Decision making for Farmers: A Case Study of Agricultural Routing Planning

Full Paper

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Abstract

Agricultural business is shifting to a stronger integration of information technology and data analysis to optimise the management and operations of small- and large-scale farms. In particular, computer support for decision-making is critical for farmers who want to decrease the cost of operations and control their (semi-)automated fleet of agricultural machines. This paper develops an optimisation module for decision support in Agricultural Routing Planning (ARP). The output is expected to help farmers to decide on the most efficient route for their harvesting machines. Specifically, the aim of this study is to contribute to optimisation solutions by introducing a new methodology called a Lovebird Algorithm, to address the routing problem. The Lovebird Algorithm acts as an optimisation tool to screen alternatives and focus only on efficient ones. The experimental results show that the proposed algorithm can save 8% of the non-working distance compared to the Genetic Algorithm and Tabu Search.

Keywords: decision making, agriculture, routing planning, Lovebird Algorithm

1 INTRODUCTION

The main objective of Decision Support Systems (DSS) is to help, improve, and potentially automate the decision-making process (Turban et al. 2005). A decision-making process based on an optimisation technique is related to the recognition and solution of optimisation problems. Computer programs that solve optimisation problems are an essential element of several DSS (Bernus and Holsapple 2008).

Agricultural Routing Planning (ARP) is intended to optimise the design of machines' movements for agricultural field operations inside the farmer's field. The optimised design can minimise the length of routes travelled by machines, thereby saving costs and time associated with agricultural field operations (Utamima et al. 2018, 2019a). Utamima et al. (2019b) formalise the published ARP case with a mathematical model and optimise the published dataset of ARP. Seyyedhasani and Dvorak (2018) implemented multiple machines and minimised the total travel duration of every machine. Backman et al. (2015) used fluid turning in a manoeuvre, while Bochtis and Vougioukas (2008) minimised the non-working distance of machines used in a field.

To date, no DSS studies have addressed ARP. Recent studies on agricultural DSS focus on a different application. A DSS based on the optimisation model in fish farming is used to maximise the operators' profits (Cobo et al. 2019). The cultivation process of DSS is simulated through a bioeconomic model to obtain the optimal solution under certain conditions. Hafezalkotob et al. (2018) used a DSS to select the best olive harvesting machine among several alternatives. The output is expected to develop and improve the economic conditions in the agricultural field to meet food demand. A DSS based on the prediction model is proposed for the improvement of irrigation in agriculture (Giusti and Marsili-Libelli 2015; Navarro-Hellín et al. 2016).

The focus of this study is on building an optimisation module as an element of DSS. The ARP optimisation concentrates on the planning of routes for machines inside several agricultural fields for harvesting operations. In this research, each agricultural field has several established tracks with symmetrically-planted crops. These tracks can be traversed by both agricultural machines and harvesters. The decision-maker needs to determine which sequence of tracks will cover the shortest distance. ARP belongs to the class of NP-complete problems that makes an exact optimisation impossible as it is too time-consuming and complex to be applied (Marinakis et al. 2017). Therefore, this research develops a variation of an evolutionary algorithm called the Lovebird Algorithm.

This research contributes the development of a new algorithm (Lovebird Algorithm), and its application is represented in an optimisation module of DSS in ARP. The rest of this paper is organised as follows. Section 2 presents a literature review of current studies in DSS and ARP. Section 3 formalises the decisional problem with a mathematical formula of ARP and describes the proposed method. Section 4 presents the experimental results and analysis, while Section 5 suggests avenues for future research and concludes the paper.

2 LITERATURE REVIEW

Recent studies have proposed several decision support systems for agriculture. A DSS in fish farming is intended to optimise production strategies. The DSS contains an optimisation module that uses Particle Swarm Optimisation to optimise seabream aquaculture production (Cobo et al. 2019). A fuzzy-based DSS is proposed to improve irrigation in agriculture by deciding whether irrigation is needed and determining the amount required according to a set of rules involving variations of several weather variables (Giusti and Marsili-Libelli 2015). Navarro-Hellín et al. (2016) improved the DSS in irrigation by considering the soil measurement to precisely predict the irrigation needs. An agro-climate decision support tool is proposed to helps users to run crop simulation models for the targeted crops (Han et al. 2019).

The ARP problem involves minimising the distance travelled by machines when performing field operations inside an agricultural field (Utamima et al. 2019b). This problem has been altered and extended regarding the targets [e.g., improvement of time (Seyyedhasani and Dvorak 2018), minimisation of the headland distance (Backman et al. 2015)], specific field operations [e.g., herbicide application (Conesa-Muñoz, Bengochea-Guevara, et al. 2016), potato cultivation (Zhou et al., 2015), or orchard operation (Bochtis et al., 2015)] and limitations [e.g., restricted machine limit (Bakhtiari, et al., 2013), and obstacles (Zhou, et al., 2014)].

Previous studies on ARP focused mostly on real-case problems and solved these by means of several established algorithms. GA has been adapted for machine routing to decrease the total distance travelled in biomass transportation (Gracia et al. 2014). Sethanan and Neungmatcha (2016) used Particle Swarm

Optimisation (PSO) for route planning in sugarcane field operations, while Valente et al. (2013) employed Harmony Search to optimise coverage path planning in vineyard parcels. A hybrid Simulated Annealing was used for route planning of autonomous vehicles in herbicide application (Conesa-Muñoz, Bengochea-Guevara, et al. 2016).

Based on the previous research, two research gaps can be stated. First, despite the variations of DSS in agriculture, no formal studies apply the ARP in the context of farmers' decision-making. Therefore, this study is the first to consider ARP for such decision-making. Second, most studies use the currently-established algorithms rather than improving an algorithm for better results. Hence, the need to develop a better algorithm to improve the quality of ARP solutions.

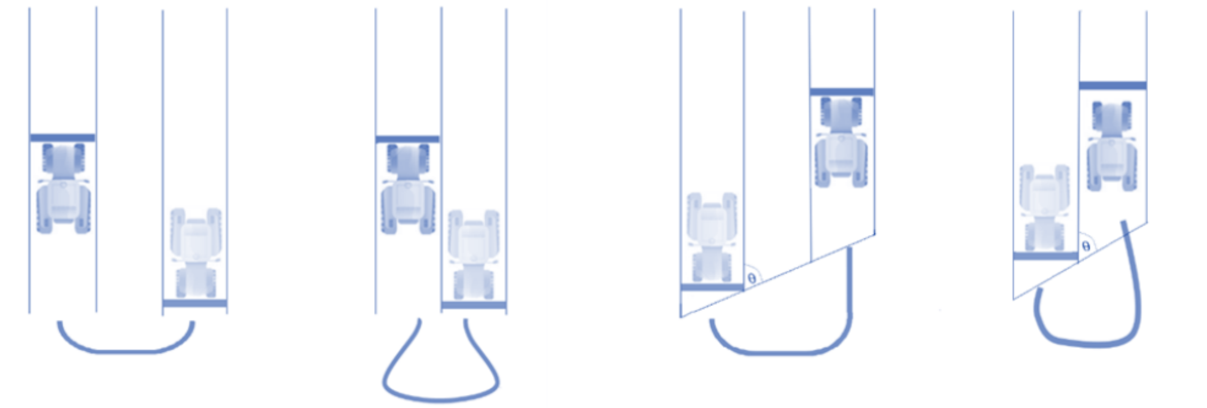
3 MATERIALS AND METHOD

3.1 Problem Formulation

In ARP, a field has several established tracks with symmetrically-planted crops. These tracks can be traversed by both agricultural machines and harvesters. Each field has a headland area which is the crop-free area where machines perform manoeuvres to go to the next track. In the problem of interest, the machines need to start and end at the Depot. The farmer needs to determine which sequence of tracks in all fields will cover the shortest distance.

The tracks in ARP represent nodes in a graph, which must be visited by a machine. The arcs interfacing two nodes represent paths for the machines to move from one node to its neighbours. The machines can move to another track with a specific type of manoeuvre in the headland area of the field. Four manoeuvres are considered like shown in Figure 1: flat(Π), bulb(Ω), Flatθ ($\Pi\theta$), and Bulbθ ($\Omega\theta$). Note that $0 < \theta \leq 90$. Fig. 1(a-d) show an illustration of the four manoeuvres. If $\omega \geq r > \omega/2$ (ω = width of the track, r = turning radius of machines), the flat turn can occur only when the machine skips one or more tracks; otherwise, the bulb turn will be performed (Bochtis and Vougioukas 2008). A similar condition is also applied to Flatθ and Bulbθ with $\theta < 90$.

Suppose graph G contains a set of nodes N ($i,j \in N$) representing tracks in the fields. The set of homogeneous machines is represented as M ($m \in M$) and the set of tracks is T ($t \in T$). There are two decision variables: x_{ij}^m and x_i^m. The x_{ij}^m is equal to 1 if machine m moves from node i to node j; otherwise, it is equal to 0. The x_i^m is equal to 1 if machine m visits node i; otherwise, it is equal to 0. Equation (1) lists the objective function of the ARP in this study which is the minimisation of the non-working distance in the field. This distance is labelled 'non-working distance' since the machine is not performing an agricultural operation when making the turning manoeuvres.



a. Flat b. Bulb c. Flatθ d. Bulbθ

Figure 1: The four manoeuvres that are considered in this study (Utamima et al. 2019b)

The total working distance of every machine m is calculated with Eq. (2). The constraints of this model (Eq. 3-Eq 10) are adapted from the work of Utamima et al. (2019). The d_{ij} represents the types of manoeuvres or turns in the headland area that specifies in Eq. (3). Constraints (4)-(6) ensure that every node is visited only once by the machine. Constraint (7) guarantees that if a machine enters a node, it will also leave that same node. Constraint (8) excludes disjoint sub-tours (S) from a solution. Constraint

(9) restricts the maximum distance (B) for every machine. The last constraint (10) specifies that the decision variables are binary numbers.

$$z = \min\left(\sum_{i\in N}\sum_{j\in N}\sum_{m\in M} d_{ij}.\, x_{ij}^{m}\right) \tag{1}$$

$$Working\_Distance_m = \sum_{i\epsilon N}\sum_{m\in M} x_i^m\, l_t \tag{2}$$

s.t

$$d_{ij} = \begin{cases} \Pi(i,j) = w|i-j| + (\pi-2)\mathrm{r}, & if\,|i-j| \le \frac{2\mathrm{r}}{\omega} \ \wedge\ \theta = 90 \\ \Omega(i,j) = \mathrm{r}\left(3\pi - 4\sin^{-1}\left(\frac{2\mathrm{r}+w|i-j|}{4r}\right)\right), & if\,|i-j| > \frac{2\mathrm{r}}{\omega} \ \wedge\ \theta = 90 \\ \Pi\theta(i,j) = w|i-j|(1+\cot\theta) + r(\pi-2), & if\,|i-j| \le \frac{2\mathrm{r}}{\omega} \ \wedge\ \theta < 90 \\ \mathit{\Omega}\theta(i,j) = \pi r + \frac{4r^2 - w|i-j|(4r+\mathrm{w}\cot^2\theta+\mathrm{w})}{4r-2w|i-j|} \times \sin^{-1}\frac{w|i-j|(4r\cot\theta - 2\mathrm{w}\cot\theta)}{4r^2-\mathrm{w}|i-j|(4r+\mathrm{w}\cot^2\theta+\mathrm{w})}, & if\,|i-j| > \frac{2r}{\omega} \ \wedge\ \theta < 90 \end{cases} \tag{3}$$

$$\sum_{m\in M}\sum_{i\in N} x_{ij}^m = 1, \quad i\,, j \ne 0,\ j \in N{:}\, i \ne j \tag{4}$$

$$\sum_{m\in M}\sum_{i\in N} x_i^m = 1, \quad i\ \ne 0 \tag{5}$$

$$\sum_{m\in M}\sum_{j\in N} x_{ij}^m = 1, \quad i\,, j \ne 0,\ i \in N{:}\, i \ne j \tag{6}$$

$$\sum_{m\in M}\sum_{i\in N} x_{ij}^m = \sum_{m\in M}\sum_{j\in N} x_{ji}^m\,, \quad i, j \in N \tag{7}$$

$$\sum_{i\epsilon S} x_i^m \le \|S\| - 1, \forall S \subseteq N, \|S\| \ge 1\,, m \in M \tag{8}$$

$$\sum_{i\in N} l_i x_i^m < B\,, m \in M,\ i \in N \tag{9}$$

$$x_{ij}^m, x_i^m \epsilon \{0,1\} \tag{10}$$

3.2 Lovebird Algorithm

The representation of a candidate solution uses a permutation number as shown in Figure 2. Each track is allocated a number, and it has the sequence that will be visited by a machine. For instance, in Figure 2, the machine will visit track no. 4 right after it visits track no. 1.

Sequence:	1	2	3	4	5	6	7	8
Track:	1	4	7	3	6	2	5	8

Figure 2: A candidate solution representation

This research proposes a new algorithm called the Lovebird Algorithm to solve the ARP. The Lovebird Algorithm adapts combinatorics operators to produce the offspring (new candidate solution). Figure 3 shows the flowchart of the Lovebird Algorithm. In the beginning, the fields' details (containing every track, entrance, and Depot coordinates) and machine information (the number of available machines and the capacity) become the input of the algorithm. The initialisation phase of Lovebird Algorithms sets parameters (maximum of iterations and the size of the population) and the variables (every tracks distance to the entrances and Depot). The stopping criteria is the *max_iter,* which is the maximum number of iterations in the algorithm. The *max_iter* is set to *50n* (*n* = number of fields). The main iterations start with the calculation of the objective function based on the mathematical model that is shown in Section 3.1. Then, the Lovebird's offspring production executes one of the five choices of combinatorics operators:

a) Red: Swap the sections (Figure 4 (a))
b) Peach: Flip the sequence (Figure 4 (b))
c) Green: Interchange two tracks (Figure 4 (c))
d) Yellow: Move and push (Figure 4 (d))
e) Grey: Mix the tracks (Figure 4 (e))

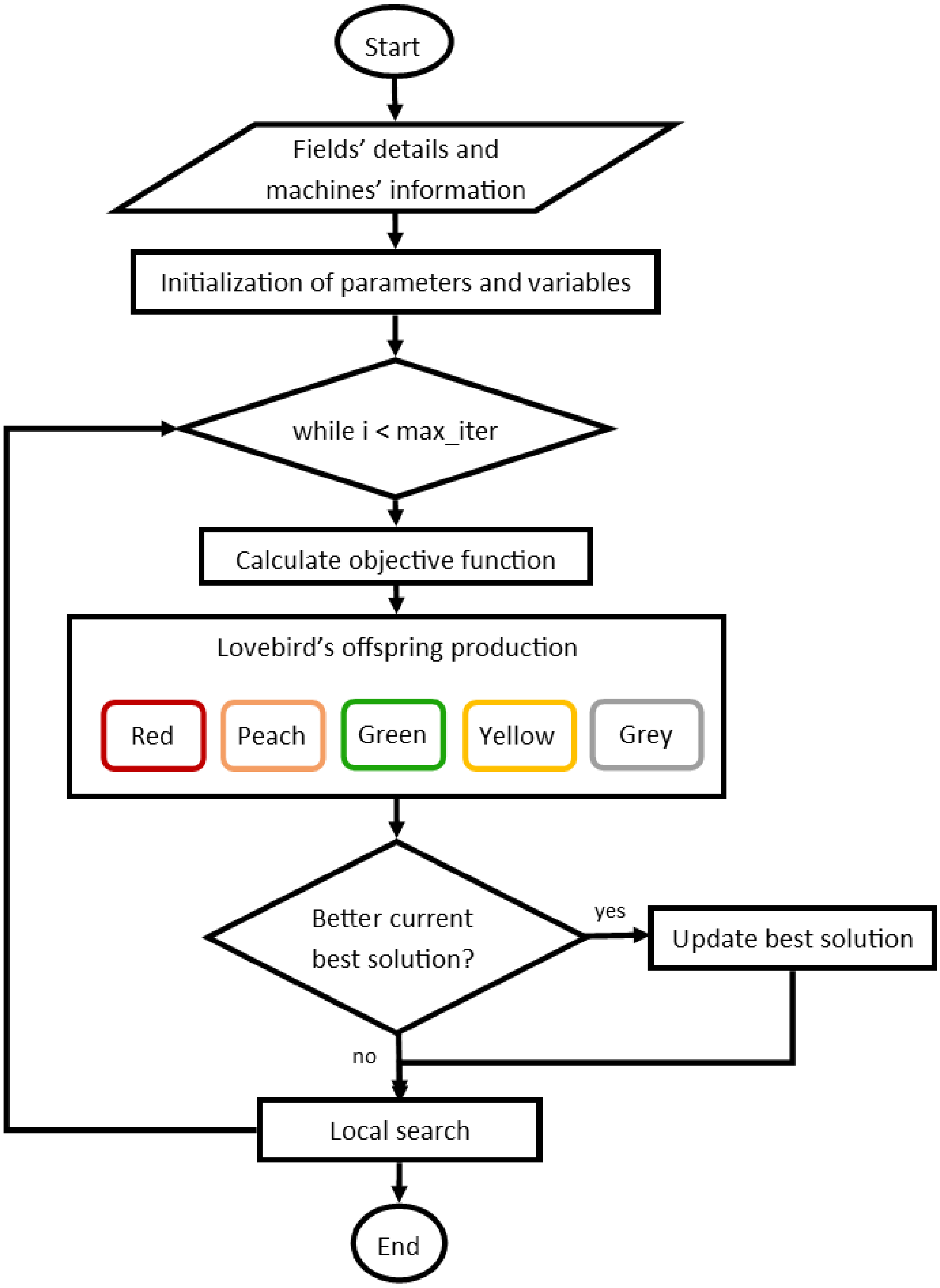


Figure 3: Flowchart for Lovebird Algorithm

Figure 4 illustrates the combinatorics operators that are used in the Lovebird Algorithm as listed previously in a-e. The offspring is the new candidate solution after the combinatorics operator has been applied, while the parent is the previous candidate solutions. The swap section (Figure 4 (a)) swaps the red section of two parents. Offspring 1 keeps the red section from Parent 2 and copies the rest of the tracks from Parent 1, while Offspring 2 does the opposite. The flip operator (Figure 4 (b)) flips over the tracks' position in the peach colour section, while the interchange operator (Figure 4 (c)) changes the position of the green section. Figure 4 (d)) shows the move and push operators that move the location of a front yellow point to a back yellow point and push forward the remaining tracks. The last operator is the grey operator that mixes the sequences of the tracks in a candidate solution.

The combinatorics operators are used as the exploration stage in a metaheuristic algorithm (Soni and Kumar 2014). The next phase involves the updating of the new candidate solutions and their objective values. The best solution among the iterations is updated if a better solution is found in the current iteration. Next, a local search scans the neighbourhood of the best solution found so far to determine whether further improvement is possible.

Parent 1	1	2	3	4	5	6	7	8
Parent 2	2	1	4	5	6	7	8	3
Offspring 1	1	2	4	5	6	7	3	8
Offspring 2	2	1	3	4	5	6	7	8

(a) Red (Swap section)

Parent	2	1	4	5	6	7	8	3
Offspring	2	1	6	5	4	7	8	3

(b) Peach (Flip)

Parent	2	1	4	5	6	7	8	3
Offspring	2	8	6	5	4	7	1	3

(c) Green (Interchange)

Parent	2	1	4	5	6	7	8	3
Offspring	2	4	5	6	7	8	3	1

(d) Yellow (Move and push)

Parent	1	2	3	4	5	6	7	8
Offspring	2	8	6	5	4	7	1	3

(e) Grey (Mix)

Figure 4: Depiction of combinatorics operators in Lovebird

3.3 The Optimisation Module in DSS

Figure 5 presents the proposed framework of an optimisation module in DSS for ARP. This framework is in line with what is stated in Cobo et al. (2019) and Ben Jouida and Krichen (2018). The input of the module consists of the coordinates of every track, entrances to each field, and the Depot. The machines' capacity and the number of machines also become input. The process starts with the calculation of track distances inside the fields and to the entrances and the Depot. Then, the Lovebird Algorithm is executed, as explained in Section 3.2. The outputs of the module are the optimised order of tracks that need to be traversed by the machines, the non-working distance, and the length of harvested tracks (working distance).

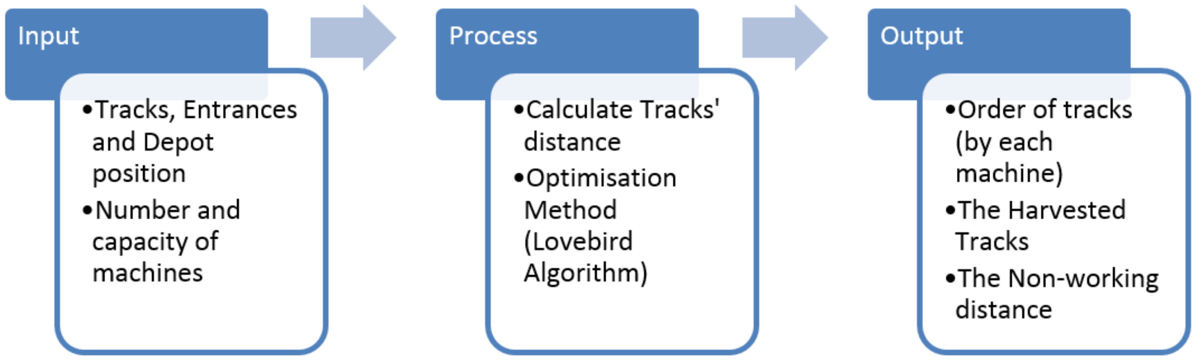


Figure 5: Framework of the optimisation module in DSS for ARP

We can integrate the proposed module in a fleet management system in agriculture (Sørensen and Bochtis 2010). This system includes an online decision support system, and the online routing will assist the farmer in running the machines. Another alternative is to add the Lovebird algorithm to a comprehensive farm management system (Sørensen et al. 2010). The new design of a farm management system considers new situations from the perspectives of both farmers and managers. Specifically, the routing algorithm can be included in one of the system modules called 'plan generation'. After that, the farmers can execute the route provided by the management system.

Based on Sørensen et al. (2010), we can derive the CATWOE (Customers, Actors, Transformation Process, World-view, and Ownership) elements of a DSS in ARP as listed below:

a. Customers: the primary customer of the DSS is the farm manager.

b. Actors: operates the DSS, in this case, is the farm manager or other farm staff.

c. Transformation process: related to the transformation of operational field data into manageable information for decision making.

d. World-view: the operational data is easily acquired and can be used to improve decision making.

e. Ownership: the farm manager as responsible to the everyday decision-maker, and decides whether the framework is of use.

f. Environmental constraints: includes the reliability and structure of information technology.

4 EXPERIMENTAL RESUTLS AND ANALYSIS

The experiments record the output of our optimisation module of DSS. At first, the Lovebird Algorithm is applied to the ARP dataset derived from previous research. Then, the Lovebird Algorithm is applied to solve the harvesting problem. Besides the Lovebird Algorithm, this research also applies GA and Tabu Search (TS) to compare the results.

The first column in Table 1 listed the dataset of ARP (based on the real field) that are taken from Bochtis and Vougioukas (2008) and Conesa-Muñoz et al. (2016). As shown in Table 1 columns 2-4, the Lovebird Algorithm can achieve the smallest non-working distance compared to those of GA and TS.

Problem Code	Non-working distance (meters)		
	Lovebird Algorithm	Genetic Algorithm	Tabu Search
A12	**146.027**	150.602	146.027
B12	**145.602**	160.602	146.027
C20	**235.491**	250.915	240.915

Table 1. The non-working distance of ARP dataset from previous research

For the harvesting problem, this research uses two kinds of fields as instances of ARP. The layout of the fields is shown in Figure 6. Each field has an entrance point, and the machines can enter the field only at that point. Also, every machine needs to start and end at the Depot. Every track is labelled with a number. The small number near the blue tracks in Figure 6 refers to the track number. For instance, in Figure 6, the first field has 18 tracks starting from the left to right, and the second field has 22 tracks (track no. 19-40). We use three machines with the same capacity (homogeneous machines). Another assumption is that each machine can harvest a maximum of 3000 meters of track.

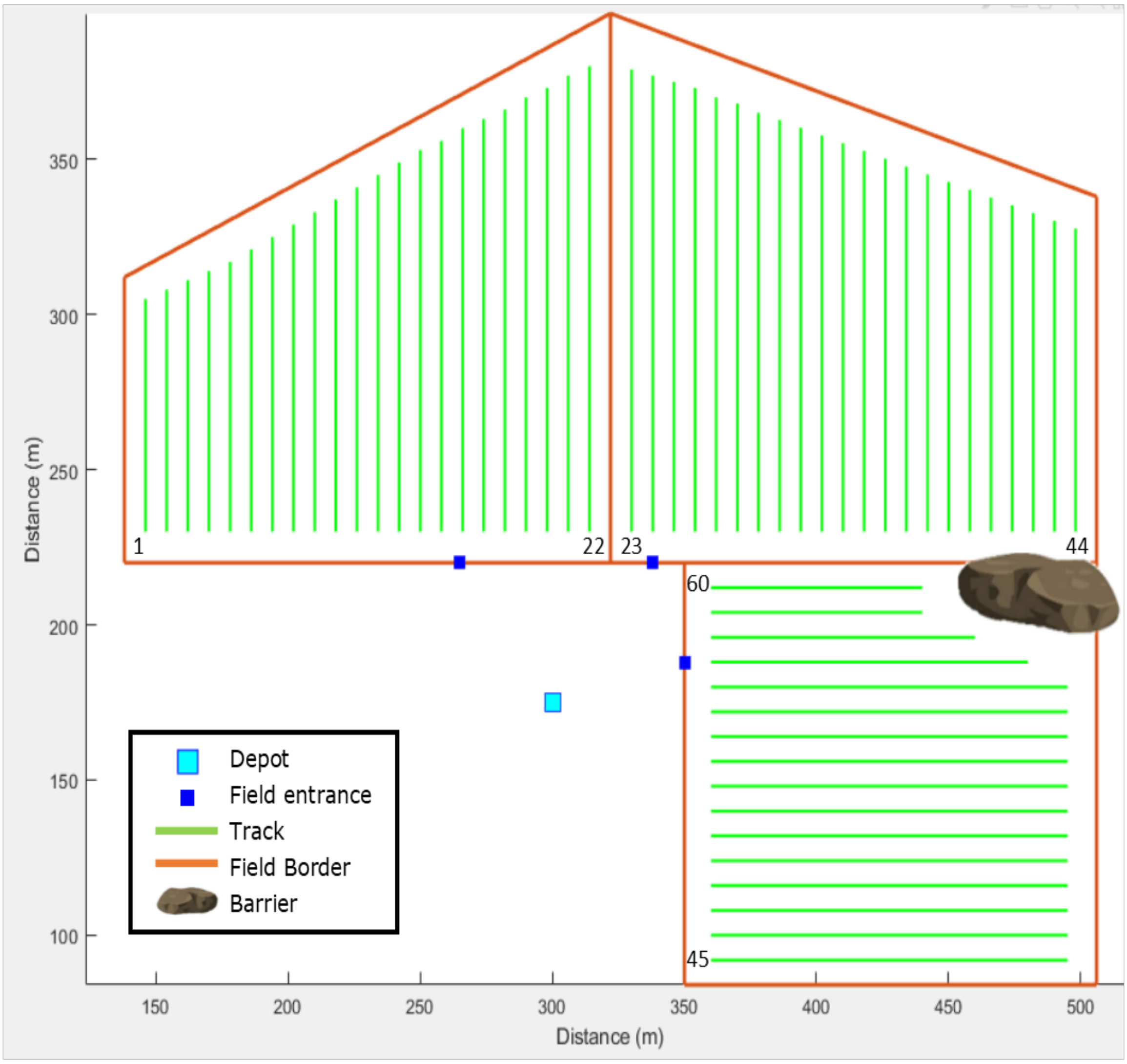


Figure 6: Diagram of three fields with 60 tracks.

Table 2 presents the results achieved with the Lovebird Algorithm compared to GA and TS. The first column in Table 2 refers to the number of fields and the total tracks in that field while the second, third, and fourth columns show the non-working distance of Lovebird Algorithm, GA, TS. The last column lists the distance reductions achieved by the Lovebird Algorithm compared to GA and TS. As shown in Table 2, the Lovebird Algorithm's solution always has the smallest non-working distance compared to those of other algorithms. The Lovebird Algorithm performs better than other algorithms because it applies several combinatorial operators that produce better solutions in ARP (Conesa-Muñoz, Pajares, et al. 2016). The Lovebird Algorithm successfully achieves an average of 8% distance reduction compared to that of GA and TS.

#Fields (#total tracks)	Non-working distance (meters)			Distance Reduction
	Lovebird Algorithm	Genetic Algorithm	Tabu Search	
2 (40)	**614.625**	673.634	634.718	6%
3 (60)	**1106.034**	1246.720	1189.704	10%

Table 2. Non-working distance comparison of Lovebird Algorithm, GA, and TS

Table 3 listed the optimised order of tracks of the Lovebird Algorithm. The first column refers to the fields and the machines used. The second column refers to the order of tracks, while the last column lists the length of the harvested tracks. The problem with two fields (Table 3 row 2-4) needs two machines to harvest the fields while the problem with three fields (Table 3 row 5-8) needs three machines. For example, in the problem with two fields, Machine 1 will go to Field 1 and harvest the tracks in the order 13, 15, 17, 18, 16, 14, 12, 11, 9, 8, 6, 5, 2, 1, 3, 4, 7, 10 and then it will go to Field 2 and harvest track no.

38, 36, 39, and 40. The rest of the tracks in Field 2 (track no. 37, 35, 33, 34, 32, 31, 29, 30, 28, 27, 25, 26, 24, 23, 20, 19, 21, 22) will be harvested by Machine 2.

Table 4 shows the comparison of the running time of the Lovebird Algorithm and other algorithms. The first column listed the problem, while the second column refers to the running time of the algorithms in seconds. The Lovebird Algorithm is able to get the faster running time in all problems compared to GA and TS.

Fields & Machine	Optimised Tracks-Order	Harvested Tracks (meters)
2 fields:		
Machine 1	Field 1 [13, 15, 17, 18, 16, 14, 12, 11, 9, 8, 6, 5, 2, 1, 3, 4, 7, 10]; Field 2 [38, 36, 39, 40]	2745
Machine 2	Field 2 [37, 35, 33, 34, 32, 31, 29, 30, 28, 27, 25, 26, 24, 23, 20, 19, 21, 22]	2159
3 fields:		
Machine 1	Field 1 [16, 14, 12, 11, 8, 7, 5, 3, 1, 2, 4, 6, 9, 10, 13, 15, 19, 20, 22, 21, 18, 17] Field 2 [34, 33]	2729
Machine 2	Field 2 [40, 42, 44, 43, 41, 39, 36, 35, 33, 34, 32, 31, 29, 30, 28, 27, 25, 26, 24, 23] Field 3 [58, 60, 59, 57, 54, 56]	2782
Machine 3	Field 3 [55, 52, 50, 48, 46, 45, 47, 49, 53, 51]	1350

Table 3. The optimised tracks'-order and the harvested tracks of Lovebird Algorithm

#Fields (#total tracks)	Running Time (Seconds)		
	Lovebird Algorithm	Genetic Algorithm	Tabu Search
2 (40)	**3.786**	4.850	4.859
3 (60)	**5.712**	6.819	7.693

Table 4. The running time comparison of Lovebird Algorithm, GA, and TS

5 CONCLUSION AND FUTURE WORKS

In regard to an agricultural field, the decision-making that is supported by a useful DSS can improve the quality of the decision. This study presents an optimisation module of a DSS in ARP that aims to decrease costs and to maintain sustainability. The Lovebird Algorithm is proposed as the optimisation method in the module to indicate the routes of machines in respect to the shortest non-working distance.

The comparison of the proposed algorithm with the Genetic Algorithm and Tabu Search shows that the Lovebird Algorithm successfully saves 8% travel distance and achieves the fastest running time in all problem instances. This study is limited to the development of the optimisation module of DSS in ARP.

Future research can focus on building the whole DSS to support decision-making in ARP. The various applications of the DSS in ARP, which include the optimised routing of the machines, can also be considered as a future direction, such as for herbicide applications, orchard operation, or fertilising operation. Another future research can focus on combining multiple systems, on improving the organisation of the field, which includes the DSS and several information systems related to fieldwork and the harvested crop management. Information about minimised routes for the machines is essential for both current and future agriculture field management. In the future, minimised routes can become the input for autonomous vehicles (without farmer onboard) that are used to harvest the fields.

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