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Evolutionary Estimation of Distribution Algorithm for Agricultural Routing Planning in Field Logistics

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Abstract

Agricultural Routing Planning (ARP), a problem in field logistics, has the objective to minimize the headland distance used by machines when performing agricultural tasks. This study gathers for its datasets the data for several fields obtained from previous research. The Estimation of Distribution Algorithm (EDA) is an algorithm that employs a probabilistic model to produce candidate solutions. This paper extends the EDA to become the Evolutionary EDA that combines a general EDA, a neighborhood search, and an elitism technique. Evolutionary EDA is tested on the optimization of ARP. The experimental results show that Evolutionary EDA can get the same or outperform the solutions generated by previously applied algorithms on ARP problems.

Keywords: Evolutionary algorithm; estimation distribution algorithm; agricultural routing planning; field logistics

1. Introduction

Agricultural routing planning in farm management is intended to design or schedule the movements of machines inside fields for agricultural tasks. A good design can minimize the distance of the machine's tours, thereby leading to cost savings. Hence, it is essential to have an optimized plan for the routing of the machines to complete agricultural field operations [1]. Figure 1 illustrates the layout of an agricultural field. The field has several established tracks with symmetrically planted crops. These tracks can be traversed by both agricultural machines and harvesters.

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Nomenclature

G	Graph $G = \{N, A\}$ representing the field's tracks
N	Set of nodes in the Graph G
A	Set of arcs in Graph G
S	Subgraph of Graph G, $\forall S \subseteq N$
i,j	Nodes indices $(i, j = 0, 1, 2, \ldots, n)$
M	Set of machines available at the depot, each referenced as m, $m \in M$
r	Minimum turning radius of a machine
w	Effective operating width of a machine
l	Length of the track in the field
B	Number of tracks in the field
d_{ij}	Maneuver's degree, i = the origin track, j = the destination track
$\Omega(d_{ij})$	Bulb type of maneuver turn executed by a machine in the headland area; executed when $d_{ij} > 2r / w$
$\Pi(d_{ij})$	Flat type of maneuver turn executed by a machine in headland field area; executed when $d_{ij} \leq 2r / w$

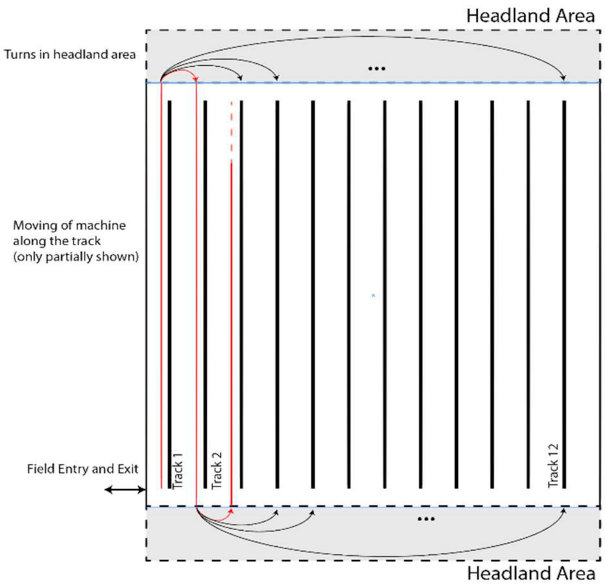

Fig. 1. Illustration of an agricultural field.

In Fig. 1, the headland areas North and South of the field refer to the headland area (crop-free) where machines perform maneuvers to go to the next track. The farmer needs to determine which sequence of tracks will cover the shortest distance, thereby reducing the overall cost. Note that we assume a rectangular field as this is the most common shape in agriculture.

Metaheuristics algorithms have been used in a diverse range of applications. In the agriculture sector, the Genetic Algorithm has been adapted for vehicle routing in biomass transportation [1], while Harmony Search was utilized to decrease the time needed for coverage optimization in vineyard parcels [2]. A hybrid Simulated Annealing was used for route planning of autonomous vehicles used for herbicide application [3], Particle Swarm Optimization was employed for route planning in sugarcane field operation [4], and Tabu Search was applied to reduce the fieldwork time in agricultural operations [5].

The Estimation of Distribution Algorithm (EDA) belongs to the class of stochastic optimization methods that use probabilistic models to get promising solutions. The probabilistic approach enhances the solution quality of EDA because the produced offspring are statistically built and sampled based on a probability model from a group of parents' best fitness [6]. As a stochastic optimization technique, the local-optima problem also arises in EDA's solution. Therefore, previous research proposed various combinations with other metaheuristic algorithms to avoid local optima, such as Genetic Algorithm (GA) to solve the job shop scheduling [7], Particle Swarm Optimization (PSO) to deal with the project makespan reduction [8], and Variable Neighborhood Search (VNS) to solve the flow-shop problem [9]. However, few studies have applied EDA for optimization in the agriculture context. Hence, this research focuses on building an EDA variant for Agricultural Routing Planning (ARP).

Most of the previous studies on ARP focused on real case studies and solved these with several different algorithms [5,10]. Those studies mostly apply existing algorithms when dealing with ARP, i.e., Clarke-Wright heuristic [5,11], Genetic Algorithm [12], and Tabu Search [5]. Therefore, the development of an extended algorithm and the application of EDA to ARP is a challenging area. Furthermore, when developing an algorithm, the experiments need to check whether the algorithm satisfies specific requirements [13]. The validation can be conducted by applying the algorithm to a set of ARP instances. Therefore, it is essential that an algorithm be tested before applying it to solve a new case that appears in ARP.

The output of this research can be embedded in a decision support system as part of an information system in the agricultural field. The decision support system that shows the optimized order of tracks helps the decision-making process of the farmer who wants to complete field operations within a shorter distance. The shorter distance results in more savings of time and fuel.

The significant contributions of this paper are (1) gathering data of rectangular fields to be datasets in ARP (2) proposing an extended variant of EDA, Evolutionary EDA (eEDA), and comparing it with algorithms in the literature in order to validate the performance of different algorithms on ARP optimization. Another contribution is the optimization of the routing of the machines to cover all tracks in fields to increase the cost savings and improve farm management.

2. Problem description

In ARP, the tracks represent nodes in a graph, which must be visited by a machine [14]. The arcs interfacing two nodes represent paths for the machines to move from one node to its neighbors. There are also a few limitations that can be considered, such as the maximum number of machines and the maximum distance that can be traveled by each machine.

The machines can move to another track with a specific type of maneuver. Since this study is concerned with the rectangular field, two maneuvers are considered: flat(Π), and bulb(Ω) turns. Fig. 2(a-b) show an illustration of the flat and bulb maneuvers, respectively. The flat turn covers a shorter distance than the bulb turn; however, some conditions must be met. Fig. 2(c-d) shows the relationship between the width w of the track and the turning radius r of a machine, their condition (c), and the associated graph (d). In Fig. 2(c-d), since $w \geq r > w/2$, the flat turn can occur only when the machine skips one or more tracks; otherwise, the bulb turn will be performed [11].

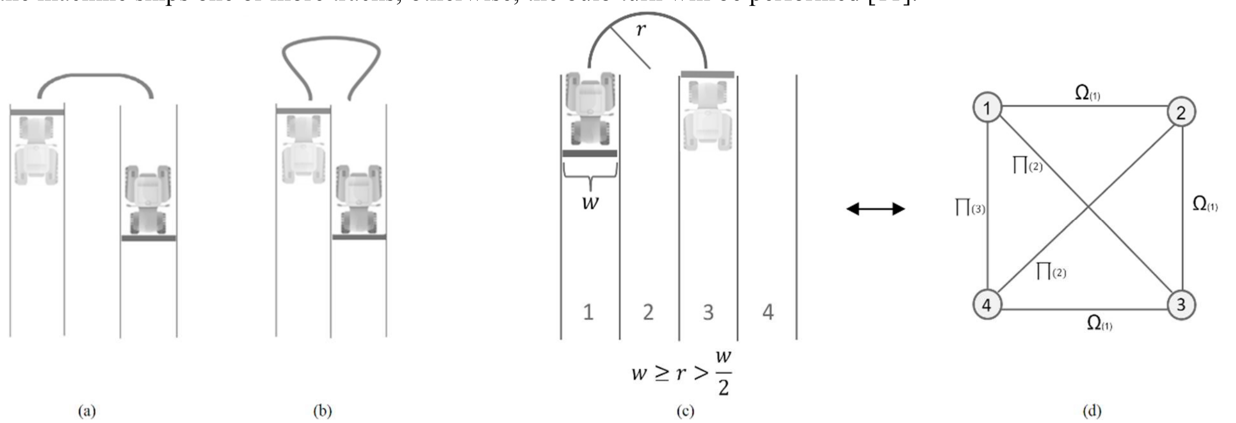

Fig. 2. The flat (a); and bulb (b) maneuver; and the connection between the maneuvers and the graph (c-d).

The mathematical model used in this study is provided in Equation (1)-(10). We use a binary decision variable x^{m}_{ij} that is equal to 1 if machine m moves from node i to j; otherwise, it equals to 0. Equation (1) provides the objective function of the ARP, minimizing the headland distance of the machines when performing their tasks in the agricultural field. Equation (2) is the total distance of the machines, which calculates all the tracks' length in the first term and adds it to the objective function in the second term. The objective function is restricted to nine constraints listed in (3)-(11). Constraints (3)-(5) present the condition and the calculation of flat and bulb turns, respectively. Constraints (6) and (7) ensure that every node is visited only once. Constraint (8) specifies that if a machine enters a node, it also has to leave that same node. Constraint (9) excludes disjoint sub-tours from a solution. The last constraint (10) specifies that the decision variable is a binary number.

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

$$Total\_Dist = l.B + \min\left(\sum_{i\in N}\sum_{j\in N}\sum_{m\in M} d_{ij}x_{ij}^{m}\right) \tag{2}$$

s.t.

$$\mathrm{d_{ij}}\begin{cases}\Pi(\mathrm{i,j}), \text{if } |\mathrm{i}-\mathrm{j}| \le \dfrac{2\mathrm{r}}{\mathrm{w}} \\ \Omega(\mathrm{i,j}), \text{if } |\mathrm{i}-\mathrm{j}| > \dfrac{2\mathrm{r}}{\mathrm{w}}\end{cases} \tag{3}$$

$$\Pi(\mathrm{i,j}) = \mathrm{d_{ij}}.w + (\pi-2)r \tag{4}$$

$$\Omega(i,j) = r\left(3\pi - 4\sin^{-1}\left(\frac{2r + d_{ij}.w}{4r}\right)\right) \tag{5}$$

$$\sum_{m\in M}\sum_{i\in N} x_{ij}^{m} = 1\ ,\ \ j\in N, i\neq j \tag{6}$$

$$\sum_{m\in M}\sum_{j\in N} x_{ji}^{m} = 1\ ,\ \ i\in N, i\neq j \tag{7}$$

$$\sum_{m\in M}\sum_{i\in N} x_{ij}^{m} = \sum_{m\in M}\sum_{j\in N} x_{ji}^{m}\ ,\ i,j\in N \tag{8}$$

$$\sum_{i\in S}\sum_{j\in S} x_{ij}^{m} \le \| S\| - 1, \forall S\subseteq N, \| S\| \ge 1, m\in M \tag{9}$$

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

3. Algorithm description

The Evolutionary EDA, being proposed in this study, is an extended variant of EDA that hybridizes the EDA with Permutation Neighborhood Search and Elitism as an evolutionary strategy. The eEDA uses a population of individuals, where each is depicted as a permutation of the track numbers in the field (The sequence of track numbers represents the order in which these are visited by a machine. The initial population of eEDA consists of randomly-generated individuals. The algorithm runs for several iterations and starts with the objective function calculation of each individual in the population. Then, the EDA procedure begins with the truncation selection, where the top fifty percent of the population is chosen [7,15]. The selected individuals are labeled as $h_1, h_2, h_3, \ldots, h_n$ $(h\in H)$ with n being half of the population size. Next, the probabilistic model is executed, which represents the importance of each track in the sequence.

The final step of the EDA procedure is the sampling that builds the new population. The pseudocode of the sampling method is listed in Fig. 3. At first, the procedure assigns a track to be placed in the first position (Line 3 of Fig. 3).

This assignment is chosen randomly from the first track of the group of selected individuals. The procedure is repeated until the last tracks are assigned. The selection uses the roulette wheel selection process (Lines 4 to 7 of Fig. 3) and is chosen proportionally based on the probability model from the previous step.

Afterward, the eEDA algorithm checks whether the current best solution is better than the global best solution so far. If there is no improvement, eEDA will perform the Permutation Neighborhood Search. Otherwise, it will go directly to the Elitism part. The Permutation Neighborhood Search is a variant of neighborhood search and mutation operators that focus on combinatorial optimization [16,17]. This study employs the swap, flip, slide, and insertion operators that are used in permutation encoding. The Elitism part records the best individuals through generations so that the prospective individuals are kept protected [18,19].

```
1 Procedure Sampling (Prob_Model, Selected_Individuals) {
2   for i=1 to Population_Size {
3     Pop[i,1] = RandSelect(Selected_Individuals[1])
4     for j=2 to Tracks_Size {
5       P ← Cumulative_probability(Prob_Model)
6       Pop[i,j] = Roulette_Wheel(P, Available_Tracks)
7     }
8   }
9 }
```

Fig. 3. The Sampling procedure of EDA.

4. Experimental results

We use five datasets from the literature to test the eEDA. Each problem is uniquely distinguished by different lengths and widths of tracks and different turning radii of the machine. The problem with 90 tracks is obtained from Seyyedhasani and Dvorak (2017) [5], while the others are from Conesa-Muñoz (2016) [3] and Bochtis and Vougioukas (2008) [11]. Three state-of-the-art algorithms are used to test against eEDA; these are Tabu Search (TS) [5], Genetic Algorithm (GA) [12,20] and Clarke Wright (CW) [5,11].

Here, we implemented the GA and TS based on the explanation in the respective publication [21,22], while we obtained the results of CW from the article itself [3,11]. The parameters of GA, TS, and eEDA are obtained from running the algorithms multiple times and record the best settings. The best parameter settings are listed in Table 1. The *tr* refers to the total number of tracks in the field. Table 2 represents the comparison of the headland distances and the total distances that are achieved by the algorithms. In Table 2, the first column is the problem code that also refers to the number of tracks in the field data. The other columns show the solutions obtained by CW, GA, TS, and eEDA, respectively. The bold value in Table 2 indicates the lowest solution found from that row (the same problem type). As listed in Table 2, eEDA is able to get the lowest headland distance and the total distance in all problem instances. TS can get the minimum result in two problems, while GA only obtain a good result in one problem. In contrast, CW is not able to get a single optimal result compared to the other algorithms.

Table 1. Parameter settings.

Parameters	Value
Number of Iterations (GA, TS, eEDA)	*25tr*
Population Size (GA, eEDA)	*6tr*
Neighborhood Search Iteration (eEDA)	*tr*
Tabu tenure (TS)	*0.5tr*

Table 2. The headland and the total distance of all algorithms.

Problem	CW*		GA		TS		EEDA	
	Headland	Total	Headland	Total	Headland	Total	Headland	Total
8	95.767	335.767	**94.439**	**334.439**	**94.439**	**334.439**	**94.439**	**334.439**
12a	176.451	656.451	150.602	630.602	**146.027**	**626.027**	**146.027**	**626.027**
12b	166.451	1006.451	160.602	1000.602	146.027	986.0267	**145.602**	**985.602**
20	235.916	1835.916	250.915	1850.915	240.915	1840.915	**235.491**	**1835.491**
90	-	-	2865.077	11865.077	2951.022	11951.022	**2680.172**	**11680.172**

*The solution of CW algorithm are obtained from [3,11]

Fig. 4 depicts the comparison of the machine's routes obtained by all algorithms for Problem 12b. In Fig. 4, the circle symbol represents the start of the route while the diamond symbol refers to the end of the route. The routes and the distances of CW, GA, TS, and eEDA are described in Fig. 4(a-d), respectively. The shortest route is the solution of eEDA (Fig. 4(d)), and the longest route is the one produced by CW (Fig. 4 (a)). Fig. 4 also demonstrates that in order to obtain the shortest route, it is not essential to ensure that all the maneuvers make flat turns; they can make bulb turns as well. GA's route (Fig. 4(b)) has a bulb turn and has a shorter distance than CW. Both eEDA and TS create routes with two bulb turns, and the distance is shorter than GA. The route of eEDA (Fig. 4(d) at the top) makes a shorter flat turn than the one produced by TS (Fig. 4(c) at the top), making eEDA's solution much better. Fig 5 describes the route using eEDA to solve problem 90. There are three homogeneous machines used in this problem, represented by the different colors. In this problem, the flat turn is the dominant maneuver.

Fig. 6 depicts the convergence process of GA, TS, and eEDA for problems 20(a) and 90(b). The X-axis is the generation, while the Y-axis is the objective function value. GA's solution to problem 20 is worse than the others, while the one for Problem 90 is better than TS after half of the generations. TS converges the fastest in problem 90; however, it seems to be trapped in a local-optima since the solution is not improved after approximately a quarter of the total iterations. For both problems, eEDA's solution is always better than those of other algorithms. The eEDA's objective function converges fast and ends with the best solution compared to GA and TS. Overall, the eEDA's convergence process is better than those of GA and TS.

The eEDA combines EDA and the permutation neighborhood search in its structure, enabling the algorithm to both explore and exploit the candidate solution. Both CW and TS focus only on exploiting the solutions without exploring it, while GA focuses only on exploring the solution. These reasons enable eEDA to outperform CW, GA, and TS.

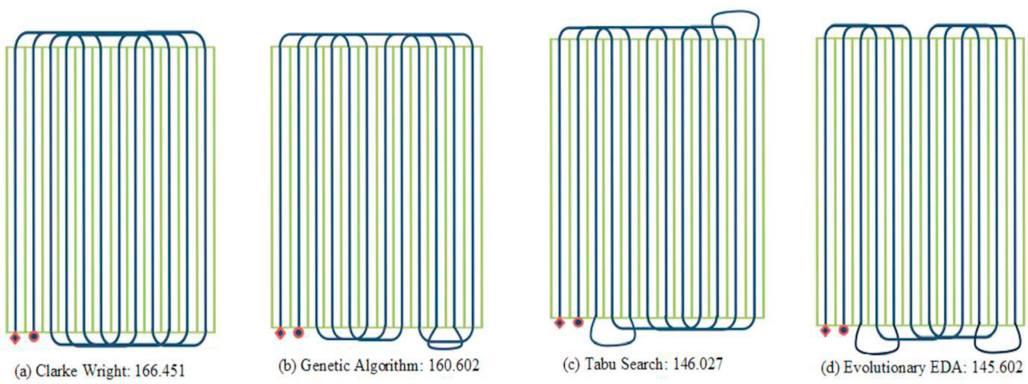

Fig. 4. The machine' route and solution for problem 12b.

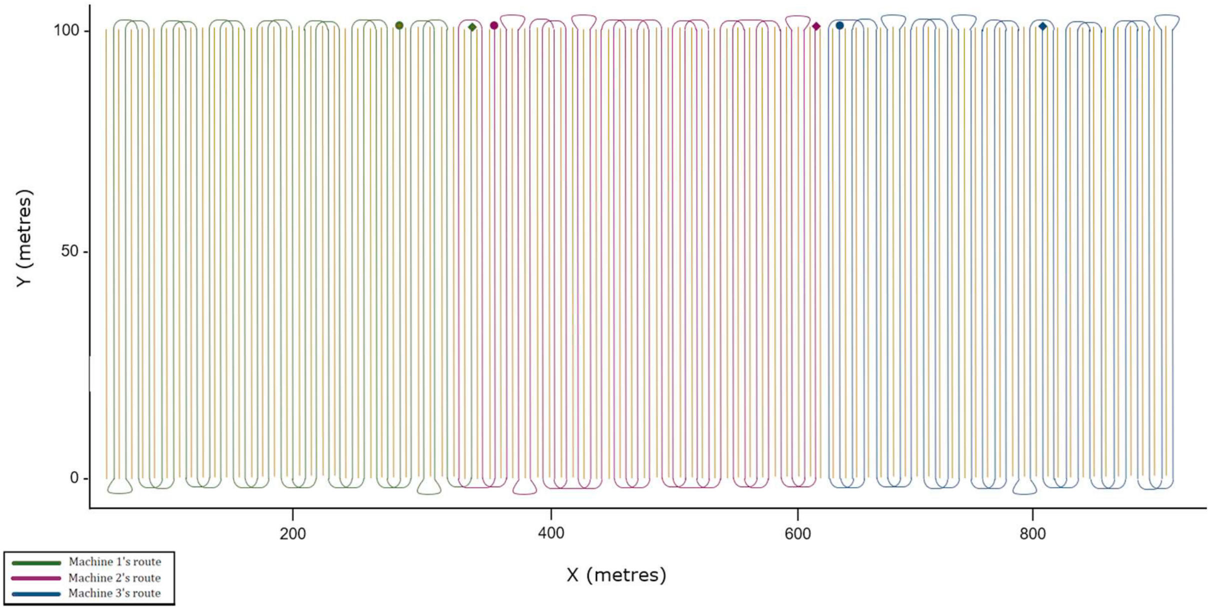

Fig. 5. The eEDA's route for problem 90.

Fig. 6. The convergence graph for (a) Problem 20; and (b) Problem 90.

5. Conclusion

This study is a preliminary study that gathers several data from previous studies describing different rectangular fields in ARP. Then, an extended version of EDA, called Evolutionary EDA, is proposed to solve the ARP problem. This research conducts a comparative study of datasets from published experiments using different algorithms. The algorithms that are used for comparison are Clarke Wright, Genetic Algorithm, and Tabu Search. The experimental results demonstrate that eEDA outperforms the other algorithms.

Since there is no standard dataset in ARP, future research could focus on developing benchmark datasets with different sizes and layouts. The generation of ARP data for a practical purpose that considers actual situations can also be another focus of future study. The development of algorithms can also be regarded as another future research path, given that there is still a limited dominant algorithm for finding optimal solutions in ARP.

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