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Paper number and page range

Paper number on the line below **2400944**
Pages 1-12

An ASABE Meeting Presentation
DOI: https://doi.org/10.13031/aim.20
Paper Number: 2400944

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Scheduling of Robotics or Machinery Operations in Agricultural Fields: A Review

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Written for presentation at the
2024 ASABE Annual International Meeting
Sponsored by ASABE
Anaheim, CA
July 28-31, 2024

ABSTRACT. *Robots and machines have helped farmers with many repetitive and physically demanding tasks such as plowing, spraying pesticides, irrigation, land monitoring, and harvesting. Efficient allocation or scheduling of robots and machines in agricultural field operations is crucial for modern farming to achieve a high profit margin. This article provides a comprehensive review of the problems and methods published in the open literature for scheduling and task allocation of agricultural robots and autonomous machines, to support the future improvement and implementation of these techniques. The review is divided into the following categories: i) types of scheduling problems, ii) different scheduling methods, and iii) validation environment of algorithms. This review also provides insights into future research questions that need to be answered.*

Keywords. *Scheduling methods, agricultural robotics, task allocation*

I. Introduction

The agricultural industry has faced difficulties throughout the years, such as drastic environmental changes, labor shortages, land limitations, and regulations (Syngenta, n.d.; AgAmerica, 2020). Pests and plant diseases in crops severely affect this industry with an estimated combined loss of up to 290 billion USD to the world economy (Gula, 2023). The increase in the average age of farm workers, currently at 41 years old in the USA (NCFH, 2022), is also a concerning issue as workers may experience declining health or productivity due to the extended physical demands of the job, which in turn may reduce their ability to work, exacerbating the already existing problem of lack of manual labor. These challenges, together with the increase in world population, which amounted 8.04 billion in 2023 (USA Census Bureau, 2023), has forced farmers, scientists, and engineers to find alternatives or solutions to increase agricultural production in a sustainable, efficient, and cost-effective manner (Gao et al., 2018; Defterli et al., 2016).

Agricultural robots and machinery have already aided growers in labor-intensive and repetitive operations such as pruning, water irrigation, and harvesting, lowering labor dependency, and reducing production costs (Zimmer et al., 2021). Using robotics and machinery relieves farmers' physical stress to a certain degree, but also comes with great challenges (Javaid et al.,2022). Factors that must be considered in automated agricultural operations include navigation throughout uneven terrains, obstacle avoidance, and adaptability to changing farm conditions (Xaud et al., 2019; Li and Xu, 2022).

In open-field environments, it is desired that robots and machinery are adaptable to different crops, cultivation methods, and unstructured layouts (Bechar and Vigneault, 2016). Sometimes, different terrain conditions will give robots and machinery different challenges in field operations (Badgujar et al., 2023). Most robotics in open fields are limited in their ability to adapt to variations in their hardware, equipment, or field conditions, making them less robust and flexible in certain scenarios (Bechar and Vigneault, 2016).

For greenhouse operations, farmers control and regulate the environment, such as light exposure, water irrigation, temperature, and humidity, creating the appropriate conditions for crops to grow and achieve a desired quality. To maintain these conditions, farmers incur expensive production costs which means higher sale prices (Ghani et al., 2019). Greenhouses contain multiple obstacles, such as plants, support structures, and equipment that robots need to navigate around (Jiang et al., 2022). Challenges and improvements still need to be made, considering that the conditions can be modified in the greenhouse environment.

To enhance operation efficiency, increase operation adaptability, and reduce the probabilities of single-point-of-failure, teams of robots or machinery are expected to perform more agricultural operations, such as harvesting and phenotyping (Mapes et al., 2022; Gao et al., 2018). Therefore, there is an urgent need to find an efficient way to organize farming tasks and/or coordinate autonomous vehicles. To date, research has been done on using different scheduling methods to adapt to different farming models, methods, and situations. For example, the integration of blockchain technology has been proposed to enhance transparency and resource utilization in agricultural machinery scheduling (Yang et al., 2020). A multi-objective algorithm has been used to allocate appropriate agricultural machinery to specific farmland operations and plan appropriate driving routing for each agricultural machine considering uncertainties (Liang, 2022).

In this paper, we conduct a detailed survey about recent developments in solving scheduling problems in agricultural field operations and their proposed solutions or algorithms. It is worth mentioning that there are many review papers that exist discussing current development and future research directions in agricultural machinery and robotics in field operations. For example, Thayer et al., (2018) outline the challenges and limitations of ground robotics in diverse agricultural environments providing insight into different agricultural robotics configurations. In the work of Lytridis et al., (2021), cooperative robotics in agriculture fields was surveyed, identifying challenges and state-of-the-art of the field. Kulbacki, et al. (2018) provided a review of using drones in remote sensing and their application in smart farming for productivity and yield increases. Furthermore, Gu et al., (2020) present a review of scheduling methods to improve irrigation efficiency. Karampelia et al., (2023) provide a review of unmanned aerial vehicles (UAV) task allocation to improve energy efficiency and their use in precision agriculture. Bochtis et al., (2014) presented an overview of advancements in agricultural machinery management from the point of view of capacity, task times, route planning, scheduling, and performance evaluation. Defterli et al., (2016) reviewed robotic technologies used for strawberry fields and discussed their different operations, electrical and mechanical systems. Lastly, Carpin, (2022) provides an overview of scheduling problems for mobile robots, focusing on the orienteering problem and its variations. Different algorithms developed by their research group are also reviewed addressing the single-agent, multi-agent, and stochastic versions of the problem (Carpin, 2022).

The present study focuses on robotic and machinery task allocation and scheduling, covering a wide range of topics that appeared in papers published by researchers worldwide. For instance, we include a summary of scheduling papers from different geographic regions and different agricultural products, an analysis of various scheduling algorithms (centralized/decentralized, auction-based, heuristic approaches, etc.), and their integration with agricultural machinery and robots, considering communication protocols and real-time decision-making. Specific operations such as planting, harvesting, and irrigation are highlighted, alongside strategies for resource optimization and reducing operational costs.

The paper will be organized into the following four sections. In Section II, "Types of Scheduling Problems" will be discussed. In Section III, "Scheduling Methods," we will discuss different scheduling methods used in agricultural scheduling operations and their implementations. In Section IV, "Validation Environment of Algorithms", we will review those algorithms tested in simulated environments with or without real farm settings and configurations. Lastly, in Section V, "Future Directions", research directions are suggested to encourage more efforts to investigate this area.

II. Types of Scheduling Problems

Modern agricultural operations require complex tasks such as plowing, sowing, irrigation, spraying, and/or harvesting while relying on information collected from different sensing platforms (Fountas et al., 2020). Although most of single robot implementations are still not mature enough to be widely adopted by growers, many researchers have already started thinking about a frontier question: how to effectively schedule robots or autonomous machinery to achieve common objectives under different resource or physical constraints. This section discusses the specific challenges associated with different regions, agricultural products, and operations.

II. 1 Regions

The papers reviewed in this study comprise several regions of the world, where 21 correspond to Asia, 12 to Europe, and 7 to North America as shown in Fig. 1. Please note that, if a paper is written by authors from more than one continent, all related continents will be added by 1.

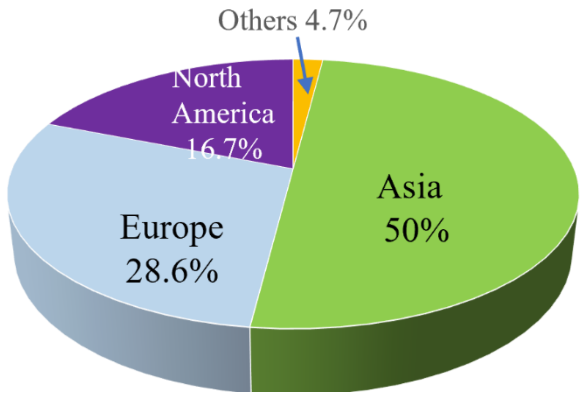

Figure 1. Publicly accessible papers were written by authors worldwide, and about 50% of the papers reviewed in this study come from Asia.

Unique challenges arise due to region-specific topologies and resources that shape and bring forward a variety of scheduling problems. In Asia for example, with 59.1% of the world's population (Worldometer, n.d.) and about 35% of the planet's arable lands (FAO, 2023), the rapid increase in urbanization and the decrease of natural resources, fertile lands, and other factors have driven the use of fragmental farmlands as a common farming practice (Tan et al., 2006). This inhibits the mechanization of different agricultural practices making harvesting one of the biggest challenges within agricultural scheduling, where precision and timing are important for minimizing losses and ensuring a successful harvesting period (Ritchie and Roser, 2019). In (He et al., 2018), they consider this land topology in their algorithm and apply it for the case of rural areas in the Anhui province of China, where traditional wheat harvesting methods (designed for large-scale arable lands) cannot be implemented.

In Europe and North America, small to large scales of arable lands and diverse planting patterns (USDA, 2019; European Commission, 2020) pose different challenges in agricultural task scheduling compared to Asia's fragmented farmland practices. In Europe, one of the scheduling problems arises in vineyards, where precisely timed collaboration between humans and robots for the cultivation of grapes demands for an efficient management method of agricultural tasks such as serving, harvesting, box filling, and product transportation (Lippi et al., 2023a). In the Netherlands, irrigation and fertilizer delivery for root crops represent an important objective in scheduling applications where time and location impact their health, nutrient management, and disease prevention while optimizing the use of water (Cobbenhagen et al., 2018). Moreover, American agricultural products are diverse (USDA, 2019), which demands agricultural scheduling solutions to each unique problem. In the case of grapes, the scheduling problem focuses on the coordination of multiple robot operations within a time and budget constraint in a vineyard for precision irrigation (Thayer et al., 2020).

II. 2 Agricultural Products

It is necessary to develop a specific scheduling method targeting challenges associated with different agricultural products since each may pose specific challenges in farm management. However, we noted that most surveyed papers are for generic products, not customized for a particular type of crop.

As shown in Table 1, specialty crops demand labor-intensive operations in fields such as irrigation, disease detection, and harvesting. To reduce labor dependance, many researchers have studied cooperative robots in conducting those operations and correspondingly different scheduling algorithms have been investigated for specialty crops such as strawberries (Mapes et al., 2022; Lytridis et al., 2021; Peng et al., 2020) and grapes (Lippi et al., 2023a, Thayer et al., 2020; Carpin, 2022; Hizatate and Noguchi, 2023). In vineyards, grapes destined for wine production require a certain amount of water to promote flavor and sugar content; thus, an appropriate irrigation scheduling is needed to prevent vine health deterioration and product yield losses (Thayer et al., 2020).

Other scheduling algorithms that consider the use of relatively large size autonomous machines or robots have been researched for crops such as wheat (He et al., 2018), beans (Karampelia et al., 2023), and sugar beet (Anokić et al., 2020).

II. 3 Operations

For different farming operations, it is important to consider the diverse scheduling problems present such as harvesting, irrigation, and phenotyping. Also, this provides us with an understanding of problems and solutions that can impact time consumption and reduction, operational costs, and yield increase of agricultural products and operations (Fountas, 2020).

As shown in Table 1, scheduling algorithms have been investigated for simulated operations such as harvesting (Mapes et al., 2022; Lippi et al., 2023a; Dai et al., 2023), harvesting transportation aid (Peng et al., 2020), machine maintenance (Hu et al., 2020), weeding (Guo et al., 2024), irrigation (Cobbenhagen et al., 2018; Kan et al., 2021), ploughing (Chen et al., 2021), and pesticide spraying (Sun et al., 2019; Hizatate and Noguchi 2023).

Table 1. Products and Operations in Agricultural Robotic and Machinery Scheduling Problems

Authors	Year	Agricultural Products	Operations
Wang, M. et al.	2023	/	Static sensor network for monitoring
Hu et al.	2020	/	Maintenance service for harvesting
Guo et al.	2024	Crops (not specific)	Weeding
Lippi et al.	2023a, 2023b	Table grapes, vine	Reaching & transportation aid
Peng et al.	2020	Strawberry	Harvesting & transportation/aid
Conesa-Muñoz et al.	2015	/	Multipath planning
Edmonds et al.	2021	Row crops (not specific)	Data collection/row crop inspection
Cobbenhagen et al.	2018	Root crops (e.g. spring wheat)	Irrigation
Anokić et al.	2020	Sugar beet	Resource transportation
Dai et al.	2023	/	Harvesting
Thayer et al.	2020	Vineyard	Irrigation
Zuniga Vazquez et al.	2021	Cotton, guayule, guar	Production planning, machinery scheduling
Li, Y. et al.	2022	/	Pesticide application route planning
Chen et al.	2021	Crops	Ploughing
Sun et al.	2019	/	Watering, sowing, and pesticide spraying
Barrientos et al.	2011	Vineyard	Aerial imaging/area partitioning
Thayer et al.	2018	Vineyard grapes	Irrigation
Mapes and Xu	2022	Strawberry	Harvesting
Cao et al.	2021	Crops	Harvesting & transport
Kan et al.	2021	Vineyard grapes	Irrigation
Sun et al.	2020	/	Pesticide spraying
He et al.	2018	Wheat	Harvesting
Hizatate et al.	2023	Vineyard	Pesticide spraying

III. Scheduling Methods

We have identified three main categories that cover the different approaches to scheduling methods that have been applied in agricultural operations using robots or autonomous machinery. Scheduling methods consider in one way or another the level of authority in the planning and execution process (centralized/decentralized), the variety of tasks and the types of agents that can perform them (homogeneous/heterogeneous), and the solution method of the proposed scheduling problem (heuristic/"exact"). It is worth noting that most of the methods have been tested in simulated environments and not with actual robots on farms. We attribute this to the fact that teams of autonomous robots haven't been widely adopted to work on farms.

III. 1 Centralized vs Decentralized Methods

A centralized scheduling method for task assignment involves a central station for the coordination of robots and machinery coordination. The central station, e.g. a leading robot, collects information from the group, makes scheduling decisions, and sends the commands to the team. Correspondingly, in decentralized approaches, robots or autonomous machinery share information with each other and have authority over their resources and decisions. Typically, centralized approaches generate optimal solutions and are relatively easy to implement. However, as the complexity of the scheduling problem grows (more robots, constraints, and tasks), centralized approaches become intractable, and decentralized methods are preferred due to their flexibility, computational efficiency, and scalability at the expense of optimality.

As shown in Fig. 2, most of the papers we surveyed employed centralized methods. For example, Santilli et al., (2021) used a centralized greedy algorithm to arrange tasks among robots and humans for their H2020 PANTHEON project, in which precedence constraints were addressed by a Petri net. As another example, Lippi et al., (2023b) tackled the problem of assigning robots to assist human operators using a mixed integer programming algorithm in a centralized fashion. Additionally, for cooperative unmanned ground vehicles (UGV), Souza et al., (2022) presented a mixed integer linear programming scheduling model for a fleet of homogeneous autonomous electric agricultural vehicles that considers the equipment and availability of the robots. The decision aspect of the algorithm is not distributed between the vehicles since they are controlled by a central authority that processes all the information and provides the actions to the robots (Souza et al., 2022). A collaborative product innovation system is presented by Luo and Zhang, (2016), focusing on centralized machinery scheduling to improve operations in numerous farmlands.

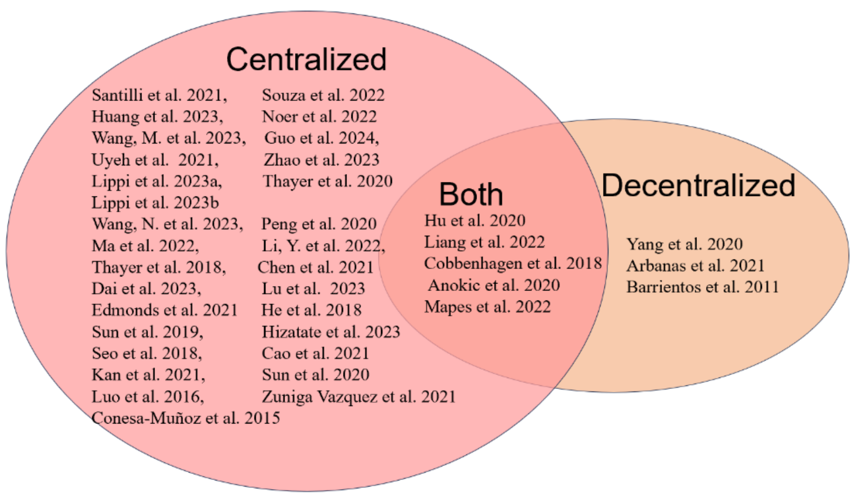

Figure 2. Scheduling algorithms are either centralized, decentralized, or both.

There are only a handful of papers using decentralized scheduling methods in autonomous operations in agricultural fields. For instance, in (Yang et al., 2020), the blockchain concept is introduced in a simulated agricultural machinery scheduling problem.

It is interesting to see that there is a similar low number of papers that use a mix of both methods, where the algorithms have centralized and decentralized layers. For instance, in the algorithm in (Mapes et al., 2022), two layers use negotiation strategies between neighbors (decentralized), while a third layer provides a centralized solution in case the negotiation method fails. As another example, Hu et al., (2020) proposed a dynamic covering model with particle swarm optimization (PSO) that involves a two-stage methodology for agricultural machinery maintenance for dynamic planning capacity.

It is worth noting that it does not matter if an algorithm is centralized or decentralized, the robots in the system should be equipped with communication systems and compatible interfaces allowing smooth coordination and cooperation between them. This permits cooperation and the use of their diverse abilities in tasks like planting, spraying, irrigation, and harvesting improving efficiency and output.

III. 2 Homogeneous vs Heterogeneous

Agricultural machinery is often designed to address a specific task; hence, several types of machines are needed in complex farm operations. These vehicles vary in size, functionality, flexibility, level of autonomy, and can operate in different environments such as air, ground, or underwater, as shown in Fig. 3. During the formulation of a scheduling problem, the type of machine used to perform the tasks is a crucial design parameter that is almost exclusive to each proposed algorithm. Robots and machinery with identical characteristics (homogeneous) can simplify the solution of the problem while addressing a very limited number of tasks (like a sprayer robot could be used for irrigation and pesticide delivery but not for harvesting). On the other hand, considering multiple machines with different characteristics (heterogeneous) for various tasks increases the complexity of the problem but addresses a more general and dynamic scenario for scheduling in farms.

As an example of homogeneous robots/machines in agricultural fields, Mapes et al., (2022) assumed all harvesting robots in a strawberry field are the same, leading to the same constraints for convenience in developing the scheduling algorithm. Many agricultural robots are electrically powered, and their charging sequence needs to be scheduled as done in (Uyeh et al., 2021), where all involved robots have the same settings. Also, a team of homogeneous unmanned aerial vehicles (UAVs) were used in plant protection activities where both path planning and task allocation were considered (Li, Y. et al. 2022).

Many papers designed their scheduling algorithms considering autonomous heterogeneous robotics. A very clear example is the design of scheduling algorithms where UAVs, ground robots, and human operators carry out their tasks in a working farm environment (Santilli et al., 2021). Some studies like (Liang, 2022) proposed a heuristic algorithm which works for autonomous agents that have different characteristics although no specific agricultural operations or vehicles were referred to.

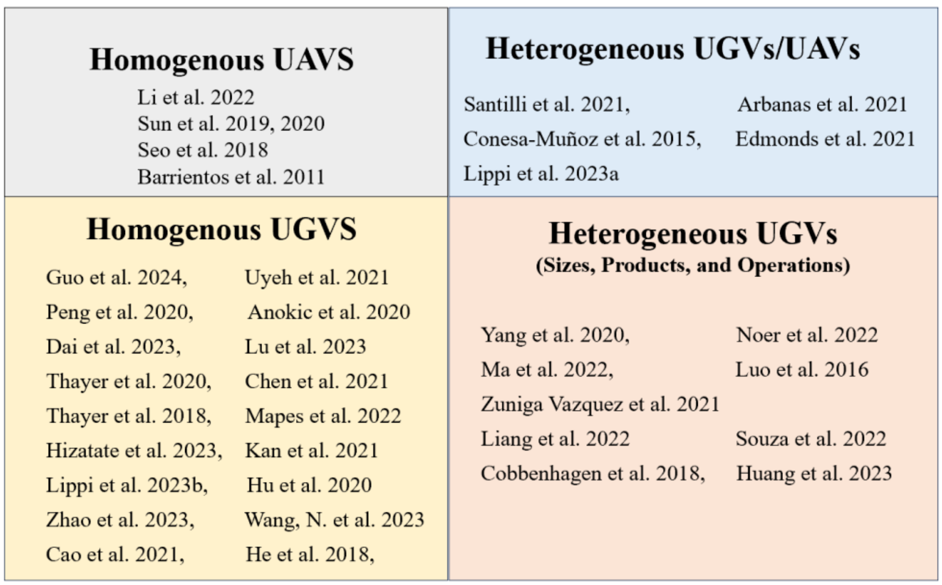

Figure 3. Homogeneous and heterogeneous robots and/or machinery have been the subject of study for scheduling algorithm development.

III. 3 Heuristic vs "Exact"

The largest difference between those scheduling methods in the surveyed papers is if a method is "heuristic" or "exact". Here we will say a method is "exact" if they have a rigorous analysis of the algorithm's convergence and optimality, or if a solution is guaranteed.

In the category of "exact" methods, a non-exclusive list of example papers includes auction-based (Mapes et al., 2022), mixed integer linear program (MILP) (Souza et al., 2022), integer linear program (Noer et al., 2022), Dijkstra's algorithm (Wang, N. et al., 2023), greedy method (Seo et al., 2018), and branch and bound search (Peng et al., 2020), as well as bidding method (Cobbenhagen et al., 2018) and evolutionary algorithm (Arbanas et al., 2021) combined with MILP. Furthermore, (Zuniga Vazquez et al., 2021) introduce an integer linear optimization for identifying optimal scheduling decisions for crops to maximize farmers' profits. The proposed model integrates multi-crop and machinery planning into a single model and also allows crop rotation in defined period sets (Zuniga Vazquez et al., 2021). The model differentiates between crops and considers irrigation water requirements (Zuniga Vazquez et al., 2021). As can be seen in Fig. 4, many scheduling problems in agricultural operations have been formulated in the MILP framework, where objective function and constraints are all assumed to be linear. However, most of those papers using MILP are validated in simulation that does not have many real farm setting considerations.

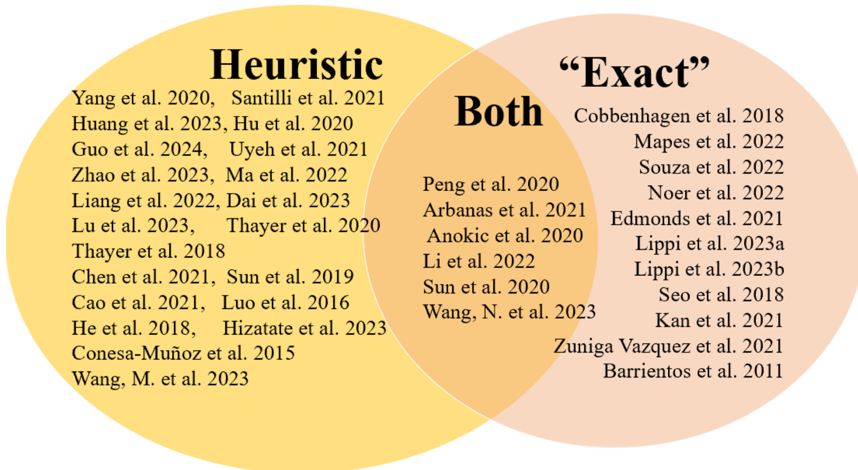

Figure 4. There are different heuristic and “exact” methods for robotic and machine scheduling problems in agricultural fields, and some of them are a mixture of them.

Heuristic methods, unlike "exact” methods, focus more on finding suboptimal or feasible solutions than finding the optimal one, however, they can effectively handle nonlinear dynamics and constraints. These kinds of approaches use strategies inspired by nature phenomena or stem from practical experiences. Many of these heuristic methods can be scalable or applied to real-world scenarios, but generally, they don’t guarantee the optimal solution to their presented problem. Some example heuristic algorithms include hybrid particle swarm optimization (Huang et al., 2023), a greedy algorithm with Petri net (Santilli et al., 2021), evolutionary algorithm (Uyeh et al., 2021), and genetic algorithm and its variations, such as the implementation of a blockchain structure (Yang et al., 2020), multilayer structure (Hizatate and Noguchi, 2023), a modified fuzzy hybrid (Luo et al., 2016), simulated annealing method (Chen et al., 2021) and metropolis criterion with an ant colony algorithm (Zhao et al., 2023). It is interesting to see in (Ma et al., 2022) that a multi-population co-evolutionary genetic algorithm is used for solving a formulated mixed-integer programming problem of dynamically scheduling shared agricultural machinery satisfying the requirements of farming services on demand. A method put forward for farmland machinery task assignment was the combination of a dynamic and static assignment model based on an ant colony and an improved ant colony algorithm (Cao et al., 2021). (Sun et al., 2020) suggested a heuristic rule inspired by a dragonfly's behavior using a mixed integer linear program for task coordination within an agricultural environment through centralized homogeneous cooperative UAV systems.

We have seen papers propose algorithms that include both heuristic and “exact” approaches to solve the scheduling problem in a hierarchical structure. In (Anokić et al., 2020), a heuristic approach based on neighboring variable search is used when the size of the cooperative robots is large, while an “exact” method solving a MILP is used for a small-scale system. To reduce task time in a teamwork approach, Lu et al., (2023) use a multiple-objective multiple traveling-salesman problem (MO-MTSP) for multiple robot task allocation using a collaborative discrete artificial bee colony (CDABC) algorithm.

IV. Validation Environment of Algorithms

Scheduling problems in autonomous agricultural robots/machines have not been a hot topic until recently; as can be seen in the reference list, most papers discussed herein were published in the last five years. Correspondingly, most of the scheduling problems we surveyed are validated in a simulated environment and not in real agricultural fields. Simulated models, to a certain extent, allow researchers to test, visualize, and enhance their scheduling algorithm performance before hardware experiments become available. This section examines those papers in the following two categories as shown in Table 2, validation in simulation environments without specific farm settings, and environments with detailed or real farm settings.

IV. 1 Validation in Simulation without Specific Farm Settings

As can be seen in Table 2, a significant percentage of the reviewed papers validated their scheduling algorithms in simulation settings without considering specific field settings. Those studies focused on their theoretical contributions of algorithms or applying mathematical tools from other domains in agricultural robotic or machinery problems. For example, Souza et al., (2022) applied a mixed integer programming (MIP) algorithm to a scheduling problem for a fleet of heterogeneous electric robots, in which the simulation environment is generic and does not have many specific settings of agricultural fields or operations.

IV. 2 Validations in Simulation with Real Farm Settings

Real farming settings are used in some studies to create an environment with a certain degree of fidelity to test their proposed scheduling algorithms. For example, both Peng et al., (2020) and Mapes et al., (2022) constructed their simulation validation environment considering the semi-structure layout of commercial strawberry fields, where robots cannot cross beds in any row and only one or two robots can exist in a row. Monte Carlo runs were used in these papers to either validate its branch and search algorithm in scheduling robots to transport harvested strawberries by human pickers (Peng et al., 2020) or a distributed, negotiation-based tri-layer algorithm to schedule robotic harvesters when certain events arise (Mapes et al., 2022).

In some other studies, the simulation environment is not set up for a specific product, instead, it is constructed considering a certain type of operation. For example, Hu et al., (2020) tested their agricultural machinery maintenance scheduling algorithm in a simulation based on real data about farm topologies, vehicle speed, maintenance requirements, constraints between response time and task starting time, etc. Hizatate and Noguchi, (2023) and Thayer et al., (2018), tested their respective pesticide application and irrigation scheduling algorithms in simulated orchards considering their real-farm settings. In (Hizatate and Noguchi, 2023), the amount of pesticide consumed and the need to replenish a robot were considered as constraints. In the case of (Ma et al., 2022), they analyzed rice harvesting operations and compared the results with production data from three companies in an open field simulation environment with real data for agricultural machinery scheduling.

Also, we have seen papers talking about utilizing robots to collect real field data that is used to construct high-fidelity simulations for validating their scheduling algorithms. In (Kan et al., 2021), they use a combination of simulated data and real-world experimental datasets to validate their algorithm. To obtain simulated data for the comparison, they used a controlled environment with a predefined number of rows and columns (Kan et al., 2021). A portable emitter actuation device was mounted in a robotic arm on a robot moving through a vineyard for required emitter adjustments (Kan et al., 2021).

There are a few studies that are neither for specific products nor for specific farm operations. For example, in (Uyeh et al., 2021), a scheduling algorithm was developed for battery charging scheduling problems, in which many constraints coming from batteries are considered, while not many considerations of the field or operations are in the simulation environment.

Table 2. Algorithms have been tested in different simulation environments.

Validation Environment		
No Specific Farm Settings		Real Farm Settings
Yang, et al. 2020	Thayer, et al. 2020	Peng, et al. 2020
Santilli, et al. 2021	Seo, et al. 2018	Ma, et al. 2022
Souza, et al. 2022	Sun, et al. 2020	Edmonds, et al. 2021
Huang, et al. 2023	Luo, et al. 2016	Cao, et al. 2021
Noer, et al. 2022	Anokić, et al. 2020	He, et al. 2018
Hu, et al. 2020	Wang, M. et al. 2023	Hizatate, et al. 2023
Guo, et al. 2024	Arbanas, et al. 2021	Kan, et al. 2021
Uyeh, et al. 2021	Liang, et al. 2022	Zhao, et al. 2023
Lippi, et al. 2023a	Li, Y. et al. 2022	Zuniga Vazquez, et al. 2021
Dai, et al. 2023	Sun, et al. 2019	Chen, et al. 2021
Lu, et al. 2023	Wang, N. et al. 2023	Thayer, et al. 2018, 2020
Cobbenhagen, et al. 2018		Mapes, M. et al. 2022

V. Future Research Directions

As can be seen, most of the papers surveyed in this study were published within the last five years, and there are very few or almost none scheduling studies that were published more than 15 years ago. Scheduling algorithm research will go on an uptrend along with the development and the progressive adoption of robotics and/or autonomous machines in agricultural field operations and management. Here are a few research directions based on the authors' point of view.

(i) When validating or simulating a proposed scheduling algorithm, high-fidelity models should be used including actual farm layout (e.g., geometry, weather conditions, and terrain conditions), real plant parameters (e.g. geometry and growth pattern), accurate sensing and actuation capabilities (e.g. field of view in vision and range in the communication), etc. This is one crucial research gap between theoretical study/algorithm development and hardware demonstration. Furthermore, realistic constraints will affect the development of scheduling algorithms.

(ii) As we have shown in this study, there are very little (almost none) studies that included real hardware (robots or machines) in validation or demonstration. It will significantly increase growers' adoption rate of scheduling solutions after seeing successful hardware demonstrations.

(iii) It will be beneficial to researchers and designers if reliable, plug-and-play type wireless communication software/firmware is available. It is time-consuming to program such reliable software so robots in a team can communicate with each other, significantly lowering the challenges in hardware implementation of robot/machine scheduling.

(iv) The inclusion of machine learning or artificial intelligence methods for scheduling problems in agriculture is an area that needs to be investigated. Artificial intelligence can help obtain insights that are data-driven, especially when the problem domain is large, and many domain parameters are uncertain.

VI. Conclusion

The progressive adoption of robots and machines in agricultural operations has allowed farmers to tackle issues related to labor shortages, ever-increasing labor costs, and to manage larger areas of land while producing higher yields. The use of single large-sized robots/machines becomes ineffective for these purposes as the complexity of farm operations increases, and teams of smaller robots/machines are preferred due to their flexibility and adaptability, avoiding single-point-of-failure problems. This has introduced the need for strategies to efficiently manage the diverse types of machines and allocate resources to successfully address a wide variety of tasks on a farm. In contrast to other technologies used in robotic platforms or an ensemble of machines, scheduling problems have attracted relatively less attention. This review article summarizes the up-to-date scheduling and task allocation research and development in agricultural field robotic operations. All the surveyed papers (not exclusive), found via Google Scholar, are included in the categorized discussion: problems, methods, and validation environment. With this survey, we expect to shed light on emerging challenges that need to be addressed to fully exploit the efficiency and profitability of multi-robot/machines in the current agricultural industry revolution.

Acknowledgments

This work was supported by the National Science Foundation under Grant No.1924622. Additionally, part of Yunjun Xu's work was supported by the intramural research program of the U.S. Department of Agriculture, National Institute of Food and Agriculture via grant number 2024-67022-41788. The findings and conclusions in this preliminary publication have not been formally disseminated by the U. S. Department of Agriculture and should not be construed to represent any agency determination or policy.

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