Instituto Nacional de Investigación y Tecnología Agraria y Alimentaria (INIA)
Available online at www.inia.es/sjar
http://dx.doi.org/10.5424/sjar/2013113-3865

Spanish Journal of Agricultural Research 2013 11(3): 652-660
ISSN: 1695-971-X
eISSN: 2171-9292

Operations planning for agricultural harvesters using ant colony optimization

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Abstract

An approach based on ant colony optimization for the generation for optimal field coverage plans for the harvesting operations using the optimal track sequence principle *B-patterns* was presented. The case where the harvester unloads to a stationary facility located out of the field area, or in the field boundary, was examined. In this operation type there are capacity constraints to the load that a primary unit, or a harvester in this specific case, can carry and consequently, it is not able to complete the task of harvesting a field area and therefore it has to leave the field area, to unload, and return to continue the task one or more times. Results from comparing the optimal plans with conventional plans generated by operators show reductions in the in-field nonworking distance in the range of 19.3-42.1% while the savings in the total non-working distance were in the range of 18-43.8%. These savings provide a high potential for the implementation of the ant colony optimization approach for the case of harvesting operations that are not supported by transport carts for the out-of-the-field removal of the crops, a practice case that is normally followed in developing countries, due to lack of resources.

Additional key words: B-patterns; harvesting planning; field efficiency.

Introduction

The adoption of information-based technologies in agricultural management may ultimately enable reliable autonomous field operations and improve operational efficiency. For this outcome a renewed focus on the usage of advanced systems both in terms of technology and management measures is needed (Sørensen & Bochtis, 2010). As for example, the adoption of auto-steering and navigation-aiding systems can provide the basis for the execution of optimal field area planning in terms of travelling distance or other criteria, although the primary objective of these technology systems has been to help operators to relieve stress and relax during driving (Bochtis & Vougioukas, 2008). In particular, optimized route and path planning is one of the most important requirements voiced by farm managers and machine contractor managers as an integrated part of advanced fleet management systems for agricultural machinery (Sørensen & Bochtis, 2010).

It has been concluded from extensive field studies that have been carried out based on geo-referenced technologies (global position system-GPS, and geographic information systems-GIS) that machinery efficiency could be improved significantly by computing optimal fieldwork patterns for the agricultural machines which minimize the turning time (Auernhammer, 2002; Reid, 2002). According to Hansen *et al.* (2003), optimization of the combine harvesting pattern in corn fields can increase harvesting efficiency substantially. Pre-planning of combine movement in the field and the use of vehicle position indicators via GPS will contribute to a major improvement in overall efficiency. Taylor *et al.* (2002) have used DGPS data obtained during yield mapping operations to evaluate the potential for improving harvest efficiency. They concluded

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Received: 16-12-12. Accepted: 18-07-13.

Abbreviations used: ACO (ant colony optimization); ACS (ant colony system); CVRP (capacitated vehicle routing problem); GIS (geographic information system); GPS (global position system); TSP (traveling salesman problem); VRP (vehicle routing problem).

that harvest efficiency depends more upon turning time rather than on unloading time. Hence, farm managers could improve harvest efficiency first by modifying harvest patterns to minimize turning and secondly by unloading grain on-the-go. Benson *et al.* (2002) supported these conclusions by simulation studies of the in-field harvest operations in the ARENA simulation modeling language. Furthermore, the implementation of optimal plans in the case of the agricultural operations executed by vehicles carrying time-dependent loads (such as the case of harvesting) the risk for soil compaction can be reduced significantly (Bochtis *et al.*, 2012). Emerging planning and scheduling approaches and tools based on simulation have also been presented recently dealing with optimization issues inherent in agricultural fleet management in biomass related operations (Busato *et al.*, 2007; Berruto & Busato, 2008).

Bochtis (2008), by introducing *B-patterns*, showed the potential for the implementation of computational optimization approaches in cases of single or multiple machinery systems operating in one or multiple geographically dispersed fields. *B-patterns* are algorithmically-computed optimal fieldwork patterns based on the approach of expressing the field coverage as the traversal of a weighted graph. The weight of the graph arcs could be based on any relative optimization criterion, such as total or non-working travelling distance, total or non-productive operational time, risk for soil compaction (in the case of vehicles carrying time-dependent loads). An implementation of *B-patterns* in conventional agricultural machines, supported by auto-steering systems, was presented by Bochtis & Vougioukas (2008). The experimental results showed that, by using *B-patterns*, the total non-working distance could be reduced significantly by up to 50%. The mission planning of an autonomous tractor has also been built on this approach (Bochtis *et al.*, 2009a).

Crop-harvesting operations require precise routing guidelines for the harvest vehicles. A significant type of time loss is the time a harvester spends for maneuvering at the headlands. Ali *et al.* (2009) proposed a combination of vehicle routing problem (VRP) and minimum cost network flow problems in order to determine the optimal routes for combine harvesters as well as feasible positions for grain transfer between the combine harvesters and tractors.

In this paper, an approach based on ant colony optimization for the generation of *B-patterns* for optimal field coverage for the agricultural harvesters operations is presented. Specifically, the approach addresses the case where the harvester unloads to a stationary facility located outside of the field area, or in the field boundary. This case belongs to the type of operations: "a single primary unit in a deterministic input material flow operation using a stationary facility unit" according to the classification of the field operations provided by Bochtis & Sørensen (2010). In this operation type there are capacity constraints to the load that a primary unit, a harvester in this specific case, can carry and consequently, it is not able to complete the task of harvesting of a field area and has to leave the field area to unload and return to continue the task one or more times.

Material and methods

In general, two scenarios are available for unloading of combine harvesters: intermittent and on-the-go. In the case of the intermittent unloading, the combine harvester unloads the harvested grain carried in its grain hopper to the specified place (facility unit) at regular intervals determined by its grain hopper capacity. To perform this scenario, the harvester must stop the operation and travel to the facility unit such as a depot or silo and after unloading the grain it has to return to the field and continue the harvesting operation. In the case of the on-the-go scenario, a tractor trailer follows the combine harvester in the field to unload the grain once a combine harvester reaches its determined grain hopper capacity. In intensive farming systems, such as the ones in developed countries, the uploading process takes place according to the on-the-go scenario. However, in many of the developing countries, such as Iran, intermittent harvesting is used. Also there are harvesting cases for some crops such as cotton where usually a harvester unloads its hopper at a predetermined out-of-field location.

For the planning problem under question, the optimization criterion is the minimization of the non-working travelled distance where a harvester is traveling without harvesting. The nonworking distance can be categorized as *out-field* and as *in-field* nonworking travelled distance. The first category refers to the length of the paths that connect the location where the harvesters stops its operation and the location where it leaves the field or the position of the facility unit if it is located in the field boundary and the paths that connect the location where the harvester enters the field or again the location of the facility unit in the

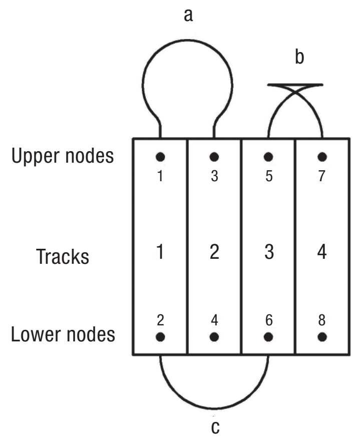

Figure 1. Representation of tracks, their nodes, and prevalent types of headland turnings: (a) Ω-turn, (b) T-turn, (c) Π-turn.

case where it is located in the field boundary and the location where the harvester commences the operation again. It is worth noting that the on-road travelled distance (if any) is not taken into account since it is the same independently of the plan that will be executed.

The in-field nonworking distance refers to the total length of the maneuvers executed by the harvester during the headland turnings. This distance depends on the harvesters' related characteristics (minimum turning radius, operating width) and the harvesters' maneuverability constraints due to field geometry. For the calculation of the distances that the harvester travels at the headlands three general types of harvester's maneuvers have been considered, namely, the T-turn, the Ω-turn, and the Π-turn (Fig. 1).

Modelling as a *B-patterns* approach and CVRP

According to the *B-patterns* approach, as is depicted in Fig. 1, each track is described by two points corresponding to two nodes in a graph. Abstractively, these nodes correspond to the "customers" in the vehicle routing problem (VRP) methodology. As mentioned earlier, in the case of the intermittent harvesting scenario, there is the presence of capacity constraints in the VRP. Consequently, the problem of motion sequence generation for the examined case is formulated as a capacitated vehicle routing problem (CVRP). The CVRP is an *NP*-hard problem since it contains the traveling salesman problem (TSP) as a sub-problem. It consists of two nested problems. The first is a bin-packing problem where the goal is to arrange the "customers" into a number of routes. Then, for each of the routes, a shortest tour visiting all the "customers" assigned to a particular route has to be found, which involves solving a TSP (Toth & Vigo, 2001). In the CVRP n customers have to be served from one central depot, which is typically identified by the index 0. Each customer i has a non-negative demand b_i for the same merchandise and for each pair of customers (i, j) a travel time d_{ij} between the two customers is given. The customers are served by a fleet of vehicles of equal capacity B. The goal in the CVRP is to find a set of routes that minimizes the total travel time such that (1) each customer is served once by exactly one vehicle, (2) the route of each vehicle starts and ends at the depot, and (3) the total demand covered by each vehicle does not exceed its capacity B. Once a vehicle reaches its limit, it returns to the depot.

In the proposed formulation, the vertices of the CVRP correspond to the two ends of operating rows of the field and yield from each vertex can be preset as half of the corresponding yield for that track. The numbering method of rows (tracks) and vertices is shown in Fig. 1. The costs correspond to the in-field and out-field non-productive distance. This cost is computed based on the kinematic constraints of the vehicles and on the geometrical space constraints of the field.

Ant colony optimization

The metaheuristic algorithm ant colony optimization (ACO) was adopted for the solution of the CVRP due to its low computational requirements. Considering the uncertainty inherent in field operations due to the uncontrolled operational environment such as yield variability and machinery blockages, the advantage of low computational time makes it feasible to re-plan an optimal fieldwork pattern for the remaining non-harvested field in case of an unexpected deviation from the initial plan.

ACO is a population-based, general search technique that has been adopted for the solution of complex combinatorial problems. Ant colony system (ACS) is one of the most popular forms of the main ACO algorithms and was chosen for the solution of the graph optimization problem inherent in the generation of *B-patterns* which from the optimization process point of view is a pure routing problem. ACS has been shown to be very efficient in solving routing problems

(Gambardella & Dorigo, 1996). ACS is organized in two main stages (Dorigo & Gambardella, 1997), namely (i) a construction of an initial solution phase, and (ii) an updating phase of the pheromone trail consisting of local and global updates. In a given state of the solution process, each ant builds a solution and it computes a set of feasible expansions from it. The decision on the selection of the specific move to expand the state takes into account the following two values: the attractiveness of the move, η_{ij}, as computed by some heuristic information according to the information on the problem, and the pheromone trail level of the move, τ_{ij}, that indicates how effective the move was in previous states. Given the attractiveness and the pheromone trail level, the probability of the k^{th} ant making the transition from node i to node j is given by:

$$p_{ij}^{k} = \begin{cases} \dfrac{[\tau_{ij}]^{\alpha}\,[\eta_{ij}]^{\beta}}{\sum_{j \in N_i^k} [\tau_{ij}]^{\alpha}\,[\eta_{ij}]^{\beta}} & \text{if } j \in N_i^k \\ 0 & \text{otherwise} \end{cases} \qquad [1]$$

where $\eta_{ij} = 1/d_{ij}$ is a heuristic value, α and β are parameters which determine the relative influence of the pheromone trail and the heuristic information, and N_i^k is the feasible neighbourhood of ant k when being at node i, that is, the set of nodes that ant k has not visited yet. When complete solutions have been built, pheromone trails are updated. The updating process includes the evaporation of the pheromone on all arcs, in a first stage, and, in a second stage, the deposition of pheromone by all of the ants on the arcs, which are part of the computed solutions. The ACS local update is performed each time that node i is connected to node j in the solution. The pheromone τ_{ij} is then modified:

$$\tau_{ij} = (1-\rho)\tau_{ij} + \rho\tau_0 \qquad [2]$$

where $\rho \in (0, 1]$ is the pheromone evaporation rate, τ_0 is the initial pheromone value defined as $\tau_0 = 1/(n \cdot C^{nn})$, where n is the number of nodes included in the current solution and C^{nn} the objective function produced by the execution of one ACS iteration without the pheromone component. In each iteration of the basic ant colony method, each ant builds a step-by-step solution. A global update is carried out at the end of each iteration when a complete solution has been produced by each ant. Only the ant that has produced the best-so-far solution is allowed to add pheromone after each iteration while the only graph node connections modified are those of the produced solution, T^{bs}. The update formula can be written as:

$$\tau_{ij} = (1-\rho)\tau_{ij} + \Delta\tau_{ij}^{bs} \quad \forall (i,j) \in T^{bs} \qquad [3]$$

where $\Delta\tau_{ij}^{bs} = 1/C^{bs}$, where C^{bs} is the length of a best-so-far graph path.

All the related computation processes were implemented in an Intel® Core™2 Due CPU with 4 GB RAM, using the version 7.8 (R2009a) of MATLAB® technical programming language.

Results and discussion

A number of experiments were carried out in order to prove the adoption of the ACO algorithm for the generation of the *B-patterns*.

Small-sized problems, in terms of the number of tracks, are presented for illustration purposes having as a basis the Iranian farming system. It has been assumed that the harvester has to unload at a predetermined place (*e.g.*, a silo, or at the field side). The maximum grain hopper capacity of the combine harvester used was measured as 2,600 kg. Harvester minimum turning radius was measured $Rmin = 5.4$ m and the effective operating width was $w = 4.5$ m. This relation between the harvester characteristics ($w < Rmin < 2w$) reduces its maneuverability. By doing so, the problem difficulty and the necessity for an optimal plan is increased. The average yield of wheat in Iran farms of 3,670 kg ha^{-1} was used as the average yield of fields. Two sets of experiments were performed corresponding to two fields referred to as "field A" and "field B" to demonstrate the optimal paths that result from the above-mentioned optimization method. For finding the solution to the specific coverage problem the parameters of the ACO algorithm were set as: $\alpha = 1$, $\beta = 2$, $\rho = 0.01$ and the number of iterations (t) $=1000$. With more iterations the solution will be more reliable but on the other hand, computing time will be increased. As is mentioned above, the factors $\eta_{ij} = 1/d_{ij}$ and $\tau_0 = 1/(n \cdot C^{nn})$ have been represented. The number of ants to be used was equal to the number of nodes in each problem. Furthermore for each problem instance 10 runs were performed to improve experiment accuracy.

For the first scenario, the harvesting of a rectangular field was considered. The dimensions of the field were 90×120 m^2 = 10,800 m^2 (= 1.08 ha) and it was divided into 20 operating tracks. The specific field area corresponded to an expected average yield of 3,966 kg of yield demanding the execution of two "routes" in total considering the harvesters capacity (2,600 kg). A "route" is designated as the closed cycle composed of

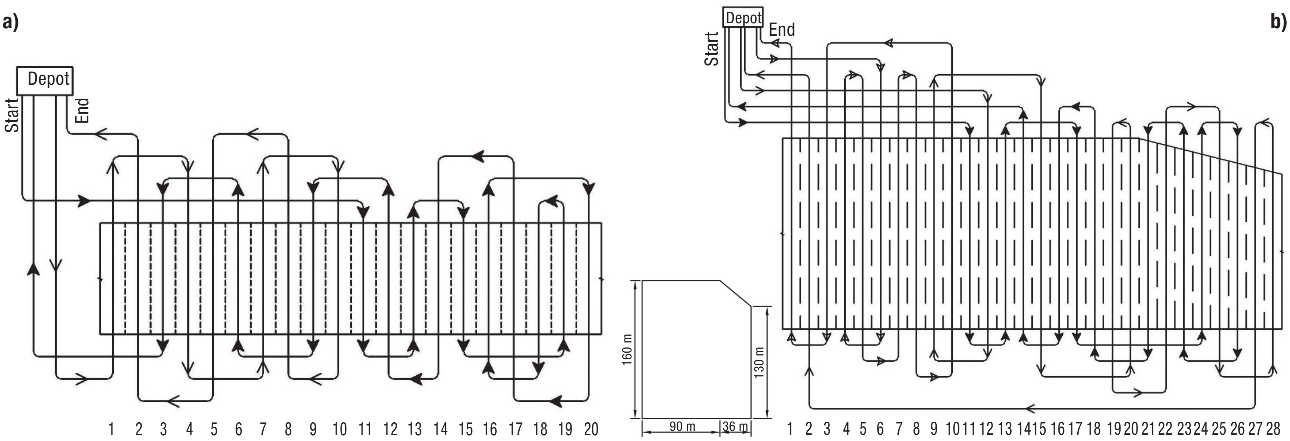

Figure 2. *B-patterns* generated for covering: (a) Field A, and (b) Field B.

the part operations of driving from the facility unit location to the position where the harvesting is resumed, harvesting a field area corresponding to a grain quantity that fills the grain hopper, and finally, driving to the location of the facility unit and unloading the grain hopper.

Fig. 2a shows a result of solving the problem with the CVRP model. The planning model assigns field vertices to combine harvester paths, taking into account crop yield and combine-harvester grain hopper capacity. Each path indicates the starting position for a combine harvester, the area to be covered in the field, and the position where the combine harvester is expected to reach capacity according to the average expected yield.

The solution of the problem, including optimum path pattern and the full capacity locations is given in Table 1. In the optimal solution the length of the optimal path was 1,061.2 m when including the transport distance and 362.7 m excluding transport distance. The total computational time was 114 s. Fig. 3a provides the convergence of the optimal solution by ants' path searching for the case of field A.

In the second scenario, the harvester is going to operate in a 28-track trapezoid shaped field. The dimensions of the field and harvester paths map are shown in Fig. 2b.

The optimal solution of the problem, including all necessary information is given in Table 1. As can be seen in Fig. 2b, the harvester reached full capacity in two locations and returned to the depot for unloading the grain hopper.

Fig. 3b provides the convergence of the optimal solution by ants' path searching for the case of field

Table 1. Final computational results of optimization algorithm

	Field A	Field B
Optimum path pattern (vertex base)	Route 1: 0 21 22 26 25 29 30 38 37 35 36 32 31 39 40 34 33 27 28 24 23 17 18 12 11 5 6 0 Route 2: 0 2 1 7 8 14 13 19 20 16 15 9 10 4 3 0	Route 1: 0 21 22 26 25 33 34 48 47 51 52 46 45 41 42 36 35 31 32 28 27 0 Route 2: 0 23 24 18 17 29 30 40 39 37 38 44 43 49 50 56 55 53 54 4 3 0 Route 3: 0 11 12 8 7 9 10 14 13 15 16 20 19 5 6 2 1 0
Optimized path length (m)	1,061.2	1,470.8
Full capacity point (s)	6	27 3
Best path length (without depot travelling) (m)	362.7	690.8
Iteration reference number	892	885
Ant reference number	30	24
Total computational time (s)	114	225

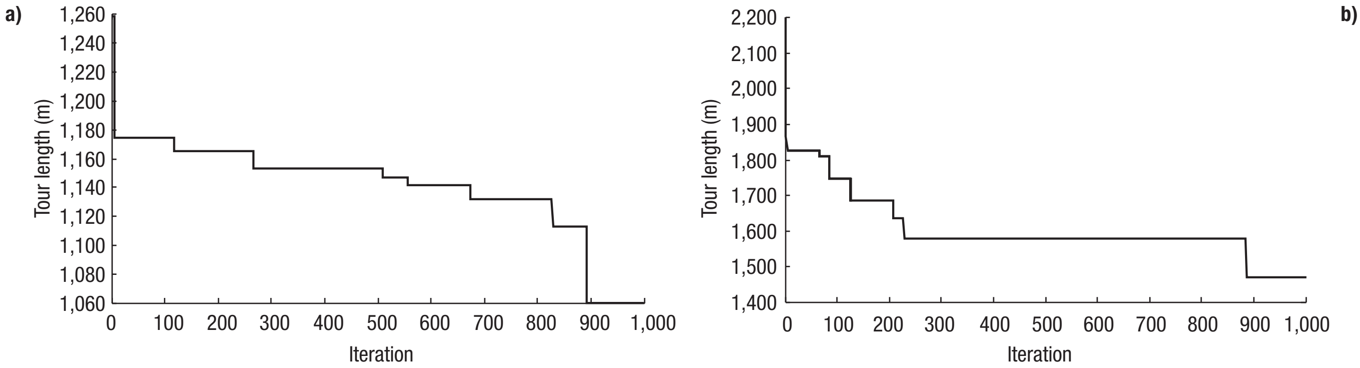

Figure 3. Evolution of best tour length: (a) Field A and (b) Field B.

A. The presented solution is reached after 885 iterations.

In order to compare the optimal sequences with conventional harvesting practices, two patterns proposed by two interviewed operators were considered. The patterns (σ^{exp1} and σ^{exp2}) suggested by the operators for the specific field and machinery features were for field A (Figs. 4a and 4b, respectively):

σ^{exp1} = {0 34 33 31 32 28 27 35 36 8 7 3 4 10 9 21 22 18 17 23 24 20 19 25 26 30 29 0 37 38 6 5 1 2 12 11 15 16 14 13 39 40}

σ^{exp2} = {0 6 5 13 14 20 19 15 16 28 27 21 22 10 9 23 24 12 11 35 36 26 25 31 32 2 1 0 7 8 40 39 37 38 30 29 33 34 18 17 3 4}

and for field B (Figs. 5a and 5b, respectively):

σ^{exp1} = {0 7 8 6 5 25 26 40 39 9 10 18 17 41 42 36 35 45 46 50 49 0 55 56 24 23 19 20 12 11 15 16 34 33 37 38 44 43 29 30 54 53 0 51 52 2 1 13 14 28 27 31 32 48 47 3 4 22 23}

σ^{exp2} = {0 7 8 2 1 13 14 18 17 21 22 20 19 23 24 46 45 43 44 40 0 39 35 36 42 41 49 50 56 55 51 52 32 31 27 28 26 25 29 30 4 0 3 11 12 6 5 15 16 38 37 33 34 48 47 53 54 10 9}

These paths were proposed based on the personal experience of the operators. Operators attempted to prevent the implementation of the sharp turns as much as possible. In addition, they tried to commence and complete each individual route from the side of the field which is closer to the depot direction.

Nonworking distance, savings and field efficiency are presented in Table 2. The "savings" rows lists the percent of savings for the nonworking distance achieved by adopting the optimal patterns instead of planning based on the traditional pattern. For determination of field efficiency of the different paths, the distance based field efficiency (Bochtis *et al.*, 2009b) was used. The distance based field efficiency is given by the ratio of the effective travelling distance of the machine,

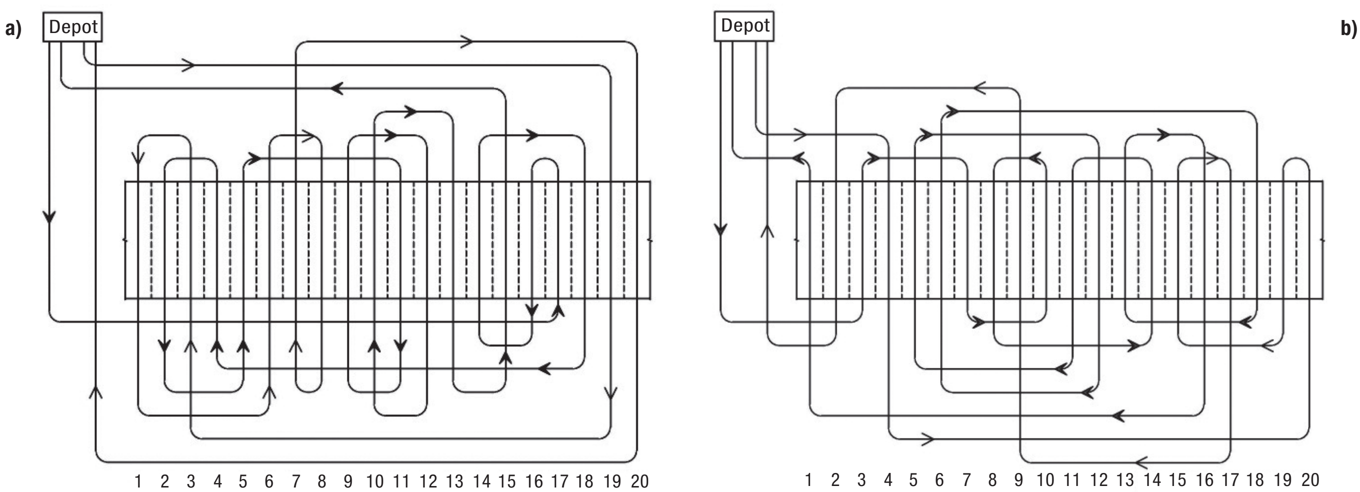

Figure 4. Harvest patterns suggested by the operators for covering field A: (a) σ^{exp1}, and (b) σ^{exp2}.

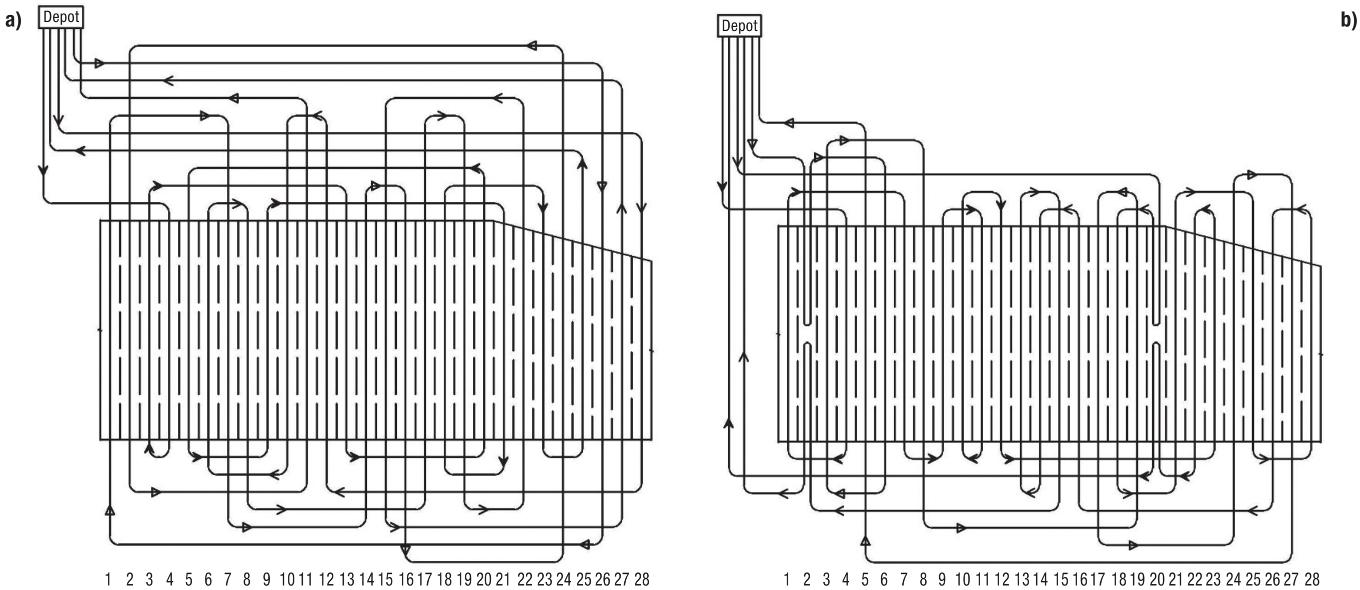

Figure 5. Harvest pattern suggested by the operators for covering field B: (a) σ^{exp1}, and (b) σ^{exp2}.

while operating, and the total distance travelled by the machine:

$$E_{f(distancebased)} = d_{ef}/d_{ef} + d_{nef} \quad [4]$$

where d_{ef} is the effective travelling distance and d_{nef} is the non-effective distance.

It is clear for the obtained results that the generated optimal track sequences beyond minimizing the non-working distance in each field, also reduces the distance traveled from field to the unloading facility and back. The algorithmic approach achieves this automatically by computing the most appropriate entry and exit tracks for fields for each individual route derived from the capacity constraints of the operation.

The savings on the nonworking distance depend on the operation such as field geometry, operating width, and machine minimum turning radius and can be as high as 40% (Table 3). Reduction in nonworking distance directly affects nonproductive time.

Finally, in order to study the effect of using a mobile transport unit such as a tractor-trailer, moving solely at the headlands, a scenario of harvest operation executed by a harvester and a supporting transport unit was also examined. As expected the total field efficiency was increased by 84.5% instead of 74.7% in the case of the no support from a transport cart harvester, due to complete elimination of the out-of-field travelled distance. However, it has to be noted that this increase represents the efficiency of the harvester and not the system harvester-transport unit. There was also an increase on the in-field efficiency of the harvester to 88% instead of 86.3% in the case of the no support from a transport cart harvester. This was caused by the reduction in the in-field nonworking distance as a result of the relaxing of the capacity constraints of the optimization problem that relieves the optimal solution to take into account the exit and entry points represen-

Table 2. Measured non-working distances for different patterns and the corresponding savings by adopting the optimum planning

Pattern	Field A			Field B		
	σ^{op}	σ^{exp1}	σ^{exp2}	σ^{op}	σ^{exp1}	σ^{exp2}
In-field nonworking distance (m)	362.7	535.5	626.4	690.8	1,090.6	855.6
Savings (%)	—	32.3	42.1	—	36.7	19.3
Field efficiency (distance-based) (%)	86.9	81.8	79.3	86.3	79.9	83.5
Total nonworking distance (m)	1,061.2	1,477	1,293.4	1,470.8	2,615.6	1,987.1
Savings (%)	—	28.2	18	—	43.8	26
Field efficiency (distance-based) (%)	69.3	61.9	65	74.7	62.4	68.6

Table 3. Implementation of the method for the headland unloading module (in field B)

Optimum path pattern (vertex base)	*0 1 2 6 5 11 12 10 9 13 14 18 17 21 22 28 27 23 24 30 * 29 35 36 34 33 37 38 42 41 43 44 48 47 51 52 50 49 55 56 54 * 53 45 46 40 39 31 32 26 25 19 20 16 15 7 8 4 3 0*	
Iteration reference number	Total nonworking distance (m)	Field efficiency (Total) (%)
677	795.5	84.5
Full capacity point (s)	In-field nonworking distance (m)	Field efficiency (in-field) (%)
(*) 30 54	591	88

ting the fieldwork tracks in this specific case, for each one of the resulting route of the harvester in the capacity constrained case.

Although it is not in the scope of the current research to precisely identify the effect of the optimal plans with other operational parameters, it is expected that the reduction of the nonworking distance will lead to a corresponding reduction of fuel consumption and total operational time. The resulted increase in operational efficiency is very important especially for the case of the large harvesters as the nonproductive time elements represent a greater proportional loss in potential machine production (Sørensen, 2003).

As final conclusions, an approach based on ant colony optimization for the generation of optimal field coverage plans following the principle of *B-patterns* for harvesting operations was presented. The case where the harvester unloads in a stationary facility located out of the field area or in the field boundary was examined. Results from comparing the optimal plans with conventional plans generated by operators showed savings in the in-field nonworking distance in the range of 19.3%-42.1% while savings in the total non-working distance were in the range of 18-43.8%. These savings demonstrate a high potential for the implementation of the approach for the case of harvesting operations not supported by transport carts for the out-of-the-field removal of the crops, a practical case that is normally followed in developing countries due to lack of resources. However, *B-patterns* are, in general, strongly counter-intuitive to be generated by human operators. Moreover, their execution is constrained by the ability of the operator to distinguish the next track to be followed, according to the optimal plan, at the end of the track currently being harvested since in the most cases these two tracks are non-adjacent. Dedicated programmable navigation-aiding systems having as basis auto-steering systems which have been developed in recent years are needed to support the execution of this kind of patterns. Certainly, the adoption of these advanced technologies in the agricultural production systems in developing countries might seem contradictory, at a first consideration. However, the potential benefits derived from the reduction of the operational cost can compensate the purchasing cost of these auto-steering technologies.

Acknowledgements

The authors wish to acknowledge Parham Bakhtiari (Faculty of Engineering, Bu-Ali Sina University, Hamedan, Iran) for provided advice and assistance with the designing of the proposed algorithm described herein. We also express our gratitude to the anonymous reviewers, whose detailed feedbacks have led to significant improvements of the paper.

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