Route planning for multiple N-trailers in manual harvesting operations

Leonardo Guevara[1], Rui P. Rocha[2] and Fernando Auat Cheein[1]

Abstract— **This work proposes a short or medium-term alternative to complete automation of the manual harvesting process by introducing a team of robotic N-trailer vehicles to support the crop transportation task. Since the use of multiple vehicles working in the same workspace implies their coordination, this work proposes a high-level planning strategy that allows coordinating the routes of every vehicle. The proposed strategy includes a harvesting sequence generation and an initial route planning, both based on centralized global information, but also an online route planning based on decentralized local information exchanged between vehicles. Moreover, the proposal includes a vehicles departure scheduler which aims to maintain a harvesting operation without interruptions. In order to make the planning strategy robust against the variability on the harvesting rate and the uncertainties about the actual yield per track, the global information is updated online based on local information from the vehicles.**

I. INTRODUCTION

For the past few years, mobile robotics and automation technologies have been successfully integrated in agricultural processes [1]. Most of the literature has focused on optimizing fully automated operations such as seeding, spraying, monitoring, and grain harvesting operations [2]–[4]. However, in specialty crop harvesting, the developed robots have not successfully replaced yet the judgment, dexterity, and speed of experienced pickers [5]. In this context, rather than fully automating the harvesting task and thus replacing hand picking, it is more worth to automate crop transportation in order to create a semi-automatic harvesting system that takes advantage of both human dexterity and automated transportation efficiency. Recent works [5], [6], have presented solutions for this problem by using a team of small robots moving next to the pickers along the tracks, collecting the harvested crop into small containers, and then transporting the filled containers to a collection station. However, since small robots have a limited payload capacity, their use is also limited to specific kinds of crops such as strawberries, raspberries, or table grapes. On the other hand, in the case of harvesting of apple, peers, or avocados, it is preferred the use of tractor-trailer systems, a.k.a. N-trailer vehicles to transport big containers and improve harvesting efficiency. Despite its scalable payload capacity, the use of an N-trailer vehicle introduces specific maneuverability constraints which should be considered during the route planning as was recently presented in [7].

In this context, this paper proposes for the first time a high-level route planning strategy to supervise a team of robotic N-trailer vehicles during manual harvesting operations. In contrast with centralized (off-line) route planning approaches such as [2], [4], the proposed strategy considers a combination of global planning that produces initial routes using a priori knowledge of the workspace, but also local planning that recalculates routes according to new information available about changes in the workspace and harvesting rate. The proposed route planning strategy is complemented by i) a field division into areas, ii) optimal temporary deposit location, iii) a scheduler to determine the vehicles time departures in order to reduce non-productive times, and iv) a harvesting sequence generator which considers the expected yield per track covered, and maneuverability constraints related with the number of trailers towed.

The remainder of paper is organized as follows. Section 2 presents the background and problem description. Section 3 describes the proposed strategy. Section 4 shows preliminary results obtained through simulations. Section 5 presents the conclusions.

II. PROBLEM STATEMENT

A. Harvesting procedure for hand-picked fruits

In general, the manual harvesting process can be split into two main tasks: i) picking and placing the fruit into containers (e.g. a basket, tray, bag, or bin), and ii) collecting the filled containers and transporting them to a collection station [8], [9]. According to the fragility of crop to be harvested, the capacity of the container used vary. In the case of strawberries, raspberries, blackberries, and table grapes, small trays are preferred to maintain good product quality and reduce the damage during their transportation [8]. These small trays allow the use of small robots as was presented in [5], [6]. On the other hand, in the case of fruits such as apples, pears, oranges, and avocados, large capacity bins are preferred to load more fruit, but they are generally too big to be transported by small robots or pickers. This latter case is addressed in this paper where bigger machinery is required to transport the bins to the collection station.

B. N-trailer vehicles in harvesting operations

Since the use of heavy machinery produces negative effects on the soil properties, and the space between tree rows is narrow, the machinery used for fruit harvesting operations

*This work was partially supported by the Advanced Center for Electrical and Electronic Engineering AC3E, Basal Project FB0008, ANID, DPP-UTFSM-Chile, ANID-REDES project-180129, ANID-PFCHA/Doctorado Nacional/2018 21180470, FONDECYT grant 1201319, and the "Becas Iberoamérica. Santander Investigación" scholarship program.

[1]Leonardo Guevara and Fernando Auat Cheein are with the Electronic Engineering Dept., Universidad Técnica Federico Santa María, Valparaíso, Chile. cesar.guevara@sansano.usm.cl fernando.auat@usm.cl

[2]Rui P. Rocha is with University of Coimbra, Institute of Systems and Robotics, Dept. of Electrical and Computers Engineering, Portugal rprocha@isr.uc.pt

is generally based on sub-compact or compact tractors. These tractors have enough payload capacity to tow trailers with more than one bin. According to the harvesting strategy chosen, the tractor tows a different kind and number trailers as follows:

1) Stationary loading: In this strategy, the empty bins are distributed to the field before the harvest begins. During the harvesting operation, the filled bins are collected by tractors towing a hydraulic bin trailer that collect and transport the bins. Since the space between rows, a.k.a. tracks, is too narrow for the vehicle to move next to the bins, this strategy requires that the vehicle enters the track, picks up the bin, and exits in the opposite direction. This implies that the driver requires to drive a tractor-trailer system in backward motion, which complicates the driving task [10], limiting this strategy to use a single large trailer which can collect up to four bins [8]. Furthermore, this strategy introduces excessive soil compaction since it requires the vehicle to travel the same track several times until all the bins are collected.

2) On-the-go loading: As is illustrated in Fig. 1, in this strategy, the pickers place the harvested fruit directly into bins placed on passive trailers pulled by a tractor which is moving next to the pickers at speeds dictated by the group harvesting rate. Since there are no bins along the track obstructing the path of the vehicles, backward motion is not required, thus this loading strategy allows: i) the tractor to tow an arbitrary number of trailers (limited only by the payload capacity of the tractor), ii) to complete a track in a single trip if the total payload capacity of the tractor-trailer system is enough. This class of tractor-trailer system is also called N-trailer and it is characterized by having a scalable payload capacity, but due to the passive nature of the hitches between trailers, a collision risk appears during turning maneuvers. According to [7], a simple solution to reduce the risk of collision is to limit the turning radius of the N-trailer vehicle during harvesting sequence planning in order to restrict the transitions between contiguous tracks.

a)

b)

Fig. 1. a) N-trailer vehicle transporting the bins along the tracks, b) Workers picking and placing the harvested fruits into the trailers bins. (Photos courtesy of Fruiture Advisors, SL)

C. Harvesting scheduling problem

In this paper, on-the-go loading is assumed for the harvesting process because it allows using N-trailer vehicles. In this mode of operation, it is important to always have a N-trailer vehicle moving next to the group of pickers to maintain continuous harvesting. Despite the N-trailer vehicle has a scalable payload capacity, it is still finite, therefore the vehicle has to interrupt the operation for unloading the filled bins at a collection station and then resume the harvesting by towing empty bins [1].

Harvesting operations without interruptions are possible by having a perfect knowledge of the harvesting rate to determine when exactly a N-trailer full of load should be replaced by another one with empty bins. However, in a semi-automatic harvesting process with manual picking, picker performance, yield density, and random effects cause the harvesting rate to vary in dynamic and non-deterministic ways. Recent works, such as [5], [6], have presented interesting solutions to capture the variability in human behavior and performance during harvesting. The human activity model utilizes stochastic variables (e.g., picking time, walking speed) that can be estimated by measurements during harvesting. These estimated variables are important for predictive scheduling of transporting harvest-aid robots where a central computer acts as a supervisory controller, which computes the assignments of robots to pickers and the timing of robots departures [6].

III. Proposed strategy

This paper proposes a cooperative route planning strategy for a team of N-trailer vehicles to improve the efficiency of semi-automatic harvesting operations. To this aim, the following assumptions and conditions are considered:

- The a priori information include: the availability of machinery and workers, a 2D Euclidean representation of the field, and estimations about the pickers harvesting rate and expected yield per track.
- There is a temporary deposit (TD) where every vehicle must start each run (towing trailers with empty bins) and finish it (towing trailers with filled bins).
- There is enough number of tractors and trailers to have at least one active N-trailer vehicle working and a backup N-trailer vehicle waiting at the TD for scheduling purposes.
- Every tractor has the necessary equipment to allow the N-trailer system to navigate in an autonomous way without collisions, compute local planning, and communicate with other entities.
- The passive trailers have the necessary equipment to estimate their load and orientation.
- There is a static central computer (CC) located in the TD which computes global planning and communicates with the vehicles.

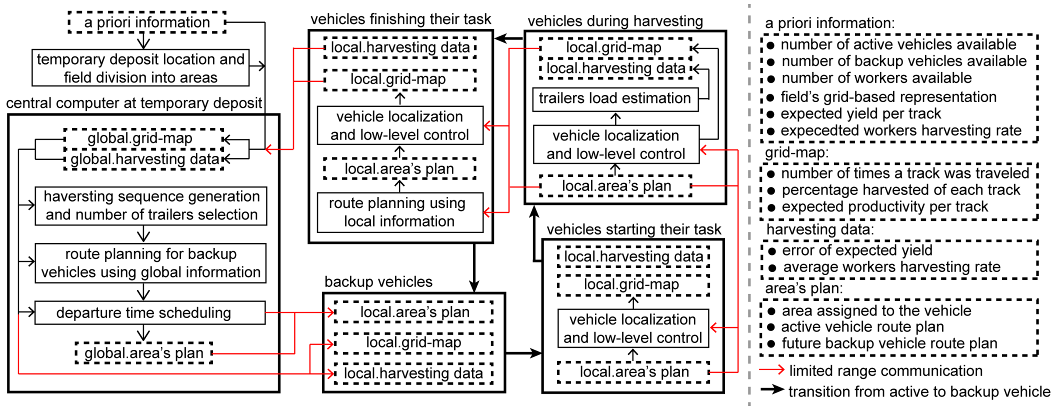

Fig. 2. General architecture of the proposed route planning strategy using global and local information.

- The communications between two entities are allowed within a limited range.
- The field is divided into areas where each area is assigned to a specific group of pickers supported by an N-trailer vehicle.
- The group of pickers must follow the harvesting sequence dictated by the route plan of the vehicles.
- The field tracks must be parallel, there must be exactly two opposite headlands were turnings are executed, and there must be at least a main way contiguous to the field (left or right side).

Thus, based on the previous assumptions, Figure 2 shows in a general way the architecture of the proposed strategy. The scheme highlights in bold the entities that intervene in the cooperation problem. These entities include the CC and vehicles separated into four operation stages, from being an active vehicle (AV) to becoming a backup vehicle (BV). The scheme also differentiates computational processes (solid lines) from data (dashed lines). It is important to note that there are four types of data structures used by entities (detailed on the right side of the diagram). According to the entity which stores the data, it can be treated as global or local information.

To address the uncertainties about the workspace during the harvesting operation, the global information used by the CC is continuously updated with the local information from the vehicles whenever a AV returns to the TD to unload filled bins. The updated version of the global information is then used for harvesting sequence generation, vehicle route planning, and BVs scheduling. Once a BV becomes an AV, it can exchange its local information (vehicles positions and route plans) with other nearby vehicles to ensure collision-free navigation between vehicles. When a vehicle has finished the planned harvesting sequence, it starts a route planning process to return to the TD by using its local information. During this local planning, the vehicle can obtain additional local information from other nearby vehicles as long as they are into the communication range.

The main components of the proposed strategy are described in detail in the following subsections.

A. Field division into areas

Before starting the harvesting operation, the proposed strategy requires dividing the field into areas, each of which will be harvested by a specific group of pickers. To this aim, the total number of vehicles available N_v is divided into two groups such as $N_v = N_{av} + N_{bv}$, where N_{av} is the number of AVs which are supporting the pickers, and N_{bv} is the number of the BVs which are waiting at the TD to resume the operation of the AVs. Then, the number of areas N_a is assigned according to the number of AVs such that $N_a = N_{av}$. To ensure a continuous harvesting operation, it is suitable to assign the same number of AVs than BVs, but due to the economic cost of requiring as many vehicles, it is expected to have least a BV at the beginning of the harvesting process. Each time a AV returns to the TD, the distribution of vehicles is updated such that $N_{av} := N_{av} - 1$ and $N_{bv} := N_{bv} + 1$.

B. Grid-based representation of the field

Let $T = \{1, 2, 3, \ldots\}$ be the ordered set of the track indexes where the value of the track indexes increases towards the positive direction of the x-axis. Then, as it is illustrated in Fig. 3, the field can be represented as a 2D grid where each grid point has integer coordinates of the form (i, j), being $i \in T$ and $j \in \{-1, 0, 1\}$. More specifically, the upper headland corresponds to the grid points with coordinates $(i, 1)$, the lower headland corresponds to the grid points with coordinates $(i, -1)$, while the crop area of track i corresponds to the grid point with coordinates $(i, 0)$. This grid-based representation can be applied to both convex and non-convex fields [11]. If each grid point denoted by $s_{i,j}$ is considered as a state, then, the states space, that is the countable set of all states, is given by:

$$S = \bigcup_{j=\{-1,0,1\}} (i, j), \quad i \in T \tag{1}$$

C. Temporary deposit location

The selection of the TD location is an important factor that influences the harvesting process efficiency since according to its location, the times and distances traveled by the

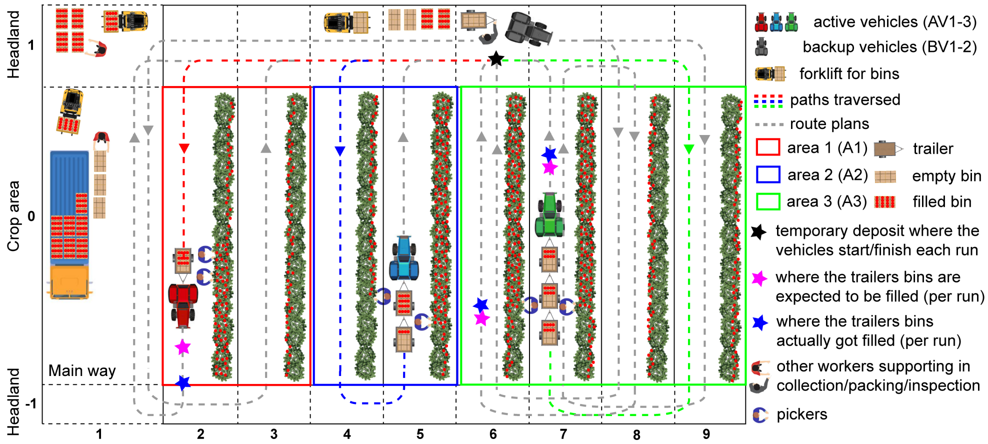

Fig. 3. Grid-based representation of the field showing an example of the multiple N-trailers route planning during manual harvesting operations (dimensions are not scaled for the purpose of illustration).

vehicles to unload filled bins may vary [3]. Thus, in order to minimize the total distance traveled by the N-trailers, we propose to solve the following optimization problem:

$$\underset{(i,j)\,\in\,S}{\arg\min} \sum_{n\in T} \sum_{m\in\{-1,1\}} \|l_{n,m} - l_{i,j}\|\, p_n \tag{2}$$

where, the resulting coordinates (i, j) represents the optimal location of the TD in the 2D grid world, $l_{i,j}$ represents the coordinates of the grid point $s_{i,j}$ in a 2D Euclidean world, p_i represents the expected yield of the ith track, and $j = 0$ is excluded from the solution to ensure that the TD is located at the headlands.

D. Harvesting sequence generation

The pickers motion direction determines which headland (upper or lower) is used by the vehicles to enter the tracks. Thus, the aim of the harvesting sequence generation is to compute route patterns that match with the motion direction of the pickers. The N-trailer capability to make transitions at headlands is constrained by the number of trailers chosen following the methodology in [7]. Then, knowing the transition constraint and the payload capacity of the set of trailers, the sequence generator seeks to choose a route that ends in the same headland as the TD. In the case that the last traversed track was non-completely harvested, the harvesting sequence of the BV will complete that track, having as a condition to enter the track using the motion direction of the pickers. Figure 4 shows the grid maps used to generate the sequences presented in the example of Fig. 3. The number of trailers used on each run of A3 is different since it is determined according to the expected yield to be covered on each sequence. Furthermore, it is important to notice that sequences end in the same headland as the TD, and that the starting points of each run respect the pickers motion direction. During the sequence generation process, the main way, headlands, and non-completely harvested tracks are considered as free regions (white grids) to move. On the other hand, tracks that do not belong to the assigned area, and tracks completely covered, are considered as restricted

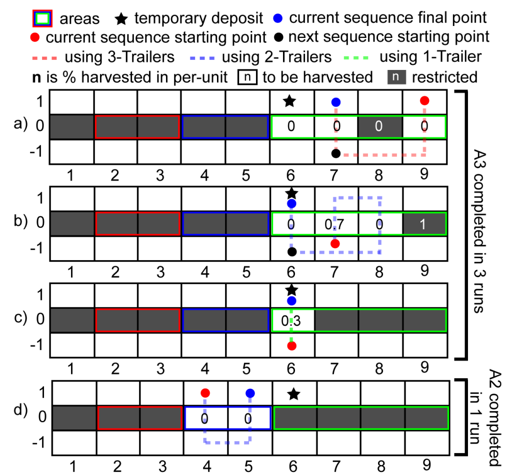

Fig. 4. Grip maps representing the harvesting sequence generation when: a-c) A3 is fully-covered in 3 runs; d) A2 is fully-covered in a single run.

regions (gray grids). The example in Fig. 4a shows a special case where following the methodology presented in [7], the transition from track 9 to 8 is not allowed for a 3-trailer vehicle, then, to reduce the collision risk during headland turning, track 8 is restricted during the sequence generation.

E. Vehicle route planning

Route planning can be computed by both the CC (using global information) and by the on-board computer of each tractor (using local information). The route planner using global information generates the initial route that the vehicle at the TD follows to reach the starting point of the harvesting sequence planned for that run. Examples of this route planning are shown in Fig. 5b-d. On the other hand, the grid map in Fig. 5a shows an example of the route planning based on local information where the starting point is the last point of the planned harvesting sequence and the goal is the TD. The grid-maps in Fig. 5 correspond to the planned routes presented in the example of Fig. 3.

The route planning algorithm is based on the wellknown Geometric Goal Directed Search (A*) [12]. This algorithm aims to determine a sequence of states $R = \langle s_I, \cdots, s_{i,j}^k, s_{i,j}^{k+1}, \cdots s_G \rangle$, which represents the shortest route from the initial point (vehicle position into the grid) denoted by $s_I \in S$ to the given goal $s_G \in S$. The A* algorithm evaluates each possible elements of R by combining the cost of moving from the state $s_{i,j}^k$ to $s_{i,j}^{k+1}$ denoted by $h(s_{i,j}^{k+1})$, and the cost to get from $s_{i,j}^{k+1}$ to the goal s_G denoted by $g(s_{i,j}^{k+1})$. The total cost $f = h + g$ is calculated for each possible successor $s_{i,j}^{k+1}$ and the state with the smallest $f(s_{i,j}^{k+1})$ is selected as a successor. In this work, the cost $h(s_{i,j}^{k+1})$ has been modified from the traditional version to minimize not only the distance traveled but also the soil compaction (product of traveling on a track more than once). To this aim, the evaluation of possible successors $s_{i,j}^{k+1}$ is done by computing the following total cost function:

$$f(s_{i,j}^{k+1}) = \underbrace{\left\| l_{i,j}^k - l_{i,j}^{k+1} \right\| (1 + t_{i,j}^{k+1})}_{h(s_{i,j}^{k+1})} + \underbrace{\left\| l_{i,j}^{k+1} - l_{s_G} \right\|}_{g(s_{i,j}^{k+1})}, \quad (3)$$

where, superindexes k and $k+1$ denote the current state and the possible successor, respectively, l_{s_G} are the coordinates of the goal s_G in a 2D Euclidean world, and $t_{i,j}^{k+1} \in \{0, 1, 2, \cdots\}$ represents the number of times that a successor have been traversed before. Finally, the optimal route R to travel from s_I to s_G is constructed with the set of successors that minimized the total cost (3). If only the distance traveled criterion is considered, then, the gray route in the example Fig 5a would correspond to the optimal route. But, when including the soil compaction criterion, the red route becomes the optimal route since the cost h includes a penalty term that increases the value of h according to the number of times that the possible successor has been traveled before. This penalization is affecting only possible successors that belong to crop areas, i.e. headlands and main way are not penalized such that $t_{i,j}^{k+1} = 0$ for $j \neq 0$.

As shown in the grid maps of Fig. 5, the headlands, the main way, and the tracks already covered can be considered as possible successors, while the tracks that do not belong to the area assigned to the vehicle, and the tracks that have not yet been harvested, are considered as obstacles. It is important to highlight that when vehicles are within their communication range, their local information can be exchanged and generates a grid map with fewer restrictions, as it is shown in Fig. 5 where the track 4 is also considered as a possible successor although it belongs to another area.

F. Vehicle departure time scheduling

Since the BVs must travel a certain distance from the TD to the point where it is planned to resume the operation of the previous vehicle, a predictive scheduling must be performed to determine the time in which the BVs should depart to avoid harvesting operation interruptions. The BV departure time is estimated based on the calculation of the time it takes for the previous AV to reach the point where all its bins are filled minus the time it will take for the BV to reach that

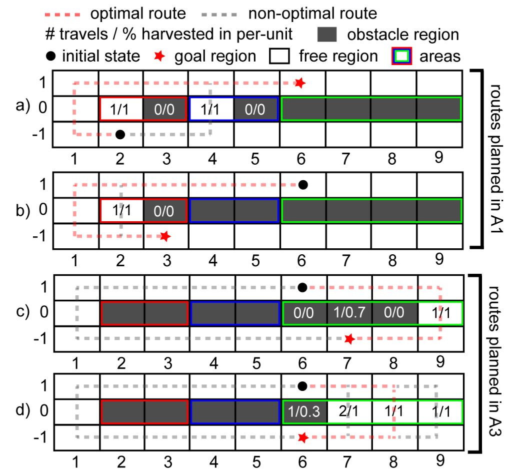

Fig. 5. Grid maps representing the vehicle route planning when: a) AV1 is returning to the TD using local information from AV2; b) BV1 is resuming A1 using updated global information; c-d) BV1-2 are resuming A3 using non-updated global information.

point. The efficacy of the departure time calculation depends on the information about the pickers harvesting rate and expected yield per track which are estimated by the vehicles during motion.

When the error between the expected and actual yield is significant, then the point along the track where the bins are expected to fill up is not reliable. In this situation, the scheduler decides not to activate a BV for that area until the AV returns to the TD and updates the global information using local information. Figure 3 shows an example of this situation, where it is expected that AV1 will not completely harvest track 2 in the first run, thus, the backup vehicle (BV1) should complete it. The latter does not happen since the error between the expected and actual point where the bins got filled differs significantly (indicated with magenta/blue stars), therefore, the scheduler decides that BV1 does not activate until AV1 returns to the TD and updates the global information. Once the global information has been updated, the harvesting sequence generated for the second run indicates to BV1 that track 2 it should not be repeated because it was already completed in the first run.

On the other hand, in the case of A3, the expected yield is reliable enough for the scheduler to decide to activate the BV departure time prediction in order to reduce non-productive times. In this case, the harvesting sequence for the second run is computed using global information that has not been updated by the local information of AV3, since BV1 departs before AV3 returns to the TD. In the case of the third run, the harvesting sequence used by BV2 is generated without considering the local information from BV1, but it does that based on the local information from AV3.

IV. Preliminary Results

In order to evaluate the performance of the proposed route planning strategy, a simulator of semi-automatic harvesting operations was implemented in Matlab. Figure 6 shows snapshots of the visual output generated by the simulator,

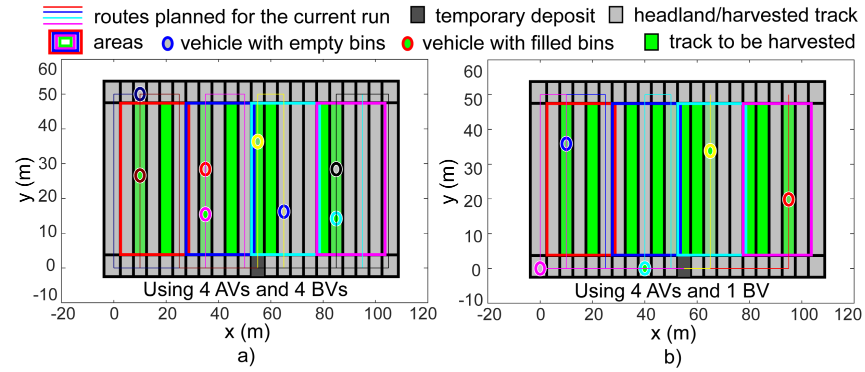

Fig. 6. Snapshots of the simulator after 50 min of harvesting the same field using 4 AVs with a) 4BVs b) 1 BV.

which depicts the field as a combination of Euclidean and grid-based representations. The simulator has been developed to be able to recreate and evaluate different scenarios, which include variability in the machinery availability, field length, yield density, harvesting rate, and communication restrictions. For each time iteration, the simulator shows the evolution of the tractors positions (colored circles) following their route plans (colored lines). The fill color of the circles and the tracks vary between grey or green according to the harvested state of the track or the N-trailer load state. The pickers are not shown in the visual output, but their stochastic behavior was included by using a random variable with normal distribution to generate a dynamic harvesting rate. The simulation ends when all the tracks have been covered, delivering metrics to qualify the harvesting operation efficiency. The metrics include pickers non-productive time, the total time to complete harvesting operation, distance traveled by the vehicles, and the number of times each track was traversed. Figure 6 shows two illustrative examples of the evolution of harvesting operations after 50 min of being implemented the proposed route planning strategy. These graphical results show the benefits of having enough machinery availability to allocate one BV per each AV (case a). This case produces fewer interruptions and thus the pickers are able to cover more tracks in the same time window than when the machinery availability limits the use of a single BV for all the AVs (case b).

V. Conclusions

This paper described the use of multiple robotic N-trailer vehicles to support the pickers during manual harvesting operations. A high-level route planning strategy is proposed to coordinate the vehicles departure times and generate routes that optimize the use of the machinery available while minimizes the total distance traveled, the total non-productive time, and soil compaction. In order to robustify the approach, the route planning is not completely centralized since routes can be recalculated by any vehicle on motion according to new information available about changes in the workspace. Since it is a work in progress, it was shown only preliminary simulation results that are planned to be completed in the future work with extensive tests that evaluate the strategy in different scenarios using the simulator. Finally, although the strategy assumes the use of robotic vehicles, as a short-term alternative, it could be implemented with manned vehicles, where the harvesting sequence, departure times, number of trailers, and vehicle routes computed can be used as guidelines by the human operators and pickers.

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