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Agricultural rout planning with variable rate pesticide application in a greenhouse environment

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Abstract The use of robotics in executing agricultural tasks has significantly improved productivity over the years as a result of automation in performing such activities as spray, harvesting, planting etc. In order to optimize both crop yield and quality while minimizing costs, there will be need for the application of navigation strategies. These will provide optimal as well as autonomous navigation capability which is built entirely upon field coverage plan thereby making robot navigation approach a paramount scheme. In this paper, the autonomy of an agricultural mobile robot is enhanced in a structured environment (greenhouse farm) to locate an optimum route such that the robot performs a selective and variable spray of pesticides to the plants. To realize this, a robust vehicle routing problem (VRP) scheme is designed to navigate the robot autonomously while making intelligent decisions to fulfil the pesticide demands at each node (infected plants). The improved non-dominated sorting genetic algorithm (INSGA-III) is adopted to solve this fully integer problem based on three (3) test cases carried out with 8, 32 and 56 infected plants respectively for validation. The results obtained show a trade-off solution as the Optimal INSGA-III is significantly lower than NSGA-III in terms of solution quality. On the other hand, a significant reduction in run times of between 66% and 76% and 76–93% was obtained for all test case scenarios for population sizes of 100 and 1500 respectively.

1. Introduction

In agriculture, pesticide application refers to the practical method wherein pesticides (e.g. herbicides or fungicides) are dispensed to target crops or other plants. Although the use of pesticides is necessary in modern agriculture, they are still toxic and hazardous to general creatures as well as the environments [1]. Manual method for pesticide application in a greenhouse involves an operator moving about while manually and selectively spraying the target crops by means of a backpack sprayer [1,2]. Despite the use of protective pesticide equipment, the human operator is still vulnerable to toxic and hazardous chemicals that can lead to complications [1]. Hence, it is necessary to make use of an autonomous pesticide sprayer in order to avoid human exposure to these chemicals. The device could,

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further, ensure that calculated amount of spray is applied to all plants accordingly which will additionally minimize wastes due to improved accuracy and precision [1]. Uniform pesticides application throughout the entire farming field is a common norm in most farming practices even though pest and diseases display an uneven spatial distribution [3-5]. However, the current development of selective spraying only focuses on the infected area and only a few literatures have explored the way to reduce the mobile robot navigation costs whilst executing the spray task especially in multi-objective application [6–9].

Agricultural mobile robots are capable of executing virtually all navigation actions autonomously, but providing an optimal and complete field coverage strategies created on this navigation capability hereby, makes it an active research area [10-15]. The foremost challenge of field coverage planning is the non-deterministic polynomial time (NP-Hard) nature of the problem and therefore, optimal solutions are computationally problematic [16,17]. In general, routing problems have a peculiar challenge which has compelled the advancement of algorithms that can deliver practically optimal solutions in a reasonable time frame [18-21]. The processing power of the computer has been inadequate in previous decades because they could not handle the metaheuristic search algorithms that were developed. This is however, as against the conventional heuristic methods developed for search of possible solutions. Therefore, route optimization algorithms for agricultural vehicles are a very functional area of research. Many researchers have proposed some novel and more efficient approaches of converting the field coverage problem to a Travelling Salesperson Problem or a VRP and, are currently exploring new *meta*-heuristics to optimally provide routes solutions more efficiently [22-25]. However, efficient solutions have not been provided for the VRP problem and consequently, there is a trend towards providing the optimal routes for agricultural vehicles (including robots) on agricultural lands through various *meta*-heuristic algorithms. More advanced and recent *meta*-heuristic algorithms, like Tabu Search algorithm [26-28], Fluid Search optimization [29], Simulated Annealing [29-31]and, Evolutionary Algorithms for example, Genetic Algorithms [32–36] are proposed to accomplish an in-depth search for probable results but are more cumbersome in terms of computational complexities [13,37]. The type of problem and the model of the *meta*-heuristic algorithm affect both, how long the calculation takes and the extent of optimization that can be achieved [38]. The objectives considered in order to meet up with the research goal are: (1) Transform the robot assignment into a VRP that permits the minimization of time to complete spray activity in the greenhouse via the minimization of distance travelled and the turns made by the robot. (2) Establish solutions to the VRP transformation that have been developed and (3) Implementation of the INSGA-III to solve the multi-objective routing problem for robot navigation inside the greenhouse. The current study is conducted to overcome run time problem for NSGA-III in the robot route finding problem under limited capacity constrain. The main highlights of the current work which distinguishes this study from the works in the previous literatures are:

- Considering variable spray dosage (drain capacity limit) limited capacity
- Adopting INSGA-III for the optimization and comparing the performance with NSGA-III.

The INSGA-III has not been previously applied for this problem and the remaining part of this paper is presented as follows: Section 2 presents the related works. Section 3 presents the methodology which covers the navigation plan, the greenhouse layout and the navigation algorithm. Variable dosage and the techniques adopted for optimization schemes were described in Section 3. while the results section is covered in Section 4 and the conclusion summarises the paper in Section 5.

2. Related works

Many researchers have worked and proposed different optimization perspectives as relates to the problem of field completion time, costs, optimal field coverage and many more. For instance, TS was applied to agricultural VRP in [39-41] to find the route for multiple agricultural machines to reduce the field completion time with the objective of maximizing the field capacity and minimizing the operational time and cost. The objectives have been reduced to a single objective with the priority to minimizing the field completion time. The performance of TS has been accessed and it demonstrates superior performances as regards the solution quality in comparison with the Modified Clarke-Wright Algorithm. However, another approach to optimal field coverage was proposed in [42] which is based on ant colony optimization algorithm. The paper sought for the optimal route for combine harvesters which facilitated the unloading of stationary facility located outside the field area or within the field boundary. In a related approach, a variant of PSO (GLNPSO), was applied in [43] to solve mechanical harvester routing problem (MHRP) of sugarcane field processes having accessibility constraints, with the objective to maximize total sugarcane yield while minimizing the total distance simultaneously. By way of comparison, the GLNPSO outperforms the NSGA-II in terms of quality and underperforms in execution time.

Different variants of the NSGA-II applicable to finding the optimal routes for both single and fleet of vehicles in general and agricultural VRP have been reported in [32-36]. However, they are considered as reliable tools used in solving multi-objective optimization problem and their solutions are generally adjudged to be satisfactory in terms of quality. However, some inconsistencies of the algorithm especially in resolving multi-objective problems having complex and non-dominated solutions were reported by Reed et al. in [44]. This led to further investigation for improved version of the algorithm (NSGA-III) to seek for a better and more efficient Pareto optimal solutions as proposed by [45]. Building upon this development, Mahmoud et al. implemented the NSGA-III in [4], to minimize the routing angle the travel and total distance of an agricultural mobile robot to perform a spray operation in a greenhouse environment. Despite the NSGA-III consistently showed a significant improvement regarding the solution quality and feasibility to solve engineering optimization problems as well as other benchmark functions, a setback was recorded in terms of execution time. This is as a consequence to non-dominated solutions in which increases sharply when the number of objectives increases. The effect of this is an eventual loss of extreme points which indicates the extent of solution diversity [46].

The aim of this research article is to determine an optimal pathfinding for an agricultural robot to perform a complete and variable spray operation in the greenhouse. The greenhouse considered in this regard has a predefined route where the robot can have access to each of the plant coordinates. This includes among many components, ensuring the lowest cost in terms of the time and distance for the overall spray operation of the infected plants while also satisfying a constraint condition such as the robot tank capacity. Although, the standard VRPs are usually designed to work with robots with capacity restraints for both pesticide and charging, this investigation is only restricted to pesticide capacity in order to focus on the spray activity. The proposed approach is based on an INSGA-III in which, an elimination mechanism is used to cut down the selection efforts instead of the usual selection mechanism to find the optimum solution to the VRP. The main novelty in this case is the resolution of the path-planning problem for an autonomous robot that acts in a greenhouse environment by adopting the variable spray operation.

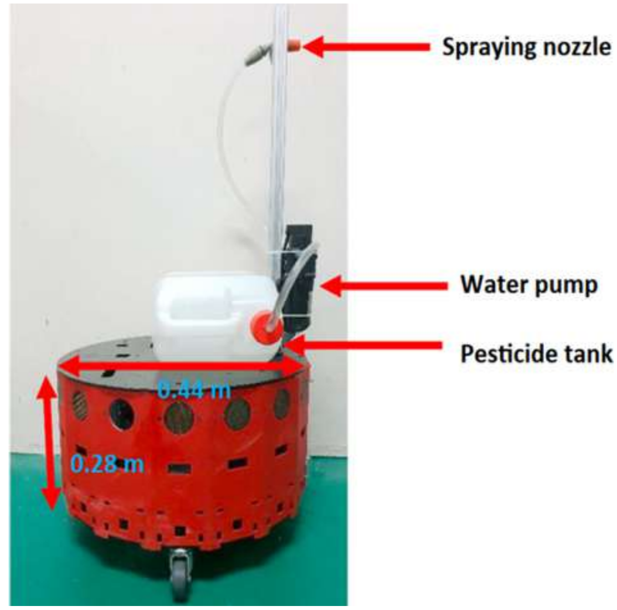

Fig. 1 The mobile robot system.

3. Methodology

3.1. Mobile robot system

The method for implementing the spraying process involves the use of a practical agricultural mobile robot having a circular base with the following parameter [4]. A radius of 0.22 m, weight of 8.6 kg and 0.28 m height. The model has two main wheels driven by DC motor of LO-COG GM9434K332 (Ametek, Pennsylvania, USA) description fitted with incremental encoder and stabilized by a castor wheel. The components involved in the pesticides spray activity includes the following: A 0.5 L/min spraying nozzle, pesticide tank with 1 L capacity fitted with a 70 W water pump having 6 L/min maximum flowrate. An Arduino Mega (8-bit ATMega2560 processor) is used to control the robot motion via the wheel speed while the motors are driven by IC driver MD10C 10A. Fig. 1 shows the mobile robot system with a circular base structure.

3.1.1. Time of travel calculation

Assuming the robot to have a constant speed, the time becomes a linear function of the total distance which therefore reduces the problem to two objectives. In reality, a constant speed assumption for robot model is not always a satisfactory one and therefore, the movement is decomposed in two actions:

1- The robot corrects the angle and targets the next node.
2- The robot moves to the targeted node with maximum allowable speed.

In the above methods, the robot always targets a straightforward path towards the next node thereby making the speed to change while it travels. The following function which fits to data can be used to evaluate the time of travel T_L, in a linear movement as represented in Eq. (1).

$$T_L = ae^{-bL} + cL + d \tag{1}$$

where$L$, is the distance traveled and $a, b, candd$ are fit constants. Similarly, linear motion regression approach is used to obtain the angular speed, ω of the robot as shown in Eq. (2):

$$\omega = a\theta \tag{2}$$

Since the angular speed is a linear function of the angle of rotation, the rotation speed and the time of rotation are constant for all angles. Then the time of rotation can be represented as in Eq. (3):

$$T_\theta = \frac{\theta}{\omega} = \frac{1}{a} = \frac{1}{1.128} = 0.8865 \ \text{sec} \tag{3}$$

The so obtained time functions for rotation and linear movements are then used to obtain the total time of travel and the angle of rotation for each visit sequence or route. Each route consists of all the plants to be visited in a specified sequence and then, the start and end point (depot) which are connected by roads. The problem therefore, is defined in terms of finding the optimal route that passes through all plants only once with minimal time, distance and rotation. The robot problem for greenhouse, as discussed in the introduction can be formulated as a VRP characterized by a single vehicle, single depot and deterministic variable demand. The formulation is as follows:

$$\min \ \vec{F}(\vec{X}) \tag{4}$$

$$1 \leq X_i \leq N \tag{5}$$

and subject to capacity limitation defined in Eq. (6)

$$\sum_{i=1}^{K} d_i \leq C \tag{6}$$

where X_i is an integer, K is the loop size for the vehicle before revisiting while$d$ is the demand of each plant. Since the problem is an integer multi objective optimization, the vector form of the objective functions is used. The objectives are presented in the vector form as in Eq. (7)

$$\vec{F} = \begin{bmatrix} T \\ \Theta \\ L \end{bmatrix} \quad (7)$$

where T is the total time of travel, Θ is total angle of rotation and L is total distance travelled.

3.2. Problem formulation

3.2.1. The greenhouse geometry

The geometry of the greenhouse with plants pots arranged in 8 rows is represented in planar view after having been converted into black and white photo as shown in Fig. 2. The white area is the allowed region and the black area is the occupied region (not allowed)

From this figure and based on the robot radius which is 20 cm, occupancy grid is developed using binary occupancy grid function using robotics toolbox in MATLAB and inflated by an inflation function by the radius of the robot. It is therefore required to obtain a discrete model of the unoccupied space on the plan of greenhouse. Using a probabilistic road map function (PRM), the discrete model is developed by 2000 nodes and thereby making the available space discretised in set of (x, y) values with connecting lines. The next step is to find the shortest paths between a pair of plants that are required to be sprayed and the shortest path algorithm in MATLAB robotic toolbox, which implements the A* method, is applied. The output is the shortest path between each pair of plants which are required to be sprayed on the discrete plan of the greenhouse.

The robot problem can now be redefined to find the minimum route which consists of these roads in where the objective functions are minimized. Since the problem is multi objective, the solution is represented in the pareto form. To realize the objective function, it is necessary to understand the road between two plants and Fig. 3 shows a typical road between two plants on a discrete plan. However, this consists of three nodes and connecting straight lines with each road having lines and angles of path corrections. Then, the total length and total angle of rotation for the road connecting two plants are the sum of all the absolute values of the length and angles.

Since paths are selected from a discretized space, it is important to choose a path which is as straight as possible. In fact, the best pass is the path which minimizes the time and as straight as possible. To measure the straightness of a path, assume that we are traveling from i to 1 to i, then to i + 1, from i to 1 to i there is a straight line and from i to i + 1 is another straight line. There is an angle between these two lines called φ_i. The best path is the one in which φ_i is the smallest value or in another word, all points lie on a straight line. In real application this is not possible since:

1- Points are selected from randomly discretized space.
2- There are obstacles which make straight paths impossible.

3.2.2. Objectives

For each route, which includes the time to refill, the objective functions are evaluated as:

$$T = \sum_{i=1}^{K-1} T_{L_i} + \sum_{i=1}^{K-1} T_{\theta_i} \quad (8)$$

$$L = \sum_{i=1}^{K-1} L_i = \sum_{i=1}^{K-1} \sqrt{(x_{i+1} - x_i)^2 + (y_{i+1} - y_i)^2} \quad (9)$$

$$\Theta = \sum_{i=2}^{K-1} \tan^{-1} \frac{y_{i+1} - y_i}{x_{i+1} - x_i} - \tan^{-1} \frac{y_i - y_{i-1}}{x_i - x_{i-1}} \quad (10)$$

where, T is the total time of traversal, T_{θ_i} is the time to make a turn, L is the total distance and Θ is the routing angle.

3.2.3. Sequence of visit

Visit vector $\vec{X}$ shows the order in which the robot visits the plants. This vector needs to be modified to a sequence in which 'return to refill' is added. The algorithm to execute the plant visit order considering the capacity of the robot is given in Table 1.

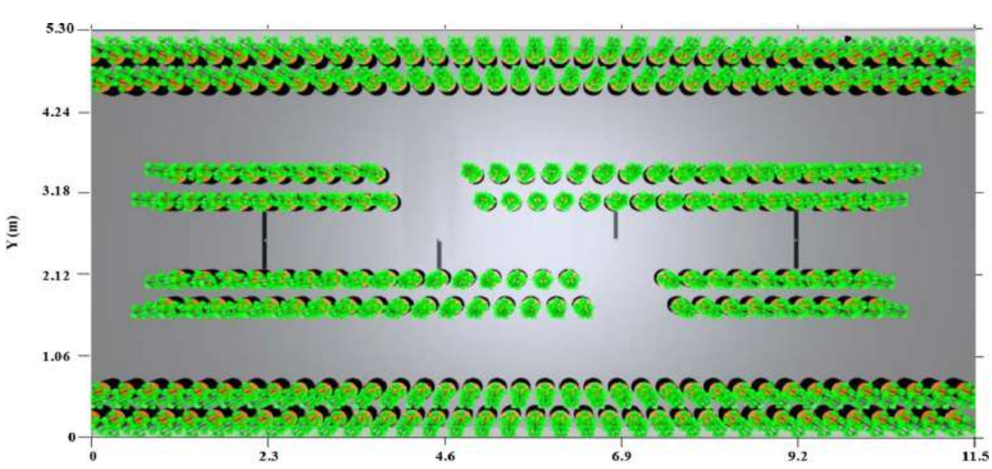

Fig. 2 Greenhouse with plants locations [4].

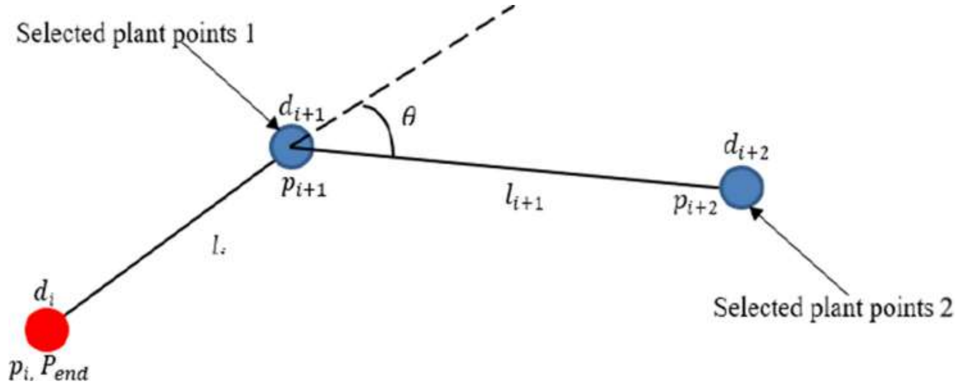

Fig. 3 A path between two plants.

Table 1 Algorithm for plant visit order.

Algorithm 1: plant visit order

1. Set the capacity at maximum, the tank is full at starting (Depot).
Set **Seq**. (1) = 0, **C** = **TC**. ∀ plants in **X(i)**; //Initialize the sequence and available spray.
2. Visit plant **X(i)** and spray the plant.
Then the current capacity is **C** = **C**−d_i.
3. IF **C** < d_{i+1}, go to refill
C = **TC**,
Seq. **(j)** = **X(i)**
Seq. (j + 1) = 0 //Add the Depot node number to the sequence
ELSE **Seq**. **(j)** = **X (i)**. //Sequence at current visit is set only.
4. IF i = **N** (number of plants to visit)
Seq. **(j** + 1) = 0 (return to depot). //Add the Depot node number to the sequence
5. End

Where, d_i is the pesticide demand for a given infected plant, **C** is the tank capacity and **N** is the total number of plants. The above procedure converts the visit vector $\overrightarrow{X}$ to Seq. which includes refilling. This is followed by evaluating the objective functions for each Seq. Using the sequence, roads between two consecutive plants (i.e. plants and depot), are added to construct the route and thereafter, the route length, angle, and time of travel are calculated.

3.2.4. Dosage

Three test cases are presented and the results are evaluated as follows: The cases considered have different sizes which are 8, 32, and 56 plants. The capacity of the spray tank is 4 L and the dosage for each plant is selected by uniform random function from the given set of values: {300,350,400,450,500}ml so that each plant dosage is a random value selected from the given set. The values are obtained from on the previous spray observations in the greenhouse [4].

3.2.5. Plants locations

Since there are 8 rows in the green house, a random selection of any given number of plants from each row is applied in a way that same number of plants are selected from each row. This implies that the robot must travel across the greenhouse and face all obstacles while the plant locations are chosen using random number generators of uniform distribution in MATLAB. To make the numbers unique, *randperm* function is used. Table 2 and 3 present the input data for all the cases.

3.3. Proposed NSGA-III based algorithm

Optimization with NSGAIII and INSGA-III versions are conducted here. The improved version has higher speed but not without its attendant trade-off. Hence, the performance of the improved version in terms of time and optimal solution should be evaluated. On the other hand, the operation time for NSGA-III becomes high especially when the population size is large. The proposed INSGA-III algorithm has an edge over NSGA-III in the sense that, as the optimization progresses through successive generations, it will not be necessary to maintain all population sizes at each iteration. In fact, by a proposed ranking system, population is reduced along the optimization process which increases the speed of the method. Despite that NSGA-III is efficient in solving numerous standard functions and some optimization problems like the agricultural VRP, the conventional NSGA-III still has some setbacks. For instance, the number of non-dominated solutions in combined population might surge abruptly when the number of objectives increases. Hence, this increases the execution time of the selection process. More so, the conventional NSGA-III can lead to loss of farthest

Table 2 Data for case 1 (8 plants) optimization problem.

No.	*St*	1	2	3	4	5	6	7	8
Dosage(l)	0	0.45	0.35	0.5	0.4	0.45	0.35	0.3	0.3
X (m)	0.86	9.60	10.33	2.33	10.04	7.56	1.89	3.78	6.55
Y (m)	2.09	4.48	4.48	4.00	2.87	2.53	1.41	1.01	1.01

Table 3 Data for case 2 (32 plants) and case3 (56) optimization problems.

Case 2 (32 plants)				Case 3 (56 plants)							
NO	Dosage(l)	X(m)	Y(m)	NO	Dosage(l)	X(m)	Y(m)	NO	D	X(m)	Y(m)
St	0	0.86	2.09	**St**	0	0.86	2.09	**33**	0.35	5.96	2.53
1	0.3	1.45	4.48	**1**	0.3	9.60	4.48	**34**	0.3	10.62	2.53
2	0.4	4.95	4.48	**2**	0.5	3.78	4.48	**35**	0.3	5.67	2.53
3	0.4	5.53	4.48	**3**	0.45	3.20	4.48	**36**	0.5	9.31	1.41
4	0.3	7.85	4.48	**4**	0.3	8.73	4.48	**37**	0.3	1.02	1.41
5	0.35	2.18	4.48	**5**	0.3	5.82	4.48	**38**	0.3	4.80	1.41
6	0.35	7.71	4.48	**6**	0.45	5.53	4.48	**39**	0.35	7.85	1.41
7	0.3	7.13	4.48	**7**	0.45	10.18	4.48	**40**	0.4	5.67	1.41
8	0.45	10.91	4.48	**8**	0.35	2.18	4.48	**41**	0.35	1.89	1.41
9	0.3	7.56	4.00	**9**	0.3	4.80	4.48	**42**	0.4	4.51	1.41
10	0.5	10.18	4.00	**10**	0.45	10.33	4.48	**43**	0.5	5.53	1.01
11	0.35	9.31	4.00	**11**	0.35	8.87	4.48	**44**	0.45	2.62	1.01
12	0.3	11.06	4.00	**12**	0.5	5.38	4.48	**45**	0.35	9.89	1.01
13	0.45	7.71	2.87	**13**	0.35	5.96	4.48	**46**	0.4	8.44	1.01
14	0.45	5.38	2.87	**14**	0.45	4.22	4.48	**47**	0.5	4.65	1.01
15	0.4	1.75	2.87	**15**	0.3	8.15	4.00	**48**	0.3	4.07	1.01
16	0.35	6.84	2.87	**16**	0.3	2.33	4.00	**49**	0.35	3.78	1.01
17	0.3	7.85	2.53	**17**	0.35	8.73	4.00	**50**	0.35	10.33	1.01
18	0.45	10.62	2.53	**18**	0.3	6.98	4.00	**51**	0.35	1.60	1.01
19	0.3	5.96	2.53	**19**	0.5	11.06	4.00	**52**	0.4	6.25	1.01
20	0.4	7.56	2.53	**20**	0.35	1.16	4.00	**53**	0.45	3.05	1.01
21	0.3	3.93	1.41	**21**	0.4	6.69	4.00	**54**	0.3	8.87	1.01
22	0.4	6.55	1.41	**22**	0.4	4.07	2.87	**55**	0.3	3.64	1.01
23	0.35	2.76	1.41	**23**	0.4	2.91	2.87	**56**	0.45	2.76	1.01
24	0.3	1.31	1.41	**24**	0.4	6.25	2.87				
25	0.45	10.47	1.01	**25**	0.35	8.87	2.87				
26	0.4	6.98	1.01	**26**	0.5	10.33	2.87				
27	0.5	9.89	1.01	**27**	0.3	1.45	2.87				
28	0.45	4.95	1.01	**28**	0.35	3.20	2.87				
29	0.35	10.91	1.01	**29**	0.4	4.36	2.53				
30	0.45	5.09	1.01	**30**	0.35	6.55	2.53				
31	0.45	6.84	1.01	**31**	0.4	3.20	2.53				
32	0.5	3.35	1.01	**32**	0.4	10.33	2.53				

points, yet, it indicates the extent of diversity in the solutions [46]. Moreover, the agricultural VRP here has numerous constraints and thus, the INSGA-III will be introduced in to solve the multi-objective agricultural VRP problem defined above. The improved algorithm is achieved by introducing an elimination strategy through a mechanism and the enhancement of the efficiency of the selection process. Therefore, the amount of eliminations is greatly reduced when compared with the conventional algorithm. Fig. 4 is the INSGA-III operation diagram showing all the major components of the algorithm. Further to earlier introduction, the base optimization algorithm used here, is the NSGA-III which is modified to accept integer variables. The problem is fully integer and all the operators including random generators, mutation and crossover operators are converted to fully integer ones in such a way that inputs and outputs are fully integer. The main concern with the problem is that X must be a unique permutation of numbers between 1 to N. This implies that, the constraint of uniqueness must be applied on all operators and random population generator itself to ensure that all solution points satisfy the uniqueness of the constraint. In order to perform an optimization for NSGA-III and INSGA-III, large initial populations are selected. The justification is that with large population size, the time difference measurement is more accurate, and it is an assurance that INSGA-III will not be stuck with a poor local minimum since the population size reduces with iteration. The comparison is conducted separately for each case while the setup for comparison of methods are presented as well.

Step 1: Specify decision variables and numerical ranges in total path travelled by the agricultural mobile robot, overall time of transaction and the total rotation (routing) angle

Step 2: Select objective functions to be optimized

Step 3: Initialize algorithm parameters, such as cross rate, mutation rate, cross index and mutation index. Set population size$N$, maximum iterations I_m and numerical range of state variables. $Sett = 0$

Step 4: Generate H well-spread reference points according to population size

Step 5: Randomly initialize population P_t according to numerical ranges of decision variables

Step 6: Generate offspring population Q_t by genetic operation using parent population P_t. The size of both P_t and Q_t is N

Step 7: Merge P_t and Q_t to obtain a combined population R_t. Fix individuals that are out of range using constraint handling method. Adopt Newton-Ralph method to calculate load flow. Calculate fitness value and CV of each individual in R_t

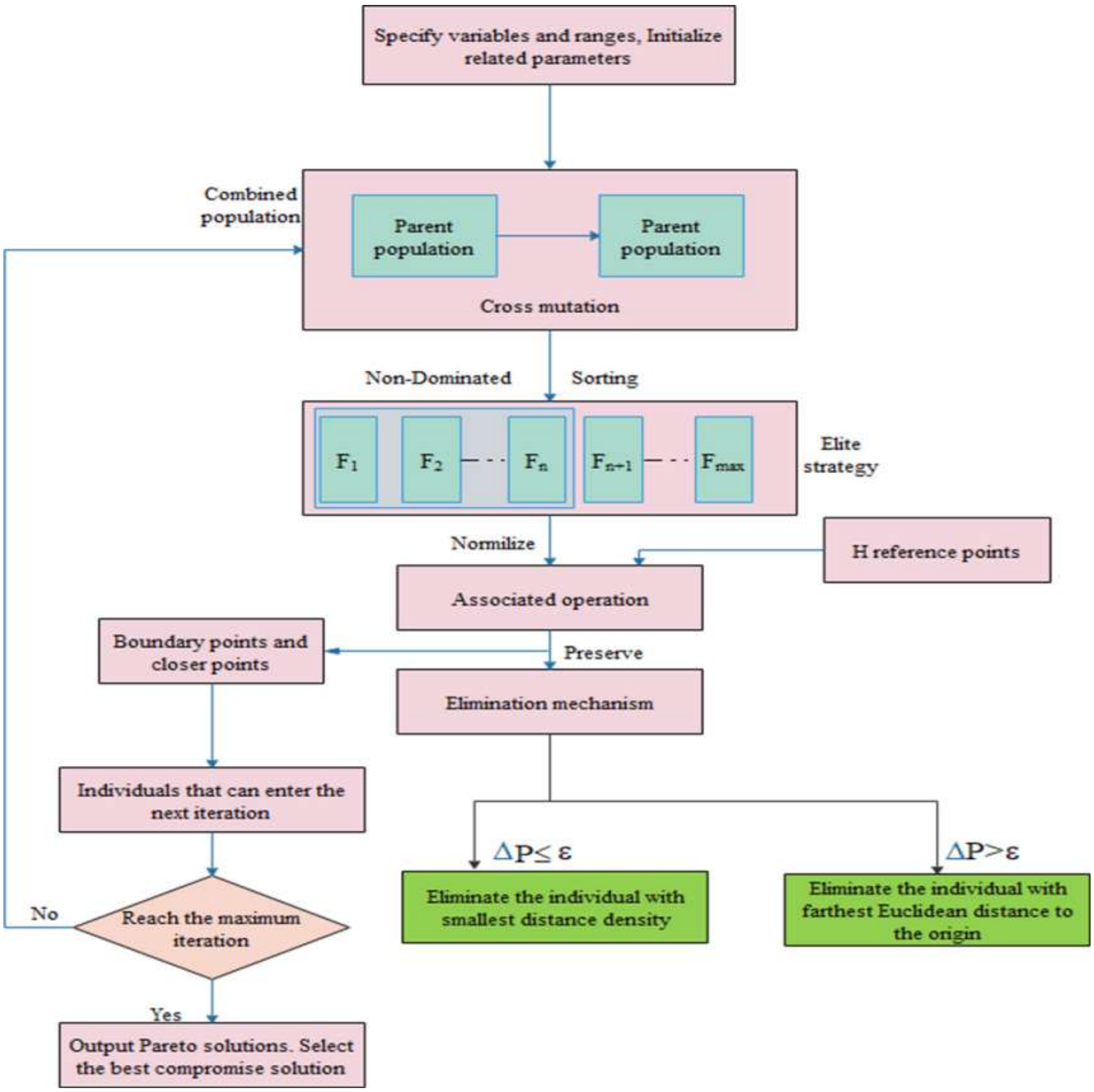

Fig. 4 INSGA-lll operation diagram [46]

Step 8: Stratify R_t according to constrain-domination principle to obtain layers $F_1, F_2, F_3 \cdots$.

Step 9: Construct $S_t = \phi, i = 1$. Execute $S_t = S_t \cup F_n, (n = 1, 2, 3..)$ until the size of S_t is equal to or greater than N If the size of S_t is exactly equal to N, $P_{t+1} = S_t$ and turn to Step 11; otherwise, continue to perform the following steps.

Step 10: Normalize objective values in S_t and associate them with reference points. Compute ΔP and adaptively eliminate $K = |S_t| - N$ individuals from S_t, and then $P_{t+1} = S_t$. Preserve boundary points and closer points before elimination.

Step 11: $Sett = t + 1$. If $t = I_m$, output the PSs of Ma-OPF problem; otherwise, repeat Step 6 to 11.

Step 12: Find the best compromise solution (BCS).

4. Results and Discussions.

After applying the NSGAIII algorithm on three cases, *pareto* frontiers are obtained for each case. Then the optimal point is selected based on the distance criterion based on Eq. (11).

$$bestF = \min |F_{pareto}| \tag{11}$$

In addition to NSGA-III and INSGA-III with large number of initial population size, two different cases are introduced as well to determine the significance of the initial population size. Cases with letter (A) represent NSGA-III solver with initial population of 100 while cases with letter (B) represent INSGA-III solver with initial population size of 100. All runs here are performed on the same computer with same MATLAB version and the results presented shows a comparison between case A and B in Table 5 as follows.

4.1. Case 1: 8 infected plants

The optimization was performed using the parameters in Table 2 and Table 3 and the pareto frontier for (A) NSGA-III and (B) INSGA-III is a 3D plot with both cases showing same optimal points as shown in Fig. 5 where the red point signifies the optimal point. In the case of 8 plants, the population increases to 500 and the run time is high as expected while results are compared with 100 initial population cases in terms of accuracy and time as shown in Table 4.

Table 4 Setup and optimal point values for four comparative scenarios. Case 1 (8 plants).

	NSGA-III	INSGAIII	A	B
Initial population size	500	500	100	100
Number of variables	8	8	8	8
Number of iterations	400	400	400	400
Run Time (s)	3105.20	1777.53	144.01	115.75
End population size	500	500	100	82
Optimal Total time (s)	781.93	364.73	781.93	781.93
Optimal Total angle (rad)	44.44	72.08	44.66	44.66
Optimal Total distance (m)	29.84	29.08	29.84	29.84

Table 5 Setup and optimal point values for four comparative scenarios. Case 2 (32 plants).

	NSGA-III	INSGAIII	A	B
Initial population size	1000	1000	100	100
Number of variables	32	32	32	32
Number of iterations	400	400	400	400
Run Time (s)	12953.35	850.94	314.01	109.45
End population size	1000	79	55	31
Optimal Total time (s)	2445.34	2511.47	2326.98	2976.36
Optimal Total angle (rad)	157.66	152.08	137.19	164.40
Optimal Total distance (m)	79.93	86.53	73.35	99.99

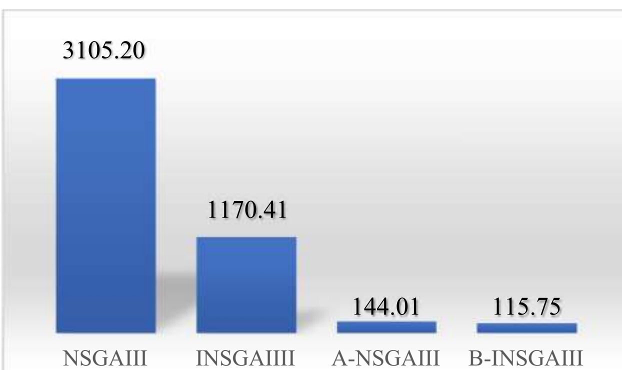

Fig. 6 Run time(s) comparison for different scenarios and 8 plants problem (Case1).

All the four sets of solutions attained the same values as case 1, despite the population size and method. But the best sequence might vary due to geometrical symmetry in routes (a route may be chosen in reverse order as well). Fig. 6 shows how the time varies between different case scenarios. The run time reduces drastically while the optimal point is similar for all runs. The reduction of time for large number of initial populations is significant in case of INSGAIII. The results summary obtained by implementing the INSGAIII are shown as follows:

- Time is reduced by 62.31% at population of 500.
- Time is reduced by 19.62% at population of 100. (comparing A and B).
- Population size does not affect the optimal point for 8 plant problem.

4.2. Case 2: 32- infected plants

The optimization was performed using the parameters in Table 2 and Table 3 while the pareto frontier for (A) NSGAIII and (B) INSGAIII is a 3D plot with NSGAIII showing higher optimality as shown in Fig. 7 where the red point signifies the optimal point.

When the number of decision variables increase, the initial population size also increases. In the case of 32 plants, the population increases to 1000 and the run time is high as expected while results are compared with 100 initial population cases in terms of accuracy and time as shown in Table 5.

The optimal values differ for different scenarios as can be seen, as expected, in the case B which shows the worse performance but significantly low time of operation. Furthermore, the values for scenario A has the minimum best objectives among all even by comparing with the 1000 initial population based on NSGA-III. This shows non-existence of a direct dependency of high initial population with best results and as well, shows how unpredictable the problem is. To make a

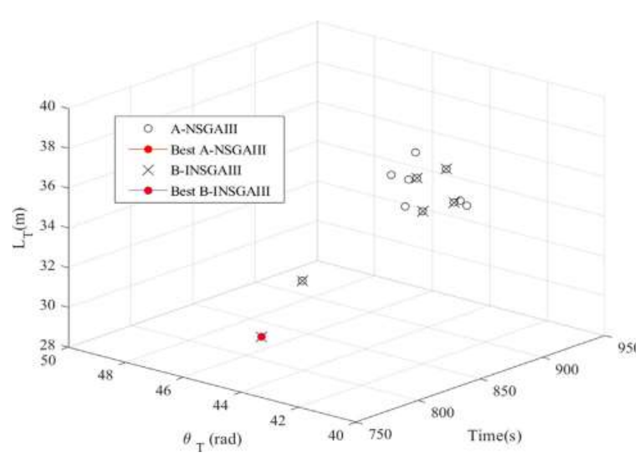

Fig. 5 Comparing pareto for two A-NSGAIII and B-INSGA-III for 8 plants.

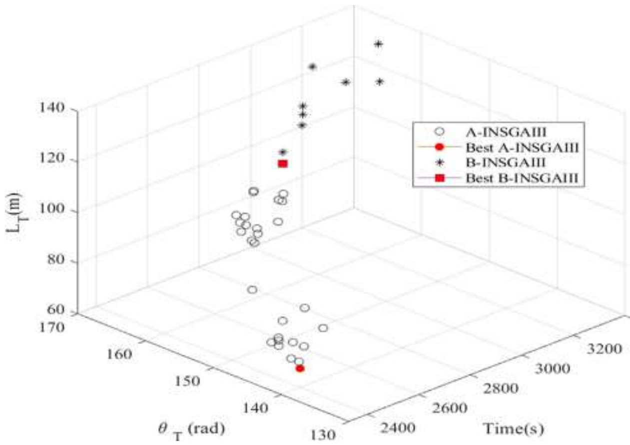

Fig. 7 Comparing pareto for two A-NSGA-III and B-INSGA-III for 32 plants.

comparison between the objective functions, the best optimal is selected and the percentage change belonging to other scenarios compared to this point are calculated and plotted for each scenario as shown in Fig. 8.

In Fig. 8, the optimal objective functions variation in comparison to the optimal case are shown. The total distance for the (B) INSGA-III with 100 population size is 136.3% which means that the total distance in this case is 36.3% higher than the optimal case. The total score is a measure of the distance to origin and is expressed in mathematical form as in Eq. (15):

$$TotalScore = 100 \times \frac{\sqrt{(Total\ \ Time)^2 + (Total\ \ Distance)^2 + (Total\ \ Angle)^2}}{\sqrt{3}} \tag{12}$$

The total score for the poorest case is 128.2% which means that the poorest run is 28.2% deviated from the best optimal point and the maximum deviation value is 36.3 percent. The data in this graph should be interpreted alongside the run time comparison as presented in Fig. 7 while the reduction in time is significantly high for scenarios with INSGA-III. In summary, the improvement in applying INSGA-III on 32 plants problem holds by considering the following points:

- The run time is reduced by 93.43% at population of 1000 while the total score is less than 10% higher.
- The time is reduced by 65.14% at population of 100 while the total score is 28.2% higher and maximum deviation from the optimal is 36.32. (comparing A and B only)
- The increase in population size does not affect the optimal point for case 2 as shown in Fig. 9.

4.3. Case 3: 56-Infected plants

The optimization was performed using the parameters in Table 2 and Table 3 with the pareto frontier for (A) NSGA-III and (B) INSGA-III represented as 3D plot. As shown in Fig. 10, the NSGAIII shows higher optimality where the red point signifies the optimal point.

For the case of 56 plants, the initial population increases to 1500 since the number of decision variables is 56 and the comparison between all scenarios are as shown in Table 6.

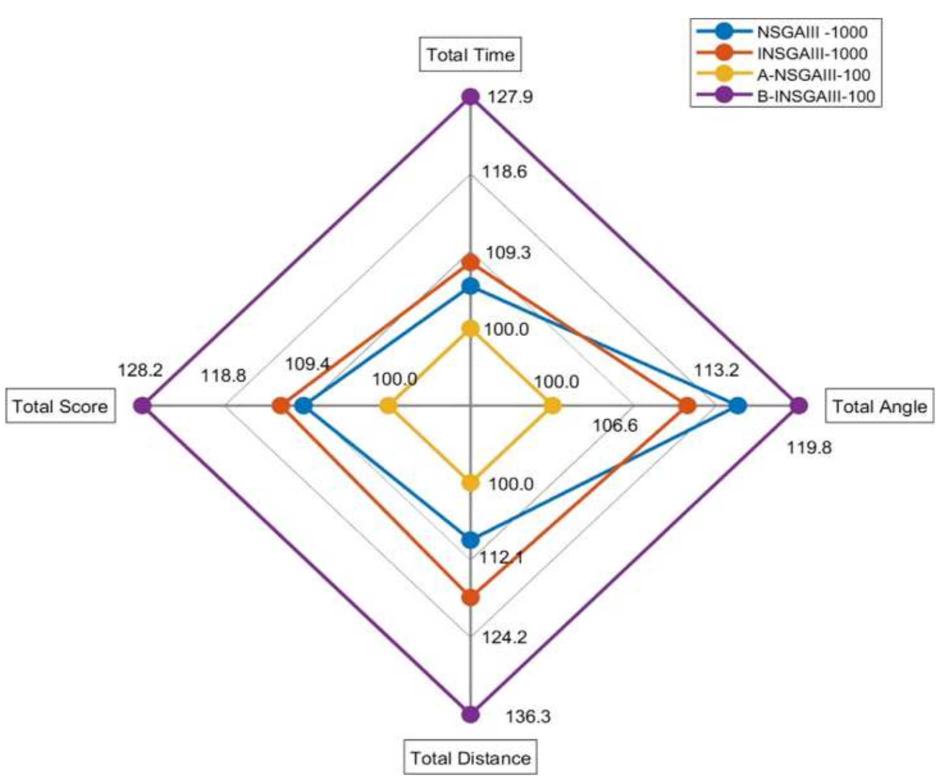

Fig. 8 Comparison of optimal objective functions in different scenarios for case 2 (32 plants).

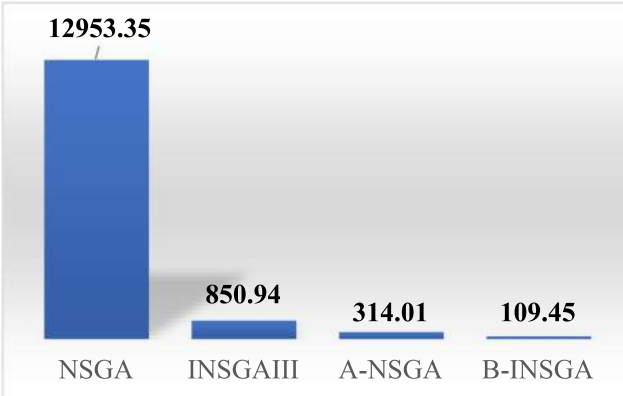

Fig. 9 Run time(s) comparison for different scenarios and 32 plants problem (Case2).

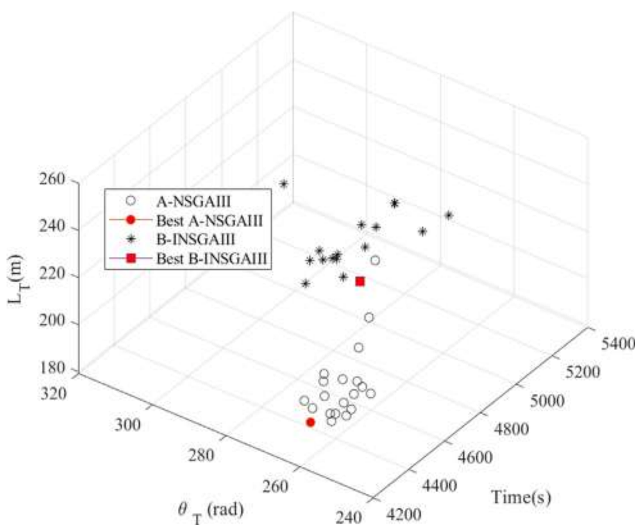

Fig. 10 Comparing pareto for two A-NSGA-III and B-INSGA-III for 56 plants.

Accordingly, the plot of the deviation from the minimum gives us an insight to the performance of the scenarios. It is worth mentioning that values on the chart show the values at plot grid points not the values for each scenario. The values for each scenario are provided in Table 7. Fig. 11 shows the comparison between the objective functions, the optimal solution and the percentage change of other scenarios.

Table 7 Scores and deviations for optimal values for different scenarios in Case 3 (56 plants).

	NSGAIII	INSGAIII	A	B
Total Time	100	108.42	105.55	115.16
Total Angle	100	100.88	100.95	103.12
Total Distance	100	98.27	96.06	112.57
Total Score	100	102.61	100.93	110.40

The best optimal is NSGAIII with 1500 population. However, the deviation from optimal point is not significantly large for other scenarios. The NSGAIII with 100 population size gives total score of 100.93 with even lower optimal value for distance. The INSGAIII shows better accuracy in comparison to best optimal point with only 10.4% deviation or increase in total score. To better analyse the performance of INSGAIII, time of run is compared and plotted for all scenarios as shown in Fig. 12.

4.4. Summary of findings

In summary, applying INSGAIII on case3 (56 plants) results in:

- The run time is reduced by 93.67% at population of 1500 while the total score is less than 3% higher.
- The run time is reduced by 76.62% at population of 100 while the total score is 10% higher and maximum deviation from best optimal is 15.62%. (comparing A and B)
- Increase in population size does not affect the optimal point significantly for 56 plants.

The best sequences are presented here for all cases in both NSGAIII and INSGAIII. In Fig. 13, the optimal visit sequence including refilling is presented for each of the different cases and optimization method. All the solutions show the same sequence but the first one is in reverse order. In Figs. 14 and 15, optimal sequence is presented for different cases as well. From the results, it can be observed that all the 32 cases have 4 refills and all the 56 cases have 6 refills for all scenarios. The 'ST' in the figures stand for starting point which is point of refill.

Table 6 Setup and optimal point values for four comparative scenarios. Case 3 (56 plants).

	NSGA-III	INSGAIII	A	B
Initial population size	1500	1500	100	100
Number of variables	56	56	56	56
Number of iterations	400	400	400	400
Run Time (s)	33191.62	2101.90	889.08	207.88
End population size	1500	27	33	17
Optimal Total time (s)	4112.38	4458.57	4340.60	4735.64
Optimal Total angle (rad)	261.34	263.63	263.82	269.51
Optimal Total distance (m)	194.79	191.41	187.12	219.27

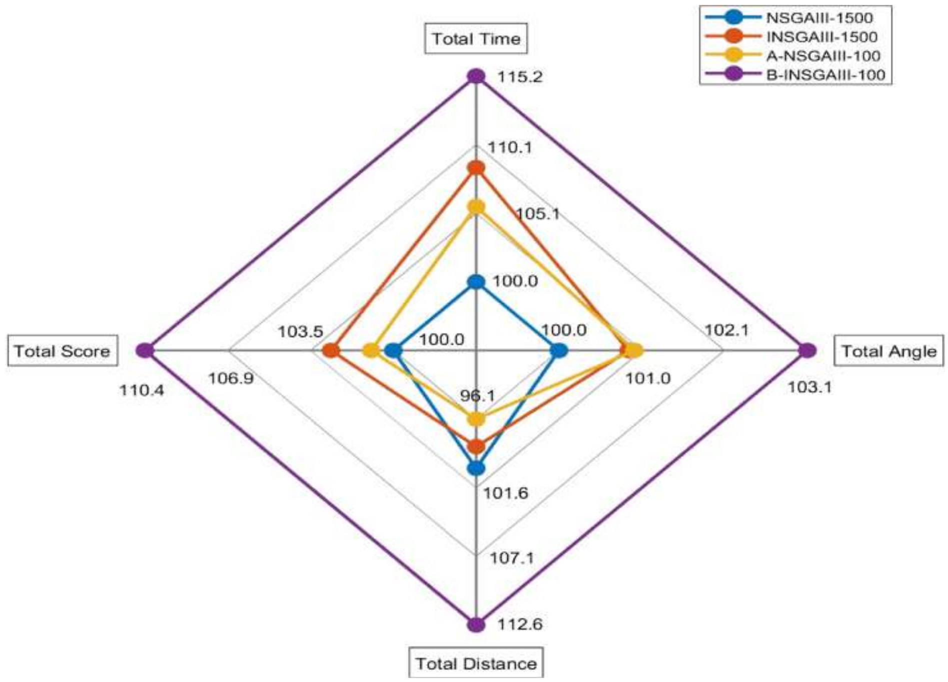

Fig. 11 Comparison of optimal objective functions in different scenarios for case 3 (56 plants).

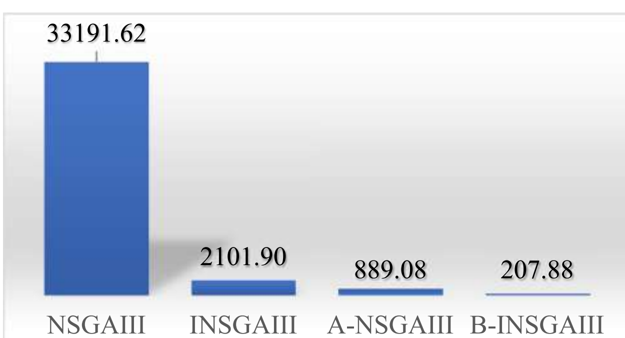

Fig. 12 Run time(s) comparison for different scenarios and 56 plants problem (Case3).

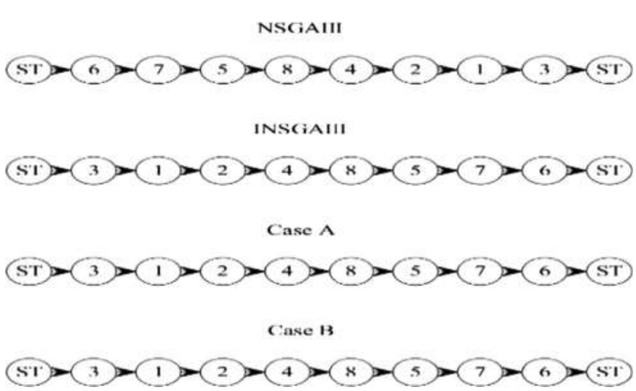

Fig. 13 Optimal sequences for case 1.

5. Conclusion

Path optimization for greenhouse robot application is conducted here using experimentally evaluated time functions, NSGAIII and INSGAIII approaches. The required dosage for each plant is considered a variable while the robot capacity is fixed and refilling is necessary. The solution to the presented VRP by optimization methods (NSGAIII and INSGAIII) for three different cases (8 plants, 32 plants and 56 plants) and different initial population sizes are presented here. Run time and best optimal points are evaluated and compared for different scenarios. In summary, the main findings are:

- All scenarios provide similar best optimal point for case 1 (8 plants).
- For case 2 (32 plants), INSGAIII shows deviation of 28% in total score at 100 population size.
- For case 3(56 plants), INSGAIII shows deviation of 10% in total score at 100 population size.
- The run time is reduced by 93% for large population size and 66 to 76% in low population size for case 2 and 3.
- In case 1, the run time reduction is 62 and 19%, for large population size and a population size of 100 respectively when INSGAIII is applied but the same optimal point is obtained.
- The larger the number of decision variables, the larger the time reduction as observed.
- Large population size does not necessarily correlate with better solution. A population size of 100 seems to be enough for this problem for all cases. However, for 56 plants (case 3), deviation by 2% is observed in total score from the optimal point.

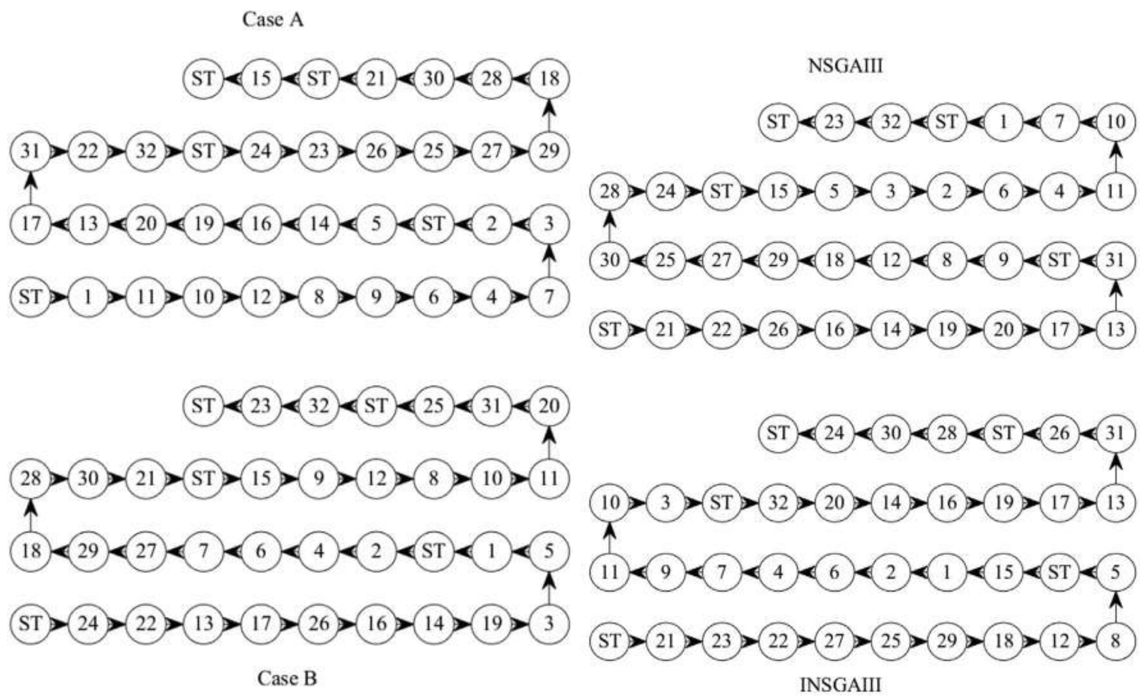

Fig. 14 Optimal sequences for case 2.

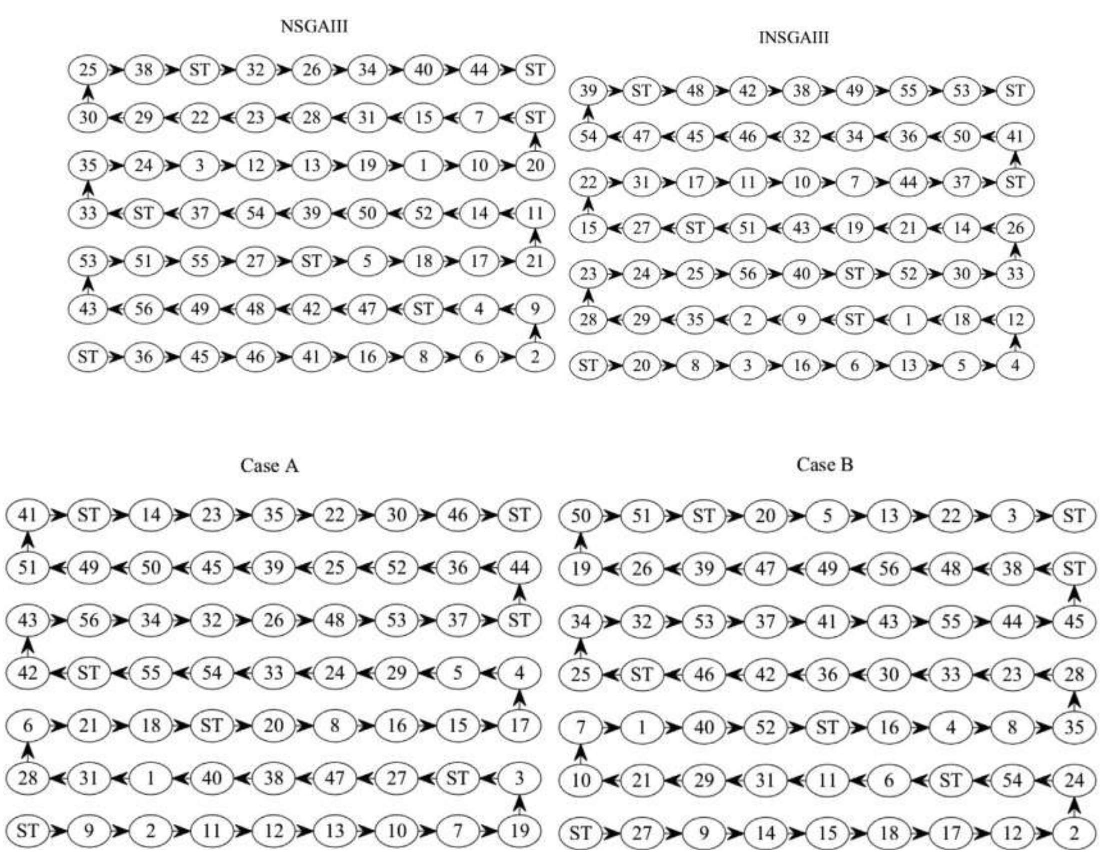

Fig. 15 Optimal sequences for case 3.

- Based on the findings, reduction in run time between 20 and 76 % is expected for small problem size even with population size of 100, when the INSGA-III is applied. The deviation is 28% (total score) maximum when the improved version is applied.
- Based on the values, INSGA-III has advantage over the NSGA-III in terms of performance if the run time is critical and it does not affect the optimal point significantly.

Finally, the INSGAIII shows a significant time reduction in solving the problem presented and the improved speed comes with reduced accuracy in final optimal point. However, the time difference is large and the final optimal points are relatively close (high accuracy is observed in final optimal point for INSGAIII if NSGAIII results are considered as reference). For a larger population and problem size, the reduction in size becomes more obvious. For application of INSGAIII requiring higher initial population, it will be recommended to balance up the time-accuracy (optimality of final point). Although this work considers the pesticide demand in variable rates, the approach adopted is deterministic as pest infestation is determined through mapping and use of devices like cameras, satellites, etc. The need to adopt indeterministic pesticide demand by introducing active demand management approach is of paramount importance. Moreover, the extension to this work in the aspect of internet-of-things (IOT) could further enhance this method into the real-world computing scenario.

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