Medical Device Demand Modeling for Supply Chain Analysis

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Abstract

This poster presents two complementary models developed to predict medical device demand under both routine and emergency scenarios. Foresight forecasts baseline medical device demand using historical data, while Landfall simulates demand spikes during hurricanes, factoring in geographic and socioeconomic vulnerabilities. Together, these models support decision-making for resource allocation, supply chain resilience, and disaster preparedness.

Introduction

The Office of Supply Chain Resilience (OSCR) is responsible for evaluating, overseeing, and reporting on risks that could cause disruptions or shortages within the medical device supply chain. In supply chains, demand drives upstream supply chain requirements, and understanding this demand is crucial to strategic efforts that assess and build resilience in medical device supply chains. In an effort to improve visibility on national demand,, and to understand key drivers of supply chain activity and risk more effectively, FDA has undertaken a modeling effort to predict future device demand under status quo and emergency conditions. Two complementary approaches to characterizing demand are shown: first to establish an understanding of baseline medical demand on a national level, and second to predict incremental demand driven by specific events, e.g., hurricanes.

Foresight: Time Series Forecasting

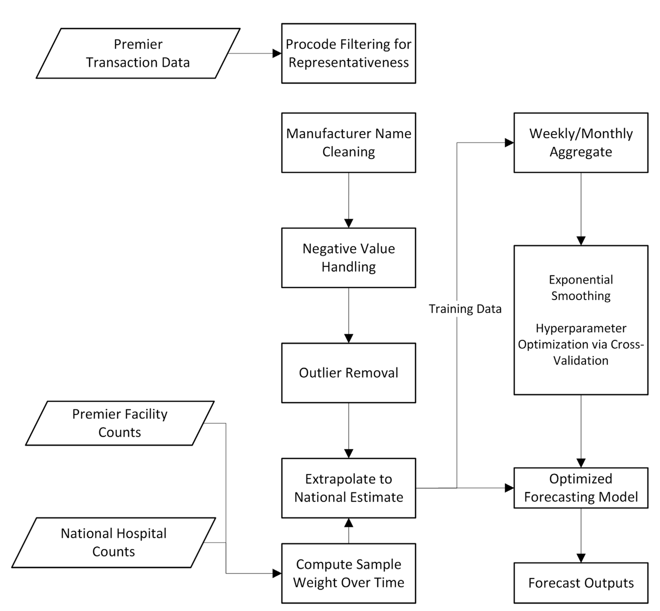
The objective of Foresight is to provide a robust, centralized, automated, and data-driven approach for estimating future demand for medical devices at a national level, where the approach is broadly generalizable across products. This establishes an understanding of status quo demand patterns which can be leveraged to characterize the scope of impact for supply chain disruptions and provides a baseline to contextualize analyses about changes in the medical device market.

Methods

Data: While data representing true demand does not exist, historical purchases approximate medical device consumption and can be treated as a proxy signal for demand. OSCR purchased and utilized this type of data set that provides transactional level data from a subset of healthcare facilities in the U.S. Data features of interest include transaction information (date, volume purchased, landed spend), facility characteristics, manufacturer/vendor, and geographic information.

Data Transformations: Data cleaning and other transformations were conducted to meet the needs of the modeling effort, informed by input from the data vendor:

- Procode Filtering: A set of criteria were created to identify which procodes to include in the analysis based on transaction frequency, volume, and recency.
- Name Cleaning: Manufacturer name standardization is used to minimize artificial distinctions between manufacturer names driven by minor naming inconsistencies.
- Negative Value Handling: An algorithm was developed to temporally align the negative purchase volume (representing corrections and returns) with the associated original order.
- Outlier Removal: An algorithm was developed to identify extreme outlier transactions and flag them as unreliable to improve data quality and model performance.
- Extrapolating to a National Estimate: An approximate national estimate is obtained based on the fraction of facilities represented in the external dataset compared to the national number of facilities each year as reported by the American Hospital Association.



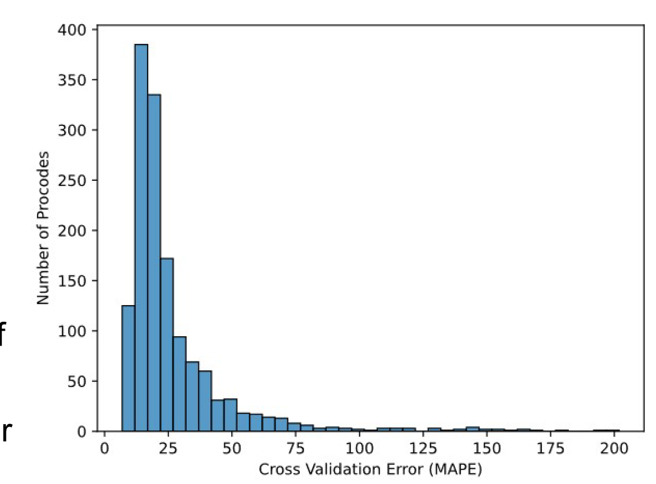
Forecasting: Several models were tested (including ARIMA, LSTM, XGBoost, and Prophet), with exponential smoothing selected for its balance of performance, computational efficiency, and explainability. Hyperparameter optimization was done using expanding window cross-validation (CV), and the data was decomposed into trend, seasonality, and residual components.

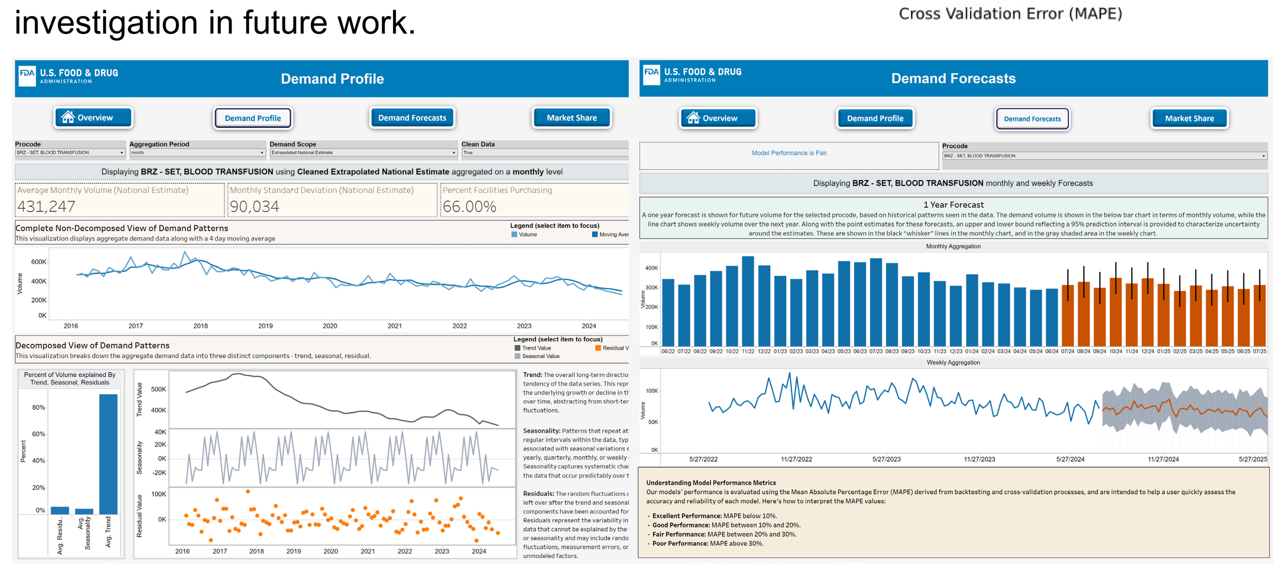
Tech Stack: Foresight is built using **Tableau** for the frontend and **Python** (including **Pandas**, **statsmodels**, **Scikit-Learn**, **Optuna**) for data processing and forecasting. It updates on a weekly cadence to incorporate new data. **Git** is used for version control.

Results & Discussion

Forecasts for approximately **1,400 procodes are included** in Foresight after filtering criteria are applied. Both backtesting (using the CV framework to generate historical forecasts) and cross validation were used to measure the model performance.

The **median cross validation MAPE was 19.6%,** providing OSCR with informative forecasts for the majority of forecasted procodes, improving visibility into anticipated demand. Approximately 10% of procodes report poor performance (a CV MAPE greater than 50%) warranting further investigation in future work.





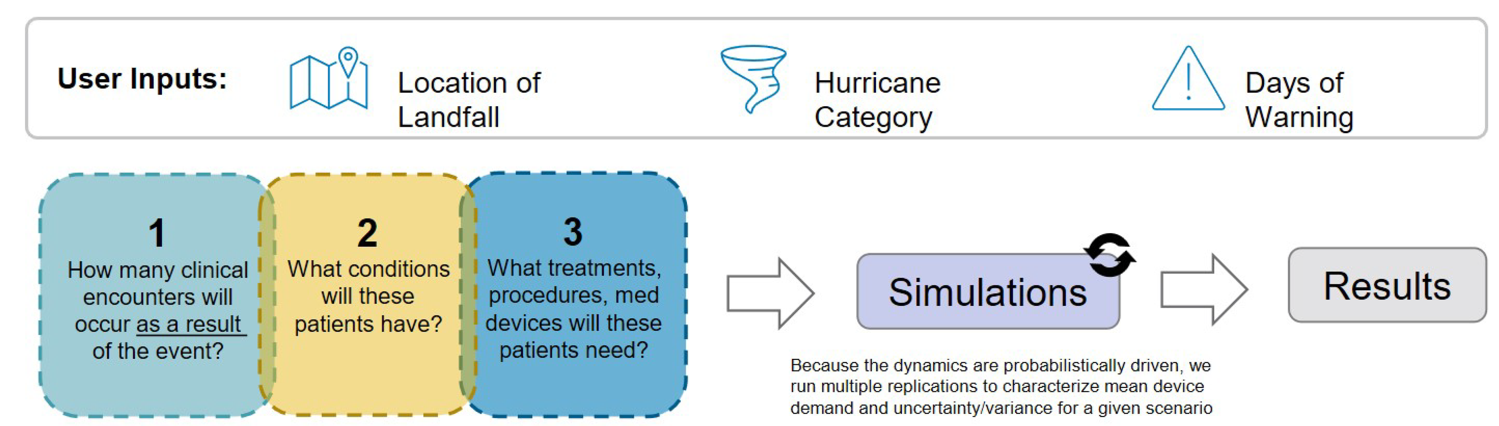
Landfall: Hurricane Scenario Computational Model

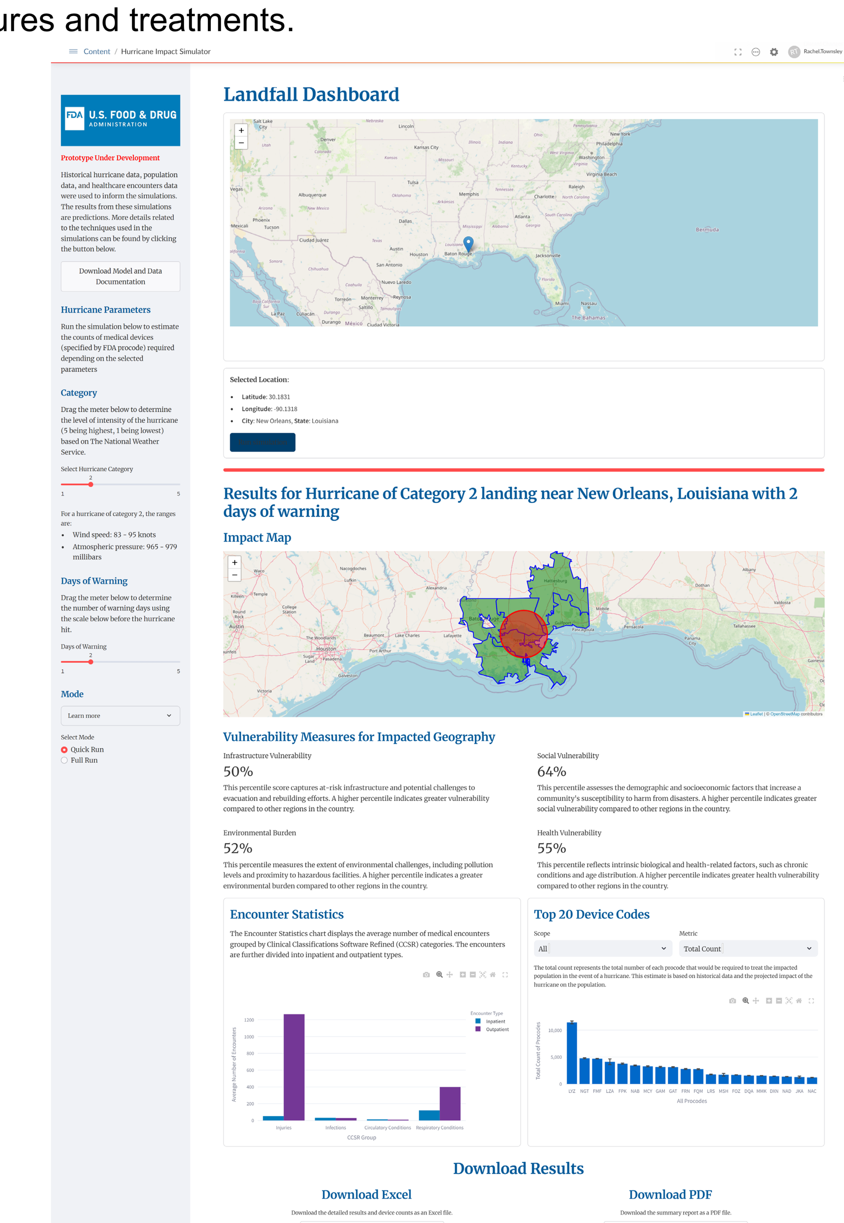
In addition to a foundational understanding of status quo demand provided by Foresight, OSCR is interested in understanding the impact of a range of events on medical device demand. As one of several event scenarios, Landfall predicts incremental medical device demand driven by a major hurricane event. Key objectives for this modeling effort were 1) **Modularity** to ensure flexible, generalizable, and scalable structure to allow for easy adjustments to accommodate different scenarios or scenario-specific needs; 2) **Transparency** such that the chain of inference is intuitive and digestible to users to establish trust in the model and encourage user adoption; 3) **"What if" Capability** so that users can evaluate the impact of different inputs associated with a variety of scenarios; and, 4) **Context** so that medical device demand driven by the scenario is put in the context of baseline demand in order to understand the magnitude of impact and risk.

Methods

The Landfall application uses three inputs: location of landfall, hurricane category at landfall, and days of warning. Based on these inputs, the model operates through three modules:

- **Module 1**: Predicts excess clinical encounters using census data, CDC socioeconomic data, and a geographic infrastructure index for the impacted region. Historical data from AHRQ's Hurricane Fast Stats characterizing observed excess encounters following hurricane events informs a Bayesian Poisson regression to predict encounter counts based on the scenario inputs.
- **Module 2**: Assigns relevant health conditions to each encounter using a meta-analysis of typical hurricane-related conditions and ICD-10 codes. Data from HCUP's National Inpatient Sample and NIH's All of Us dataset inform the relative frequency of health conditions for inpatient and outpatient encounters, respectively.
- **Module 3**: Provides clinical estimates for medical device usage based on the health conditions predicted. A panel of clinicians was convened to identify relevant procodes for each ICD-10, and provided low, expected, and high usage estimates for medical devices required for procedures and treatments.





Tech Stack: Landfall is built using **Streamlit** for the front-end and **Python** (with **PyMC**, **Pandas**, and **NumPy**) for data processing and Bayesian inference. It's hosted on a **Posit Connect** server, ensuring secure and scalable deployment. **Git** is used for version control.

Results & Discussion

Performance Evaluation: Bayesian model diagnostics ($\hat{R}$~1, trace plots) confirm stable posterior distributions indicating reliability in simulated counts, and predictions for ED and inpatient encounters were generally accurate, with count differences between **50–100** for ED, and **30–60** for inpatient settings. External validation against Hurricane Wilma data showed the model's prediction (2972 excess encounters) closely aligned with the actual 3206.

Next Steps: Current model relies on Hurricane Fast Stats data that includes hurricanes up to 2017. Efforts are underway to acquire **more recent data and update the model**.

Conclusions

The Foresight and Landfall models both provide critical tools for forecasting medical device demand in response to different challenges: baseline trends under normal conditions and/or seasonal fluctuations (Foresight) and disaster scenarios like hurricanes (Landfall). Together, they form a comprehensive framework that: 1) supports supply chain resilience by identifying potential increases in demand across both routine and emergency situations; 2) utilizes advanced modeling techniques to ensure flexibility and accuracy in predicting healthcare needs following a major hurricane event; and, 3) informs proactive planning, offering insights that can inform policy adjustments and preparedness strategies for both stable and volatile periods.

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