Comparison of Intermittent Demand Forecasting Methods in Predicting the Repair of Simulators based upon System State

Corey Hendricks, D.Eng
Leidos
Orlando, FL
Corey.T.Hendricks@Leidos.com

ABSTRACT

According to a 2022 report released by the Department of Defense (DoD) Inspector General "The inability to produce accurate and timely forecasts of joint logistics needs created an unmitigated risk to the DoD's ability to plan and logistically support operations and contingencies." (DoD-IG, 2022). This assessment is one in a series of reports surrounding the ability for the DoD to perform material forecasting. In 2015 U.S. Government Accountability Office (GAO) report, DoD supply chain management has been classified as a high-risk area since 1990, due in part to weaknesses in accurately forecasting the demand for spare parts.

This paper ranks multiple machine learning and statistical approaches to determine the most accurate method for forecasting repairable part demand in U.S. Army simulators. The assessment will leverage Root Mean Squared Error (RMSE) and the Mean Absolute Error (MAE) values to assess the accuracy of the forecasting method. The motivation for this paper is there are relatively few studies that compare the performance of statistical and machine learning forecasting methods in performing intermittent demand forecasting of repair parts for military systems (Ahmed et al., 2010; Makridakis, Spyros Spiliotis, E Assimakopoulos, 2020; Makridakis et al., 2018) Of the few comparative studies that have been performed, several of them place computational limitations on the machine learning methods, thus limiting model accuracy.

This paper removes the computational limitation placed against machine learning methods when comparing the achieved accuracy to statistical models. Additionally, this paper addresses the practical issue of assessing forecasting accuracy while dealing with an inventory suffering from part obsolescence, which is common in military systems (Teunter et al., 2011). The results of this paper found that Support Vector Regression (SVR) is the most accurate method when forecasting repairable and consumable part demand for simulators classified as NMC, PMC, and FMC. However, K-Nearest Neighbor Regression (KNNR) tied the accuracy of SVR when forecasting material demand when the system was in a PMC state.

ABOUT THE AUTHORS

Dr. Corey Hendricks has over 20 years working as a leader in the development, operations, and sustainment of simulation and training solutions for Department of Defense customers. Currently Corey serves as a solutions architect for the Multi-Domain Solutions Division within Leidos Defense. In this role he is a technical leader in the design and implementation of scaled, distributed software-based solutions leveraging trusted AI & ML Models. As a Solutions Architect he is responsible for providing technical leadership to multidisciplinary development teams in the design, development, testing, implementation, fielding, and support of distributed simulation systems. Corey received his Doctor of Engineering degree from The George Washington University. He has a Master of Science in Modeling and Simulation from the University of Central Florida. Also, he has several other graduate and undergraduate degrees.

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INTRODUCTION

In April of 2015, the Government Accountability Office (GAO) released an assessment identifying the Army's inability to effectively manage excess inventory. The "GAO identified (Department of Defense) DoD supply chain management as a high-risk area due in part to ineffective and inefficient inventory management practices that have contributed to high levels of excess inventory relative to total inventory" (Hinton, 1999)The assessment highlighted that while the U.S. Navy and U.S. Air Force had successfully met the target objectives, the U.S. Army had failed to do so. Results of the assessment showed that the Army held an excess inventory balance of spare parts that were valued at $3.6 billion. "The Army's calculation of its inventory to meet requirements was not in accordance with Army guidance and resulted in potentially underreporting its amount of on-hand excess inventory to the Office of the Secretary of Defense (OSD)" (GAO, 2015)In the 2018 U.S. National Defense Strategy, resilient and agile logistics were highlighted as a key tenant for modernization (United States Government, 2018). One of the subtenants for this effort is the improvement of material demand forecasting. The selection of an accurate predictive model based upon defined use cases is necessary for the Army to improve their forecasting capabilities. Sufficient stock of parts must be on hand to enable the system to achieve operational availability requirements for military operations. Conventional statistical methods have been historically utilized to project the intermittent demand of spare parts. The use of some historical methods have led to inaccurate forecasts which are associated with slow-moving inventory and increased storage costs (Syntetos & Boylan, 2005).

The objective of this research is to provide a reference for the selection of the best performing forecasting method by comparing the accuracy of multiple statistical and machine learning forecasting methods and then assessing if there is a statistically significant difference in the results. This study will utilize the operational availability of the system which include simulators operating in a Non-Mission Capable (NMC), Partially Mission Capable (PMC), or Fully Mission Capable (FMC) state. Corrective action work orders for systems that do not impact functionality or performance but may affect usability are associated with FMC. These work orders address issues that, while not critical to the system's operation, can still impede the ease of use or convenience for the soldier. For example, a display screen with a faulty backlight or a user interface with unresponsive buttons can be frustrating and reduce the effectiveness of the system. This research will utilize parts identified on maintenance records that classify the system as NMC, PMC, or FMC as the demand signal for the decrement of spare parts out of the inventory. Data associated with this research was limited to unclassified systems that are under maintenance in which the data is collected manually through a work order on the US Army's Warfighter FOCUS (WFF) program. Systems of interest in this research have an operational availability requirement of less than 99%. The data used in this study is limited to work orders collected on the and are associated with the following systems:

Aviation Combined Arms Tactical Trainer (AVCATT)
Close Combat Tactical Trainer (CCTT)
Combined Arms Collective Training Facility (CACTF)
Digital Range Training System (DRTS)
Engagement Skills Trainer (EST)
Gunnery Maintenance Driver Trainers (GMDT)
Joint Multinational Readiness Center (JMRC)
Laser Marksmanship Training System (LMTS)
National Training Center (NTC)
Tactical Engagement Simulation Systems (TESS)

Wireless Independent Targeting System (WITS)

Work orders utilized in the research, are limited to ones which are classified as corrective action (non-scheduled maintenance) with a start date of the 4th of May 2012, through 30th of April 2017, of the WFF program. While there are a wide variety of statistical and machine learning methods for predicting intermittent demand, this research is limited to the use of 7 forecasting methodologies.

DATA

Collection of Data

The data for this research was obtained from the U.S. Army's work order repository called the "ATMP Bidder's Library", which was used for acquiring the Army Training Aids, Devices, Simulations and Simulators (TADSS) Maintenance Program (ATMP) contract. The ATMP Bidder's Library contains the complete maintenance actions associated with the sustainment of all simulators, starting from year 4 through the end of year 9 of the WFF program. 21 million maintenance records are associated with these systems. There were no missing data elements found in any record. Each record has 33 associated features, describing various aspects of the maintenance action. Several maintenance actions have multiple records in the dataset due to the use of multiple parts associated with a single work order.

Data Preparation

Data cleansing was performed on the repair part number and repair part name fields. This activity focused on standardization of several part numbers and descriptions as several similar parts were procured by different vendors. The repair part name and repair part number fields were selected using the work order data. A manual sorting process was performed on the repair part name. Parts named similarly or performed similar functions were grouped together. Most parts were identified by generic description, a comma, and then a detailed description (e.g., Hard Drive, SATA II). All similar part descriptions were associated with a common part name (e.g., Hard Drive) and through this process the distinct amount of part numbers used in the research is reduced from 35,307 to 26,322. The distinct part numbers totaling to 26,322 are broken out by each system. Table 1 identifies the quantities of the original unique parts and the quantities removed to result in the final count of parts that was used for the analysis.

Table 1. Data Cleansing Part Number Reduction

System	Original Number of Unique Parts	Reduced Number of Unique Parts	Remaining Number of Unique Parts
AVCATT	1,580	1,157	423
CACTF	1,800	930	870
CCTT	2,906	498	2,408
DRTS	3,778	560	3,218
EST	1,772	802	970
GMDT	6,153	1,752	4,401
JMRC	2,817	486	2,331
LMTS	279	186	93
NCM3	48	11	37
NSTD	392	291	101
NTC	5,335	2,312	3,023
LCT, TES, WITS	8,447	-	8,447
Total	35,307	8,985	26,322

Statistical Forecasting Methods

Three statistical methods are used in this research. They are, the Simple Exponential Smoothing (SES) method, Teunter Syntetos and Babai's (TSB) variant of Croston's method, and Dynamic Optimized Theta Method (DOTM). The SES method was selected due to its historical capability of accurately performing demand forecasting (Croston, 1972). TSB was selected due to its ability to overcome challenges associated with intermittency in demand, estimation bias due to intermittency, and part obsolescence (Teunter et al., 2011). DOTM was selected because of the high accuracy forecasting material demand during the international demand forecasting competition called M3 (Makridakis & Hibon, 2000).

Machine Learning Forecasting Methods

Support Vector Regression (SVR) was selected due to its low errors reported in multiple time series forecast studies (Islek & Oguducu, 2017; Kilimci et al., 2019; Williams, 2003). Multi-layer Perceptron (MLP) was chosen for its high accuracy in several studies (Gamberini et al., 2010; Gutierrez et al., 2008; Islek & Oguducu, 2017; Lolli et al., 2019; Pawar & Tiple, 2019). Random Forest (RF) was selected based upon the high level of accuracy reported in previous studies (Ahmed et al., 2010; Loh, 2014; Ronaghan, 2018; Spiliotis et al., 2020). K Nearest Neighbor Regression (KNNR) was chosen for its ability to provide consistent level of accuracy when performing time series forecasting ((Ahmed et al., 2010; Dehlavi, 2020; L.Devroye, 1994; Mahato et al., 2018)).

All machine learning (ML) models use a predefined number of previous periods, called a step back value, to determine the expected forecast value for the next period. The duration of the step back period varies by the ML forecasting method used. The number of periods included in the step back value prevents the models from under or over fitting the training and testing data. Tuning this value impacts the error associated with each model by hundreds or even thousandths. Multiple trials were performed with each method by varying the step back period from 1, 4, and 10 periods. The step back periods of 1, 4 and 10 represent the lower, median, and upper quartiles for historical part demand affecting system state.

As performed in Spiliotis et al's comparison of statistical and machine learning forecasting methods, data is scaled before training the machine learning model to between 0 and 1 (Spiliotis et al., 2020). Scaling the data before training a machine learning model is a vital step that can significantly enhance model performance and improve the accuracy of predictions. The MinMaxScaler function in the SciKit learn module in python version 3.6.9 is the code that executes the scaling of the data prior to training.

RESULTS

This results section presents a comprehensive analysis of the performance of different forecasting methods, utilizing key error metrics such as Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE). To provide a clear and understandable comparison, the mean performance and rankings of each forecasting method are displayed using RMSE and MAE. These metrics are crucial in evaluating the accuracy of forecasting methods, with lower scores indicating higher accuracy. The tables included in this section list the scores for both RMSE and MAE, alongside the comparative rankings for each method. This structured presentation allows personnel involved in material demand planning to quickly identify the most reliable forecasting methods, facilitating better decision-making in logistics and supply chain management.

While RMSE and MAE scores will indicate the most accurate measure, it is important to identify if there is a statistically significant difference in the results produced by each forecasting method. Analysis of Variance (ANOVA) is the comparative tool selected to assess if there is a significant difference in the results. By evaluating the ANOVA F and P values, it becomes evident that a significant difference exists between the selected forecasting methods. An F score greater than 2.10 for this study identifies that at least one group mean is more significant than the others. A P value of less than 0.05 identifies that there is a statistically significant difference in the results produced by the forecasting methods. This statistical validation is crucial for military logistics personnel, as it confirms the reliability of the forecasting methods used in this study.

Understanding these results is essential for various roles in military logistics, including Logistics Officers, Supply Chain Managers, and Inventory Control Specialists. By leveraging the most accurate forecasting methods, these professionals can ensure that critical repair parts are available when needed, minimizing downtime and enhancing operational readiness. For example, accurate forecasts allow Procurement Officers to align inventory levels with actual demand, reducing both stockouts and excess inventory. This optimization of resources not only reduces costs but also ensures timely repairs, maintaining the operational availability of essential systems.

Furthermore, the ability to forecast with greater accuracy enables a more agile and responsive supply chain, capable of adapting to changes in operational demand. This agility is particularly important in dynamic military environments where unexpected demands can arise suddenly. Accurate forecasting ensures that soldiers have reliable access to fully functional equipment, enhancing their efficiency and effectiveness in the field. For instance, resolving minor usability issues through precise demand forecasts ensures that soldiers experience minimal disruption, maintaining high operational standards and overall mission capability.

Forecasting Material Demand for NMC Systems

This use case focuses on the intermittent demand of parts that are associated with a simulator becoming Non-Mission Capable (NMC). The approach uses all six years, 334 periods, of corrective action maintenance records where EST, AVCATT, CCTT, GMDT, or LMTS simulators are classified as inoperable. Each forecasting model is trained on 282 periods while the forecast horizon for this hypothesis covers 52 periods. There are 1,586 unique repairable and consumable part numbers associated with these maintenance actions are included in the training and testing dataset.

Table 2. RMSE and MAE results of all forecasting methods for NMC

	Performance		Rank	
Method	Non-Mission Capable			
	RMSE	MAE	RMSE	MAE
Statistical Methods				
Simple Exponential Smoothing (SES)	0.199	0.143	7	7
Teunter Syntetos and Babai (TSB)	0.161	0.010	5	5
Dynamic Optimised Theta Model (DOTM)	0.199	0.143	6	6
ML Methods				
Support Vector Regression (SVR)	0.100	0.026	1	1
Multi-Layer Perceptron (MLP)	0.149	0.089	3	4
Random Forest (RF)	0.148	0.089	2	3
K-Nearest Neighbor Regression (KNNR)	0.156	0.076	4	2

Table 3. MAE ANOVA results for NMC

NMC MAE ANOVA	Sum of Squares	Degrees of Freedom	F	P
Forecast Method	22.489	6	3.064	0.005
Residual	13573.26	11095		

Roles, such as Logistics Officers, Demand Planners, and Supply Chain Managers, can leverage the findings of this use case to significantly enhance material demand forecasts for Non-Mission Capable (NMC) systems. By integrating the top-performing Support Vector Regression (SVR) method, which exhibited the lowest RMSE (0.100) and MAE (0.076) values, these professionals can develop more accurate and reliable forecasts. The consistent performance of SVR, outperforming methods like SES and DOTM by substantial margins, indicates that adopting SVR will lead to better anticipation of part demands required for system repairs. This improvement is statistically validated, as the F value (3.064) surpasses the critical value (2.099), and the P value (0.005) is significantly below the 0.05 threshold, ensuring the reliability of these results.

Utilizing this information, Inventory Control Specialists and Procurement Officers can adjust their current forecasting methods to align inventory stock levels with the more accurate predictions provided by SVR. This adjustment allows for a more responsive and efficient supply chain, as inventory levels will be more closely matched to actual demand. This reduces the likelihood of stockouts or overstock situations, optimizing resource allocation and reducing costs. By integrating SVR-based forecasts, these roles can quickly respond to changes in demand for NMC systems, ensuring that repairs can be conducted without unnecessary delays, thereby improving the operational availability of essential systems.

Developing material forecasts based on the operational availability of systems enables logistics, supply chain, and inventory managers to respond more effectively to user demand. With SVR providing a statistically significant improvement in forecasting accuracy, these managers can make data-driven decisions that align with the operational needs of the military. This approach ensures that critical systems remain functional and mission-capable, reducing the impact of NMC status on overall operational effectiveness. By focusing on the operational availability of systems, forecasting methods become more precise, supporting the timely provision of materials and enhancing the readiness and resilience of military operations. This proactive approach to logistics and supply chain management fosters a more agile and responsive military force, capable of meeting the dynamic demands of modern warfare.

Forecasting Material Demand for PMC Systems

The approach to test this hypothesis is to use all six years, 334 periods of corrective action maintenance records where EST, AVCATT, CCTT, GMDT, or LMTS simulators is classified as PMC. Each forecasting model is trained on 282 periods while the forecast horizon for this hypothesis covers 52 periods. The reduced forecast horizon is due to the lack of work orders that classified any system in the Research as PMC. There are 959 unique repairable and consumable part numbers associated with these maintenance actions are included in the training and testing dataset.

Table 4. RMSE and MAE results of all forecasting methods for PMC

	Performance		Rank	
Method	Partially Mission Capable			
	RMSE	MAE	RMSE	MAE
Statistical Methods				
Simple Exponential Smoothing (SES)	0.137	0.066	7	7
Teunter Syntetos and Babai (TSB)	0.129	0.054	4	3
Dynamic Optimised Theta Model (DOTM)	0.137	0.066	6	6
ML Methods				
Support Vector Regression (SVR)	0.098	0.020	1	2
Multi-Layer Perceptron (MLP)	0.131	0.058	5	5
Random Forest (RF)	0.125	0.054	3	4
K-Nearest Neighbor Regression (KNNR)	0.109	0.020	2	1

Table 5. MAE ANOVA results for PMC

PMC MAE ANOVA	Sum of Squares	Degrees of Freedom	F	P
Forecast Method	2.107	6	2.607	0.016
Residual	903.078	6706		

Demand planners will be able to enhance material demand forecasts for Partially Mission Capable (PMC) systems by utilizing the insights from this use case, which analyzed the performance of various forecasting methods over a 52-week horizon for 959 unique part numbers. The data indicates that the Support Vector Regression (SVR) method consistently achieved the best performance with an RMSE of 0.098, while the K-Nearest Neighbors Regression (KNNR) method performed best in terms of MAE with a score of 0.02. The significant difference in forecasting accuracy, confirmed by the F value (2.607) being greater than the critical value (2.099) and a P value of 0.016, underscores the statistical reliability of these methods. By adopting SVR and KNNR for intermittent demand forecasting, demand planners can achieve a more accurate prediction of the parts needed to maintain simulator functionality.

With this improved forecasting capability, material planning decisions can be more precise and effective. For example, demand planners can better anticipate the need for repairable and consumable parts, ensuring that critical components are available when simulators become partially mission capable. This foresight allows for proactive inventory management, reducing the risk of stockouts and minimizing downtime. By focusing on the parts with the highest likelihood of demand, planners can optimize inventory levels, reducing excess stock and associated holding costs while still meeting operational requirements.

Additionally, the ability to forecast intermittent demand accurately enables demand planners to coordinate more effectively with procurement officers and maintenance planners. With reliable forecasts, procurement officers can negotiate better terms with suppliers, knowing the precise quantities required over the forecast period. Maintenance planners can schedule repairs more efficiently, ensuring that the necessary parts are on hand to address issues promptly, thereby enhancing the overall readiness and reliability of the simulators. This integrated approach to material planning, supported by data-driven forecasting methods like SVR and KNNR, ensures that partially functional systems can be quickly restored to full operational capability, maintaining mission readiness and effectiveness.

Forecasting Material Demand for FMC Systems

This hypothesis uses all six years, 334 periods of corrective a maintenance records for all systems identified in this Research. Each forecasting model is trained on 282 periods while the forecast horizon for this hypothesis covers 52 periods. There are 21,471 unique repairable and consumable part numbers associated with these maintenance actions which are included in the training and testing dataset. This hypothesis tests each forecasting method's ability to predict all the repair parts that are associated with a non-scheduled maintenance action.

Table 6. RMSE and MAE results of all forecasting methods for FMC

	Performance		Rank	
Method	Fully Mission Capable			
	RMSE	MAE	RMSE	MAE
Statistical Methods				
Simple Exponential Smoothing (SES)	0.872	0.512	4	6
Teunter Syntetos and Babai (TSB)	0.850	0.408	3	3
Dynamic Optimised Theta Model (DOTM)	0.927	0.577	6	7
ML Methods				
Support Vector Regression (SVR)	0.645	0.330	1	1
Multi-Layer Perceptron (MLP)	0.773	0.392	2	2
Random Forest (RF)	0.873	0.499	5	5
K-Nearest Neighbor Regression (KNNR)	0.938	0.481	7	4

Table 7. MAE ANOVA results for FMC

FMC MAE ANOVA	**Sum of Squares**	**Degrees of Freedom**	**F**	**P**
Forecast Method	1.157 e+03	6	2.159	0.044
Residual	1.342 e+07	150290		

Multiple roles can significantly improve their forecasting for Fully Mission Capable (FMC) systems by leveraging the statistical analysis provided. The consistent RMSE (Root Mean Square Error) and MAE (Mean Absolute Error) results indicate that the Support Vector Regression (SVR) method is the most effective for forecasting intermittent demand associated with non-scheduled maintenance actions. Logistics Officers, Supply Chain Managers, and Demand Planners can integrate SVR into their forecasting models to achieve more accurate predictions for repair parts needed over a 52-week forecast horizon. This integration ensures that the required parts are available when needed, enhancing the readiness and reliability of FMC systems.

Inventory Control Specialists and Procurement Officers can use this information to adjust their current forecasting methods to align inventory stock levels with the more accurate predictions provided by SVR. This adjustment allows for a more efficient and responsive supply chain, reducing the likelihood of both stockouts and overstock situations. By adopting SVR-based forecasts, these roles can quickly respond to changes in demand for non-scheduled maintenance parts, ensuring that repairs can be conducted without unnecessary delays. This approach optimizes inventory levels, reduces costs, and enhances the operational efficiency of the supply chain, ensuring that fully mission-capable systems remain operational without interruption.

Failures in FMC systems that do not impact their core functionality or performance can still have usability impacts on soldiers. These usability issues, while not critical, can affect the overall efficiency and effectiveness of military operations. For example, a minor malfunction in a communication system that does not impede its primary function might still create inconveniences or slowdowns for the user. By accurately forecasting the demand for parts associated with such non-scheduled maintenance actions using SVR, logistics, supply chain, and inventory managers can ensure that even minor issues are promptly addressed. This proactive approach enhances user experience, maintains high operational standards, and supports the overall mission capability of the military forces, ensuring that all aspects of system performance, including usability, are consistently maintained.

CONCLUSION

In military logistics, accurate material demand forecasting is crucial for maintaining operational readiness and efficiency. The research outlined above demonstrates that employing advanced forecasting methods, specifically Support Vector Regression (SVR), significantly enhances the ability of various roles to predict material needs more precisely. This improvement is particularly evident in the forecasting for Non-Mission Capable (NMC) and Fully Mission Capable (FMC) systems, where the accuracy and responsiveness of the supply chain directly impact operational effectiveness.

For NMC systems, the integration of SVR has shown a marked improvement in forecasting accuracy, with RMSE values as low as 0.100 and MAE values of 0.026. By leveraging these accurate predictions, Logistics Officers, Supply Chain Managers, and Demand Planners can ensure that critical repair parts are available when needed, reducing system downtime and enhancing mission readiness. Inventory Control Specialists and Procurement Officers benefit from these precise forecasts by aligning inventory levels more closely with actual demand, minimizing both stockouts and excess inventory. This optimization of resources not only reduces costs but also ensures that repairs can be conducted without delays, maintaining the operational availability of essential systems.

The use of SVR in forecasting intermittent demand for FMC systems further highlights the benefits of advanced forecasting methods. Although the accuracy for FMC systems was lower, with RMSE of 0.645 and MAE of 0.330, the use of SVR still provided a statistically significant improvement over other methods. This improved accuracy allows logistics and supply chain managers to better predict the need for parts associated with non-scheduled maintenance actions. By addressing these needs promptly, even minor usability issues that do not impact the core functionality of systems can be resolved swiftly, ensuring that soldiers experience minimal disruption. For example, a minor communication system fault that doesn't impede functionality but affects usability can be quickly rectified, thereby maintaining high operational standards and soldier efficiency.

The value provided to soldiers through these enhanced forecasting methods is substantial. Better predictions lead to a more agile and responsive supply chain, capable of quickly adapting to changes in operational demand. Soldiers depend on the reliability and availability of their equipment, and accurate forecasting ensures that their needs are met promptly. This agility is particularly crucial in dynamic operational environments where unexpected demand can arise suddenly. The ability to forecast with greater accuracy means that logistics and supply chain managers can preemptively address potential issues, ensuring that soldiers are always equipped with fully functional and reliable systems.

Recommendations for Future Research

Future research should test the effect of determining a statistically significant difference between forecasting methods when using different error measures. This research utilized two error measures to determine the results for each hypothesis. When determining if there was a statistically significant difference in accuracy between the forecasting methods the results varied based upon which error measure was selected. Future studies should consider additional forecasting methods to determine if a better forecasting model can be applied to this data set. Additionally, the smoothing constraints for Simple Exponential Smoothing (SES) and Dynamic Optimized Theta Method (DOTM) was optimized automatically using the Sci-Kit learn library. Researchers could use different libraries to tune the models manually to see if an improvement in results is achieved. Lastly future studies could increase the forecast horizon by using additional data from subsequent contracts to assist the Army with developing a strategic forecast.

REFERENCES

Ahmed, N. K., Atiya, A. F., El Gayar, N., & El-Shishiny, H. (2010). An empirical comparison of machine learning models for time series forecasting. *Econometric Reviews*, *29*(5), 594–621. https://doi.org/10.1080/07474938.2010.481556

Croston, A. J. D. (1972). Forecasting and Stock Control for Intermittent Demands Published by : Palgrave Macmillan Journals on behalf of the Operational Research Society Stable URL : https://www.jstor.org/stable/3007885 REFERENCES Linked references are available on JSTOR for this. *Operational Research Quarterly*, *23*(3), 289–303.

Dehlavi, K. (2020). A Machine Learning Model for Predicting the Procurement Lifetime of Electronic Units in Sustainment-Dominated Systems. In *The George Washington University*.

DoD-IG. (2022). Evaluation of the DoD's Actions to Develop Interoperable Systems and Tools for Forecasting Logistics Demand Across the Joint Logistics Enterprise. *DODIG-2022-088*. https://media.defense.gov/2022/May/04/2002989683/-1/-1/1/DODIG-2022-088_REDACTED.PDF

Gamberini, R., Lolli, F., Rimini, B., & Sgarbossa, F. (2010). Forecasting of sporadic demand patterns with seasonality and trend components: An empirical comparison between holt-winters and (s)ARIMA methods. *Mathematical Problems in Engineering*, *2010*. https://doi.org/10.1155/2010/579010

GAO. (2015). *DEFENSE INVENTORY Services Generally Have Reduced Excess Inventory, but Additional Actions Are Needed Report to the Subcommittee on Readiness, Committee on Armed Services, House of Representatives United States Government Accountability Office*. *April*. https://www.gao.gov/assets/670/669756.pdf

Gutierrez, R. S., Guerrero, G. C., Solis, A. O., & Mukhopadhyay, S. (2008). Lumpy demand characterization and forecasting performance using neural networks. *IIE Annual Conference and Expo 2008*, 1623–1628.

Hinton, H. (1999). *Defense Inventory: Continuing Challenges in Managing Inventories and Avoiding Adverse Operational Effects*. United States. General Accounting Office. https://www.govinfo.gov/content/pkg/GAOREPORTS-T-NSIAD-99-83/pdf/GAOREPORTS-T-NSIAD-99-83.pdf

Islek, I., & Oguducu, S. G. (2017). A Decision Support System for Demand Forecasting based on Classifier Ensemble. *Communiation Papers of the 2017 Federated Conference on Computer Science and Information Systems*, *13*, 35–41. https://doi.org/10.15439/2017f224

Kilimci, Z. H., Akyuz, A. O., Uysal, M., Akyokus, S., Uysal, M. O., Atak Bulbul, B., Ekmis, M. A., & Silva, T. C. (2019). An improved demand forecasting model using deep learning approach and proposed decision integration strategy for supply chain. *Complexity*, *2019*. https://doi.org/10.1155/2019/9067367

L.Devroye. (1994). On the Strong Universal Consistency of Nearest Neighbor Regression Function Estimates. *Annals of Statistics*, *22*(3), 1371–1385.

Loh, W. Y. (2014). Fifty years of classification and regression trees. *International Statistical Review*, *82*(3), 329–348. https://doi.org/10.1111/insr.12016

Lolli, F., Balugani, E., Ishizaka, A., Gamberini, R., Rimini, B., & Regattieri, A. (2019). Machine learning for multi-criteria inventory classification applied to intermittent demand. *Production Planning and Control*, *30*(1), 76–89. https://doi.org/10.1080/09537287.2018.1525506

Mahato, V., O'Reilly, M., & Cunningham, P. (2018). A comparison of k-NN methods for time series classification and regression. *CEUR Workshop Proceedings*, *2259*, 102–113.

Makridakis, Spyros Spiliotis, E Assimakopoulos, V. (2020). *M5-Competitors-Guide-Final-10-March-2020*. https://mofc.unic.ac.cy/wp-content/uploads/2020/03/M5-Competitors-Guide-Final-10-March-2020.docx

Makridakis, S., & Hibon, M. (2000). The M3-competition: Results, conclusions and implications. *International Journal of Forecasting*, *16*(4), 451–476. https://doi.org/10.1016/S0169-2070(00)00057-1

Makridakis, S., Spiliotis, E., & Assimakopoulos, V. (2018). Statistical and Machine Learning forecasting methods: Concerns and ways forward. *PLoS ONE*, *13*(3), 1–27. https://doi.org/10.1371/journal.pone.0194889

Pawar, N., & Tiple, B. (2019). Demand Forecasting of Anti-Aircraft Missile Spare Parts Using Neural Network. *Proceedings of the 3rd International Conference on Electronics and Communication and Aerospace Technology, ICECA 2019*, 572–578. https://doi.org/10.1109/ICECA.2019.8821903

Ronaghan, S. (2018). *The Mathematics of Decision Trees, Random Forest and Feature Importance in Scikit-learn and Spark*. Towardsdatascience.

Spiliotis, E., Makridakis, S., Semenoglou, A. A., & Assimakopoulos, V. (2020). Comparison of statistical and machine learning methods for daily SKU demand forecasting. *Operational Research*, *0123456789*. https://doi.org/10.1007/s12351-020-00605-2

Syntetos, A. A., & Boylan, J. E. (2005). The accuracy of intermittent demand estimates. *International Journal of*

Forecasting, *21*(2), 303–314. https://doi.org/10.1016/j.ijforecast.2004.10.001
Teunter, R. H., Syntetos, A. A., & Babai, M. Z. (2011). Intermittent demand: Linking forecasting to inventory obsolescence. *European Journal of Operational Research*, *214*(3), 606–615. https://doi.org/10.1016/j.ejor.2011.05.018
United States Government. (2018). *National Defense Strategy*. 23.
Williams, C. K. I. (2003). Learning With Kernels: Support Vector Machines, Regularization, Optimization, and Beyond. *Journal of the American Statistical Association*, *98*(462), 489–489. https://doi.org/10.1198/jasa.2003.s269