Proceedings of the Annual General Donald R. Keith Memorial Conference
West Point, New York, USA
May 4, 2023
A Regional Conference of the Society for Industrial and Systems Engineering

Improving Robotic Painting Utilization at an Air Logistics Complex Depot

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Author Note: The cadet authors are all first-class cadets at the U.S. Air Force Academy, partnering with the Warner-Robbins Air Logistics Complex. We would like to thank our faculty advisors for their expertise in the completion of this capstone research analysis. The views expressed herein are those of the authors and do not reflect the position of the United States Air Force Academy, the Department of the Air Force, or the Department of Defense.

Abstract: One mainstay within all United States Air Force operations has been and will continue to be the necessity of maintaining aircraft. To support more efficient maintenance processes, the 402nd Commodities Maintenance Group at the Warner Robins Air Logistics Complex (WR-ALC) located in Warner Robins, Georgia seeks to implement robotics into their painting processes. Unfortunately, restrictions within the software and physical limits of the robotic painting arms have resulted in difficulties in obtaining widespread acceptance and use of robotics in the unit. To alleviate this issue, we created a Uniform-Cost Search algorithm with a user interface to output viable aircraft part placement to ensure the robotic arm can paint multiple parts at once. The search algorithm produces valid part combinations 95% of the time and saves an average of 45 minutes per painting cycle. Implementation of the software at the WR-ALC is expected to increase usage of the robotics arms, allowing maintenance to be completed faster, removing one of the bottlenecks of the depot maintenance operations, and saving the 402nd $600,000 each year.

Keywords: Uniform-Cost Search Algorithm, Aircraft Maintenance, Robotic Painting

1. Introduction

The 402nd Commodities Maintenance Group at the Warner Robins Air Logistics Complex (WR-ALC) in Georgia paints over 500 types of parts for several aircraft and systems, such as the C-5, C-17, C-130, F-15, and JSTARS. Traditionally, aircraft parts are hand-painted. However, the 402nd recently implemented three 8-axis robotic arms to perform this work more efficiently (see Figure 1). The robotic arms are constrained by several factors, such as range of motion, the proximity of parts, and booth size. These factors limit how parts may be placed within the painting booths.

Figure 1. Robotic Painting Arm at WR-ALC

To paint a part, the operator places a part in the booth and the software creates a painting path for the robotic arm. This process takes several minutes. Only after the pathing software is complete will the operator know if 100% of the part can be successfully painted in its location. If the pathing fails, the operator must guess a new location for the part and restart the entire process. Due to these inefficiencies, the 402nd returned to painting by hand. As a result of this, the WR-ALC currently has several unused assets, totaling $4.8 million, and has failed to improve its painting output, causing a bottleneck in its operations. Furthermore, the 402nd would prefer to place several parts in the booth at once, which complicates the solution space by allowing more avenues for a failed pathing. According to Shane Groves, the current WR-ALC Robotics Subject Matter Expert, successful implementation of the robotic painting processes is expected to increase output from 12 parts per day to 24 parts per day, save more than $600,000 per year, and limit the hazardous conditions faced by personnel (Forbes 2022).

1.1 Problem Statement

The 402nd has millions of dollars in robotic painting equipment sitting idle due to difficulty in user implementation. To utilize this technology properly, the decision process for where each part will sit in the booth must be simplified. The question then becomes how can the 402nd's painters find valid locations for each possible aircraft part combination quickly to incentivize using their new, robotic technology. Additionally, each painting arm's efficiency compared to painting by hand is dependent on the number of parts that can be painted at a time. However, every part added into the pathing algorithm increases its time to calculate and the probability that the locations will fail. Therefore, any solution must balance the 402nd's desire to fit as many parts as possible in the painting booth against its requirement for easy usage.

1.2 Related Work

The body of literature that applies to this problem primarily exists in two categories. First, is literature related to overarching machine learning and data processing methodologies. According to the literature, Artificial Neural Networks (ANNs) offer advantages over traditional statistical methodologies due to the lack of assumptions that ANNs require (Abiodun et al.). Additionally, Uniform-Cost Search (UCS) algorithms offer low computing costs in addition to proven success in determining distance transformations (Verwer, 1989). UCS algorithms have been employed to search entire solution spaces, which may be feasible for various problems depending on computational restrictions and data size (Setz, 2022). These techniques serve as potential options for finding viable part placements within the painting booth.

The second group of literature encompasses work that relates directly to problems like our own. For example, Foy et al. (2021) created a machine-learning model for placing pedicle screws more accurately and quickly than other methods. They utilize a neural network to determine the proper device placement. Specifically, they found that a "neural network can…minimize the preoperative time…for image-guided surgery" (Foy et al. 2022). Similarly, Qiu et al. (2020) studied the optimal placement of aerial base stations using deep neural nets to identify high-coverage placement strategies. In general, the literature describes how to conduct specific machine learning techniques, as well as specific applications of various techniques to problems of optimal placement strategies.

The final research pertained to packing problems. The packing problem involves integrating as many objects as possible into the specified area. This research concluded with the realization that the problem being asked to solve has a limitation on the number of parts able to be placed in the booth. As opposed to attempting to maximize objects into one area, our team instead sought feasible solutions that depended on several constraints due to the robotic arm itself. The limitation came directly from the WR-ALC Robotics Subject Matter Expert (Hopper et al., 1999).

1.3 Organization

In this paper, Section 2 describes the methodology, including data and data collection. Section 3 explores the analysis and results obtained. Section 4 describes the conclusions, recommendations for implementation, and recommendations for future areas of research or continued work.

2. Methodology

2.1 Data and Data Collection

The team collected the data using the Titan Pathing Software given to us by the WR-ALC. For each part, we collected data on the X and Y values for the center of mass of each part. These two values determine where the part will be located in the booth if it were a 2-dimensional plane. We also tracked seven other metrics that remain constant for each part. The metrics are shown below in Table 1. Due to resource constraints, the team approached data collection from a design of experiments approach, attempting to isolate the extreme values at which a plane part could be painted. For extreme values, we found four successful "extremes" in each corner of the booth for each part. This requires a minimum of 16 data points per part. In the end, if the paint coverage is 100.0 for the sides of the part that are being painted, the trial will have a success equal to one, otherwise, success equals zero. After collecting data, the team has 303 known successful locations and 35 known failed locations.

Table 1. Example data collected for C17 Rudder

Trial	Plane	Part	X	Y	Z	Roll	Pitch	Yaw	NUMPARTS	Coverage	SUCCESS
1	C17	C17 Rudder	7.65	7.85	1.438	90	-90	0	1	100,41.5	0
2	C17	C17 Rudder	7.65	7.6	1.438	90	-90	0	1	100,61.9	0
3	C17	C17 Rudder	7.65	7.5	1.438	90	-90	0	1	100,61.9	0
4	C17	C17 Rudder	7.65	7.1	1.438	90	-90	0	1	100,100	1

2.2 Assumptions

In the development of the model, we utilized a few key assumptions. First, we assumed that the shape of each part could be represented as a rectangle. This is because each part is painted on a rectangular platform, which covers a greater area than the part. Thus, we did not want to ignore the platform in generating solutions. Second, we assumed that a maximum of four parts would be painted at one time. This assumption came from the client's expert knowledge. Placing greater than four parts in the booth makes the workspace inoperable and causes issues for the operators who need to maneuver around the booth. Third, we assumed that the Z, Roll, Pitch, and Yaw values for each part remain constant. This is because the parts are restricted by the platforms that they are placed on. Lastly, we assumed that the Titan Robotics software provided to us generated accurate data points.

2.3 Methods

After careful consideration of the problem tasked to our team, we have decided that the solution should be completed by creating software that involves numerous steps, along with multiple models. The first step is collecting data for each part, which is mentioned and described in section 2.1. After collecting data on each part, we built a program that implements the following processes. Our program contains a database of successful and failing coordinates for each part combination. After filling our success database sufficiently, we constructed a Uniform-Cost Search (UCS) algorithm (see Equation 1) that searches the solution space for X and Y values of multiple parts.

When in use, the operator will enter the parts that they wish to paint, and the UCS algorithm will output the 10 best-identified solutions for the operator to choose from. If an incoming request has been solved before, then the software immediately outputs the results from the database. If a request is a new combination of parts, then the software utilizes the Search Algorithm to output a prediction for a valid orientation. This process can be seen in Figure 3 from start to finish. In short, if the database has a previous success, it directly outputs that success. If the request is not in the database, the UCS algorithm provides a set of potential solutions.

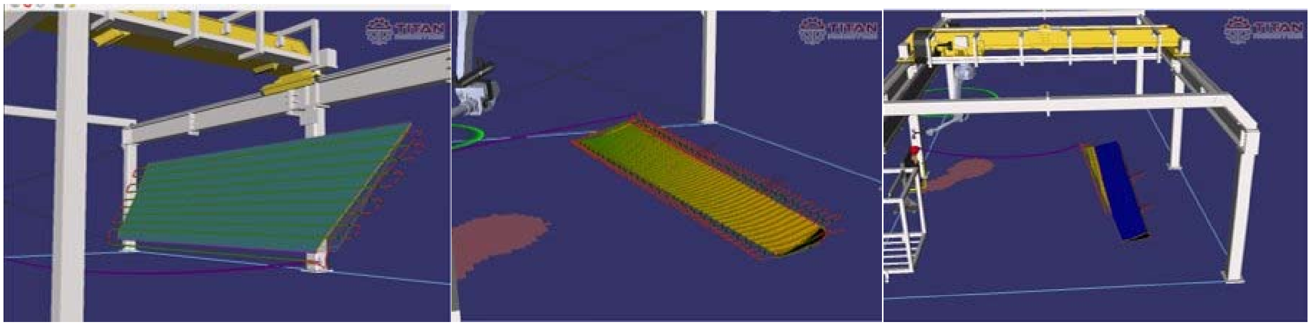

Figure 2. Titan Pathing Software used for Data Collection

After receiving the potential solution, the operator has the opportunity to denote whether the output was a true success or a failure. The model updates based on this information, ensuring that it will improve over time as the database of known successes and known failures becomes larger.

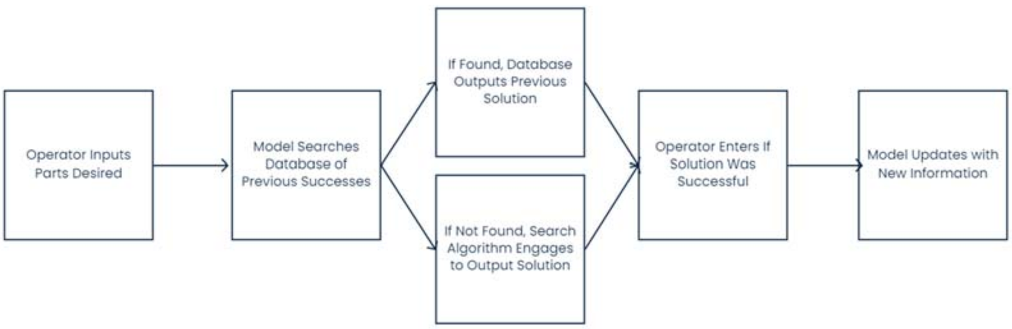

Figure 3. Model Flow Diagram

2.3 Model

The Z, roll, pitch, and yaw values will be predetermined based on painting constraints for each part. Thus, the model only needs to predict the X and Y values. The algorithm creates potential combinations based on known locations that were successful for painting each individual part. From these combinations, the algorithm selects those which maximize the distance between the centers of each part. In order to offer the operator greater autonomy, the model will output the 10 best solutions as well as a visual depiction of each solution. After each use, the model will save the new data and increase its training set, allowing it to improve over time.

Because the model needs to include options for greater than two parts, the model calculates the distance between each part. The algorithm then finds the minimum distance between any two parts, with the overall objective to maximize the minimum distance between any two parts entered. Euclidean distance is utilized to calculate the distance between each part (see Equation 1).

$$\text{maximize} \;\; \min\{d_{12}, d_{13}, d_{23}, \ldots, d_{nm}\} \quad where \;\; d_{ij} = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2} \tag{1}$$

3. Results and Analysis

The team built and trained a model that can successfully predict viable locations for anywhere from one to four parts in the booth. The model's predictions are valid and adequately pathed in accordance with the simulation software utilized to collect data. The algorithm run-time remains under five seconds, outputting several viable options for each combination.

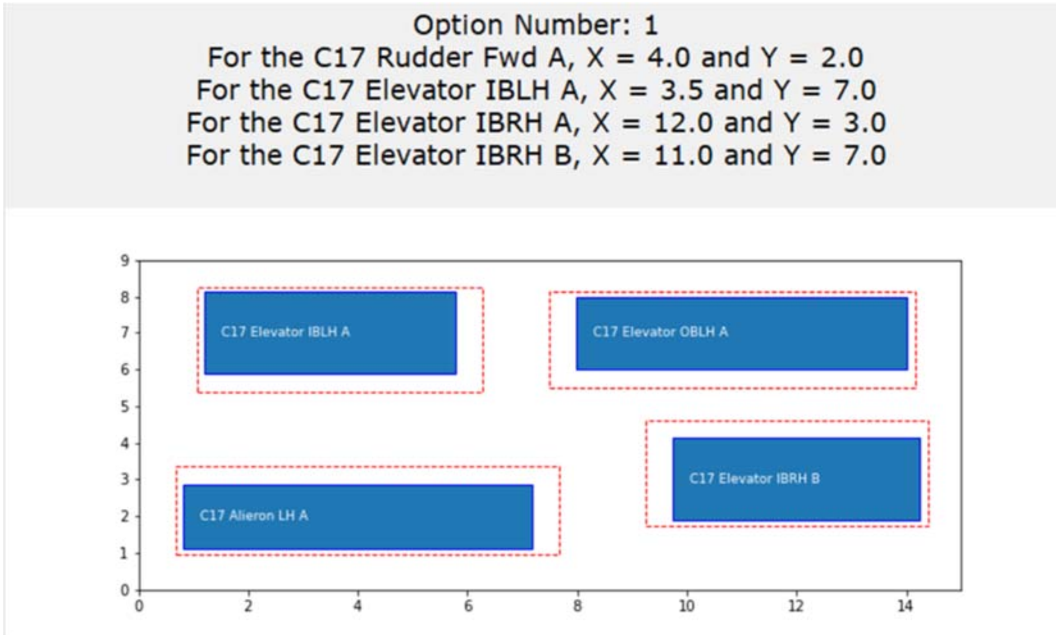

Figure 4. Example Output

The final output allows the user to visualize where the parts should be located (see Figure 4) in addition to X and Y coordinates for each part. This prevents the possibility of rework, ensuring that the parts are placed in viable locations on the first attempt. Because the model outputs 10 potential options, this provides the operator flexibility in selecting the best option given their expert knowledge. Furthermore, because the model will continually update the database with known successful combinations, over time the error rate will tend toward 0%.

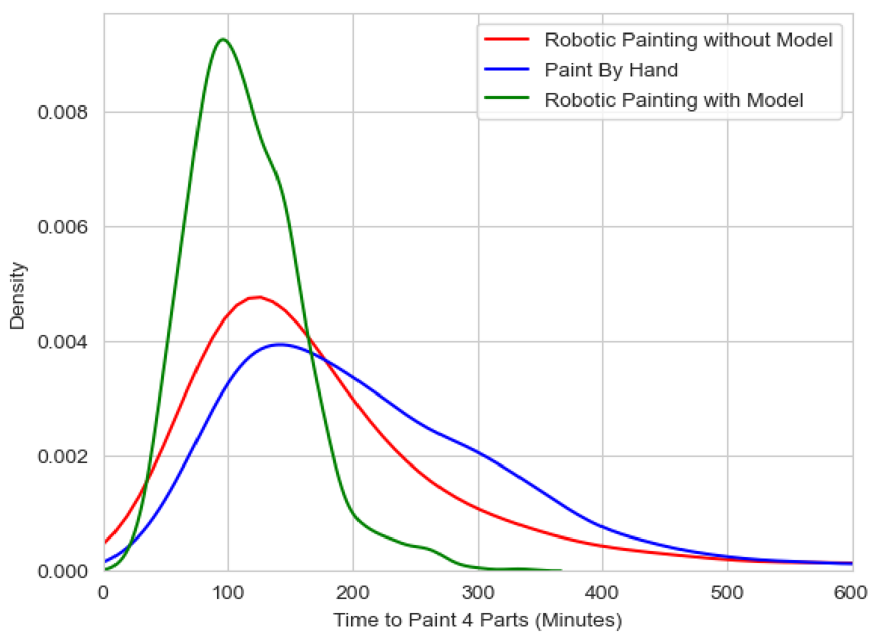

Figure 5. Simulation Results

ISBN: 97819384964-4-8

By implementing the model and user interface, robotic painting becomes more feasible at the WR-ALC. A simulation was run to determine the impact of utilizing the robot arms with the software in comparison with the alternatives of painting by hand or without the software (see Figure 5). Each step in the painting process along with probabilities of success and distributions of time for each step were given by the 402nd. This successful implementation will decrease the variability in time and the average time required to paint part combinations. The model helps to make painting multiple parts in the booth more feasible and time efficient.

4. Conclusions, Recommendations, and Future Research

The UCS model, utilized through the user interface, should be implemented at WR-ALC. Operators should use the model to obtain potential options for part placement in the booth. The operator should seek to maximize the number of parts in the booth at once, with a maximum of four parts. After obtaining this potential option, the operator should continue their work as normal, with greater confidence of success.

Through the implementation of this model with the robotic painting processes, the 402nd Commodities Maintenance Group will reduce the time to paint multiple parts, allowing the operators to use the robot arms efficiently. Furthermore, successful implementation of the robotic painting will save $600,000 per year and limit personnel's exposure to hazardous conditions.

The generated UCS model currently pulls from 303 known successes and 35 known failures. A recommendation is for continued use of the model. After each use, follow the user interface on adding the combination to the database. This will increase the number of known successes and failures within the database. Additional solutions will increase model efficiency and accuracy for the model.

The current model is appropriate for painting up to four aircraft parts. Before painting can happen, de-painting needs to take place. With that, the current model may likely be applied to this process of robotic laser paint removal. Further research on various artificial intelligence (AI) techniques may support more flexible solutions. These solutions could result in never seen before solutions, rather than using known successes in the current model. Furthermore, the model could be updated to allow the user to input all parts that need to be painted on a given day and output an optimal set of combinations for the entire day.

5. References

Abiodun, O. I., Jantan, A., Omolara, A. E., Dada, K. V., Mohamed, N. A., & Arshad, H. (2018). State-of-the-art in artificial neural network applications: A survey. *Heliyon*, *4*(11), e00938.

Forbes, Gail. (2022). *AFRL division wins award for cold spray robot.* Defense Visual Information Distribution Service (DVIDS).

Foy, M., Siemionow, K., Forsthoefel, C., Gawel, D., & Luciano, C. (2021). Autonomous lumbar spine pedicle screw planning using machine learning: A validation study. *Journal of Craniovertebral Junction and Spine, 12*(3), 223-228.

Hopper, E., & Turton, B. (1999). A genetic algorithm for a 2D industrial packing problem. *Computers & Industrial Engineering*, *37*(1-2), 375-378.

Qiu, J., Lyu, J., & Fu, L. (2020, June). Placement optimization of aerial base stations with deep reinforcement learning. In *ICC 2020-2020 IEEE International Conference on Communications (ICC)* (pp. 1-6). IEEE.

Setz, B., Haghshenas, K., & Aiello, M. (2022). Energy Smart Buildings: Parallel Uniform Cost-Search with Energy Storage and Generation. *arXiv preprint arXiv:2211.08969*.

Verwer, B. J. H., Verbeek, P. W., & Dekker, S. T. (1989). An efficient uniform cost algorithm applied to distance transforms. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, *11*(4), 425-429.