Proceedings of the Annual General Donald R. Keith Memorial Conference
West Point, New York, USA
May 2, 2024
A Regional Conference of the Society for Industrial and Systems Engineering

Identifying Parts Commonalities Across The F-35 Fleet to Improve Sustainability with Jenkins Optimization

Chase Clemence[1], Andrew Aderhold[1], Seungmin Shim[1], Thai Tran[1], Adam Ackerman[1], Brian Lemay[1], Matthew Durchholz[2]

[1]Operations Research Program,
United States Air Force Academy,
Colorado Springs, CO 80841

[2]Lockheed-Martin Corporation

Corresponding author's Email: BLemay@umich.edu

Author Note: The cadet authors are all first-class cadets at the U.S. Air Force Academy, partnering with Dr. Matthew Durchholz from Lockheed-Martin. 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: The distribution of F-35 parts across supply depots can have drastic effects on costs associated with urgent demand requests. Given the fact that F-35s are located around the world, having parts located near F-35s when they need them can save a significant amount of time and money. By identifying similar groups of F-35s, Lockheed-Martin can improve their distribution plan, leading to reduced costs, fewer sustainability issues, and decreased downtime for the fleet. Our team explored cluster modeling to find optimal groupings of F-35s based on part similarity across various functional logistics control numbers (FLCNs). Specifically, K-Means clustering and Jenks Natural Breaks Optimization - a one-dimensional equivalent to KMeans were utilized to group F-35s given a predefined number of clusters. We found that clusters were not similar in size when limiting the number of clusters to whole numbers between 2 and 4, but observations within had fairly similar 'commonality scores.' The team's work injects commonality into daily supply chain operations that previous findings did not consider. We recommend that Lockheed-Martin utilize the clusters generated to improve sustainability and readiness across the F-35 fleet and reduce costs.

Keywords: Commonality, Cluster Analysis, Sustainment

1. Introduction

Lockheed-Martin, a global aerospace and defense company, is the primary contractor for the United States' F-35 Lightning II Joint Strike Fighter program, a pioneering initiative shaping modern military aviation. The United States Department of Defense plans to acquire approximately 2,500 F-35 fighters with a total life cycle cost of $1.7 trillion; this makes it one of America's most expensive programs. F-35 fighters are non-homogenous and complex with a variety of configurations and mission sets across the fleet, convoluting part supply planning. Given the uniqueness of F-35s across the fleet, determining the best locations to store parts is challenging. Identifying groups of F-35s (i.e. "grouping" them) that share specific parts could help inform part distribution decisions by Lockheed-Martin. While cost savings produced from commonality may have motivated the joint acquisition by the United States, opportunities remain for the program to employ techniques that leverage commonalities and reduce costs. The current grouping of the F-35 fleet across the joint force and international partners – by training, mission set, or other present-day arrangements – may be contributing to complications such as costly urgent buy requests, lack of inventory, increased maintenance, and readiness setbacks. Though grouping aircraft by commonality in place of the current approach can save billions of dollars over the lifespan of the F-35 program, research has not yet identified how aircraft should be grouped to minimize costs. In summary, Lockheed-Martin's mission to advance technology and its commitment to commonality in the F-35 program converge in the imperative to enhance the grouping of F-35 tails, generating substantial long-term cost savings and significantly improving the efficiency of sustainment efforts, aligning perfectly with Lockheed-Martin's mission to deliver advanced technology for the betterment of humanity.

The current arrangement of the F-35 fleet across the joint force and international partners contributes to complications such as costly urgent buy requests, lack of inventory, increased maintenance, and readiness setbacks. In the existing system, there is a relationship between tail numbers (e.g., functional logistics control number – or FLCN) and part numbers but not every tail number is linked to a specific part number. The current approach involves counting the occurrences of each part across different tail numbers for a given FLCN. For instance, if there are 50 tail numbers associated with one part and 20 tail numbers with another part, the system assumes the most common part applies to all tail numbers within that FLCN. This method results in urgent buy requests, higher costs, and increased downtime. It can be described as a "naive" approach, where the company sends the most common part in an FLCN to all F-35s even if that part is unfunctional in certain aircraft tails. This method may not be the most cost-effective way to manage this capability. Each of these aircraft are unique in the sense that they each have a variety of distinct parts and FLCNs. FLCNs are identifiers for different sets of components and resources required for specific functions of an aircraft. Each F-35 tail has a set number of combinations of FLCNs and parts; while some share common combinations, the majority are unique to tails. For example, one F-35 with a simple mission set, such as training, may have 1794 FLCNs and 1640 parts. Another F-35 with a more complex mission set, such as testing and research, may have up to 1842 FLCNs and 2100 parts.

To improve the system, we need to challenge the assumption that the most common part applies universally to all tail numbers: the current "naive" approach utilized by Lockheed-Martin. This shift aims to minimize expensive urgent buy requests. Instead, we explore an alternative form of overlap that considers the FLCN and part precedence. Part precedence is a measure of utility, with a higher part precedence number indicating how effectively a part would operate within a specific FLCN. When planning for spare parts, the strategy is to group them in the most common configuration, covering the highest number of tails. However, it becomes impractical to plan at extremely detailed levels. The key is to enhance coverage by introducing a single "common" configuration that does not precisely match any specific tail number. This approach seeks to optimize spare planning by broadening the scope and reducing the need for minute, tail-specific details.

1.1 Problem Statement

Lockheed-Martin currently lacks a method for identifying groups a F-35s that are similar to one another from a parts perspective. Having such a capability enables them to improve the distribution of parts across the F-35 fleet.

1.2 Related Work

Previous scholarly works provide valuable insights into the concepts related to clustering, commonality analysis, focusing and supply chain management that can be applied to the current situation with the F-35 fleet. To start, the team looked for articles detailing real-world problems like Lockheed-Martin's. Feser and Bergman (2000) explore interregional industrial transfer and sensitivity analysis in identifying industrial clusters. Lorentz, Hilmola, Malmsten, and Singh (2016) analyze how macroeconomic shocks affect subject matter experts (SMEs) using cluster analysis. Trappey, Trappey, Chang, and Huang (2010) provide a clustering approach for automobile logistics services. These papers provide evidence of clustering techniques used in industrial settings, similar to how Lockheed-Martin could use the methods.

The next set of scholarly sources talk specifically about the technical language of bin-packing problems, clustering analysis, optimization, and more. Lodi, Martello, and Vigo (2002) discuss advances in two-dimensional bin-packing problems, offering both exact algorithms and heuristic approaches for optimization. The articles by Gates and Ahn (2019), Lawrence Dale Thomas (1991), Cedeño and Gürsel (1997), and Changpinyo, Liu, and Sha (2013) delve into clustering analysis and similarity measures, offering methods for assessing clustering results and finding commonality between components. These articles provide the technical knowledge needed to develop an appropriate model.

The final theme of papers the team explored related to background and sustainability within the F-35 industry. Ingenbleek and Krampe (2023) examine resource allocation in the supply chain and its influence on sustainability. These reviews guide the development of clustering algorithms and commonality analysis for the F-35 project, offering valuable tools and methods. Additionally, the articles by Albon (2019), Jans, Degraeve, and Schepens (2008), Rand (1971), Thonemann and Brandeau (2000), and the U.S. Government Accountability Office reports provide crucial background information on the F-35 aircraft, its maintenance challenges, and the need for sustainment improvements. These reviews inform the context of the F-35 project and the importance of optimizing its parts and sustainment processes. Finally, Sharma and Bhat (2014) offer insights into supply chain risk management in the automobile industry, which can be adapted to the F-35 project. Overall, these literature reviews offer a wealth of knowledge and methods that can be applied to optimize clustering and commonality analysis for the F-35 aircraft and its supply chain.

2. Methodology for Data

Given the previous work that Lockheed-Martin has completed for F-35 sustainment, all data collection processes had been completed. The data consisted of a large dataset with five distinct rows: tail key, phase key, FLCN key, part number (labeled as REFNUM_key in the data), and goodness of fit of a part with a particular FLCN (defined as part precedence). The tail key column is a string that represents a certain F-35. The actual nature of the aircraft is classified, so the dataset declassifies the F-35s by associating it with a random number. Phase key is also a string of numbers, but its presence serves no purpose for commonality analysis. The FLCN key is a declassified string of numbers representing a system within the aircraft. Each FLCN has a set number of parts that have varying levels of utility associated with that specific system. The utility associated with each part/FLCN combination falls under the 'goodness of fit' column – the only integer type within the data frame. In this context of the data, a higher part precedence value means that a part works better within an FLCN than a part with a lower part precedence value. Combinations of FLCNs and parts for different F-35 tails allow for meaningful clustering to occur, especially when considering the utility of these combinations. All tails share some combinations of FLCNs and parts, whereas certain tails have combinations specific to them.

Before using the data for grouping F-35s, we performed some initial analysis to better understand the data and prepare it for future analysis. Identifying key features and attributes of the large dataset is a high priority in initial analysis. Wrangling the dataset includes eliminating duplicate part keys, dropping phase key numbers, and identifying one-to-one-to-one relationships among tail numbers, FLCNs, and parts. More specifically, for part keys that were duplicated, the team decided to keep the observation with higher part precedence. Grouping the dataset by FLCNs and parts reveals one-to-one relationships and commonality among F-35 tail numbers in the dataset. Visualizing relationships between tail numbers and part precedence gives insight into future optimization and clustering objectives. Another important visual in understanding similarities between F-35s relates FLCNs to the number of unique parts associated with that system. Additionally, extrapolating, and visualizing statistics on relationships among FLCNs, parts, and part precedence.

3. Modeling and Analysis

The primary modeling effort to best find commonalities between F-35s will be clustering algorithms. F-35s can be better sorted in a way that factors in parts that work best within them using clustering techniques. Clusters of F-35s will be generated by comparing a measure of commonality to the number of FLCNs within a particular tail. Referencing Moscato (1976), we define commonality with an entropy-based measure. The equation below details the relative commonality metric used. Specifically, p_{ij} is a fraction between 1 and the number of tails where a part exists. N represents the total number of tails within the dataset. Finally, n_i is the number of FLCNs within the data.

$$Relative\ Commonality = \frac{-\sum_{j=1}^{n_i} p_{ij} \log_2 \ p_{ij}}{\log_2 \ N} \tag{1}$$

$$p_{ij} = \frac{1}{\#\ aircraft\ tails\ where\ a\ part\ is\ present} \tag{2}$$

Relative commonality was contained within a range from [10, 28] and is associated with each unique FLCN to part combination per tail. Given that there are thousands of different FLCNs within the dataset, each with multiple parts, there will be multiple 'commonality' scores associated with a particular tail. From there, the list of commonality scores is averaged to map a singular value to one F-35 tail. The team then compared the singular commonality score, associated with a particular aircraft, to the number of FLCNs present in that same plane. Optimal clustering was applied to the data to find F-35s that are most like each other. This clustering aims to minimize variance within one cluster while maximizing the distance between other clusters. The model flexibility allows the user to input the number of clusters he/she wishes to conduct analysis with; however, to find the best number of clusters to work with, the team employs The Elbow Method, finding the inflection point on a graph that plots the number of clusters against the 'total within cluster sum of squares' (WSS). Below is the equation for WSS where the d() function represents the distance equation:

$$WSS = \sum_{i=1}^{N_C} \sum_{x \in C_i} d\left(x,\ x_{C_i}\right)^2 \tag{3}$$

$Where{:}\ x_{C_i} = Cluster\ Centroid;\ x = datapoint;\ C_i = cluster;\ N_C = clusters$

ISBN: 97819384962-4-0

Lockheed-Martin emphasized the importance of finding commonalities and differences amongst FLCNs found in every plane. In this specific case, a K-Means clustering algorithm does not work, because the data is plotted in a one-dimensional space. To find optimal classes of aircraft using the commonality scores that were calculated, the team implemented Jenks Natural Breaks Optimization. With this method, the goal was to reduce the variance within classes while maximizing variance between classes – similar to that of K-Means, but in a one-dimensional space. The process is iterative, meaning calculations must be repeated various times to achieve optimal clusters. The iterative process is meant to find optimal partitions that minimize the sum of squared deviations from the class means (SDCM). The sum of squares formula for this method is:

$$SS = \sum_{i=1}^{n} (x_i - \bar{x})^2 \tag{4}$$

The model produced by the team is dynamic for Lockheed-Martin's needs and can be applied to the full dataset. Each unique tail number that is compatible with a part in each FLCN is tabulated. For example: in a dataset containing 193 tail numbers, part #21870 is compatible with 88 tail numbers in FLCN #10023. Using this relationship along with the relative commonality equation, 'commonality scores' were calculated for each tail/FLCN/part combination. Finally, commonality scores are averaged across FLCNs. Below is a formula describing average commonality:

$$Avg.\ Commonality = \frac{Relative\ Commonality}{total\ FLCNs} \tag{5}$$

Initial commonality analysis focused specifically on FLCNs that were present in every F-35. The client emphasized that most wasted expenditures come from common FLCNs given their current "naive" approach. Using Jenks Natural Breaks Optimization and the commonality scores associated with each F-35 tail, given as an array of values, the team was able to find optimal clustering of tails given a pre-defined set of clusters. Lockheed-Martin can see exactly what F-35s are in each cluster by pulling from the nested list, labeled as 'tail_groups', within our model. This directly answers Lockheed-Martin's problem of grouping F-35's into "commonality" groups. Below is a graph representing the optimal groupings of F-35s based on commonality given 3 clusters. This visual gives us an idea of the size of each cluster.

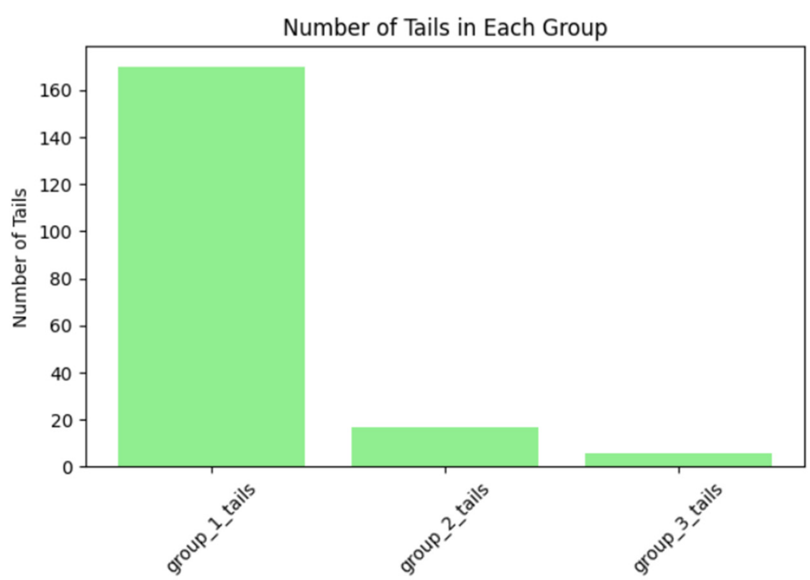

Figure 1: F-35 Groupings Using One-Dimensional Clustering

Further analysis involved finding an optimal number of clusters in which the marginal return to decreasing variance within each cluster becomes too costly. This work will be done using the Elbow Method – a function that graphs within-cluster sum of squares (WSS) against the number of clusters. The team will look at the point in the graph where the function begins to level out; theoretically, the function should approach 0. The team found that, after 5 clusters, there is no added benefit to adding additional clusters. Below is the graph of the Elbow Method generated when considering relative commonality amongst the F-35 fleet:

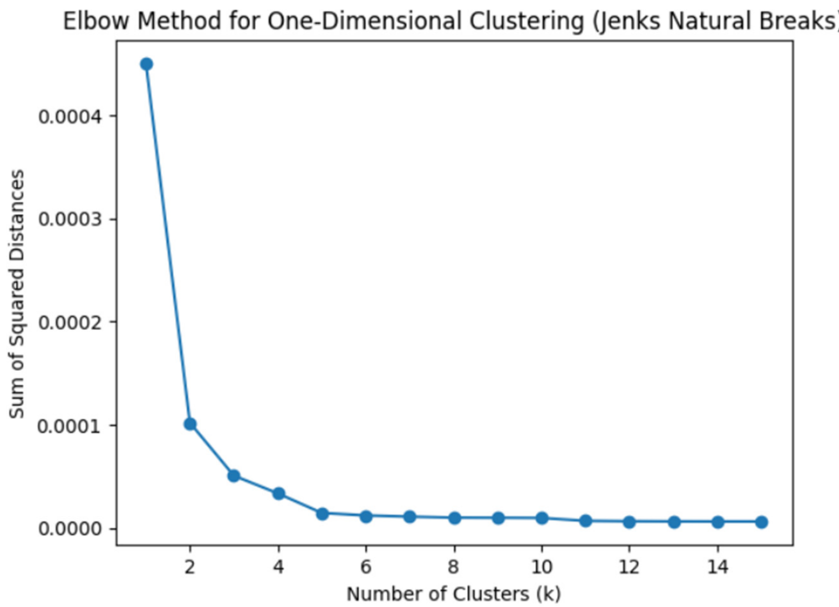

Figure 2: Elbow Method for Optimal # Clusters

Based on the results of the elbow method, which indicated that 5 clusters would be optimal, we created a graphical representation of the optimal tail grouping to visualize the cluster sizes. Subsequently, we compared this representation to a model employing 5 clusters using a naïve commonality score. This comparison aimed to elucidate the disparities between relative commonality and the naïve approach in clustering. The equation for the naïve approach commonality can be found below, alongside the two graphical representations comparing the models. This comparative analysis is vital as Lockheed Martin currently relies on a naïve approach, and we seek to assess how our new model can enhance it.

$$Naive\ Approach\ Commonality = \frac{\#aircraft\ tails\ where\ a\ part\ is\ present}{total\ \#\ of\ tails} \tag{6}$$

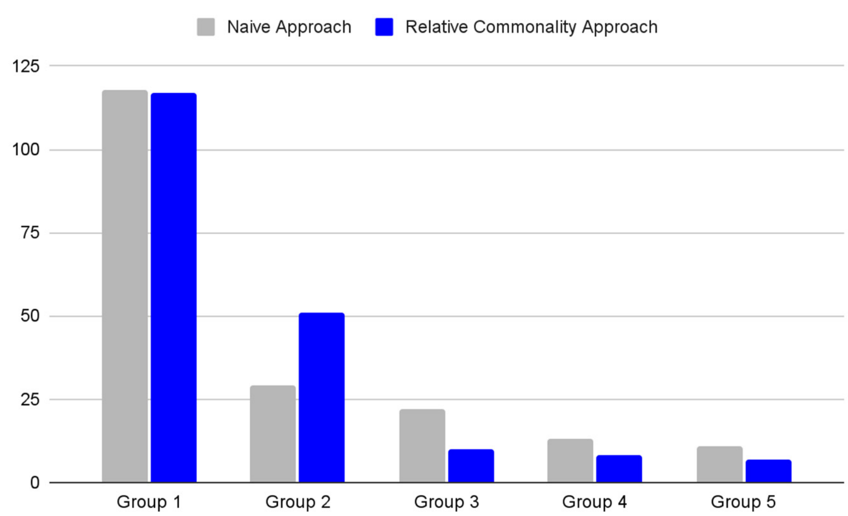

Figure 3: Difference in Tail Clustering Between Naïve and Relative Commonality Scoring

ISBN: 97819384962-4-0

4. Conclusion

The utilization of relative commonality, Jenks Natural Breaks clustering, and the Elbow Method culminated in the development of a robust model, facilitating the determination of optimal groupings within the F-35 fleet. This innovative approach represents a marked improvement over Lockheed-Martin's previous "naive" organizational methodology. Notably, the model's adaptability ensures its continued relevance amidst evolving F-35 mission parameters and configurations, providing invaluable insights for strategic planning and resource allocation.

Looking ahead, there exists an exciting avenue for further refinement and enhancement of the model by incorporating additional dimensions, such as the cost of parts or the failure rate of parts, through the application of K-means clustering. This expansion promises to deepen our understanding of fleet dynamics, enabling more nuanced decision-making and resource optimization.

In expressing our gratitude, we extend heartfelt thanks to Dr. Durchholz for his invaluable contributions and sagacious guidance throughout this research endeavor. Furthermore, we extend our appreciation to Lt Col Lemay and Lt Col Ackerman for their invaluable subject matter expertise and insightful feedback, which have greatly enriched the quality and depth of our findings. Through collaborative efforts like these, we continue to push the boundaries of knowledge and innovation in aerospace management and decision science.

5. References

Bureau of Labor Statistics, U.S. Department of Labor, The Economics Daily, Employment by industry, 1910 and 2015. Retrieved from https://www.bls.gov/opub/ted/2016/employment-by-industry-1910-and-2015.htm.

Cedeño, Angel A., and Gürsel A. Süer. (1997). The use of a similarity coefficient-based method to perform clustering analysis to a large set of data with dissimilar parts. Computers & Industrial Engineering, vol. 33, no. 1–2, pp. 225–228.

Changpinyo, S., Liu, K., & Sha, F. (2013). Similarity component analysis. Advances in neural information processing systems, 26.

Feser, E. & Bergman, E. (2000). National Industry Cluster Templates: A Framework for Applied Regional Cluster Analysis. Regional Studies, 34(1), 1-19.

GAO-23-105341. (2023). F-35 Aircraft: DOD and the Military Services Need to Reassess the Future Sustainment Strategy.

Gates, A. J., & Ahn, Y. Y. (2019). CluSim: a python package for calculating clustering similarity. Journal of Open Source Software, 4(35), 1264.

Ingenbleek, P.T.M. and Krampe, C. (2023). "Sustainability in the supply chain – understanding suppliers' resource allocation for sustainability issues". Supply Chain Management, 28(7), 28-42.

Jans, R., Degraeve, Z., & Schepens, L. (2008). Analysis of an industrial component commonality problem. European Journal of Operational Research, 186(2), 801-811.

Lawrence Dale Thomas, (1991). Commonality Analysis Using Clustering Methods. Operations Research, 39(4), 677-680.

Lodi, A., Martello, S., & Vigo, D. (2002). Recent advances on two-dimensional bin packing problems. Discrete Applied Mathematics, 123(1-3), 379-396.

Lorentz, H., Hilmola, O., Malmsten, J. & Singh, J. (2016). Cluster analysis application for understanding SME manufacturing strategies. Expert Systems with Applications, 66, 176-188.

Maurer, D., & United States Government Accountability Office. (2020). F-35 Sustainment: DOD Needs to Address Key Uncertainties as It Re-Designs the Aircraft's Logistics System. Committee on Oversight and Reform, 1.

Maurer, D., Bumgarner, J., Czyz, A., Hubbard, J., Buquicchio, V., Collymore, J., ... & GOVERNMENT ACCOUNTABILITY OFFICE WASHINGTON DC. (2021). F-35 Sustainment: Enhanced Attention to and Oversight of F-35 Affordability Are Needed.

Moscato, D. R. (1976). The application of the entropy measure to the analysis of part commonality in a product line. *The International Journal of Production Research*, *14*(3), 401-406.

Rand, W. M. (1971). Objective Criteria for the Evaluation of Clustering Methods. Journal of the American Statistical Association, 66(336), 846–850.

Sharma, S. K., & Bhat, A. (2014). Supply chain risk management dimensions in Indian automobile industry: A cluster analysis approach. Benchmarking: An International Journal, 21(6), 1023-1040.

Thonemann, U. W., & Brandeau, M. L. (2000). Optimal Commonality in Component Design. Operations Research, 48(1), 1–19.

Vasantha, Gokula, et al. "A probabilistic design reuse index for engineering designs." Journal of Mechanical Design 142.10 (2020): 101401.