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Path Planning Optimization of Automated Ground Vehicle in Inspecting Boeing 757-200 Aircraft Using Genetic Algorithm and Simulated Annealing Methods

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Abstract

Transportation plays a critical role in modern society, with air travel being a key component of long-distance mobility. Despite strict regulations by the Federal Aviation Administration (FAA) and mandatory periodic inspections, aircraft maintenance inspections are crucial for air travel safety, yet human error in manual checks can lead to critical issues. This study aims to optimize the inspection distance for AGVs inspecting the underside of a Boeing 757-200 aircraft using MATLAB R2023a simulation tools. The input data for the simulation consists of the x, y, and z coordinates of various inspection points on the aircraft, and the output is the total distance travelled by the AGV during inspection. The objective is to minimize the travel distance, calculated as a vector from one point to the next. Two optimization methods to be compared include Simulated Annealing (SA) and Genetic Algorithm (GA). The SA method involves varying parameters such as the number of iterations, initial temperature, and cooling rate. Meanwhile, the GA method varies the number of iterations, population size, and crossover and mutation percentages. The study evaluates the performance of both methods using a dataset of 34 inspection points. The results show that Simulated Annealing produces optimal path-planning distance, achieving a minimum of 85.099 meters across all parameter variations. Compared to the manual path planning result of 163.53 meters, this optimization yields an efficiency improvement of approximately 48%. This optimized solution contributes to more efficient and reliable aircraft maintenance processes, reducing human error and enhancing air travel safety and reliability." This optimized solution contributes to more efficient and reliable aircraft maintenance processes, reducing human error and enhancing air travel safety and reliability.

Keywords: Automated Ground Vehicle, Boeing 757-200, Genetic Algorithm, Optimization, Simulated Annealing

1. Introduction

Over the past few decades, studies have revealed that the number of aircraft fatalities has drastically decreased [1]. Fatalities due to component failures have declined since 1960, driven by continuous improvements in flight safety through technological advancements in aircraft, avionics, and engines. These developments, coupled with innovations such as proximity warning devices, state-of-the-art pilot training simulations, enhanced regulations due to a better understanding of human factors, improved navigation aids, efficient air traffic management, and accurate weather forecasting, have significantly elevated commercial aviation safety [2]. In the commercial aviation industry, some tasks require the visual inspection of aircraft parts. Trained workers must examine production defects, assembly errors, component failures, or damage during flight activities such as departure, flight, and landing. This inspection task is part of the aircraft's maintenance, repair, and overhaul (MRO) activities, which are essential for identifying and addressing issues before the aircraft is approved for flight. This can minimize the risk of accidents and unexpected events. Visual inspection is defined as the use of human resources, relying on the eye, with or without other assistive devices, to assess the condition of the aircraft [3].

Aviation maintenance is overseen by the Federal Aviation Administration (FAA), among other agencies. In addition to regulating various maintenance matters, the FAA enforces safety regulations in the aircraft's manufacture, operation, and maintenance. It also establishes air traffic and airspace use regulations to ensure the safety and efficiency of navigable airspace and regulate air traffic [4]. Various methods are used in the inspection process, including walk-around inspections by aircraft maintenance

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and operations teams to detect damage quickly. Additionally, General Visual Inspection (GVI) must be carried out periodically by the aircraft maintenance team. A Detailed Visual Inspection (DVI) is performed when a specific issue is suspected, whereas a Special Detailed Visual Inspection (SDVI) is conducted periodically to ensure the airworthiness of critical aircraft structures. Although the FAA defines inspection types and practices, many commercial aviation accidents and serious incidents are caused by poor aircraft maintenance practices [5]. Maintenance personnel play an invaluable and essential role in ensuring operational safety. However, as with all complex human/machine systems, some degree of human error is inevitable. It is important to recognize the term "error" should not automatically imply guilt or blame.

From a maintenance perspective, the FAA outlines basic annual and 100-hour inspection requirements outlined in 14 CFR part 91. With a few exceptions, all aircraft are required to undergo an annual inspection. Aircraft used for commercial purposes (i.e., carrying passengers other than flight crew or flight instructors) and likely to be used more frequently than non-commercial aircraft are required to be inspected every 100 hours. However, in practice, the FAA acknowledges that aviation, with all its complexities, faces both design and maintenance challenges. In the maintenance sector, ensuring the availability of spare parts remains a significant challenge for the civil aviation logistics industry in meeting operators demands.

Various studies have shown that the major causes and contributing factors to aviation incidents include installation/dismantling problems, inspection/testing issues, work practices, finishing defects, and inadequate lubrication and maintenance. A mixed-method study analyzed the official CAO database on accidents caused by maintenance failures. The study identified five broad categories of maintenance risks, such as “general (improper practices, inadequate maintenance, qualifications, training, etc.), engine, spare parts, airworthiness directives/service bulletins.” (failure to comply with AD or SB), and PD (repair of previous damage). Additionally, the study examined the impact of aircraft age and explored the relationship between aircraft age, maintenance risks, and aircraft damage due to accidents [6].

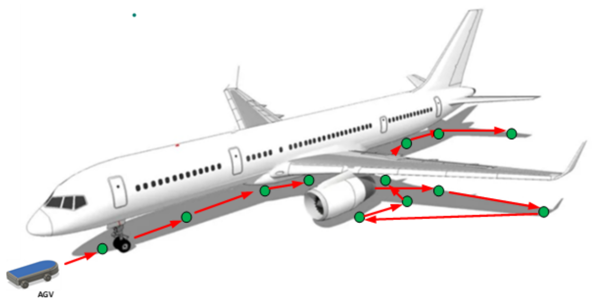


Figure 1. An Illustration of the Path Planning of An AGV Inspecting A Boeing 757-200

Automated Guided Vehicles (AGV) have been in use since the 1950s when Barret Electronics from Grand Rapids, Michigan, first developed the technology. The movement of AGVs is controlled by a navigation system that processes information obtained from sensor readings. Based on their structure, mobile robots can be categorized as wheeled robots, tracked treads, or legged robots [7]. The use of path planning for AGVs to inspect planes (Figure 1) was first developed to enable automated scanning without human intervention. This innovation improves operational efficiency during aircraft inspections. Additionally, it expands the inspection area beyond what was previously feasible due to inspector visibility limitations [8].

2. Methodology: Optimization with Genetic Algorithm (GA) and Simulated Annealing (SA)

This study uses data from the FAA's Aircraft Maintenance Manual handbook. After determining the initial data, calculations are carried out to obtain the distance value between coordinate points, which will be used as a reference for comparing the distance value to be optimized, using the following formula.

As presented in Equation (2.1), the function f(i,j) quantifies the distance, expressed in meters (m), between two spatial points. The variables x(i), y(i), and z(i) denote the Cartesian coordinates of the initial point along the x, y, and z axes, respectively, whereas x(j), y(j), and z(j) represent the corresponding coordinates of the terminal point.

The optimization process aims to determine the optimal inspection distance by varying the x, y, and z coordinates used by the Automated Ground Vehicle (AGV). This process helps identify the most effective inspection distance for inspecting the bottom of the aircraft.

The output from the optimization, either using the Genetic Algorithm (GA) or Simulated Annealing (SA), provides the optimal inspection distance. To achieve this, the optimization process involved specific parameters: SA parameters included varying maximum iterations (10,500 to 10,000), a fixed sub-iteration of 10, initial temperatures from 20°C to 70°C, and cooling rates of 90%, 50%, and 1%. GA parameters varied maximum iterations (500 to 100,000), a population size of 10, crossover percentages of 0.5 and 0.6, and mutation percentages of 0.3 and 0.4. After obtaining the results, a thorough analysis and discussion are conducted to interpret the data. The results from the Genetic Algorithm and Simulated Annealing optimizations are then compared to determine which method performs better in achieving the optimal inspection distance. Finally, conclusions are drawn based on the results and comparisons. These conclusions are presented as key discussion points, addressing the research questions and achieving the objectives.

$$f(i,j) = \sqrt{(x(i)-x(j))^2 + (y(i)-y(j))^2 + (z(i)-z(j))^2} \quad (2.1)$$

3. Results and Discussion

3.1. Validation of Optimization Method

3.1.1. Gurobi Optimizer version 11.0.2

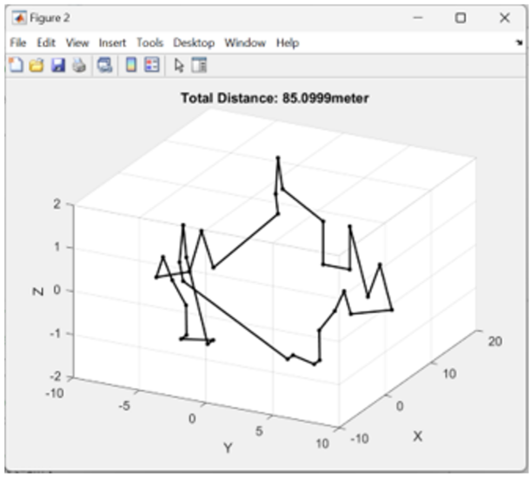
This study examines the TSP solution using Simulated Annealing and Genetic Algorithm, both metaheuristic optimization methods. However, metaheuristic algorithms do not always guarantee optimal solutions. The optimization results of these two methods were compared with the brute-force method using Gurobi in MATLAB. Based on the optimization results, the path planning distance value obtained by Gurobi is 8.80224e+01, or can be interpreted as 88.0224 meters, the result was obtained after 8185.32 seconds of computation time with 10 million iterations, finding 20 ways to solve the given TSP. It is crucial to acknowledge the computational complexity associated with the Gurobi Optimizer. The Traveling Salesperson Problem (TSP) is an NP-hard problem, and the brute-force approach employed by Gurobi involves evaluating all possible path permutations, which grows factorially with the number of coordinate points. The extended computation time and large number of iterations underscore the limitations of this method for larger problem instances. In real-world aircraft maintenance applications, the number of coordinate points can be significantly higher, and time constraints are paramount. The 8185.32 seconds required by Gurobi is impractical for routine inspections. Furthermore, real world applications can contain many more constraints than this study contained. For example, areas requiring specific tools, or specific inspection order. Therefore, while Gurobi provides a benchmark for optimality, its computational complexity renders it unsuitable for scalable, real-world applications. Metaheuristic methods like SA and GA, which offer a trade-off between solution quality and computational efficiency, are more adaptable and flexible for addressing the dynamic and complex requirements of aircraft maintenance.

3.1.2. Manual Calculation

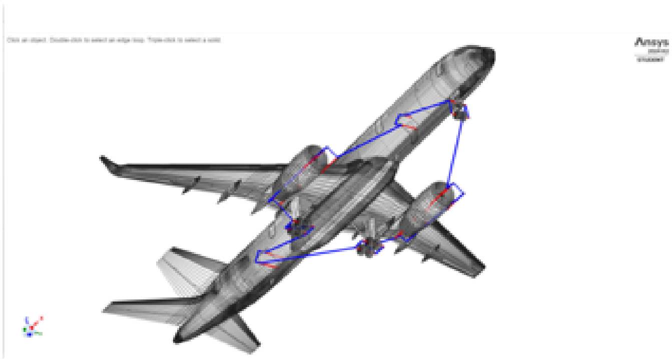
Using manual calculation with the formula in Equation (2.1), here is one of the calculations for point 3 to point 4. From the calculation above, data is obtained in the form of the path planning distance from the initial coordinates to the final coordinates specified. The data is presented in Figure 2, which is a 34×34 matrix as follows.

$$\begin{aligned} f(3,4) &= \sqrt{(x(i)-x(j))^2 + (y(i)-y(j))^2 + (z(i)-z(j))^2} \\ &= \sqrt{(18.5-18.5)^2 + ((-1)-(-1))^2 + (0-(-1))^2} \\ &= \sqrt{(1)^2} \\ &= 1\,m \end{aligned} \quad (2.2)$$

3.2. Simulated Annealing (SA) Optimization



(a)



(b)

Figure 2. (a) Path planning results, (b) Visualization in Ansys

Table 1. Simulated Annealing Parameters

Parameter	Value
Max Iterations	10,500,1000,5000,10000
Maximum number of sub iterations	10
Initial Temperature	20°C;30°C;40°C;50°C;60°C;70°C
Cooling Rate	90%;50%;1%

Simulated Annealing (SA) optimization was performed 3 times in each parameter variation. The output obtained was the shortest distance the AGV could traverse for each parameter variation. Table 1 shows the variations used.

After the SA process runs with one variation of 1000 iterations, an initial temperature of 20°C and a cooling rate of 0.1, the best optimization results are obtained, as shown in Figure 2

From Figure 2, the optimization results using one variation of SA show that the best cost value for distance produced is 85.099 meters.

3.2.1. Analysis of Path Planning Distance with Iteration Variation and Initial Temperature for Each Cooling Rate Variation

Figure 3 shows the most optimal results when the cooling rate is 1% and the iteration count is below 1000. This is because, with iterations below 1000 and an initial temperature of 20-70°C at a cooling rate of 1%, the temperature requires more iterations to reach the final temperature of 0°C, resulting in a downward trend.

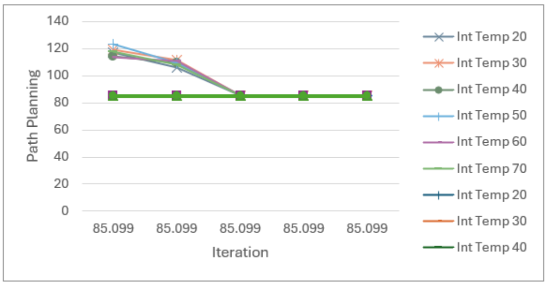


Figure 3. Graph of Path Planning Distance Comparison: Impact of 90%, 50%, and 99% Cooling Rates on Iteration and Initial Temperature

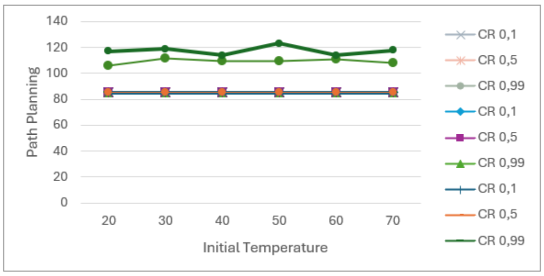


Figure 4. Graph of Path Planning Distance Analysis: Impact of Initial Temperature and Cooling Rate Across Iterations

3.2.2. Analysis of Path Planning Distance with Initial Temperature and Cooling Rate Variations across Iteration Variations

Figure 4 shows the effect of initial temperature and cooling rate in each iteration used, in accordance with the theory. It can be seen that when using 100 and 500 iterations, with cooling rates of 90% and 50%, the optimal result is obtained. However, when the cooling rate used is 1%, the result is different.

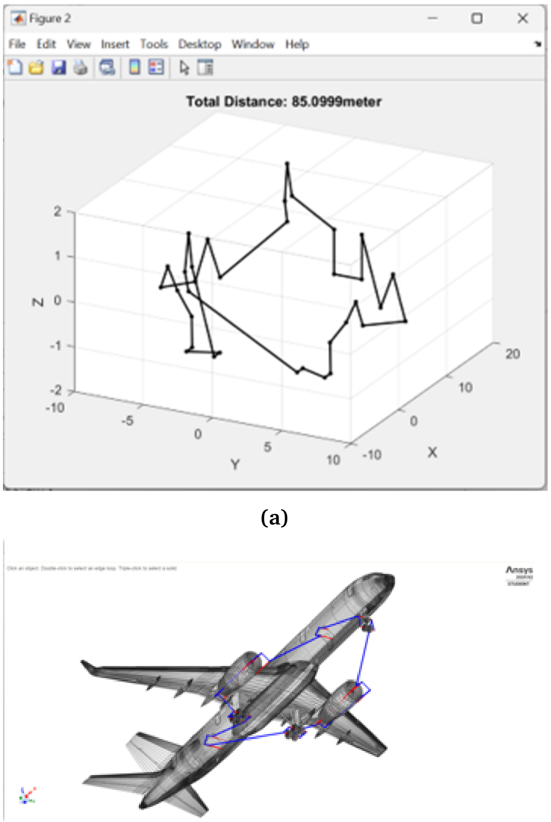
3.3. Genetic Algorithm (GA) Optimization

Genetic Algorithm (GA) optimization was carried out 3 times for each parameter variation. The output obtained was the shortest distance that the Automated Ground Vehicle (AGV) could travel for each parameter variation. Table 2 shows the variations used.

After the GA process runs with one variation of 1000 iterations, a population size of 2000 and a crossover x mutation percentage of 0.5 x 0.4, the best optimization results are obtained as shown in the figure 5 below.

Table 2. Genetic Algorithm Parameters

Parameter	Value
Max Iterations	500,1000,5000,50000,75000,100000
Population Size	10
Crossover Percentage	0.5; 0.6
Mutation Percentage	0.3; 0.4



(a)

(b)

Figure 5. (a) Path planning results, (b) Visualization in Ansys

From Figure 5, the optimization results using one variation of GA show that the best cost value for distance produced is 85.099 meters.

3.3.1. Path Planning Distance Analysis on Iteration Variations and Population Size in Each Crossover x Mutation Percentage Variation

From Figure 6, it can be observed that, based on existing theory, the results follow the theoretical basis: with each increase in iteration and population size (Npop), the optimal results found by the Genetic Algorithm (GA) tend to improve.

3.3.2. Path Planning Analysis of Crossover x Mutation Percentage Variations and Population Size in Each Iteration Variation

Based on the theoretical framework, the results shown in Figure 7 confirm that each increase in population size, along with variations in crossover and mutation percentages across iterations, brings the results closer to the optimal outcome. The slight differences between the variations in crossover and mutation percentages are observed when the crossover parameter of 0.5 x mutation percentage 0.3 is used.

3.4. Analysis of SA and GA Optimization Results with Validation Using Gurobi Optimizer 11.0.2

From Table 3, it can be observed that the path planning distance obtained using the SA method is shorter than the validation results produced by the Gurobi Optimizer. This indicates that the SA method provides valid path planning distance results. Similarly, the path planning distance using the GA method is also shorter than the validation results from Gurobi, confirming the validity of the GA method. Based on the validation results, the Gurobi Optimizer cannot achieve the same value or a lower path planning distance compared to the two optimization methods used. It is worth noting that the Gurobi Optimizer was run under a student license, which limited it to a maximum of 10,000,000 iterations.

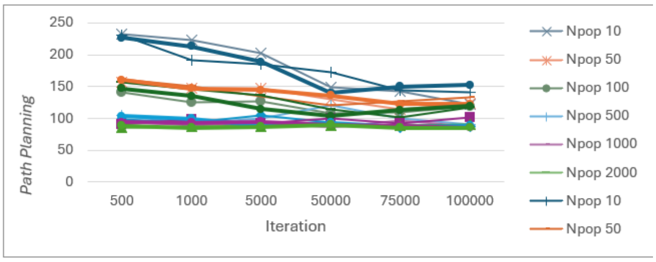


Figure 6. Path Planning Graph Against Iteration Variation and Population Size at Crossover x Mutation Percentages of 0.6 x 0.4, 0.5 x 0.3, 0.5 x 0.4

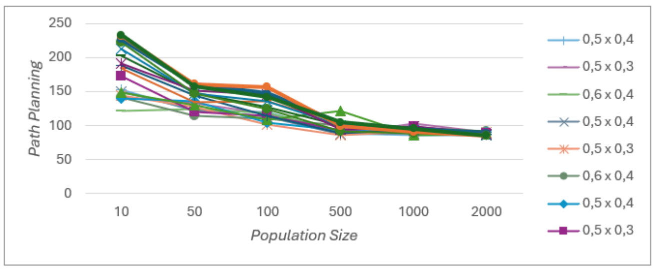


Figure 7. Path Planning Graph for Crossover x Mutation Percentage Variation and Population Size at 500, 1000, 5000, 50000, 75000, and 100000 iterations

Table 3. Comparison of Gurobi, SA, and GA Results

Criteria	Method		
	GuRoBi	Simulated Annealing	Genetic Algorithm
Path Planning Distance (m)	88.0224	85.099	85.099
Computation Time (s)	8185.32	0.86	74.21

4. Conclusions

Based on the input data obtained from the Hypothetical Federal Aviation Administration (FAA) Aircraft Maintenance Manual, the path planning developed in this study was designed to evaluate the suitability of the coordinate data provided for the underside of a Boeing 757-200 aircraft. The path planning, generated using Simulated Annealing (SA) and Genetic Algorithm (GA) methods, effectively reflects these coordinates. After validation using Gurobi on MATLAB, the result for the two variants of MEvITS polyethylene bumpers was 88.0224 meters, representing the optimal solution for the TSP problem. The Simulated Annealing (SA) method achieved an optimal path planning distance of 85.099 meters, while the Genetic Algorithm (GA) produced the same shortest distance of 85.099. Therefore, it can be concluded that both methods yield valid results, as the path planning distances obtained are shorter than those generated by the Gurobi Optimizer.

Based on experiments using metaheuristic-based methods, namely Simulated Annealing (SA) and Genetic Algorithm (GA), the results demonstrate that SA can quickly achieve optimal path planning with the shortest distance of 85.099 meters by adjusting its parameters. In contrast, although GA can achieve the same optimal distance of 85.099 meters, it requires more parameter adjustments than SA. For example, GA achieves optimal results using a population size of 2000, 1000 iterations, and a crossover x mutation percentage of 0.5 x 0.4. However, these optimal results are not consistently guaranteed and often require additional iterations for improved reliability. Increasing the number of iterations in GA enhances the likelihood of finding optimal results, but significantly increases computation time, often exceeding 2 hours. This reduces its effectiveness when seeking stable results. Therefore, the SA method is recommended for achieving optimal results with shorter computation time and greater efficiency than GA, regardless of variations in input parameters. Adapting these optimization techniques to various aircraft models requires adjustments in coordinate data, parameter optimization, constraint integration, and tool-sensor compatibility. While both methods hold potential, SA exhibits superior robustness across varying problem complexities. In scenarios with fewer coordinate points, both algorithms perform adequately, yet SA's simplicity confers a slight computational advantage. For moderate problem sizes, SA maintains its efficiency, whereas GA's performance is contingent upon precise parameter calibration. In complex scenarios involving numerous coordinate points, SA's ability to escape local optima proves advantageous, mitigating the substantial computational burden associated with GA. Consequently, SA's consistent performance across varying problem scales and its computational efficiency render it a more dependable approach for optimizing aircraft maintenance path planning.

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