Applying Automated Machine Learning to Improve Budget Estimates for a Naval Fleet Maintenance Facility

Cheryl Eisler[1] and Mikayla Holmes[2]
[1]*Centre for Operational Research and Analysis, Defence R&D Canada, 60 Moodie Drive, Ottawa, Canada*
[2]*University of Victoria, Department of Mathematics and Statistics, 3800 Finnerty Road (Ring Road), Victoria, Canada*

Keywords: Automated Machine Learning, Predictive Analytics, Budget, Overtime Hours, Fleet Maintenance Facilities, Work Orders.

Abstract: A study was undertaken to improve the accuracy of staffing overtime budget predictions for a naval fleet maintenance facility and identify primary factors associated with overtime accrual. A series of models based on facility work orders were developed using the R statistical suite and the open source package H2O.ai for automated machine learning. Along with the model's predictive capabilities for budgetary planning, primary work order attributes associated with overtime hours were also determined based on the variables of importance. These gave insight into the type of maintenance and personnel assigned to the maintenance task which contributed to the highest accrual of overtime hours. Additionally, the monthly best curve fit for past budget predictions revealed a sigmoidal relationship, which was used to assist in the prediction of fiscal year 2019/2020 budget. The budget estimate from the model was found to be within 5% of the total budget expended hours over the fiscal year. As new annual data are provided or additional facilities examined, the models can be retrained or rebuilt to include new information and allow decision makers to prepare more accurate funding estimates – potentially reserving funds for upcoming critical maintenance tasks or saving funds through alternative approaches to task management.

1 INTRODUCTION

The Royal Canadian Navy (RCN) maintains its fleet of warships, submarines and other auxiliary formation vessels using a combination of internal and external services. First-line maintenance addresses immediate, limited repairs and minor functionality issues on-board the ships. Second-line work includes corrective maintenance conducted at a repair facility, such as fixing seals or replacing bearings. The most common third-line work, known as repair and overhaul, involves repairing both damaged and worn vessel components, as well as component replacement at end of service life. Second- and third-line maintenance may be conducted internally at a Fleet Maintenance Facility (FMF) or externally through an in-service support contract. The RCN operates two such facilities, each collocated with a naval base.

Within these RCN facilities, maintenance tasks are broken down into Work Orders (WOs); where each WO is documented to capture: (1) the type of work to be completed; (2) client organization; (3) the platform on which the work is to be completed; and (4) a variety of other characteristics pertaining to the task. It may be necessary to approve the use of overtime (OT) to close WOs, as necessitated by operational requirements. The need for OT is dependent on the operational impact and urgency of the task, the current workload, and the authorized OT budget. Thus, a study was undertaken to improve the accuracy of FMF overtime budget predictions and identify primary factors associated with OT accrual (Holmes, 2020). One FMF supplied seven years of past OT data, budgets, and WO attributes to facilitate trend analysis and to identify major variables of importance for OT accrual.

A literature review was conducted to determine similar classes of problems and identify an appropriate methodology to predict both total OT for a given WO and month within the Fiscal Year (FY) that the OT is accrued based on the attributes of the WO. Based on this review and its operational capabilities, an Automated Machine Learning (autoML) approach using H2O was deemed the most applicable to the study. The results of this survey are

Eisler, C. and Holmes, M.
Applying Automated Machine Learning to Improve Budget Estimates for a Naval Fleet Maintenance Facility.
DOI: 10.5220/0010302205860593
In *Proceedings of the 10th International Conference on Pattern Recognition Applications and Methods (ICPRAM 2021)*, pages 586-593
ISBN: 978-989-758-486-2

presented in Section 2. Utilizing the common pipeline process for autoML described by Truong et al. (2019), the analysis is broken down into data pre-processing, feature engineering, model generation, and model interpretation. In Section 3.1 and 3.2, past data regarding OT and WOs were processed to establish trends, identify correlations, and develop features. Explained in Section 3.3, an autoML predictive model was developed. Section 3.4 illustrates how the model is used to estimate the FY 2019/2020 (FY19/20) OT budget with a target of ±5% accuracy. Future work to improve the model accuracy is outlined in Section 4. Conclusions presented in Section 5.

2 LITERATURE REVIEW

FMFs process hundreds of thousands of WOs every year, only a portion of which require overtime to complete. Overtime hours are accrued by personnel completing specific types of maintenance tasks, driven by a number of factors such as operational demand tempo for ready naval vessels, number, age and types of vessels in fleet, maintenance policies, supply chain logistics or tool availability constraints, resource limitations, or human resource policies.

A similar Canadian defence application using supervised machine learning algorithms (Maybury, 2018) – specifically classification and regression trees – examined the variables of importance associated with maintenance task completion times. WO were clustered based on completion times to determine the attributes which influenced length of time necessary for specific tasks. Finding such variables of importance is but one aspect of the study described herein. Further insights were obtained on data cleaning, as well as analysing and manipulating the data in the R statistical suite. This was valuable for data pre-processing.

The predictive powers of Random Forests (RF), Gradient Boosted Machines (GBM), support vector machines and general linear models were presented by Ellis et al. (2015) to predict wind power variability based on occurrence of extreme wind events of wind farms in Southern Australia. After comparing predictive power, reliability, and tuning ease, results indicated that RF and GBM generated reliable models. These techniques could be leveraged to gain insight to the general trends and correlations present in the WO datasets. As these models are also often used in automated machine learning, understanding their application and use also aids in interpreting the output from autoML tools.

Likewise relevant for the predictive outcomes of analysis, (Bartek et al., 2018) sought to optimize operating room usage by improving estimations of case-time duration to reduce the number of cases that exceed 10% of the estimated operating time. Estimates of case-time duration in operating rooms was optimized using extreme gradient boosting, which is a variation of the gradient boosting algorithm (Friedman, 2001). The way machine learning models were used to improve upon efficiency in scheduling and cost savings in Bartek et al. (2018) was emulated for the study herein to determine primary factors associated with OT for WOs. Such identification of variables of importance provided the foundation for feature engineering prior to model generation.

Tools for automating the machine learning pipeline from end-to-end to reduce the time and effort spent on repetitive tasks were explored. A variety of open source tools are available for use, and have been compared in the literature (Balaji, Allen, 2018; Gijsbers et al., 2019; He et al., 2020; Truong et al., 2019). Overall, H2O autoML is able to handle all input data types, performs well in a per model classification comparison, is open source, and is easy to use.

Notably, a tool such as H2O autoML predicts on a single output variable of interest. This informed the approach, as there were two variables to predict here: the amount of OT hours (a non-negative numeric value) and month OT accrued by WO (categorical). This combination of predictors puts the problem in a restricted subset of similar estimation tasks – where the accrual of OT hours is a combination of a failure prediction/detection and dynamic costing, and the month of accrual is time dependent. While many machine learning applications predict a single (and often binary) variable using time series (e.g., Gohel et al. (2020)), few attempt a combined variable model approach (Baykasoğlu et al., 2009; Desai et al., 2020; Ganapathi et al., 2009; Guanoluisa, 2020; Naik et al., 2019; Ozturk, Fthenakis, 2020).

3 ENGAGING THE AUTOML PIPELINE

To build a thorough understanding of the variables of importance for OT accrual, identify correlations between WO variables, and establish appropriate datasets on which to predict the output variables, it was necessary to engage a human-in-the-loop during the data pre-processing and feature engineering phases of the autoML pipeline. This enabled two separate models to be generated, followed by automatic hyperparameter optimization and architecture search. The final model interpretation was crossed checked against previous models, and the predictive analysis visualized.

3.1 Data Pre-processing

To prepare the data for exploration, the data collection, cleaning and augmentation steps were performed with significant oversight and human intervention to ensure that a solid understanding of the problem was obtained at the start of the process.

3.1.1 Data Collection

Datasets were limited to the past seven years (FY13/14-FY19/20) of information extracted from official records management systems. To predict for two variables of output, it was necessary to have two separate, although linked, datasets from which to build each model. Thus, to determine the amount of OT accrued, a dataset with all past WOs from FY13/14-FY18/19 (for model development, referred to as Dataset A) was used. A snapshot of the open WO near the beginning of FY19/20 was collected for predictive purposes (Dataset A_p). These data detailed information associated work order identification (ID), history, maintenance specifics, and financial coding.

The second dataset was only those WO that accrued OT (referred to as Dataset B). These data detailed information associated with work order identification, overtime hours by date, and classification of personnel assigned. Both datasets included numerical, categorical and time-series data.

3.1.2 Data Cleaning

Datasets included numerical (e.g., WO ID, OT Hours), categorical (e.g., Activity Type, Work Centre) and time-series data (Date of OT Hour Accrual). In many cases, the categorical fields were based on free-form text that either had to be cleaned to fit a set of consistent categories or built from a common understanding of key words in the text.

3.1.3 Data Augmentation

New data was created in the datasets by splitting free-form text fields into multiple categories. In some cases, numerical codes were aligned with text categories to link columns together, easing human interpretability.

3.2 Feature Engineering

A variety of tools were utilized to transform the raw data into features that better represent the underlying problem. These ranged from simple regression analysis to use of RFs and GBMs. To understand WO attributes that influenced the accrual of OT, data was organized by FY based on total OT accrued.

3.2.1 Feature Selection

It was important to discern whether trends between FYs had large variability prior to deciding which FYs were suitable to build final datasets for predictive modelling (Ebadi et al., 2019). First, the OT hours accrued by month, for each FY was plotted and curve fits were obtained to better establish the relationship between time and total accrual. Figure 1 illustrates cumulative OT has a sigmoidal shape with the mean average error (MAE) for a logistics function best fit of 2.8% of total hours with a standard deviation of ±0.64%. Residual plots for each fit (not shown here) were analysed and confirmed the logistics function fit (Kassambara, 2018). Logistics functions can logically be expected in situations where budgets are not immediately known at the start of the FY, the busiest seasons align with the middle of the FY, and budget caps spending near the end of the FY.

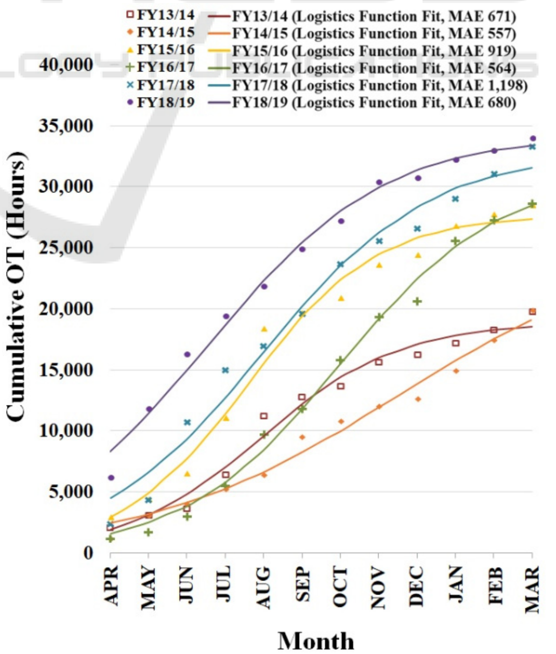

Figure 1: Cumulative OT accrual from FY13/14 to FY18/19 with logistics function fit.

When examining features, Non-Billable work was the second highest contributor of OT each FY, except in FY 13/14 where it contributed the most OT hours.

Although FY 13/14 and FY 14/15 were observably distinct from latter FYs in the fewer amount of OT accrued and who accrued OT, it was decided that FY 13/14 and FY 14/15 must be initially retained to assist training of the machine learning algorithm. Ideally, these earliest FYs will eventually be removed from the model building process once more recent data is obtained.

3.2.2 Feature Construction and Extraction

To build a model which used all available FYs as training data, Datasets A and B were stacked. To address potential issues in the use of autoML techniques, checks for multicollinearity and correlation of dataset fields were completed (Ebadi et al., 2019). A regression model that contains severe multicollinearity between variables can cause the coefficients of those variables to have high standard errors, resulting in instability when presented with new data. Multicollinearity and correlation can also cause the importance of those variables to be skewed or masked, resulting in a model which can be difficult to interpret, especially if the correlated variables are ones of interest (Allison, 2012).

Shown in Figure 2 is a sample correlation graph demonstrating strong correlation of variables from Dataset A, with darker shades of blue or red corresponding to the strength of negative or positive correlation, respectively. Figure 3 illustrates the correlation graph for Dataset B.

Algorithms that are efficient at predicting a continuous variable with only categorical variables as predictors were examined, as well as unbalanced datasets like the ones used for this study. Unbalanced datasets are those which consist of one outcome being substantially more frequent than others. For this analysis, the average number of WO which incur OT is 3.8% each FY, thus > 96% of WOs should be predicted to return zero OT hours per WO.

Also, given the high number of categories (over 100) within the data columns, it was desired to find algorithms which performed well without the need for encoding and could have dependent input variables. As such, tree-based models were pursued.

Tree-based models can handle correlation between predictor variables effectively because they only consider variables that improve the error function at each local split, inherently ignoring one of each pair of correlated variables. To interpret models which have multicollinearity, best practice is to build models with one of the correlated variables removed to determine how its presence affects relative importance calculations (Ebadi et al., 2019).

Initial models were built using simple decision and regression trees, as they provided initial insight by displaying variables of importance. For example in Dataset A, predicting the fields for Hours per WO using decision and regression trees (Therneau et al., 2017), Bill-To Code was found to be a significant variable of importance. This is expected, as Figure 2 shows that Bill-To Code was (positively or negatively) correlated with PM Activity Type, Cost Recoverable and Department. To unmask the importance of these variables, Bill-To Code was not subsequently used as an input. Furthermore, the Cost Recoverable field had little impact on the variables of importance and was not used subsequently to increase the accuracy of the PM Activity Type (Holmes, 2020).

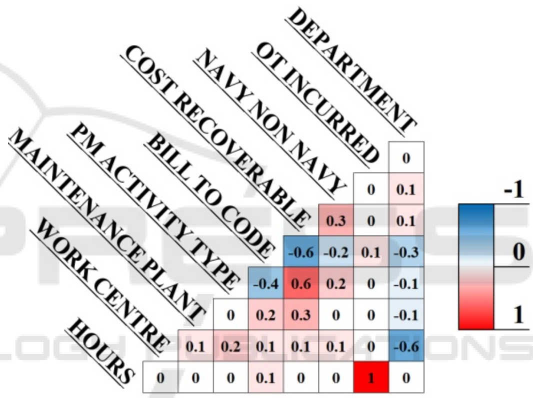

Figure 2: Correlation graph for Dataset A (all WOs).

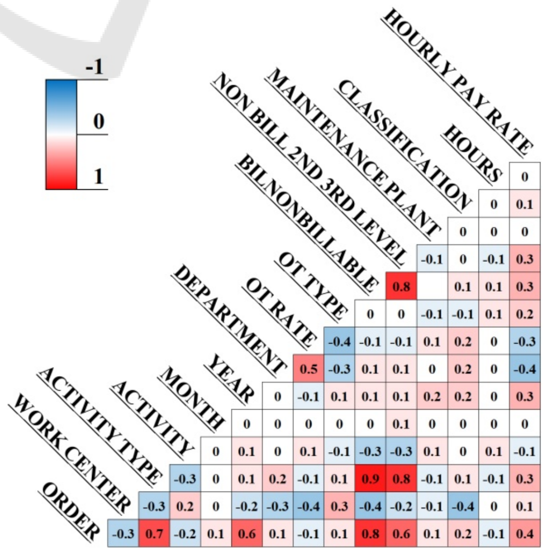

Figure 3: Correlation graph for Dataset B (only those WOs with accrued OT).

Differences in variables of importance were examined further with RF and GBM algorithms to determine if data from all FYs could be combined to obtain one large dataset to build a final model. As the standard packages in R were limited to categorical input variables with 52 levels or less, a new package for analysis was sought.

H2O is an open source package available for R (as well as other languages) that is proficient at handling big data, and is also user-friendly. It facilitates the building, training and testing of a variety of machine learning models (H2O.ai, 2020). For the remainder of the analysis, all models discussed were built using H2O's algorithms.

Both RF and GBM models were created and the error on the results for all models were compared in Figure 4. To compare each models prediction accuracy, the MAE metric from the validation data was used throughout. Seeing improvement in both the average MAE, as well as steadier variables of importance, indicated that trends were deemed to be similar enough across fiscal years to justify building a stacked dataset. Ideally, the years which showed discrepancies would be removed; however, the need for a larger training dataset was greater initially, and therefore all years will be kept in until further data is obtained.

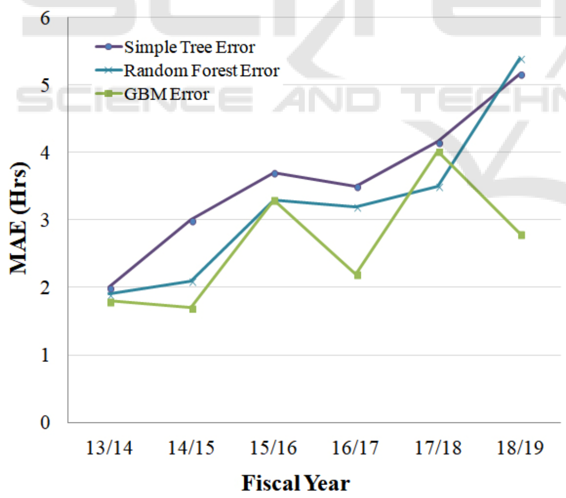

Figure 4: MAE between predicted and actual OT Hours per WO from Dataset A for all feature extraction models.

3.3 Model Generation

Next, H2O automL was used to build two models, as shown in Figure 5; one that predicted the OT hours grouped by WO and one that predicted the month in which the OT hours accrued against the WO. One model was not able to be built to predict both OT hours and months because Dataset A did not contain a date or month column to train the model on, and Dataset B was not suitable to predict OT hours, due to overestimation that would have occurred (the model would expect every WO to incur OT, which is not the case).

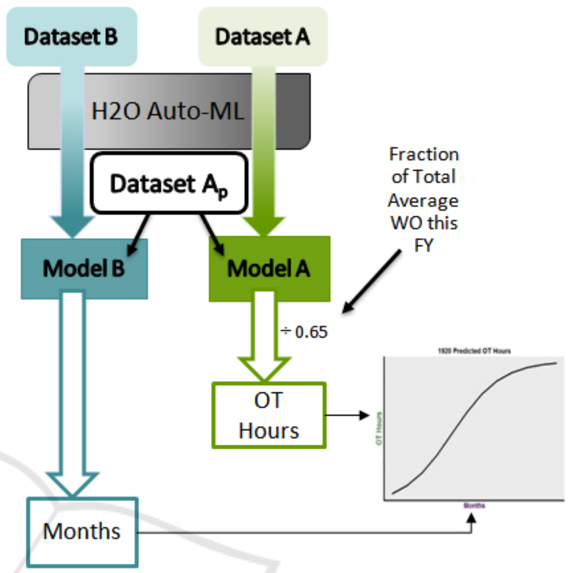

Figure 5: Models A and B, for predicting Hours per WO and Month OT Accrued.

Four assumptions were made prior to using the predictive outputs of both models:

- The pool of personnel and resources required to complete WOs will not shrink or grow significantly compared to current levels. This assumption is reasonable in a steady-state system, with no major changes to demand or supply.
- The total number of WO for FY19/20 used to predict on was 65% of the average WO total over the past six years; thus, it is assumed the model predicts 65% of OT for FY19/20, and the actual predicted values must be scaled up accordingly. Over time in a steady state system, as more data becomes available, this estimate should become more accurate.
- OT predicted by the model must be greater than or equal to zero; thus, small negative values predicted from H2O autoML's distribution support were rounded to zero. This is necessary to ensure realistic output from the model.
- The distribution of all WO for FY19/20 over time (by month) is represented by the same distribution of WO currently used to build the model. Again, likely realistic in a steady-state system or when adapting to slow trends over

time; abrupt changes require additional short-term feedback.

Dataset A was used to build Model A, which predicted the OT Hours per WO and Dataset B was used to build Model B, which predicted the Month in which the OT was accrued against the WO. Once these models were built, all planned WO for FY19/20 up to 26 June 2019 (Dataset A_p) were used as input for prediction (Holmes, 2020).

H2O autoML uses a training set, response variable and a user specified time limit to build many different models (which may include Distributed RFs, GBM, XGBoost, etc.). These models are then used to build two types of stacked ensembles, one of which is based on all previously built models, the other is built on the best model of each family (H2O.ai, 2020). Once the maximum number of models has been built, or the time limit has been reached, H2O autoML will produce a leaderboard, which displays error metrics on each model. The user can choose the best model from the leaderboard to use for predicting on new datasets. Though there are few mandatory variables to run H2O autoML, there are numerous additional hyperparameters that can be specified in order to improve upon the models interpretability and accuracy. Additionally, since most of the algorithms trained via the autoML process are ones which H2O has accessible as individual functions, the leaderboard can be used as a starting point to allow the user to refine the hyperparameter grid searches.

Random number generation also plays a role in H2O autoML depending on whether the user specifies the validation frame – H2O's term for test set – argument. Since the model needed to be comparable to the previous algorithms used, the validation and training frame split was 80/20 and then H2O autoML used 50% of the validation frame to provide leaderboard metrics.

3.4 Model Interpretation

The model output (Holmes, 2020) was used to generate a budget prediction graph for FY19/20 by fitting a logistics function for the predicted values results in Figure 6. Error bars on the predictive estimates are shown, although they are difficult to discern due to the fact that they are on the order of magnitude of the size of the marker at the start of the FY. After the completion of the fiscal year, the actual OT data was collected for comparison. As shown, the final predicted total of OT was within 5% maximum error of the actual hours reported by the FMF at the end FY19/20. Due to the smaller number of OT hours at the beginning of the year and the shape of the logistics function, the predicted graph indicated that there should naturally be more difference from the predicted value early on in the fiscal year. As the totals increase, the projections become more accurate.

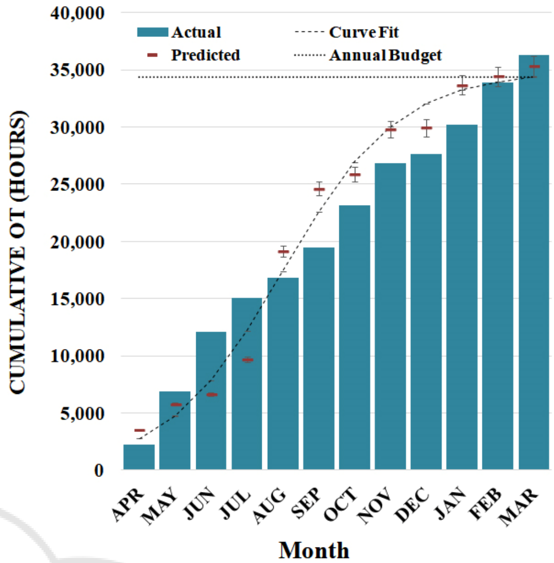

Figure 6: Cumulative OT prediction with logistics function fit, and actual accrual over FY19/20.

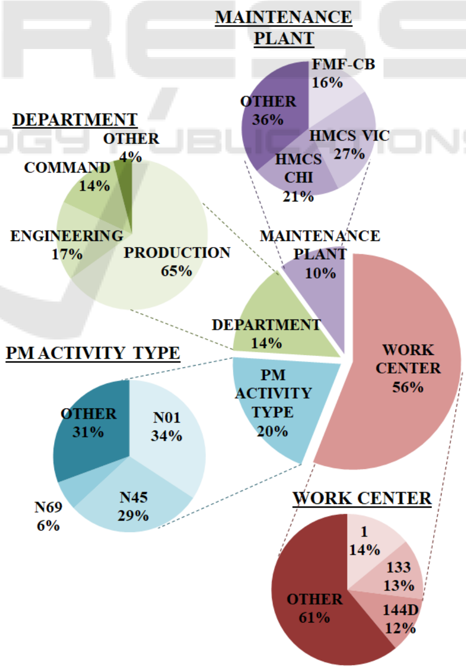

Figure 7: WO attributes as variables of importance for OT, and top 3 contributors of OT for each.

The WO attributes that are important for predicting OT accrual are summarized in Figure 7, which also identifies the top three contributors for each. The contributing attribute percentage in Figure 7 correspond to variable of importance calculations for Model A, obtained from the GBM used as the best model in H2O autoML. These OT variables of importance were also similar to those found by Maybury (Maybury, 2018) when analysing the primary attributes behind WO maintenance hours for the FMFs.

4 FUTURE WORK

Based upon the initial findings, supervised and automated machine learning algorithms available from H2O were found to be proficient at handling large, primarily categorical, datasets to build predictive models. The importance of precautionary measures required to use automated machine learning tools effectively, such as, extensive and careful cleaning of datasets with clear understanding prior to algorithm input (Ebadi et al., 2019) was noted. Similarly, the autoML H2O model was found to be highly interpretable based upon the fundamental understanding of algorithms used to conduct the analysis. The predictions resulting from the model proved to be sufficiently accurate for the purpose of this study and establish a baseline process for future predictive models.

To prepare such a model for FMF operations personnel to use at the beginning of each FY, the data from the current predicted year would be moved from Dataset A_p to Dataset A. A new Dataset A_p would be provided shortly after the new FY begins and the existing model could be re-trained or a new model using the established process could be developed. Having more recent data would also allow for the years with visibly differentiable trends in reporting to be removed from the input dataset. In-year accrual data could also be incorporated if the models were adapted to train on a monthly basis to provide faster feedback response to the system.

Along with quantifying OT accrual throughout the FY, knowledge of the specific work which impacts OT would aid the predictive power of the model. Ships' maintenance schedules are known well in advance, and better association of OT with the operational maintenance schedule for FMF OT would provide stronger linkages of when and how much OT could accrue.

Performing a similar analysis on the OT accrual at both FMFs would be beneficial, as it would allow for comparisons in policies and accrual trends. If this comparison demonstrated that the two FMFs are similar in their OT accrual patterns, then a larger, combined dataset could be used to improve the predictive model.

Finally, operationalizing these algorithms as a budgeting tool accessible from within enterprise resource management systems would allow for decision makers to have updated and readily available information on the projected OT at the start of a FY, with adjustments as new data for the FY is in included in the analysis.

5 CONCLUSIONS

This paper investigated means to improve estimates of overtime for a naval FMF using automated machine learning algorithms. Insights to major variables of importance for OT were explored. Based on the analysis discussed herein, the following conclusions are drawn:

- A logistics function fit for cumulative OT per FY provides an improved estimate for annual OT accrued.
- The use of autoML algorithms can improve OT estimates for the FMF with a maximum error of 5% observed for FY19/20.
- The use of tree-based algorithms can be informative as to what WO attributes contribute the most to OT, with quantification of relative importance over others.
- Use of multiple, related datasets enabled prediction of multiple variables.

The use of such a model would allow decision makers to prepare more accurate funding estimates over time – potentially reserving funds for upcoming critical maintenance tasks or saving funds through alternative approaches to task management.

ACKNOWLEDGEMENTS

The authors would like to thank the FMF Comptrollers for their availability and insight, as well as Mr. Andrew MacDonald for assistance with manuscript preparation.

REFERENCES

Allison, P., (2012). When can Multicollinearity Safely Be Ignored? Retrieved 1 October 2020, from http://statisticalhorizons.com/multicollinearity

Balaji, A., Allen, A., 2018. Benchmarking Automatic Machine Learning Frameworks. Retrieved from

https://arxiv.org/abs/1808.06492
Bartek, M. A., Saxena, R. C., Solomon, S., Fong, C. T., Behara, L. D., Venigandla, R., et al., 2018. Improving Operating Room Efficiency: A Machine Learning Approach to Predict Case-Time Duration. *Journal of the American College of Surgeons, 227*(4), 346-354.
Baykasoğlu, A., Öztaş, A., Özbay, E., 2009. Prediction and multi-objective optimization of high-strength concrete parameters via soft computing approaches. *Expert Systems with Applications, 36*(3, Part 2), 6145-6155.
Desai, R. J., Wang, S. V., Vaduganathan, M., Evers, T., Schneeweiss, S., 2020. Comparison of Machine Learning Methods With Traditional Models for Use of Administrative Claims With Electronic Medical Records to Predict Heart Failure Outcomes. *JAMA Network Open*. Retrieved from https://jamanetwork.com/journals/jamanetworkopen/article-abstract/2758475
Ebadi, A., Paul, P., Gauthier, Y., Tremblay, S., 2019. *How can automated machine learning help business data science teams?* Paper presented at the 18th IEEE International Conference on Machine Learning and Application. Retrieved from https://ieeexplore.ieee.org/document/8999171
Ellis, N., Davy, R., Troccoli, A., 2015. Predicting wind power variability events using different statistical methods driven by regional atmospheric model output. *Wind Energy, 18*(9), 1611-1628.
Friedman, J. H., 2001. 1999 Reitz Lecture, Greedy Function Approximation: A Gradient Boosting Machine. *The Annals of Statistics, 29*(5), 1189-1232.
Ganapathi, A., Kuno, H., Dayal, U., Wiener, J. L., Fox, A., Jordan, M., et al., 2009. *Predicting Multiple Metrics for Queries: Better Decisions Enabled by Machine Learning*. Paper presented at the 25th International Conference on Data Engineering. Retrieved from https://ieeexplore.ieee.org/abstract/document/4812438
Gijsbers, P., LeDell, E., Thomas, J., Poirier, S., Bischl, B., Vanschoren, J., 2019. *An Open Source AutoML Benchmark*. Paper presented at the 6th ICML Workshop on Automated Machine Learning. Retrieved from https://arxiv.org/pdf/1907.00909.pdf
Gohel, H. A., Upadhyay, H., Lagos, L., Cooper, K., Sanzetenea, A., 2020. Predictive maintenance architecture development for nuclearinfrastructure using machine learning. *Nuclear Engineering and Technology, 52*, 1436-1142.
Guanoluisa, D. A. Q., 2020. *Design and Implementation of a Micro-World Simulation Platform for Condition-Based Maintenance using Machine Learning Algorithms.* University of Toronto.
H2O.ai, (2020). H2O.ai. Retrieved 12 October 2020, from https://www.h2o.ai/
He, X., Zhao, K., Chu, X., 2020. AutoML: A Survey of the State-of-the-Art. *Knowledge-Based Systems (Preprint Submission)*. Retrieved from https://arxiv.org/abs/1908.00709
Holmes, M., 2020. *Predicting Overtime Hours for Fleet Maintenance Facility Cape Breton* (No. DRDC-RDDC-2020-R071): Defence R&D Canada - Centre for Operational Research and Analysis.
Kassambara, A., (2018). Logistic Regression Assumptions and Diagnostics in R. *Statistical tools for high-throughput data analysis* Retrieved 1 October 2020, from http://www.sthda.com/english/articles/36-classification-methods-essentials/148-logistic
Maybury, D., 2018. *Predictive Analytics for the Royal Canadian Navy Fleet Maintenance Facilities: An application of data science to maintenance task completion times* (No. DRDC-RDDC-2018-R150): Defence R&D Canada - Centre for Operational Research and Analysis.
Naik, J., Dash, P. K., Dhar, S., 2019. A multi-objective wind speed and wind power prediction interval forecasting using variational modes decomposition based Multi-kernel robust ridge regression. *Renewable Energy, 136*, 701-731.
Ozturk, S., Fthenakis, V., 2020. Predicting Frequency, Time-To-Repair and Costs of Wind Turbine Failures. *Energies, 13*(5), 1149.
Therneau, T., Atkinson, B., Ripley, B., 2017. Rpart: Recursive Partitioning and Regression Trees (Version R package Version 4.1-11).
Truong, A., Walters, A., Goodsitt, J., Hines, K., Bruss, C. B., Farivar, R., 2019. Towards Automated Machine Learning: Evaluation and Comparison of AutoML Approaches and Tools. Retrieved from https://arxiv.org/pdf/1908.05557.pdf