are farming operations that represent investments of tens of millions of dollars, such as sowing that defines the plant stand of any crop (Mialhe, 2013) that protects crops from pest attacks and diseases.

In this context, it is essential to emphasize that there is a vast field for studies with significant challenges concerning the operationalization of each agricultural operations (Minßen et al., 2017) within the universe of robotics, specifically in the area of multi-robots working in swarm methods. As an example, the ASABE D497 standard defines 48 different agricultural operations with distinct characteristics and parameters

Table 3
Evaluation of agricultural swarm robots technologies.

Name technology	Author	TRL	Config	Adapt	Depen	Mot	Perc	Decis
Control strategy	Guillet et al. (2017)	7	3	2	3	3	3	2
Multi-robots to 3D environment	Dornhenge et al. (2016)	6	3	2	3	3	3	2
Robot Farming System	Noguchi and Barawid, (2011)	6	3	2	2	3	2	2
Multi-robot tractors	Zhang and Noguchi, (2017)	7	2	3	3	3	3	3
Multi-robot project	Jones et al. (2020)	3	1	2	3	1	3	2
UAV haptic device	Ju & Son (2019)	4	2	2	3	3	3	3
Specialized algorithm multi-robots	Kapoutsis (2019)	3	2	3	3	1	1	3
Tanquette Bioenergetic Robot	Xaud et al. (2018)	5	1	2	2	3	3	2
Row of crops	Lemos et al. (2018)	5	1	1	2	3	3	2
Family vehicles	Davis (2012)	6	3	1	1	3	2	3
UAV productivity	Toorn (2020)	6	1	1	2	3	3	2
Modular robots	Grimstad & From (2017)	7	3	3	3	3	3	3
UAV Swarm	Albani et al. (2019)	7	2	2	2	3	3	2
Smart Farm UAV	Mukherjee et al. (2020)	6	1	2	2	3	3	2
Team of UAVs	Barrientos et al. (2011)	6	1	1	2	3	3	3
Fleet agricultural Multibots	Husskonen & Oksanen (2019)	6	2	2	1	3	3	2
MARS	Blender et al. (2016)	7	2	3	3	3	3	2
Multi-robots in unstructured environment	Ayanin (2019)	2	3	3	2	1	3	3
Agricultural robots	Le et al. (2019)	5	1	2	2	3	3	3
Micro-helicopter for denied GPS	Weiss et al. (2011)	5	1	2	3	3	3	3
Collaborative robots	Schmuck & Chli (2019)	6	3	2	3	3	3	3
Sincronized swarm robots	Sergiyenko (2016)	3	1	2	3	1	2	2
Agricultural robots	Ball et al. (2016)	7	2	3	3	3	3	3
Team multi-vehicles	Butzke et al. (2012)	7	3	3	3	3	3	3
Foraging robots	Campo et al. (2010)	4	3	3	3	3	3	3
Team robotic tractors	Johnson et al. (2009)	7	3	3	3	3	3	3
UAV Spray Swarm	Al-Megren et al. (2018)	2	2	2	2	2	2	3
Control structure for agricultural robots	Vougioukas (2012)	3	2	3	3	2	2	3
Multi-Ground Vehicles	Shin et al. (2020)	7	3	3	3	3	3	3
Swarm robots for renewable resources	Miletitch et al. (2018)	2	2	1	2	2	2	2
Rubber harvesting robot	Gangadharan & Salgaonkar (2020)	3	3	3	3	3	3	3
Multi-robot navigation	Jhang et al. (2020)	5	2	3	3	3	3	3
Cloud robotics	Khan et al. (2020)	3	1	2	2	2	1	1
Vehicle prediction route	Quann et al. (2020)	5	3	2	3	3	3	3
Total by evaluation criteria			73/102	76/102	86/102	93/102	88/102	84/102

(ASABE, 2013). For each of them, several challenges for the operationalization of a swarm robot system are presented and suggested below.

3.1. A draft of research roadmap: Gaps and works related.

Evaluating the 32 state-of-the-art technologies chosen for the seven criteria considered most critical demonstrated that the aspects of configurability, adaptability and decision autonomy are the most needed by the scientific community. Tables 3 and 4, these three criteria established by (SPARC, 2017), thus several research areas within these aspects were raised.

3.1.1. Criterion Configurability:

3.1.1.1. Hardware enhancement. According to (Albiero, 2019), the main obstacle in the developing systems adapted to the agricultural conditions is that there are many elements of automatic and robotics (used in industry and smart cities) that are very good. But, when they are part of the agricultural world with the high susceptibility of the agricultural products in the spoiling of the most varied forms, problems occur.

There is an urgent necessity of developments in robotics technologies for agricultural reality. Many processors used actually in the industry would not stand the environment of a greenhouse because the condition of moisture, temperature, and corrosive factors would destroy them quickly. The issue of connectivity is another serious problem, how will these swarm robot systems communicate wirelessly in the long distances of croplands.

Some exciting proposals presented by the literature to solve this challenge are described: (Koshy et al., 2018) developed an interesting hybrid robot by integrating a quadrotor (aerial) with a quadruped (terrestrial) system. Mertyüz et al. (2020) created a new type of transformable wheel leg robot capable of moving on flat and rough terrain. Szczecinski et al. (2017) developed a robot with a distributed control system, simulating the insect nervous system. Utter and Brown (2020) developed a platform to control heterogeneous mobile robots with wireless infrastructure in the field of modular robot prototyping. Guo et al. (2018) developed an electro-adhesion system for manipulating objects by robots; it is a monolithic, shape-adaptive electroactive gripper with self-sensing with integral dielectric elastomer actuation.

J. Chen et al. (2020) developed a sensorized pneumatic actuator with self-power in the soft robots' technical category. Baba (2020) presents a flying robot's design with thermal sensors and vision-based systems in HD images for surveillance of intelligent grids networks.

3.1.1.2. Networked swarm robots. According to (Siciliano and Khatib, 2008), networked robots are multiple robots operating together through coordination and cooperation with the help of network communication. This line of research is very challenging because through the connection between the swarm members is possible through distributive computing to emulate the behavior of animals that decentralized through simple behaviors are capable of generating complex responses at the collective level, the so-called emergent behaviors.

The great challenge in this line of research is to innovate through the mix between swarm behavior (relatively independent), coordinated behavior, and cooperative behavior. Minelli et al. (2020) developed a methodology to prevent failures in single-point robots causing loss of connectivity across the network. Roveda et al. (2020) propose a Bayesian optimization algorithm to tune both parameters, both for low-level controller parameters. Khateri et al. (2020) offer a modified method to maintain the local connectivity of a robot network. This new method is based on a traditional local network equipped with an essential operation of exchanging neighbors between two adjacent robots, so the exchange of robots can be beneficial in changing the leader rule.

Table 4
Overall remarks of selected technologies.

Name technology	Author	TRL	Overall remark	Overall remark (%)
Control strategy	Guillet et al. (2017)	7	16/18	88.89
Multi-robots to 3D environment	Dornhenge et al. (2016)	6	16/18	88.89
Robot farming system	Noguchi and Barawid, (2011)	6	14/18	77.78
Multi-robot tractors	Zhang and Noguchi, (2017)	7	17/18	94.44
Multi-robot project	Jones et al. (2020)	3	12/18	66.67
UAV haptic device	Ju & Son (2019)	4	16/18	88.89
Specialized algorithm multi-robots	Kapoutsis (2019)	3	13/18	72.22
Tanquette Bioenergetic Robot	Xaud et al. (2018)	5	13/18	72.22
Row of crops	Lemos et al. (2018)	5	12/18	66.67
Family vehicles	Davis (2012)	6	13/18	72.22
UAV productivity	Toorn (2020)	6	12/18	66.67
Modular robots	Grimstad & From (2017)	7	18/18	100,00
UAV swarm	Albani et al. (2019)	7	14/18	77.78
Smart farm UAV	Mukherjee et al. (2020)	6	13/18	72.22
Team of UAVs	Barrientos et al. (2011)	6	13/18	72.22
Fleet agricultural Multibots	Husskonen & Oks. (2019)	6	13/18	72.22
MARS	Blender et al. (2016)	7	16/18	88.89
Multi-robots in unstructured	Ayanin (2019)	2	15/18	83.33
Agricultural robots	Le et al. (2019)	5	14/18	77.78
Micro-helicopter for denied GPS	Weiss et al. (2011)	5	15/18	83.33
Collaborative robots	Schmuck & Chli (2019)	6	17/18	94.44
Sincronized swarm robots	Sergiyenko (2016)	3	12/18	66.67
Agricultural robots	Ball et al. (2016)	7	17/18	94.44
Team multi-vehicles	Butzke et al. (2012)	7	18/18	100.00
Foraging robots	Campo et al. (2010)	4	18/18	100.00
Team robotic tractors	Johnson et al. (2009)	7	18/18	100.00
UAV spray swarm	Al-Megren et al. (2018)	2	13/18	72.22
Control structure for agricultural robots	Vougioukas (2012)	3	15/18	83.33
Multi-ground vehicles	Shin et al. (2020)	7	18/18	100.00
Swarm robots for renewable resources	Miletitch et al. (2018)	2	11/18	61.11
Rubber harvesting robot	Gangadharan & San. (2020)	3	18/18	100.00
Multi-robot navigation	Jhang et al. (2020)	5	17/18	94.44
Cloud robotics	Khan et al. (2020)	3	9/18	50.00
Vehicle prediction route	Quann et al. (2020)	5	17/18	94.44

C. Chen et al. (2020) propose an off-policy learning-based dynamics for the feedback process to optimize the synchronization of heterogeneous multi-agent systems in a direct communication network. Khaluf et al. (2019) propose a new application of the ant colony optimization algorithm to allocate a robot swarm to perform a set of tasks. Meng et al. (2020) study the synchronization of networks over finite fields, which is the consensus method's generalization.

3.1.1.3. Operational strategy. The division of the agricultural field can be configured in cells, lines, bands, blocks, in short, several sets with different topologies, which in the real agricultural environment take very complex forms due to the specificities of the relief, contour lines, shape of the fields, planting configuration of cultures. All these topological parameters lead to complex logistical problems for optimizing the movement strategy of the swarm, reaching questions related to differential geometry. Cieślak et al. (2020) present a new formulation of a reactive algorithm for avoiding obstacles through a task priority structure. Kurtser and Edan (2020) present task planning for fruit harvesting robots; they use the traveling salesman paradigm to plan the sensing sequence.

Wei and Wang (2020) applied a support vector machine in a target recognition process using multi-sensors. Yu et al. (2020) propose a new adaptive controller by implementing a region-based flocking control in a robotic network system with delayed communication.

3.1.2. Criterion Adaptability:

3.1.2.1. On-board systems. This topic is a substantial scientific-technological challenge that involves multi-functions, multi-objectives, and multi-devices. The on-board systems of a TRSE are very complex, and without a pre-defined standard, there are absolutely no trivial solutions. Computer vision systems are a universe, from developing specific hardware to the elaboration of suitable firmware. When thinking about the immense range of sensors, receivers, and transducers necessary to make a swarm robot operational in the field, it is essential to divide this field of study into proprioception, exteroception, and guidance systems.

The challenges in proprioception refer to the optimization of the sensors and actuators necessary to enable the robot's operation, depending on the specific agricultural process. In terms of exteroception, the challenges are even higher, in the sense that the farm environment is very complex, unpredictable, and uncontrollable, so that the development of sensors and actuators that enable the fulfillment of the listed mission is essential. Furthermore, in terms of guidance, the agricultural environment offers immense obstacles, ranging from varying light conditions, such as irregular reliefs, in addition to complex and often discontinuous contour geometry.

Some proposals presented by the literature about this challenge are described: (L. Wang et al., 2020) studied a BS (bar-shaped) structure for a robotic multiprocessor control system of digital media to reduce bandwidth pressure and interconnection conflicts between network and memory. The authors used a BS neural network to allow for a multilayer feedforward NN. Li et al. (2019) developed a soft optical fiber curvature sensor for finger joint angle proprioception. Ozel et al. (2015) present a curvature sensor module; the device uses a magnet and the Hall effect for accurately sensing curvature measurements, ensuring contact-free sensing. Pérez et al. (2019) propose using commercial gaming technologies to create an immersive environment based on virtual reality.

Lourenço et al. (2020) study the problem of obtaining an Earth-fixed trajectory and map associated with uncertainties; they used a sensor-based map to be a SLAM Filter type asymptotic/exponential stable. Marinho et al. (2018) propose a new system for locating robots through images; the proposal is based on supervised learning using topological representations of the environment. Sudars et al. (2020) provide an extensive dataset of annotated food crops and weed images for robotic computer vision control. Tiwari et al. (2018) proposed a method to remove unfavorable environmental conditions for extracting helpful information through video and images. Yorozu and Takahashi (2020) developed a new way of detecting direction using a laser sensor installed at the height of the shin in addition to the position and speed of the body.

3.1.2.2. Distributive computing. According to (Baz and Zhu, 2019), in recent years, parallel and distributed computing has started to converge thanks to advances in high bandwidth networks and devices with massive parallelism like GPU and Intel Xeon Phi. In particular, the concept of parallelism has become essential; we have seen the development of multicore CPUs. Moreover, with a swarm of robots in the agricultural field, the functionality of a distributed computing system is immense, in terms of both capturing data and generating useful information to optimize the specific function performed.

The challenge is to integrate all this processing through wireless communication networks in the field. Another challenge is elaborating protocols that enable the smooth operation of data traffic between both member swarm and central processing at the farm's headquarters. Xu et al. (2020) proposes a digital twin structure based on cloud robotics; the robotic control capabilities are encapsulated in a Robot Control as a Service (RCaaS).

3.1.3. Criterion decision autonomy

3.1.3.1. Behavior –base systems. The great challenge of this line of research is to develop control architectures based on behavior that can be adapted to the unstructured agricultural environment; new incremental learning methods must be developed and adapted of robots based on war environments or catastrophe environments.

In this context, reinforcement learning is an excellent methodology to optimize agricultural robotic systems based on behavior. Therefore, through the "decomposition" of the behavior in small sub-behaviors is possible to reduce the size of the phase space effectively. And this is another major challenge in this line of research to find the best learning network through which the modularization of learning "policies" results in accelerated and more robust learning.

Carlucho et al. (2020) present a new intelligent control system based on deep reinforcement with a self-adaptive action on multiple PIDs to control mobile robots. Jafari et al. (2020) developed a multi-agent control system through a real-time flocking control, a new reinforcement learning technique. Lan et al. (2020) propose a control for swarming systems through a neural network algorithm that models and trains the system in a dynamically unknown environment. From this, a swarm cooperative behavior is performed through the theory of reinforcement learning. Liu et al. (2020) present the revolutionary concept of IoRT (Internet of Robotic Things) that combines IoT techniques and hardware with Artificial Intelligence (AI) in robotic systems in Smart Cities.

Malus et al. (2020) developed a dispatching system for mobile robots' transport orders through reinforcement learning based on the individual observations of each multi-agent. Qu et al. (2020) a new reinforcement learning algorithm for UAV path planning based on the gray wolf optimizer, which is a meta-heuristic algorithm that mimics the social behavior of the mammalian species Grey Wolf. D. Wang et al. (2020) developed an algorithm for multi-robot cooperatives based on deep reinforcement learning; they used an end-to-end method to train each robot-centered directly.

Kanwal et al. (2021) developed an exciting algorithm based on the population-evolutionary method, called this algorithm Artificial Immune Networks. The algorithm's kernel applies ideas and metaphors of the immune system to solve multi-disciplinary problems. Li et al. (2021) proposed a real-time visual SLAM deep-learning-based on a multi-task and self-supervised algorithm through a convolutional neural network to detect points and descriptors. Nguyen et al. (2021) propose a new unsupervised end-to-end embedding-based network algorithm aligned with the emphasis on structural information. Castellano-Quero et al. (2021) present an exciting new methodology for mobile robots to identify and overcome obstacles based on Bayesian networks.

3.1.3.2. AI reasoning methods. The essential question for robotics in elaborating the application of artificial intelligence methods is to define the suitable formats for KR. And from this definition, it is possible to find the state function that refers to generation and maintenance, in real-time, of a symbolic description of the robot's environment. This function is based on a recent situational condition of the environmental information obtained by sensors and communication with other agents involved so that decision-making is correct and optimized for solving a problem or overcoming a barrier.

Gudwin et al. (2020) developed a cognitive architecture to create an artificial mind in an autonomous robot for multiple tasks; the cognitive architecture is inspired, and theories that explain the cognition in animals and humans decompose cognitive abilities. D'Asaro et al. (2020) propose a new language to work in AI systems, the EPEC (Epistemic Probabilistic Event Calculus), that deals with a form of epistemic reasoning. Homem et al. (2020) developed a new algorithm, a case-based reasoning system that uses an exceptional qualitative representation to recover and reuse cases through relationships between objects in the environment. Lesort et al. (2020) present Continual Learning, a machine learning paradigm where data distribution and learning objectives change over time, where all training data and objective criteria are never available.

Vanzo et al. (2020) present a linguistic pipeline for semantic processing of robotic commands that combine discriminative structured learning, (Zhu et al., 2020) an interesting paradigm shift as opposed to deep learning techniques. They suggest instead of using "big data for small tasks," changing to "small data for bit tasks," they propose this change through the use of AI systems that use "common sense."

Patle et al. (2019) present a new algorithm for path planning based on Fuzzy logic and probability with a duality technique to improve performance. Hu et al. (2020) applied the Zeroing Neural Network (ZNN) method to develop a noise-tolerant model in a ZNN to solve Lyapunov time-varying equations in disturbed robotic tracking. Thuyet et al. (2020) developed a robot for sorting root-trimmed garlic using a CNN (Convolutional Neural Network); the system achieves the goal through image analysis using a deep learning model equipped with a CNN.

Jia et al. (2020) developed a model based on Region convolutional neural network (R-CNN); this model is optimized to recognize and segment the overlap of apples; a Residual Network was combined with a Densely connected CNN. Khnissi et al. (2020) implemented a new application of a predictor in recursive neural network control (RNNC) for mobile robots; this was achieved by fusing a classic neural network within a recursive application. S. Li et al. (2020) propose an adaptive neural network based on finite-time tracking as a control method for wheeled mobile in the presence of slipping with time-varying restrictions.

Ouyang et al. (2020) proposed designing an elastic joint robot-controlled adaptively by the actor-critical technique in tracking problems. Pawara et al. (2020) offer a new classification method, one-vs-one, where the deep neural network trains each output unit to distinguish it between specific pairs of classes.

3.1.3.3. Collective-level behavior. The behavior at the swarm's collective level defines the conclusion of the global mission about each specific objective of the agricultural operation. The challenge here is to develop swarm robotics techniques that enable the emergence of emergent group behaviors, such as self-organization, flexibility in joint operations, and scalability in terms of common objectives.

López-González et al. (2020) present an alternative method to achieve control of a robot formation; they use genetic algorithms to find a solution based on the appropriate angle and distance to avoid collisions. Issa and Rashid (2020) present a new method for controlling multi-robot formation by monitoring the construction of a polygon's shape with a Neighbor-Leader algorithm. M. M. Khan et al. (2020) present a new proposal to control autonomous agents' training through evolving collective behavior where an evolutionary process guides the formation of a robot swarm.

3.1.3.4. Stochastic process computing. A significant challenge for operationalizing a robotic tractor swarm in the field is the agricultural environment's extreme unpredictability. Even in a homogeneous culture sown with a uniform pattern, it has a high variability of shapes, geometries, positions, and scales.

This fact occurs due to the treatment of living elements, which interact with the climate, soil, and other living beings (micro and macroscopically). In this concept, it is necessary to enter into the area of stochastic processes so that there is a better understanding of the operational strategies and an adaptation of the decision-making algorithms against random components.

Elamvazhuthi et al. (2018) present a new structure based on partial differential equations (PDE) to control robots' ensembles with limited sensing/acting capabilities and exhibit stochastic behavior. Fu et al. (2019) propose a group decision-making methodology for handling the Multiple Criteria Robot Selection Problem (MCRSP); four methods are used for determining weight. Lombard and van Daalen (2020), present a triangular stochastic mesh (STM) to enable the mapping of the environment and enable robots' autonomous operation. Petrović et al. (2020) propose a new algorithm for trajectory planning that employs stochastic optimization to find a collision-free trajectory.

Ha et al. (2019) present planning and control of the movement of robots in environments with uncertainties through the development of the topology control method guided by the integral path. Urcola et al. (2017) present a new technique for planning robot formations using stochastic maps; this technique computes the most likely global path in defining the expected minimum length.

3.1.3.5. Multiple decision-making. Agricultural swarm robotics needs the definition of the algorithms that can be used because of the processing capacity of the machines about the extraordinarily complex and multiple decision-making problems required in unstructured agricultural environments and which has objects very fragile and variable (living beings). Olcay et al. (2020) developed a navigation structure for multi-robots in unknown areas; robots explore the environment and share information between agents that collectively allow the planning. Ponce et al. (2020) present an evolutionary distributed learning control based on the social treatment of a wound, a metaheuristic method. H. Wang et al. (2020) offer a task scheduling for heterogeneous multi-robot through the formulation of problems using mixed-integer linear programming.

Dutta et al. (2020) present the development of a replanning module for a computerized elevation planning system for cranes; the system defines the optimal collision-free elevation path for a robotized crane. Koorehdavoudi et al. (2019) study the interpellation between the manipulative actors and the decisive action; an asymptotic decision is obtained through agents interconnected by transient network dynamics. Florez-Lozano et al. (2020) present a new intelligent system that uses a multi-agent platform to detect explosive devices hidden in the ground. Olcay et al. (2020) developed a navigation structure for multi-robot in unknown areas by exploring sensing information and data sharing between agents. Ren et al. (2020) set a new decision-making method based on expert knowledge and machine learning techniques; the fuzzy-neuro technique was proposed. Zhang et al. (2020) propose an optimized exploration strategy of randomly scattered trees; they use a Rapidly-exploring Randomized Tree (RRT) technique based on a probabilistic exploration algorithm.

3.1.3.6. Particle swarm optimization. According to (Nedjah and Macedo Mourelle, 2006), particle swarm optimization is a mathematical optimization method that mimics the behavior of insect swarm. For example, when a particle discovers a good path for food, all the rest of the swarm becomes able to follow instantly the same way. This capability is exciting, especially when you have the possibility of distributed computing with networked robots. The challenge is finding the optimal path or solution for the swarm and implementing communication between the swarm robots network, optimizing the answer ahead of the swarm before the common goal.

Das and Jena (2020) proposed an algorithm to optimize a collision-free path for multi-robot through an improved version of particle swarm optimization and evolutionary operators. Y. Xu et al. (2020) used a particle swarm optimization algorithm to implement underwater robot route planning that sails due to the combination of environmental restrictions and geomagnetic orientation. Guo et al. (2020) investigate a new navigation method for an unmanned surface vehicle divided into two stages: global path planning and path control.

M. Li et al. (2020) proposes a new optimization algorithm called stability quantum particle swarm optimization (SQPSO) for multi-agent multi-task. Sai Rayala and Ashok Kumar (2020) applied the Particle Swarm Optimization (PSO) meta-heuristic algorithm to track a target by a robot and transmit noisy data due to the installation of a cheap quality sensor onboard. Zhang et al. (2019) presented an optimization algorithm based on particle filter and particle swarm optimization (PSO) in a hybrid localization system.

3.2. Evaluation of state-of-art review about research challenges

A state-of-the-art review of these issues with a focus on robotics has been carried out. Extensive research was carried out, and the papers most relevant were chosen to show the last advances. Some of these themes were published in journals dated 2021; others in 2015. This indicates the emphasis on each subject in which the research community is dedicated. However, these authors consider all the suggested topics relevant to commercially operating swarm robots' challenge for mechanized agricultural operations. Many real problems are by no means solved in terms of using unstructured agricultural environments.

For the evaluation of the 75 papers analyzed about the research question related to the commercial operation of an agricultural swarm of robots, the criteria of relevance (Rel), potential (Pot), objectivity (Obj), and environment (Env) were considered.

The relevance criterion refers to how relevant is the resource for the question. Potential refers to the research potential for solving the challenges related to the main issue (commercial operation). Already objectivity is the research object's assertiveness carried out about the question of the commercial operationalization of an agricultural robots swarm. Finally, environment refers to the contextual agricultural environment.

Table 5 was constructed to evaluate the criteria referring to the research question about the papers analysed. Each has been ranked according to an adaptation of the score defined by (Zhai et al., 2020): number three if the paper fully meets the criteria, number two if it moderately meets, and number one if it weakly meets.

Table 5 makes many pertinent considerations about the current research considering the challenges listed before an agricultural robot swarm's commercial operation. The first fact, even the most evident, is that the research presented by the papers chosen, for the most part, is not carried out with a focus on the agricultural world. Considering an overall score of 92/225, it is clear that the focus is not on the agricultural context.

This fact reinforces the perception already presented in this research that the challenges pertinent to the agricultural context, considering multi-robots in unstructured environments with fragile targets (plant and animal foods, fibers, and flowers), are not fully met. When evaluating the papers individually, it is obtained that only four of them deal with the agricultural environment. Thus, in terms of research challenges, only 5% of the research turns to the farming world, considering papers that do not focus on agriculture. But due to the operational environment specificities where the study was carried out, it can be regarded as similar. Therefore, it appears that 18% of the research is close to the agricultural environment.

Considering the criterion with the best score, the relevance of the research about the commercial operation of an agricultural robot swarm

Table 5
Evaluation of the articles on proposed research challenges.

Challenge	Author	Rel	Pot	Obj	Env	Overall remark	% Overallremark
Behavior –base systems	Carlucho et al. (2020)	2	3	1	1	7/12	58,33
	Jafari et al. (2020)	3	3	2	1	9/12	75,00
	Lan et al. (2020)	3	1	3	2	9/12	75,00
	Liu et al (2020)	3	3	3	1	10/12	83,33
	Malus et al. (2020)	1	1	2	1	5/12	41,67
	Qu et al. (2020)	2	3	2	1	8/12	66,67
	Wang et al. (2020)	3	2	2	1	8/12	66,67
	Kanwal et al. (2021)	3	3	2	1	9/12	75,00
	Li et al. (2021)	3	2	2	1	8/12	66,67
	Nguyen et al. (2021)	2	2	2	1	7/12	58,33
	Castellano-Quero et al. (2021)	3	3	3	1	10/12	83,33
AI reasoning methods	Gudwin et al. (2020)	3	3	2	1	9/12	75,00
	D'Asaro et al. (2020)	1	3	1	1	6/12	50,00
	Homen et al. (2020)	2	2	1	1	6/12	50,00
	Lesort et al. (2020)	1	3	1	1	6/12	50,00
	Vanzo et al. (2020)	1	3	1	1	6/12	50,00
	Zhu et al. (2020)	3	3	2	1	9/12	75,00
	Patle et al. (2019)	2	2	1	1	6/12	50,00
	Hu et al. (2020)	1	2	1	1	5/12	41,67
	Thuyet et al. (2020)	3	1	3	3	10/12	83,33
	Jia et al. (2020)	3	1	3	3	10/12	83,33
	Khnissi et al. (2020)	2	1	2	1	6/12	50,00
	Li et al. (2020)	3	1	2	1	7/12	58,33
	Ouyang et al. (2020)	1	1	2	1	5/12	41,67
	Pawara et al. (2020)	3	3	2	1	9/12	75,00
Collective-level behavior and Multiple decision-making	López-González et al. (2020)	3	1	3	1	8/12	66,67
	Issa and Rashid et al. (2020)	3	3	3	1	10/12	83,33
	Khan et al. (2020)	3	2	3	1	9/12	75,00
	Olcay et al. (2020)	3	1	3	1	8/12	66,67
	Ponce et al. (2020)	3	3	2	1	9/12	75,00
	Wang et al. (2020)	3	2	3	1	9/12	75,00
	Dutta et al. (2020)	1	1	2	1	5/12	41,67
	Koorehdavoudi et al. (2019)	1	1	1	1	4/12	33,33
	Florez-Lozano et al. (2020)	1	2	2	1	6/12	50,00
	Ren et al. (2020)	3	2	3	1	9/12	75,00
	Zhang et al. (2020)	3	3	2	1	9/12	75,00
Operational strategy, Networked Swarm robots and Distributive computing	Cieślak et al. (2020)	3	1	2	1	7/12	58,33
	Kurtser and Edan (2020)	3	1	3	3	10/12	83,33
	Minelli et al. (2020)	3	2	2	1	8/12	66,67
	Roveda et al. (2020)	2	3	2	1	8/12	66,67
	Xu et al. (2020)	3	3	2	1	9/12	75,00
	Khateri et al. (2020)	2	2	2	1	7/12	58,33
	Wei and Wang (2020)	2	1	2	1	6/12	50,00
	Yu et al. (2020)	2	1	2	1	6/12	50,00
	Chen et al. (2020)	3	3	3	1	10/12	83,33
	Khaluf et al. (2020)	3	1	2	1	7/12	58,33
	Meng et al. (2020)	3	3	3	1	10/12	83,33
	W. Xu et al. (2020)	3	3	3	1	10/12	83,33
Hardware enhancement and On-board systems	Koshy et al. (2018)	3	3	1	2	9/12	75,00
	Mertyüz et al. (2020)	3	3	2	2	10/12	83,33
	Szczecinski et al. (2017)	3	3	2	2	10/12	83,33
	Utter and Brown (2020)	2	1	2	1	6/12	50,00
	L. Wang et al. (2020)	2	1	2	1	6/12	50,00
	Guo et al. (2018)	2	3	1	1	7/12	58,33
	J. Chen et al. (2020)	2	3	1	1	7/12	58,33
	Li et al. (2019)	2	3	1	1	7/12	58,33
	Pérez et al. (2019)	2	2	1	1	6/12	50,00
	Baba (2020)	2	1	2	1	6/12	50,00
	Lourenço et al. (2020)	3	2	2	2	9/12	75,00
	Marinho et al. (2018)	3	2	2	1	8/12	66,67
	Sudars et al. (2018)	3	2	2	3	10/12	83,33
	Tiwari et al. (2018)	2	1	2	2	7/12	58,33
	Yorozu and Takahashi (2020)	1	3	1	1	6/12	50,00
Stochastic process computing and Particle Swarm optimization	Elamvazhuthi et al. (2018)	2	2	1	1	6/12	50,00
	Fu et al. (2019)	2	3	1	1	7/12	58,33
	Lombard and v. Daalen (2020)	2	3	1	1	7/12	58,33
	Petrović et al. (2020)	1	3	1	1	6/12	50,00
	Ha et al. (2019)	2	3	2	2	9/12	75,00
	Urcola et al. (2017)	2	3	2	1	8/12	66,67

(continued on next page)

Table 5 (*continued*)

Challenge	Author	Rel	Pot	Obj	Env	Overall remark	% Overallremark
	Das and Jena (2020)	3	3	1	1	8/12	66,67
	Yan Xu et al. (2020)	2	2	2	1	7/12	58,33
	Guo et al. (2020)	2	3	2	2	9/12	75,00
	M. Li et al. (2020)	3	3	3	2	10/12	83,33
	Rayala and Kumar (2020)	3	2	2	1	8/12	66,67
	Zhang et al. (2019)	2	1	0.2	1	6/12	50,00
Total by criteria	**75**	**176/ 225**	**163/ 225**	**148/ 225**	**92/ 225**	–	–

has an overall remark of 176/225, which indicates that 22% of the research studies in the selected papers have no relevance for the research question. That is to say, a fifth of the knowledge related to the challenges raised has no preponderance for the concrete problem of solving the technical/commercial viability issue of an agricultural robot swarm.

This fact naturally leads to the tendency presented by the potential criterion to solve the problems presented, with an overall remark of 163/225, indicating the apparent trend that papers that are not relevant to the issue will hardly have the potential to solve the problems. Thus, although the topic has great relevance in many of them, the potential is relatively low. It happens by pertinent issues, the readiness of the solution, and the reach of the answer in the face of concrete problems.

The previous considerations are reinforced by the objectivity criterion, which has an overall remark of 148/225; that is, many papers sometimes have relevance and potential for great solutions and innovations. However, they are conducted without objectivity in reaching a commercial agricultural solution, which entirely agrees that the Environment criterion is the least scored.

A possible positive hypothesis is that if these surveys with high relevance and potential are directed to adapt to the restrictions and requirements of mechanized agricultural operations, they can substantially increase objectivity. Which would modify the presented scenario in which none of the 75 papers reached the score maximum (12).

This assessment shows that the research does not solve the challenges listed when evaluating configurability, adaptability, and decision autonomy aspects. Thus, assessing state-of-the-art technologies that deal with the use of multi-robots in swarm configuration in agriculture presents obstacles that must be overcome to fulfill the multi-mission defined by agricultural mechanization operations effectively.

This paper intends to suggest that researchers of the ARRC develop a roadmap for future research aiming to operate the use of swarm robots be set in a commercial, concrete, and practical way focused on mechanized agricultural operations.

4. Conclusion

A systematic review in state-of-art about swarm robots for mechanized agricultural operations was done; 32 technologies were selected from the current literature. These technologies are surveyed in seven aspects (technology readiness level, configurability, adaptability, dependability, motion ability, perception ability, and decision autonomy) selected from the SPARC (2017) and treated as criteria for evaluating these technologies. The evaluation results detect research challenges in the three most critical aspects: configurability, adaptability, and decision autonomy.

Then another systematic review about these research challenges was carried out, and 75 papers were evaluated according to the criteria of relevance, potential, objectivity, and environment about the research question related to the commercial operation of an agricultural robot swarm. When evaluating the analyzed papers, the main conclusion is that current research does not solve the challenges that deal with multi-robots in swarm configuration in agriculture. Instead, it presents obstacles that must be overcome to fulfill the multi-mission defined by agricultural mechanization operations.

In this way, these challenges are suggested as objects for future research focused on implementing swarm robots' agricultural fields aiming at mechanized operations. Therefore, this initiative can constitute a roadmap for interinstitutional and transdisciplinary research bringing together the scientific community dedicated to robotics. Furthermore, this roadmap will make possible very fruitful interinstitutional and transdisciplinary partnerships that will be able to implement innovative and essential research so that this proposal goes off the record and becomes one carried out in the agricultural world.

CRediT authorship contribution statement

Daniel Albiero: Conceptualization, Funding acquisition, Methodology, Writing – original draft. **Angel Pontin Garcia:** Resources, Writing – review & editing. **Claudio Kiyoshi Umezu:** Writing – review & editing. **Rodrigo Leme de Paulo:** Writing – review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgment

The first author thanks the productivity grant of CNPq. The financial resources made available by the CNPq [grant number 304931/2015-2]; FUNCAP [grant number AE1-0079-000250100/13]; CAPES [grant number 2982/2013] and FAPESP [grant number 19/06078-8] and physical resources of Federal University of Ceará (UFC) and University of Campinas (UNICAMP).

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