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

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Distribution Center at DLA Distribution Susquehanna
(Image Source)
Naval Station Norfolk

Waterfront at Naval Station Norfolk (Image Source)
DLA Distribution Norfolk, Virginia (DDNV)

▶ 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

- 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

Unanticipated **workload spikes** lead to significant **delivery delays**.
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), ...
Workload at the DDNV MPC

Distribution Standard System (DSS) Record Counts
2017-01-01 to 2023-06-30

Number of Records

Week

2018 W01
2020 W01
2021 W52
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
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.

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

- \(y_t\) = workload during week \(t\)
- \(\epsilon_t\) = “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.

<table>
<thead>
<tr>
<th>Fitted Model</th>
</tr>
</thead>
<tbody>
<tr>
<td>The predicted workload $\hat{y}_t$ during week $t$ is</td>
</tr>
<tr>
<td>$\hat{y}<em>t = 1490.98 + 0.67y</em>{t-1} + 0.30(y_{t-52} - 0.67y_{t-53}) - 0.21(y_{t-1} - \hat{y}_{t-1})$</td>
</tr>
</tbody>
</table>

- **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 $\epsilon_t$'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

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

- $y_t = \text{workload during week } t$
- $\epsilon_t = \text{“white noise”}$
- **Model Parameters:** $\beta_0, \beta_1, \ldots \beta_k$, $c$, $\phi_1$, $\ldots$, $\phi_p$

- Can use an ARIMA model for $\eta_t$. 
Idea: Create variables tracking how many deployments will happen “soon”.
Dynamic Regression Model

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

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

(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
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