Naval Information Warfare Center PACIFIC

TECHNICAL REPORT 3291
NOVEMBER 2022

# Simulating Naval F/A-18 Flight Hour Execution Using Monte Carlo Techniques

Dr. Benjamin Michlin
Josh Duclos
Dean Lee
Dr. Jamal Rorie
Gary Williams

**NIWC Pacific**



Naval Information Warfare Center (NIWC) Pacific
San Diego, CA 92152-5001

This page is intentionally blank.

TECHNICAL REPORT 3291
NOVEMBER 2022

# Simulating Naval F/A-18 Flight Hour Execution Using Monte Carlo Techniques

Dr. Benjamin Michlin
Josh Duclos
Dean Lee
Dr. Jamal Rorie
Gary Williams
**NIWC Pacific**



**Administrative Notes:**
This Report was approved through the Release of Scientific and Technical Information (RSTI) process in October 2022 and formally published in the Defense Technical Information Center (DTIC) in November 2022.

NIWC Pacific
San Diego, CA 92152-5001

**NIWC Pacific**
**San Diego, California 92152-5001**

A. D. Gainer, CAPT, USN
Commanding Officer

W. R. Bonwit
Executive Director

## ADMINISTRATIVE INFORMATION

The work described in this report was performed by the Business and Enterprise Information Systems Division. The NIWC Pacific Naval Innovative Science and Engineering (NISE) Program provided funding for this project.

Released by
Donna Williamson, Division Head
Business and Enterprise Information Systems Division

Under authority of
Scott Crellin, Department Head
Command & Control and Enterprise Engineering



Editor: RJP

# EXECUTIVE SUMMARY

Naval F/A-18 squadron quarterly flight hour execution is simulated using Monte Carlo techniques. This simulation combines traditional readiness data with planning and entitlement information to accurately predict and simulate the flight hour execution of a squadron up to 90 days in advance. Furthermore, probability distribution functions are developed for each squadron prediction and allow for the direct observation of how changes to input features influence the expected flight hour execution probability distribution.

This page is intentionally blank.

# CONTENTS



## Figures

This page is intentionally blank.

# 1. INTRODUCTION

There are many benefits of using Monte Carlo simulation as compared to other analytics techniques. Monte Carlo simulation allows for the ability to directly observe the relationships between input features and resulting probability distribution functions. This then allows a user to “interact” with the simulation by directly changing features (“levers”) and monitoring how that decision propagates and changes the resulting simulation. Furthermore, Monte Carlo simulation provides a straightforward method for calculating uncertainty through a frequentist interpretation, and allows for knowledge of the underlying process to be directly integrated. This is in direct contrast to purely data-driven techniques wherein subject matter expert (SME) input cannot be incorporated directly. Furthermore, Monte Carlo simulation may often provide accurate results when there is not enough data available for machine learning.

Additional benefits of Monte Carlo simulation are readily available due to the frequentist nature of the approach and interpretation. Because the process is reliant on probability distribution functions and an emphasis on repeated experimental results, it is trivial to calculate uncertainties and confidence limits on results.

The goal of this Monte Carlo simulation is to take in readiness information, such as the number of Mission Capable (MC) aircraft that a squadron has, entitlement and funding information, and planning information to derive probability distribution functions for the flight hour execution of that squadron over the following quarter (3 months) and determine potential outcomes.

This simulation is part of the effort to improve and expand the Digital Aviation Readiness Technology Engine (DARTE) [1], and relies on predicted features and results from previous efforts including topological data analysis (TDA) [2], and temporal pattern attention mechanism enhanced long short-term memory networks and hyper-deep ensembles [3].

Section 2 discusses the data used; Section 3 discusses the Monte Carlo simulation including the interpretation; Section 4 shows the results of the Monte Carlo simulation; and Section 5 reviews the conclusions and and future work.

This page is intentionally blank.

## 2. DATA

The data used for this Monte Carlo simulation includes datasets from the three traditional pillars of readiness: manning, training, and equipment. Specifically, daily-buno level data for Naval F/A-18 VFA squadrons from AMSRR, DECKPLATE (including maint-6 reports), Navflir, ADW reports, and ACES from November 2018 to January 2022 are utilized. The resulting dataset has 1246 features and 47263 samples. Of these 1246 features, 55 are selected through subject matter expertise for potential inclusion into the Monte Carlo simulation. Although the feature set was heavily down-selected using domain knowledge to reduce the simulation space, a data-driven approach is used for simulation inclusion.

The daily-buno dataset is aggregated to the monthly level, and statistical quantities (e.g. sum, mean, standard deviation, mode) are calculated in order to retain some of the more granular information. Features with more than 25% missing data are then removed as are samples without complete target and entitlement information from ADW. The resulting dataset is 60 features and 1264 samples. No imputation is required or performed for the remaining missing data since Monte Carlo simulation can natively handle the missing data.

Engineered features are then created in order to capture additional subject matter expertise. These features include personnel ratios (fit/fill), lag variables from previous quarters and months, and future F/A-18 mission capability status. Note that the future condition values are able to be used by this simulation since they can be predicted with other methods [1–3].

Engineered features of particular importance and noteworthiness are the “MC Ratio” ($\frac{MC}{MC_{Entitlement}}$) and the flight hour entitlement defined as

$$FH_{Ent} = MESH + Transit + (\frac{Funding}{100} * Crews * 27)$$

where $MESH$ are the Mission Essential Flight Hours, $Transit$ refers to the transit hours en route to location, $Funding$ refers to the entitlement and funding allocation information, and $Crews$ are the number of pilot crews. The quantity in parenthesis corresponds to the training and readiness hours entitled to each crew.

This page is intentionally blank.

# 3. MONTE CARLO SIMULATION

The goal of this Monte Carlo simulation is to use readiness information to derive probability distribution functions for the flight hour execution of an F/A-18 squadron over the following quarter (3 months) and determine potential outcomes and their likelihood. To this end, the MC ratio is used as the primary simulation feature to predict flight hour execution over the coming quarter, however, other features are used as selection criteria and contextual features for the simulation.

An overview of the approach taken in this paper is, for each data sample, to get a distribution of the current MC feature given contextual selection criteria ($A$, $B$, $C$, ...). Then, Monte Carlo methods are used to sample from these distributions. A joint simulated probability distribution is then built for the target ($P(FH|MC, A, B, C, ...)$), and this joint fit may be used to infer and simulate the flight hour execution on new data.

## 3.1 DATA SPLIT

For the Monte Carlo simulation, only a subset of the data is used for the probability density functions (PDFs). The training set accounts for 70% of the data and is used for PDF creation; the validation set is 15% of the data and used to tune the simulation and all selection criteria and tolerances; and the final 15% of the data is the hold-out set and used to check the simulation performance. The train/test/validation split is stratified using the MC ratio, and a normalized histogram showing the split is shown in Figure 1.

## 3.2 SIMULATION CONSTRAINTS

For the Monte Carlo Simulation, only relevant data samples from the training set should be used in creation of each PDF. To determine the set of requirements and similarities that a training sample must share with the target sample in order to be included in the PDF each combination of up to 4 features, of the 55 hand-selected features, are tested. Of the 10000 combinations attempted, the optimal combination of features and selection criteria as determined by performance on the validation set are:

- MC Ratio $\pm$ 0.1,
- Previous quarter FH Ratio $\pm$ 0.05,
- Same flightline,
- Same activity phase at $t-2$ (two months prior).

Further, if there are fewer than 5 other samples (not including the target sample) in the training set, then the target sample is considered anomalous and therefore discarded. Note that this would mean that the particular combination of MC/FH/Flightline/Phase for which a PDF is to be derived has occurred fewer than 5 times over the 4 years that the dataset covers. Of the 810 samples in the training set, only 140 of them had sufficient data to be considered in the simulation.

## 3.3 FH PDF FITTING AND SAMPLING

Unfortunately, the FH Ratio does not follow a simple distribution, and a Crystal Ball Function [4] was found empirically to be the best fit function for PDF creation. The Crystal Ball Function is a Gaussian with a power-law tail that is commonly seen in nature for lossy physical processes. The Crystal Ball Function is defined as:

$$f(x;\alpha,n,\bar{x},\sigma) = N\cdot \begin{cases} \exp(-\frac{(x-\bar{x})^2}{2\sigma^2}), & \text{for } \frac{x-\bar{x}}{\sigma} > -\alpha \\ A\cdot(B-\frac{x-\bar{x}}{\sigma})^{-n}, & \text{for } \frac{x-\bar{x}}{\sigma} \leqslant -\alpha \end{cases}$$

where

$$A = \left(\frac{n}{|\alpha|}\right)^n \cdot \exp\left(-\frac{|\alpha|^2}{2}\right),$$
$$B = \frac{n}{|\alpha|} - |\alpha|,$$
$$N = \frac{1}{\sigma(C+D)},$$
$$C = \frac{n}{|\alpha|}\cdot\frac{1}{n-1}\cdot\exp\left(-\frac{|\alpha|^2}{2}\right),$$
$$D = \sqrt{\frac{\pi}{2}}\left(1+\mathrm{erf}\left(\frac{|\alpha|}{\sqrt{2}}\right)\right).$$

Here, $N$ is a normalization constant, erf is the error function, and $\alpha$, $n$, $\bar{x}$, and $\sigma$ are fit parameters. Note that $\bar{x}$ is the peak of the distribution, $\sigma$ is the width of the Gaussian, $\alpha$ is the turnover point where the Gaussian and power-law are stitched together, $n$ is a scale factor. Figure 2 shows a Crystal Ball fit to FH ratio data. While it requires more parameters to be fit than a Gaussian function, the Crystal Ball function captures the tail found in lossy physical processes and seen here. Fits are performed using the ROOT data analysis framework [5] and the ROOFit package [6]. Using this technique produces high quality fits for all samples subject to the simulation constraints discussed in Section 3.2. Figure 3 shows the value of the reduced chi-squared goodness-of-fit metric for PDF creation from fitting training data for the 140 samples which passed the constraints.

For the Monte Carlo simulation, samples will need to be drawn from the Crystal Ball PDF. Since sampling from this distribution is non-trivial, the Foam algorithm is used [7]. Foam is a general purpose Monte Carlo cellular algorithm that allows for sampling from any distribution - including those that are not well defined with singularities, poles, etc. Figure 4 shows an example of a Crystal Ball PDF as well as the generated data from sampling the distribution through Foam.

### 3.4 INTERPRETATION

Each relevant PDF is simulated (randomly sampled) 1000 times while randomly varying the MC ratio within uncertainty for each sample to produce a distribution of potential probable FH ratios. Figure 5 shows the results from a test set sample. The histogram consists of the simulated 1000 samples, the red line shows the truth value for that sample, the black line shows the mean FH ratio from the simulation, and the orange line shows the median FH ratio from the simulation. When making a “prediction” using the Monte Carlo simulation, the mean value from the simulated samples is chosen as the predicted value, and the median value provides contextual information.

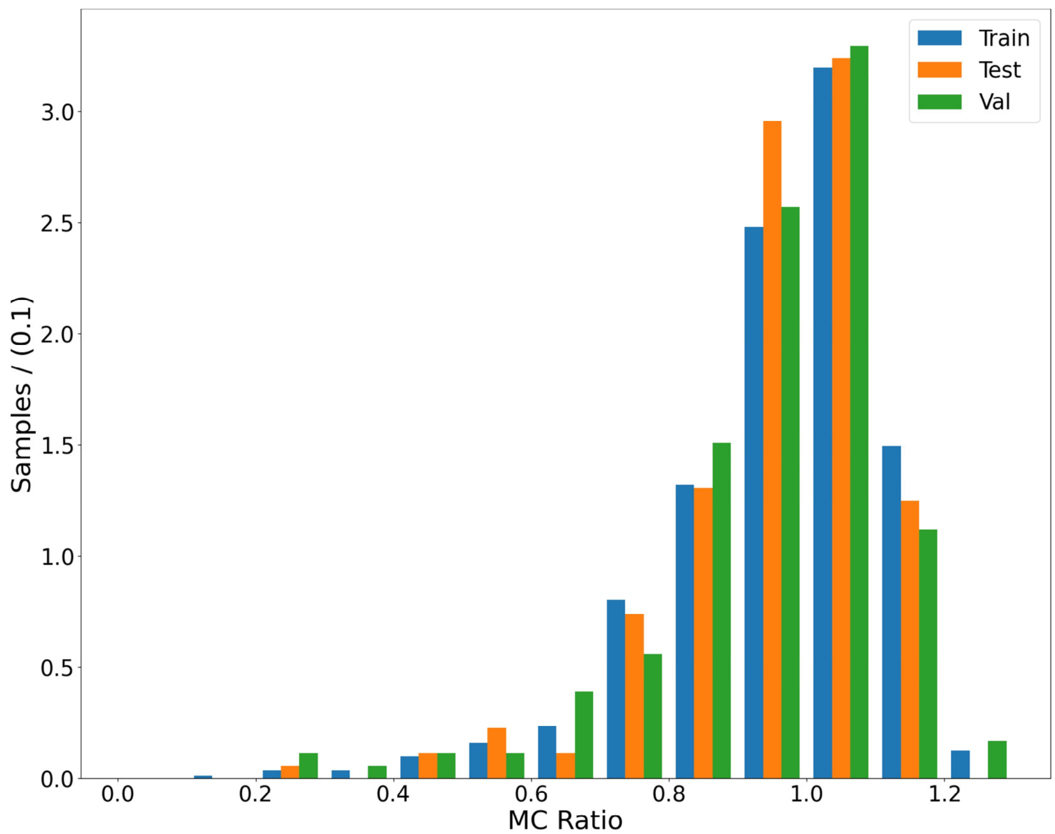


Figure 1. A normalized histogram showing the train/test/validation split stratified on the MC Ratio.

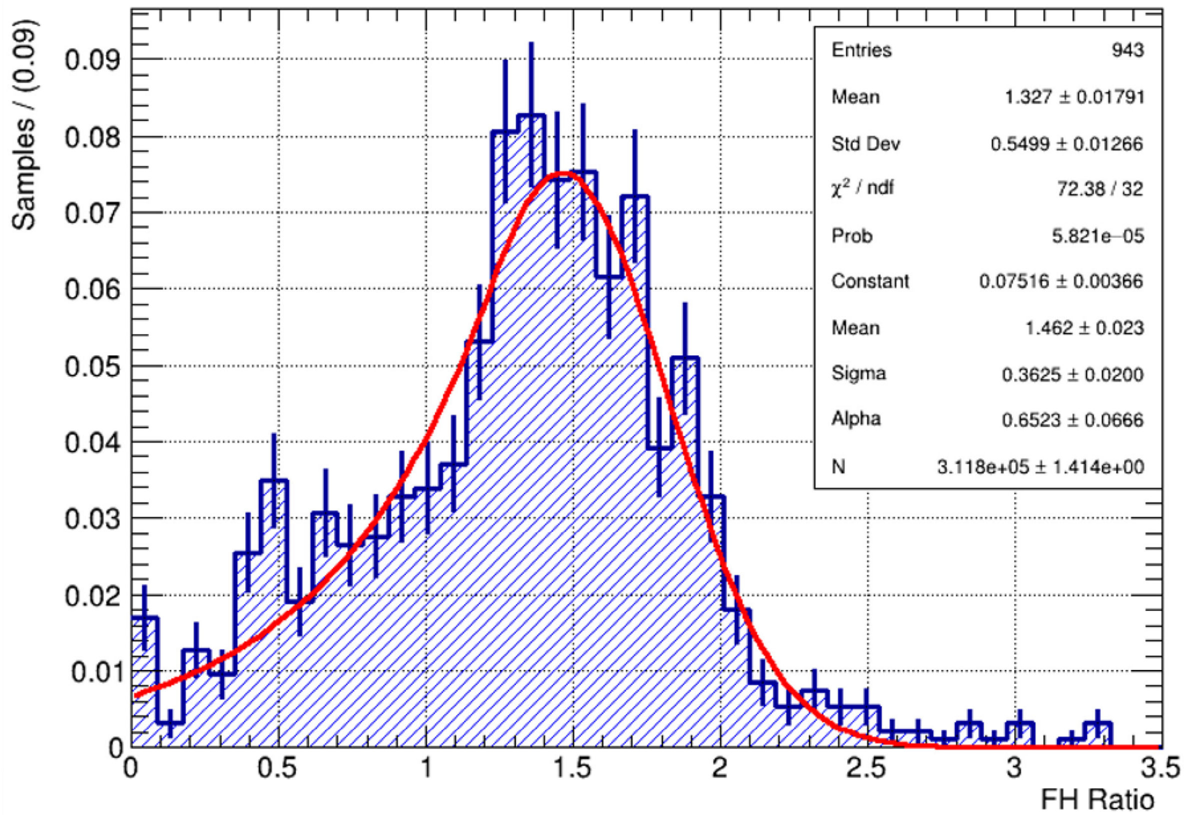


Figure 2. A normalized histogram showing the FH ratio with a Crystal Ball fit.

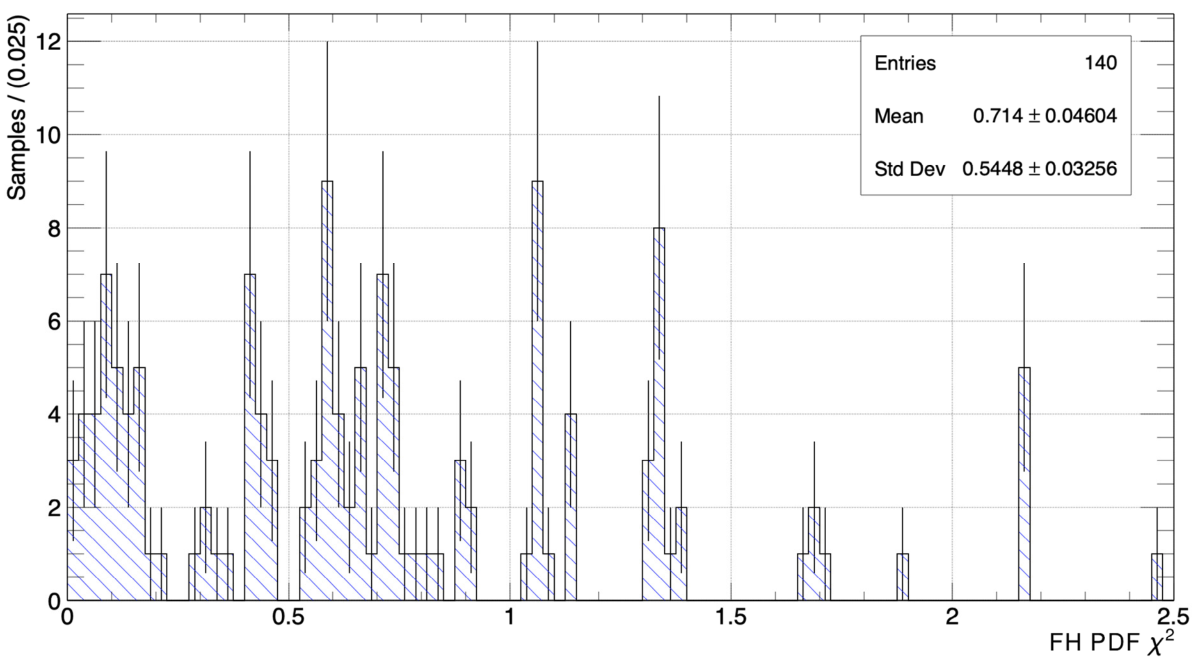


Figure 3. Histogram showing the value of the reduced chi-squared goodness-of-fit metric for the FH ratio PDFs.

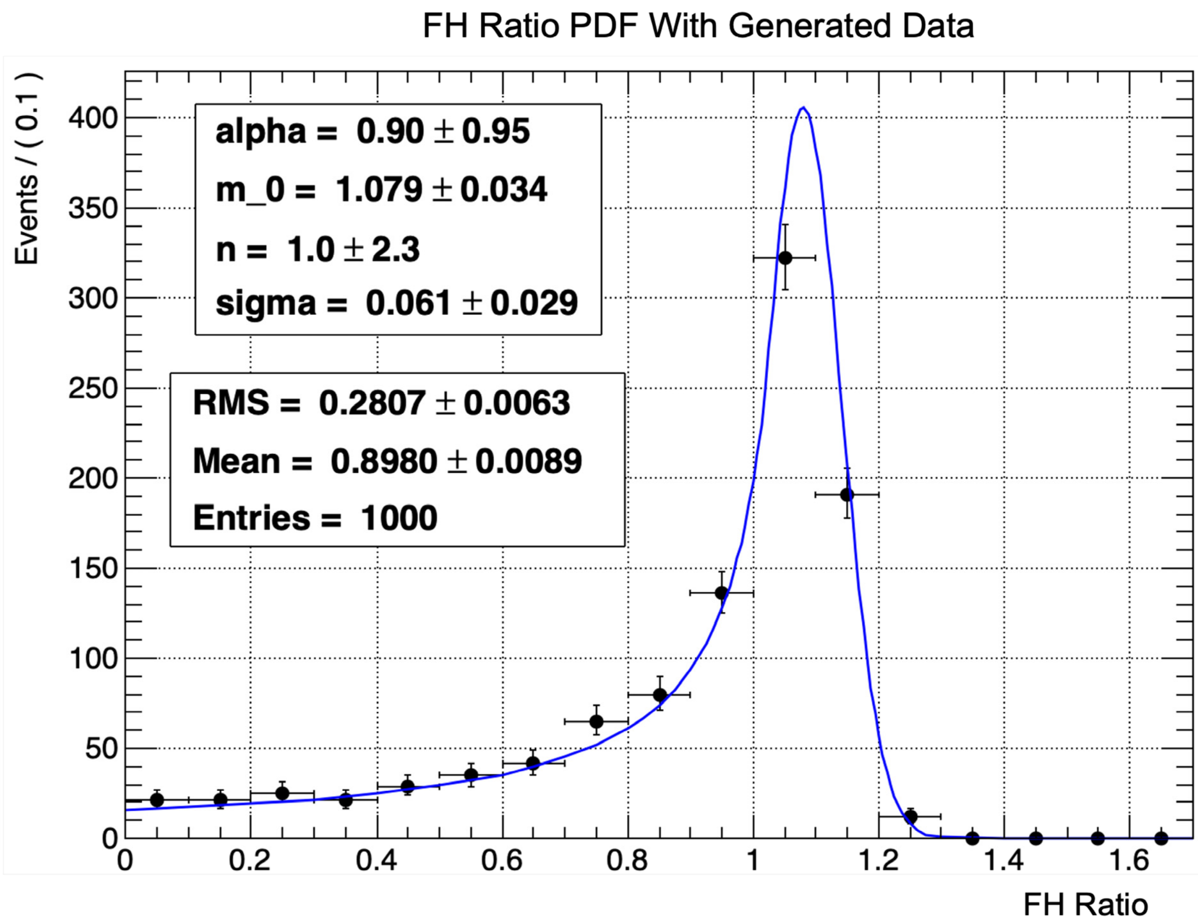


Figure 4. An example Crystal Ball PDF fit to training data, and generated data from Foam sampler.

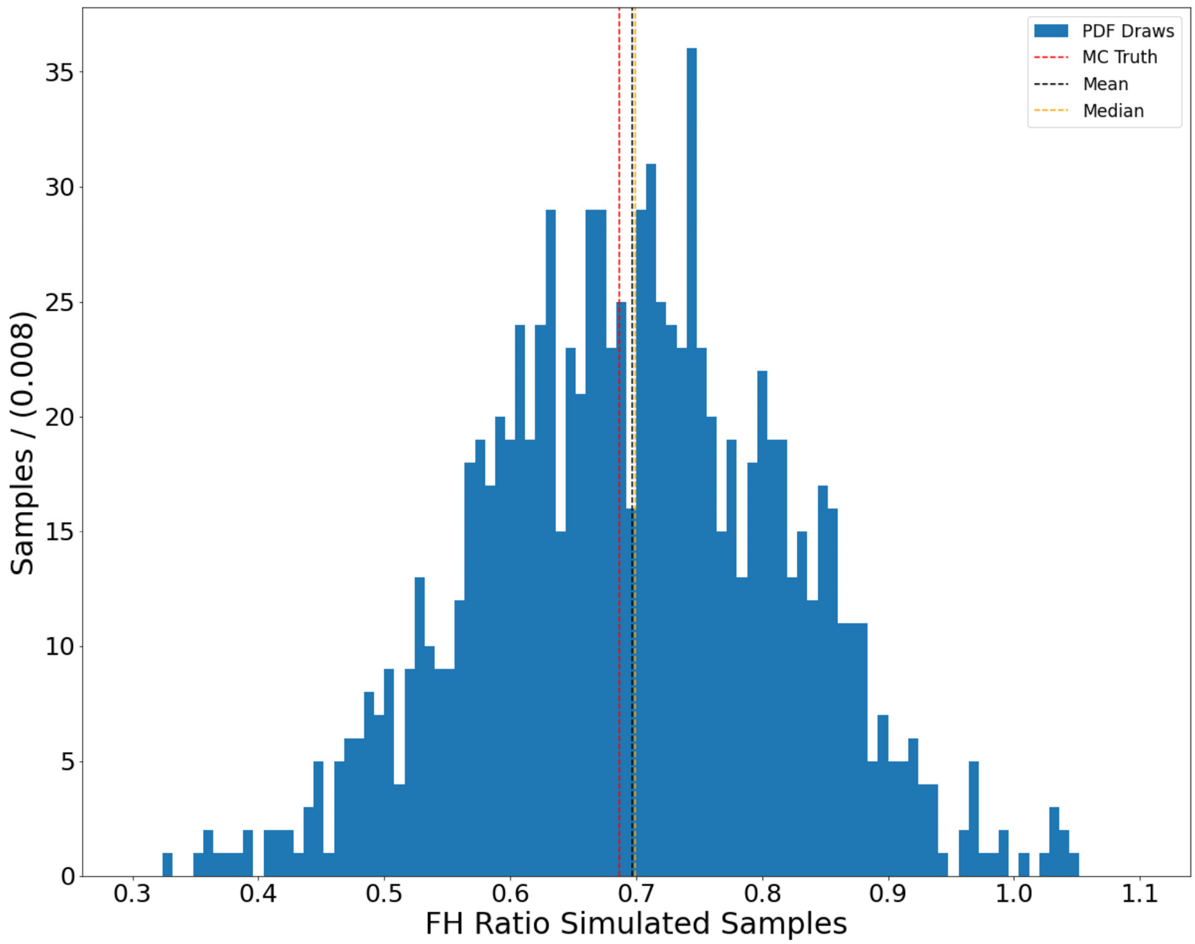


Figure 5. Simulation results from test set sample.

# 4. RESULTS

By using the prediction method discussed in Section 3.4 to use the Monte Carlo simulation to predict the FH ratio on new samples, the model performance may be measured. Figure 6 shows two-dimensional histograms of the predicted FH Ratio vs the Actual FH Ratio for the training set, validation set, and test set. The red line shows a perfect prediction. In terms of performance metrics, the training set has an $r^2$ of 0.36, the validation set has an $r^2$ of 0.46, and the test set has an $r^2$ of 0.31. The differences between the validation and test set performance is likely due to small sample sizes. It is also important to note that the training set does have a small amount of contamination since the PDF contains the true value for the sample on which predictions are performed. In any case, all of the two-dimensional histograms show good behavior, excellent results, and contain no obvious bias.

Figure 7 shows the same information as in Figure 6 but visualized as a residual with a Gaussian fit. Despite any "by-eye" discrepancies in the Gaussian fit, the reduced chi-squared goodness-of-fit metric is very good and confirms expected behavior. Figure 7a shows the training set results and shows extremely good behavior with an excellent fit, a mean consistent with zero, and no obvious bias. Figure 7b also shows an excellent Gaussian fit, has a mean fairly consistent with zero (with any discrepancies likely due to small samples sizes), and the $\sigma$ has a 58% improvement over the training set. This difference between the validation and training set results is likely due to small sample sizes and the fact that the Monte Carlo simulation was tuned to the validation set. Figure 7c also shows an excellent Gaussian fit, and the $\sigma$ is consistent with the validation set. However, we note that the mean is not quite consistent with zero and some minor bias may be seen by the presence of the high residual tail.

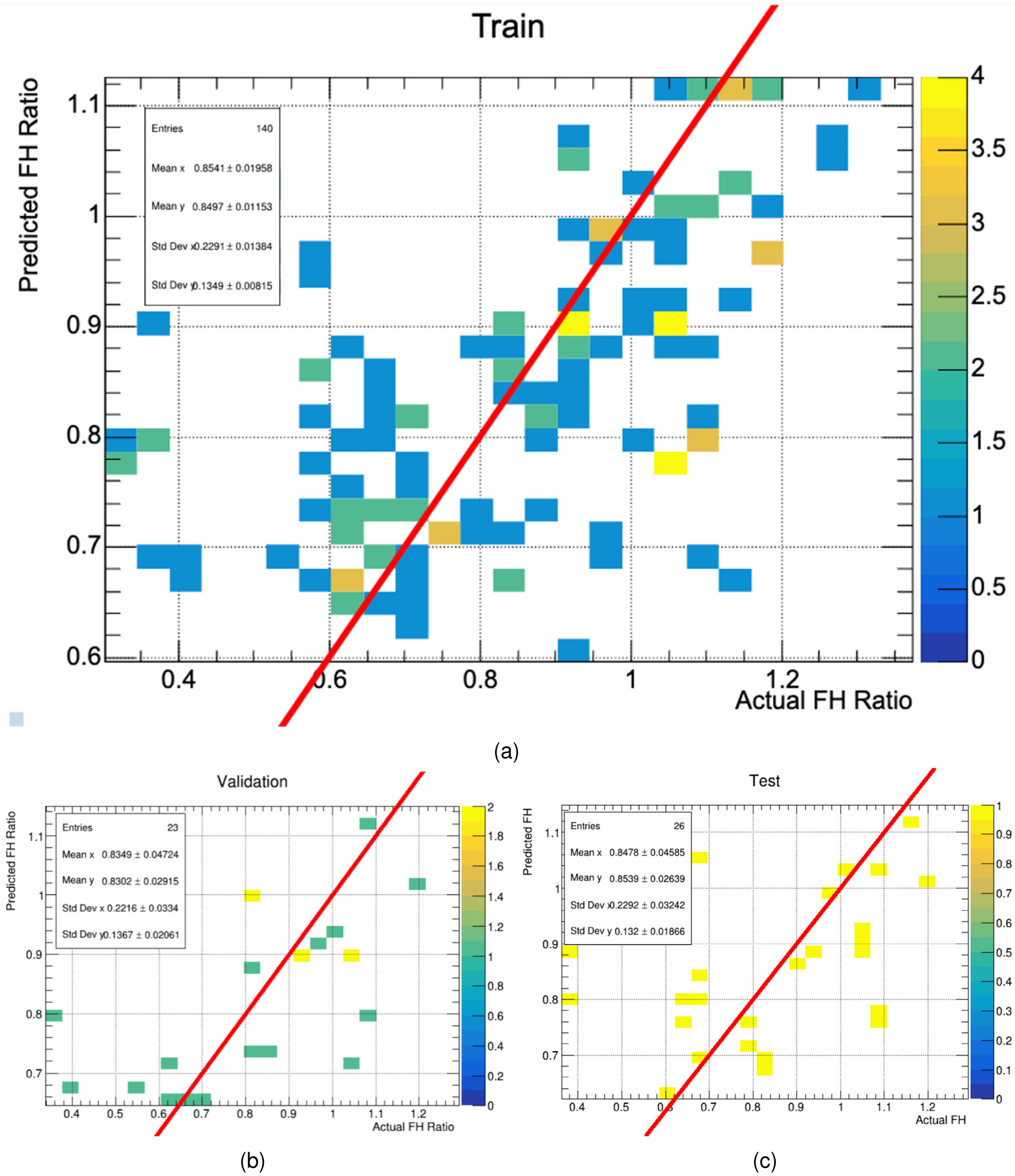


Figure 6. Two dimensional histogram of the predicted FH Ratio vs the Actual FH Ratio for the 6a training set, 6b validation set, and the 6c test set. The red line shows a perfect prediction.

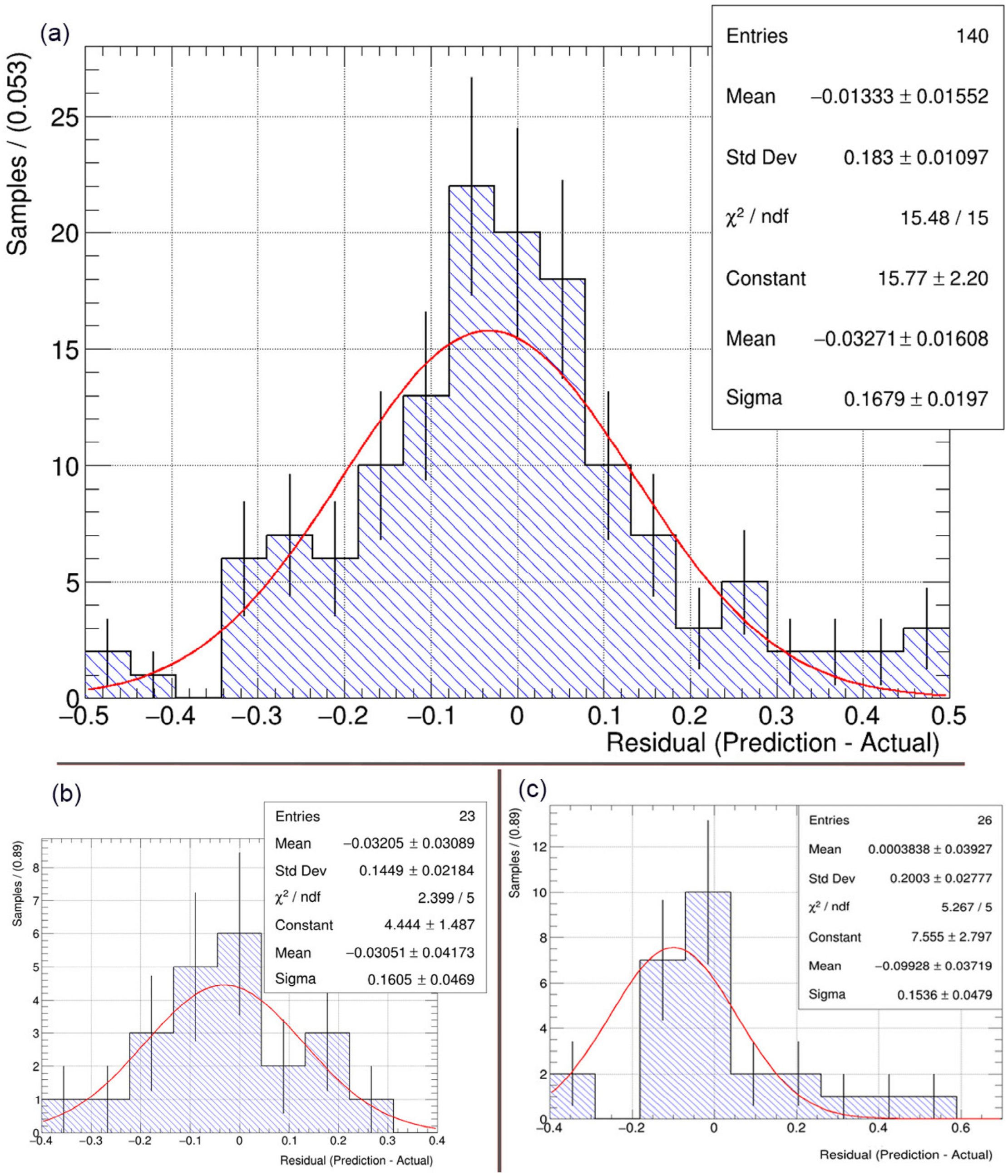


Figure 7. The residual (predicted-actual) of the results shown with a Gaussian fit. Figure 7a shows the training set, 7b shows the validation set, and 7c shows the test set.

This page is intentionally blank.

# 5. CONCLUSIONS AND FUTURE WORK

A Monte Carlo simulation has been created to take in readiness information and derive probability distribution functions which may be used to predict the flight hour execution of an F/A-18 squadron over the following quarter (3 months). The MC ratio was used as the primary simulation feature while also using a squadron's previous performance, flightline, and activity phase, as contextual features. The results are extremely promising, but more work must be performed. Further investigation is also warranted since the vast majority of the samples were determined to be "non-physical" and had very few similar samples in the 4-year dataset.

Future work includes adding more data sources, more conditional features with more accurate selection criteria, and adaptive fitting techniques in the event that the Crystal Ball Function shows a poor fit. Further, preliminary work has been completed on expanding the simulation to include more steps. Specifically, using the maintainer personnel information (fit/fill) to simulate the MC ratio, and then proceeding to use the MC ratio to predict flight hour execution.

This page is intentionally blank.

# REFERENCES


1. Michlin, B., Chang, R., Cruz, R., Duclos, J., Lee, D., Siu, V., and Yetman, C. 2019. "Predicting FA-18 Squadron Readiness and Quarterly Flight Hour Execution Using Machine Learning," Tech. rep., Naval Information Warfare Center Pacific San Diego United States.

2. Lee, D., Michlin, B., Duclos, J., Sabater, A., Rorie, J., and Williams, G. 2022. "The Shape of Naval F/A-18 Readiness," Tech. rep. AD1161692, Naval Information Warfare Center Pacific.

3. Michlin, B. A., Duclos, J. A., Williams, G. R., Lee, D., Sabater, A. B., and Rorie, J. T. 2022. "Improving the Digital Aviation Readiness Technology Engine (DARTE) with Temporal Pattern Attention Mechanisms and Hyper-Deep Ensembles," Tech. rep., Naval Information Warfare Center Pacific San Diego CA.

4. Skwarnicki, T. 1986. *A study of the radiative cascade transitions between the Upsilon-prime 2654 and Upsilon resonances*, Ph.D. thesis, PhD thesis, Institute of Nuclear Physics, Krakow, 1986. 2655 DESY-F31-86-02.

5. Brun, R. and Rademakers, F. 1997. "ROOT—an object oriented data analysis framework," *Nuclear Instruments and Methods in Physics Research Section A: Accelerators, Spectrometers, Detectors and Associated Equipment*, vol. 389, no. 1-2, pp. 81–86.

6. Verkerke, W. and Kirkby, D. 2006. "The RooFit toolkit for data modeling," *Statistical Problems in Particle Physics, Astrophysics and Cosmology*, (pp. 186–189), World Scientific.

7. Jadach, S. 2003. "Foam: A general purpose Monte Carlo cellular algorithm," *Nuclear Physics B-Proceedings Supplements*, vol. 117, pp. 821–824.

This page is intentionally blank.

# INITIAL DISTRIBUTION

| | | |
|---|---|---|
| 84310 | Technical Library/Archives | (1) |
| 53424 | Dr. B. Michlin | (1) |
| 71740 | J. Duclos | (1) |
| 53424 | D. Lee | (1) |
| 53424 | Dr. J. Rorie | (1) |
| 53424 | G. Williams | (1) |

| | |
|---|---|
| Defense Technical Information Center<br>Fort Belvoir, VA 22060–6218 | (1) |

This page is intentionally blank.

| REPORT DOCUMENTATION PAGE | Form Approved OMB No. 0704-01-0188 |
|---|---|



| **1. REPORT DATE** *(DD-MM-YYYY)* | **2. REPORT TYPE** | **3. DATES COVERED** *(From - To)* |
|---|---|---|
| November 2022 | Final | |

**4. TITLE AND SUBTITLE**

Simulating Naval F/A-18 Flight Hour Execution Using Monte Carlo Techniques

**5a. CONTRACT NUMBER**

**5b. GRANT NUMBER**

**5c. PROGRAM ELEMENT NUMBER**

**6. AUTHORS**

Dr. Benjamin Michlin
Josh Duclos
Dean Lee
Dr. Jamal Rorie
Gary Williams
**NIWC Pacific**

**5d. PROJECT NUMBER**

**5e. TASK NUMBER**

**5f. WORK UNIT NUMBER**

**7. PERFORMING ORGANIZATION NAME(S) AND ADDRESS(ES)**

NIWC Pacific
53560 Hull Street
San Diego, CA 92152–5001

**8. PERFORMING ORGANIZATION REPORT NUMBER**

TR 3291

**9. SPONSORING/MONITORING AGENCY NAME(S) AND ADDRESS(ES)**

The NIWC Pacific Naval Innovative Science and Engineering (NISE) Program
53560 Hull Street
San Diego, CA 92152–5001

**10. SPONSOR/MONITOR'S ACRONYM(S)**

NISE

**11. SPONSOR/MONITOR'S REPORT NUMBER(S)**

**12. DISTRIBUTION/AVAILABILITY STATEMENT**

DISTRIBUTION STATEMENT A.
Approved for public release: distribution unlimited.

**13. SUPPLEMENTARY NOTES**



**14. ABSTRACT**

Naval F/A-18 squadron quarterly flight hour execution is simulated using Monte Carlo techniques. This simulation combines traditional readiness data with planning and entitlement information to accurately predict and simulate the flight hour execution of a squadron up to 90 days in advance. Furthermore, probability distribution functions are developed for each squadron prediction and allow for the direct observation of how changes to input features influence the expected flight hour execution probability distribution.

**15. SUBJECT TERMS**

Monte Carlo techniques for naval F/A-18 squadron; observation analysis influence on expected flight hour execution;

| **16. SECURITY CLASSIFICATION OF:** | | | **17. LIMITATION OF ABSTRACT** | **18. NUMBER OF PAGES** | **19a. NAME OF RESPONSIBLE PERSON** |
|---|---|---|---|---|---|
| **a. REPORT** | **b. ABSTRACT** | **c. THIS PAGE** | | | Benjamin A. Michlin |
| | | | | | **19B. TELEPHONE NUMBER** *(Include area code)* |
| U | U | U | SAR | 32 | 619-553-2925 |

**Standard Form 298** (Rev.
Prescribed by ANSI Std. Z39.18

This page is intentionally blank.

This page is intentionally blank.

Naval Information Warfare Center Pacific (NIWC) Pacific
San Diego, CA 92152-5001