Fleet-Informed Workload Forecasting for the DLA Distribution Norfolk, Virginia (DDNV) Material Processing Center

Jefferson Huang, PhD

Assistant Professor
Operations Research Department
Naval Postgraduate School

This work is sponsored by the Defense Logistics Agency.

MORS Emerging Techniques Forum
Johns Hopkins University Applied Physics Laboratory
06 December, 2023

Defense Logistics Agency (DLA)

Distribution Center at DLA Distribution Susquehanna
(Image Source)

Naval Station Norfolk

Waterfront at Naval Station Norfolk (Image Source)

DLA Distribution Norfolk, Virginia (DDNV)

DDNV is co-located with the Naval Supply Systems Command (NAVSUP) Fleet Logistics Center at Naval Station Norfolk (Image Source)

- Largest tenant on the world's largest naval base.
- **Activities** include storage & warehousing, container & pier operations, facilities & equipment maintenance, ...
- **Customers** include:
  - roughly 70 **homeported** ships, including 6 aircraft carriers (CVNs)
  - **transient** ships (e.g., USS Philippine Sea in 2020)
  - local **shore commands** (e.g., Norfolk Naval Shipyard, Joint Base Langley–Eustis)

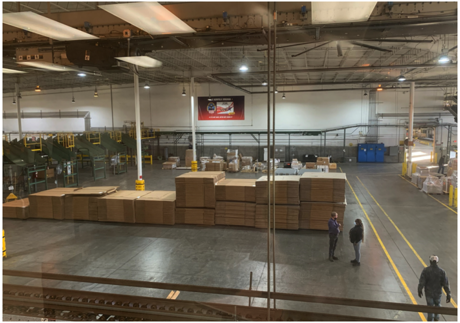
Material Processing Center (MPC) at DDNV

Inside the DDNV MPC (Image Source)

- Standardized receiving point for customer orders (e.g., F/A-18 tires, small packages).
- **Services** include customized sorting, receipt processing, and delivery services.
- Orders are received, inducted, sorted & consolidated, manifested, and delivered to aircraft carriers, amphibious assault ships, guided-missile destroyers, submarines, ...
- Approximately 40,000 transactions processed per month, on average.

Workload at the DDNV MPC

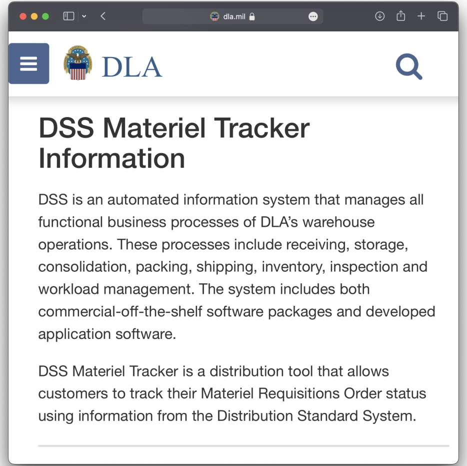
MPC Receiving Cell 1 on 13 October, 2021.



MPC Receiving Cell 1 on 08 November, 2021.

Unanticipated **workload spikes** lead to significant **delivery delays**.

Workload Data

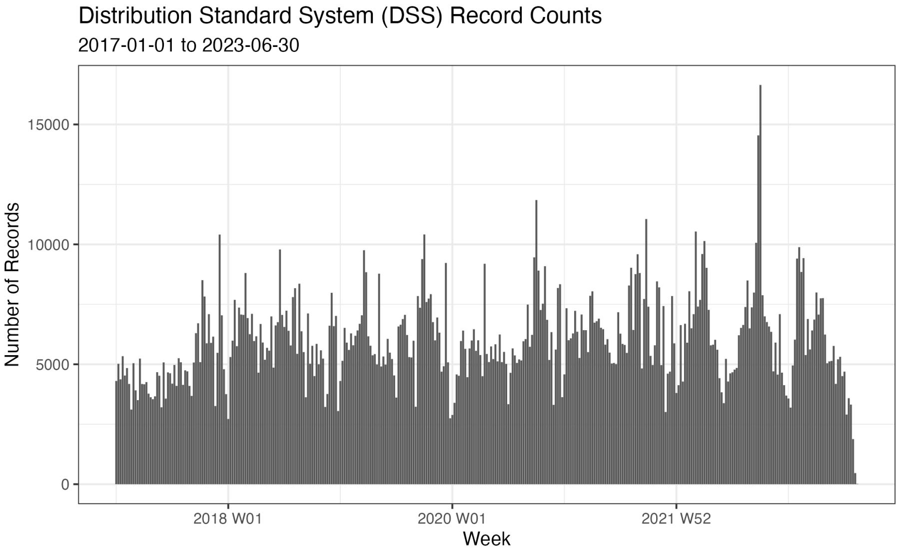


- DLA's **Distribution Standard System (DSS)** tracks the distinct products included in each order.
  - Each **row** is associated with a particular National Item Identification Number (NIIN) and Document Number.
  - The **columns** record the induction date, date shipped, order destination by DOD Activity Address Code (DODAAC), . . .

Current Workload Proxy

Weekly DSS Record Counts

Workload at the DDNV MPC



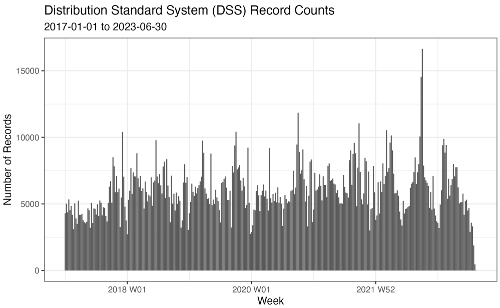
Forecasting Workload at the DDNV MPC

- Some spikes are predictable, e.g., End of Fiscal Year (EOFY).
- **Many others have been “unpredictable”.**
- Workload is driven by the needs of the Fleet.
- **DLA currently has little/no direct visibility on planned Fleet activities.**

Our FY23 Contributions

1. Initial **Data Collection** and Identification of Potential Predictors
2. Development of Preliminary **Workload Forecasting Models**
   2.1 Baseline Autoregressive Integrated Moving Average (ARIMA) Model
   2.2 Deployment-Aware Dynamic Regression Model

Starting Point: Time Series Modeling



How far can we get using **historical workload data only**?

- Current forecasts for manpower planning rely on heuristics involving historical averages and trends.

The **autoregressive (AR) model** is a standard tool for forecasting (stationary) time series.

AR(p) Model

$$y_t = c + \sum_{i=1}^{p} \phi_i y_{t-i} + \epsilon_t$$

- y_t = workload during week t
- ϵ_t = "white noise"
- **Model Parameters:** $c, \phi_1, \ldots, \phi_p$

The **ARIMA** model extends the AR model to account for non-stationarity, past forecast errors, seasonality, . . .

Baseline ARIMA Model

- **Training Data:** Weekly DSS record counts during FY18 – FY22.
- The model order (e.g., lag lengths) and seasonality were determined using the Hyndman-Khandakar Algorithm.

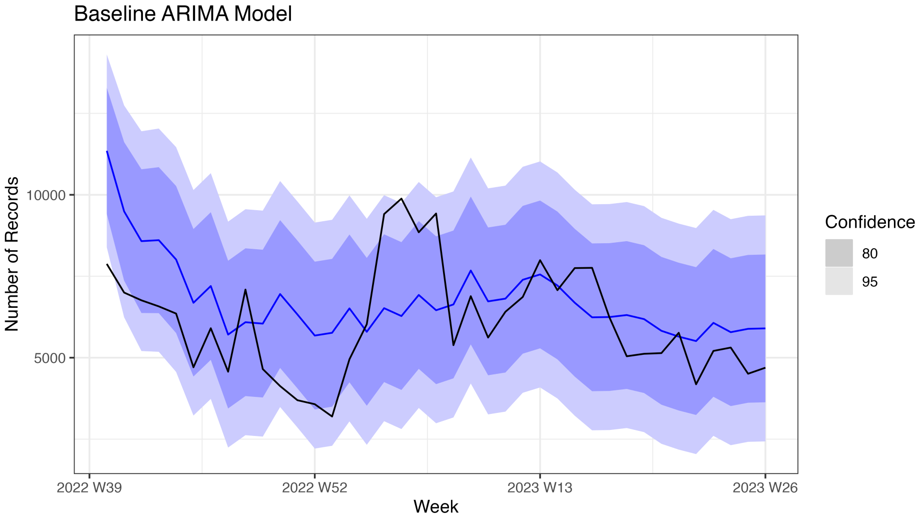
Fitted Model

The predicted workload $\hat{y}_t$ during week t is

$$\hat{y}_t = 1490.98 + 0.67 y_{t-1} + 0.30(y_{t-52} - 0.67 y_{t-53}) - 0.21(y_{t-1} - \hat{y}_{t-1})$$

- **Test Data:** Weekly DSS record counts during FY23, up to 30 June 2023.

Baseline ARIMA Model: Test Set Performance



Note: Solid Black Line = Actual Number of Records

Next Step: Regression with Autocorrelated Errors (aka **Dynamic Regression**)

Classical regression models assume that errors are uncorrelated.

Example: A standard linear regression model with k predictors has the form

$$y_t = \beta_0 + \sum_{j=1}^{k} \beta_j x_{j,t} + \epsilon_t$$

where the ϵ_t's are independent.

In a time series context, it can make more sense to allow the errors to be (auto)correlated.

- For example, model the errors with an AR model.

Definition

A **dynamic** (linear) **regression model** with AR(p) errors and k predictors has the form

$$y_t = \beta_0 + \sum_{j=1}^{k} \beta_j x_{j,t} + \eta_t$$

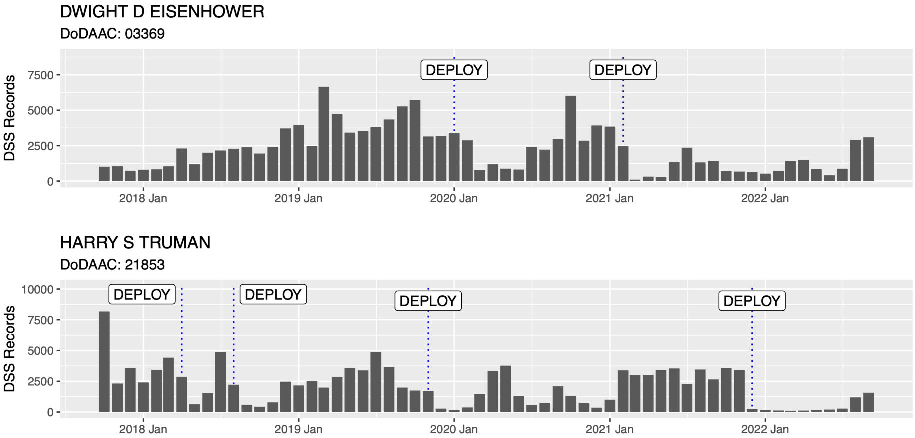
where

$$\eta_t = c + \sum_{i=1}^{p} \phi_i \eta_{t-1} + \epsilon_t$$

- y_t = workload during week t
- ϵ_t = "white noise"
- **Model Parameters:** β_0, $\beta_1, \ldots \beta_k$, c, ϕ_1, $\ldots$, ϕ_p

- Can use an ARIMA model for η_t.

Deployment-Related Predictors



Idea: Create variables tracking how many deployments will happen "soon".

Dynamic Regression Model

- **Predictors:** For $j \in \{\text{CG}, \text{CVN}, \text{DDG}, \text{LHD}, \text{LPD}, \text{SSN}\}$,

$$\boxed{x_{j,t} = \text{number of } j \text{ deployments within T-minus } w \text{ weeks of week } t}$$

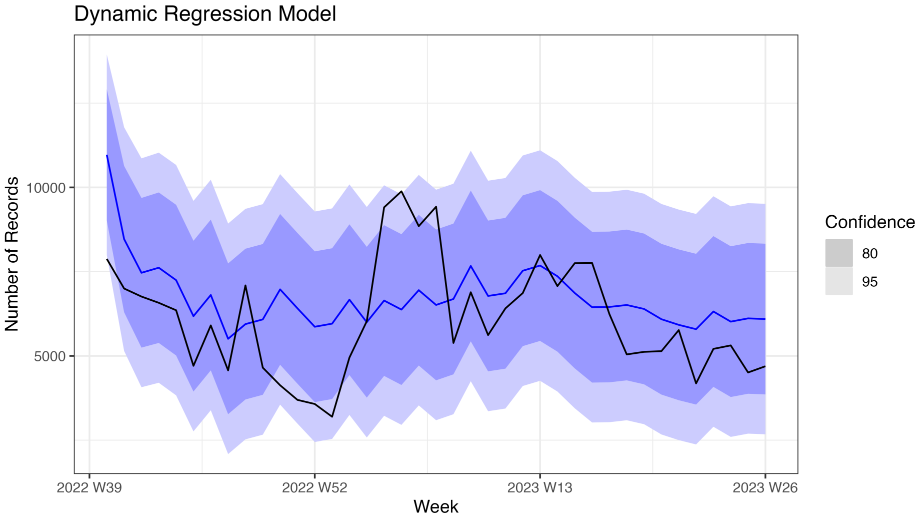
  (we used $w = 28$ weeks).

- **Training Data:** Weekly DSS record counts and **publicly releasable deployment dates** during FY18 – FY22.

- The model order (e.g., lag lengths) and seasonality were determined using the Hyndman-Khandakar Algorithm.

- **Test Data:** Weekly DSS record counts and **publicly releasable deployment dates** during FY23, up to 30 June 2023.

Dynamic Regression Model: Test Set Performance



Note: Solid Black Line = Actual Number of Records

Conclusions

1. "Vanilla" time series models capture *high-level* **workload patterns**.
   - Including deployment information can improve forecasts.
2. Still a huge amount of **forecast uncertainty**.
   - Lots of un-explained variability.
   - Use upper confidence bounds as "spike indicators"?

Ongoing Work

1. Collecting more **data**.
   - E.g., allowancing schedules, funding patterns
2. Developing better **workload measures** and **predictors**.
   - Continuing stakeholder engagement (e.g., DDNV Leadership, DLA Headquarters, Atlantic Fleet Type Commanders)
3. Evaluating/developing **other types of models**.
   - E.g., based on exponential smoothing or neural networks

Acknowledgements

US Navy Supply Corps

- **CAPT Justin Lewis** (Assistant Chief of Staff for Logistics and Readiness, Second Fleet)
- **CAPT Peter Braendeholm** (Commander, DDNV)
- **LCDR Robert Doggett** (Chief Staff Officer, DDNV)
- **LCDR Adam Davidson** (OR Grad, NPS (Sep 2023); currently at DLA HQ)
- **LCDR Kyle Combs** (OR Student, NPS)

DLA R&D

- **Danielle Williams** (Program Manager)
- **Jack Holmes** (Strategic Distribution & Disposition)

DLA Distribution Norfolk, Virginia

- **Enoch John** (Analyst & Branch Chief)