ANALYZING THE EFFECT OF PROGNOSIS ON SPARE PART INVENTORY MANAGEMENT

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Challenges in Aviation Logistics

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Industry Consolidation

Dependence on single sources, make disruptions harder to absorb

OEM Aftermarket Dependence

OEM reliance on revenue from spare parts and repair create bottlenecks in maintenance

External Shocks

Geopolitical tensions, and material shortages increase supply uncertainty

Skilled Labor Shortage

An aging workforce and talent gaps reduce productivity

Airlines incurred almost **1.1 billion USD** in excess inventory holding costs in 2025 [1]

PHM mitigates aviation supply chain disruptions through **predictive maintenance, smarter spare planning**, and **reduced operational uncertainty**.

1. Oliver Wyman, & International Air Transport Association. (2025, October). Reviving the Commercial Aircraft Supply Chain: What's holding back the commercial aircraft supply chain and where to go from here (Technical Report). International Air Transport Association.

If PHM is Promising,
Why is It’s Adoption Limited?

Key Barriers Preventing Widespread Adoption of PHM [1]

- High Complexity of Models
- Data Availability, Quality and Ownership
- Regulatory and Validation Concerns
- High Cost of Adaption
- Impact Assessment

Quantifying PHM's impact over traditional approaches is key to promoting broader adoption in aviation maintenance.

1. Teubert, C., Pohya, A. A., & Gorospe, G. (2023). An analysis of barriers preventing the widespread adoption of predictive and prescriptive maintenance in aviation.

How can the impact of Prognostics be assessed ?

Methodology

A **rolling horizon methodology**, encapsulated within a **DES** framework is used for periodic simulation of **demand forecasting, inventory replenishment, component failures** and **replacement events**

Condition Monitoring

Determine the **age/condition** of the component

Failure Prediction

Use **reliability metrics** or **prognostic** to find the period which will witness the next failure

Inventory Replenishment

Establish the most opportune **lot size** and **delivery period** for spare parts using WW algorithm

Repairs

Perform **replacements** of **failed components** based on **inventory level**

Information Feedback

Condition Monitoring

The condition monitoring step has two purposes, establishing the **“ground truth”** for component failure and **providing input to the proxy model**

Ground Truth Generation

- The **“ground truth”** refers to the actual failure date for a component
- Randomly sampled from **inverse Weibull CDF**

$$T = \eta[-\ln(1-U)]$$

- Generated every time a **new component enters the simulation**

Input for PHM Model

- At every period, a component’s **true RUL is calculated**

$$RUL = "\boldsymbol{GT}" - t$$

- The true RUL, is used by prognostics as **the input to calculate the predicted RUL**

$$RUL(pred) = RUL(true) + error$$

Condition monitoring helps **establish the true failure date (ground truth),** which serves as the reference input for **prognostics and model evaluation**.

Failure Prediction: Reliability Metrics Approach

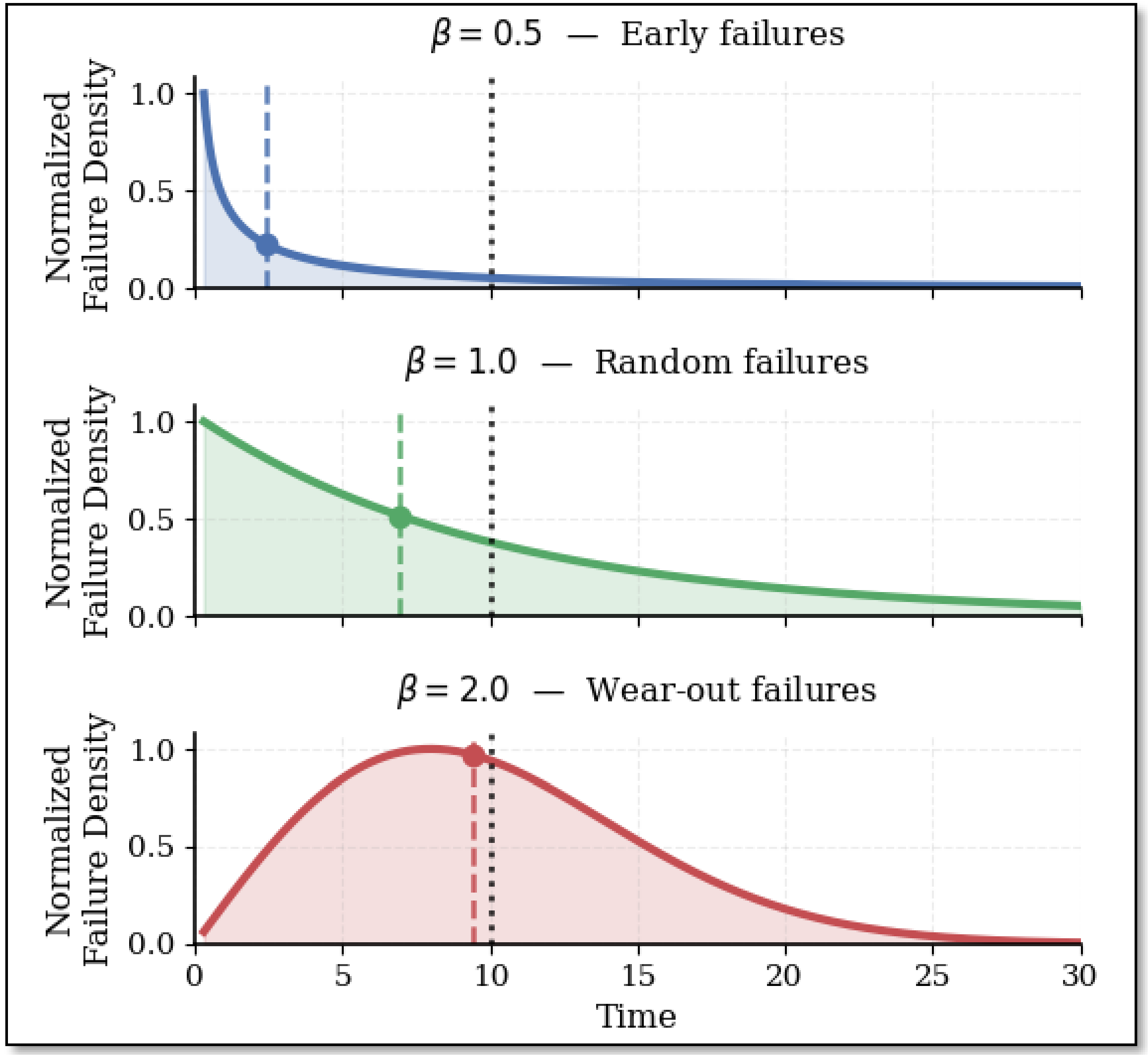
Weibull Distribution

The reliability-based approach uses component-specific data to predict failure timing using the Weibull distribution, utilizing the metrics,

- **MTBF (Mean Time Between Failures):** average time expected between successive failures
- **Beta (β):** describes the evolution of failure rate changes over time

Time to Failure

- Simply using MTBF to determine next failure could be naïve, as MTBF only **represents an average value**
- The value of **β** dictates the density of failures
- Instead of MTBF, the time where **50% of components fail (median)**, is used



Failure Prediction: Prognostics Approach

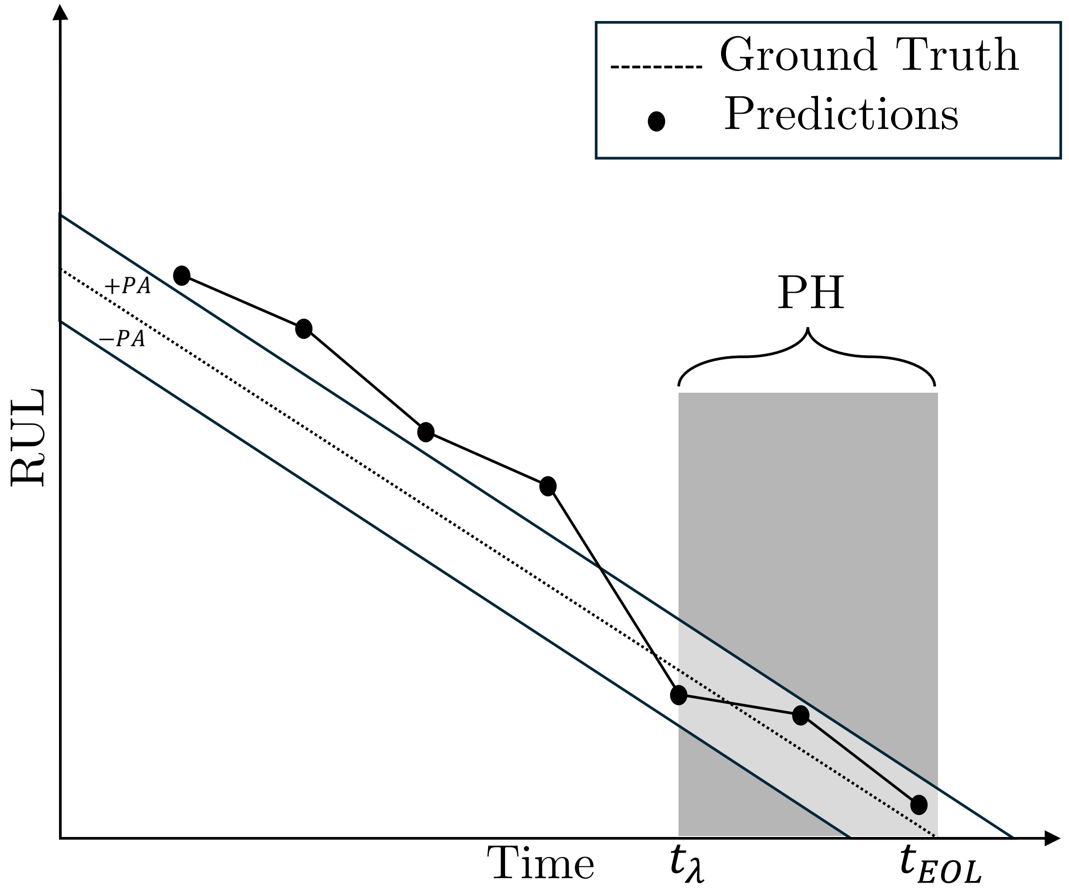
The prognostic-based approach employs a surrogate framework to **emulate** the behavior of a **real prognostic model** in order to determine **component degradation**

Prognostic Parameters[1]

- **Prognostic Accuracy (PA) :** The maximum allowable error for the RUL predictions
- **Prognostic Horizon (PH) :** Time prior to EOL at which the model's predictions consistently fall within specified error bounds

Time to Failures

- Upon entering the PH, a prognostic error is applied to the component's true EOL.
- This **error-adjusted EO**L then **serves as the basis for the predicted remaining useful life (RUL)**
- **The value of PA is always less than PH**



1. Saxena, A., Celaya, J., Saha, B., Saha, S., & Goebel,K. (2010). Metrics for offline evaluation of prognostic performance. *International Journal of Prognostics and Health Management*, *1*(1). doi:10.36001/ijphm.2010.v1i1.1336

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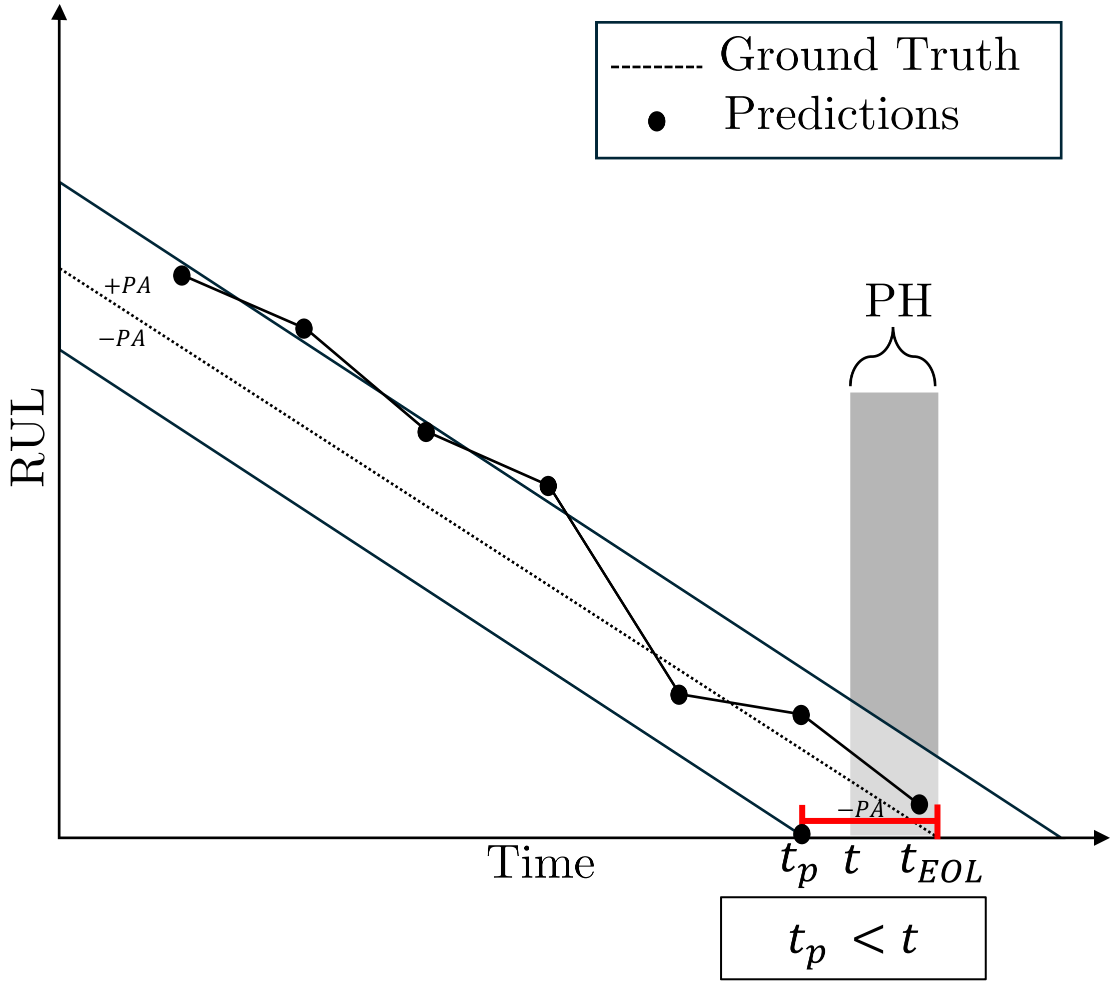


Wagner Whitin Algorithm

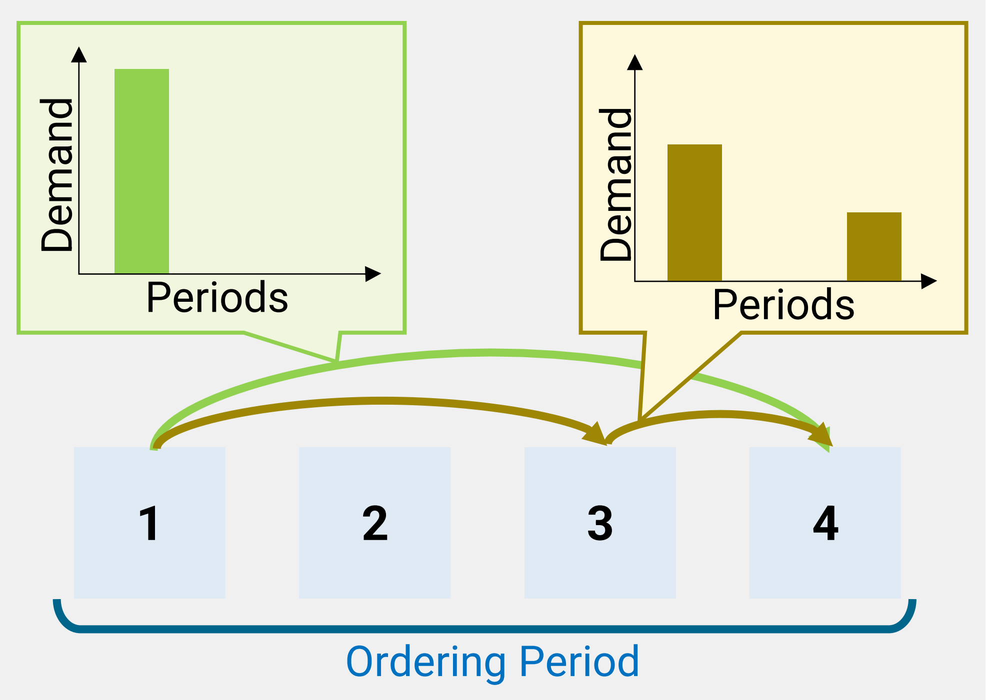
Wagner Whitin is a **dynamic programming method** that finds **the optimal ordering plan** over a finite horizon by testing all **possible last ordering points** and selecting the **minimum-cost solution**.

Objective

Minimizes total costs (setup + holding) by evaluating **all possible ordering schedules**.

Order Logic

- At each time period, the model evaluates all possible order lot groupings to satisfy future demand
- Each option assumes a different prior ordering point and calculates the corresponding total cost
- The order policy with the minimum total cost is selected



How does the Prognosis Based Forecasting perform against Reliability Based Forecasts ?

Simulation Inputs and Performance Parameters

The forecasting methods were compared against each other against a sample use case with 20 components

Input Variable	Description	Value
Total Periods	Total length of simulation	**30 Periods**
Planning Horizon	Total length of prediction window	**10 Periods**
Ordering Costs	Cost to place an order	**100 Units**
Holding Costs	Inventory cost per component	**1 Units**
Stockout Costs	Penalty when demand is unfulfilled	**10 Units**
MTBF	Mean time between failure	**10 Periods**
Beta	Weibull shape parameter	**2**

Total Costs

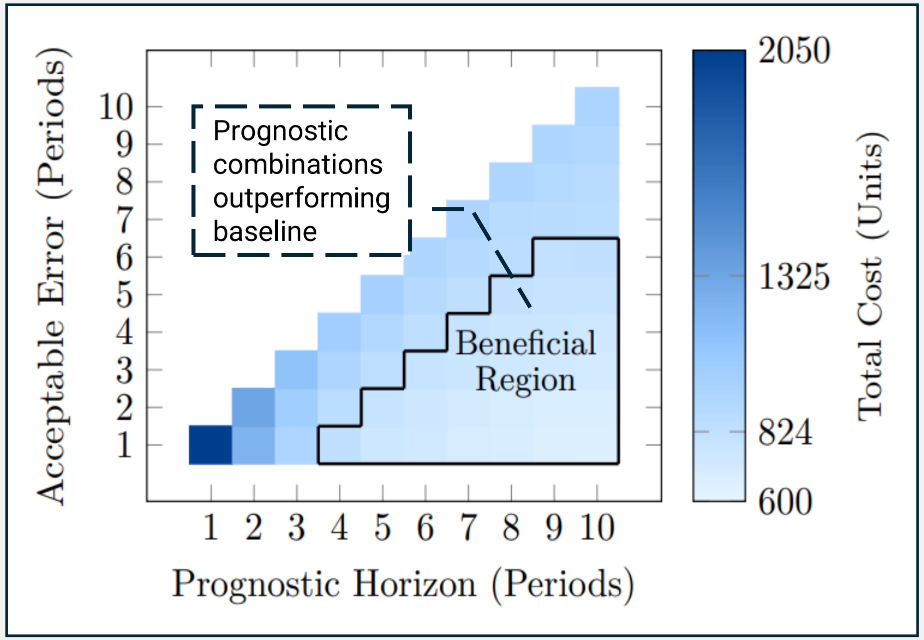
$$TC = \sum_{i=1}^{TP} Ordering\ Cost_i + Holding\ Cost_i + Stockout\ Cost_i$$

Service Level

$$SL = \left(1 - \frac{\sum_{i=1}^{TP} Shortage_i}{\sum_{i=1}^{TP} Demand_i}\right) * 100$$

Results: Effect on Total Cost

The **total cost comparison** between **reliability (baseline – 824 units)** and **prognostics** means of demand generation is represented in heatmap



> Beyond a certain threshold, improvement in prognostics do not yield tangible benefits

Impact of PH

Increment in PH is beneficial for total cost

- Earlier accommodation of demand in inventory planning
- Improved order consolidation to limit ordering

Impact of PA

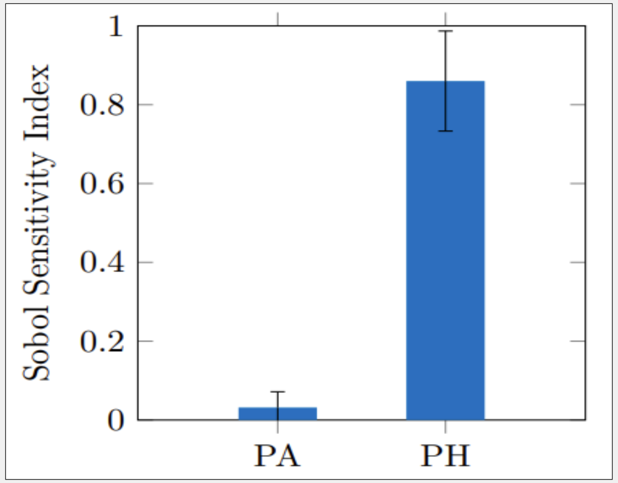
Total cost also **improves with better prediction quality**

- More accurate representation of demand
- Holding cost and stockout penalties less likely

> Prognostic metrics have different degree of contribution on performance

First-Order Sobol Sensitivity Analysis

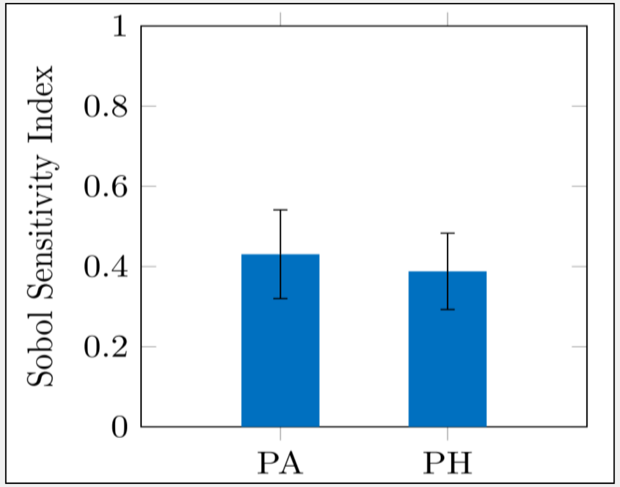
Direct Influence of Prognostic Parameters on Total Cost



Ordering Cost is Dominant

PH is the driving factor for total cost variation

- High Ordering Costs punish frequent ordering → Longer prognostic horizon allows better order consolidation
- PA is detrimental to cost performance when orders are late; effect further diminished due to lot sizing



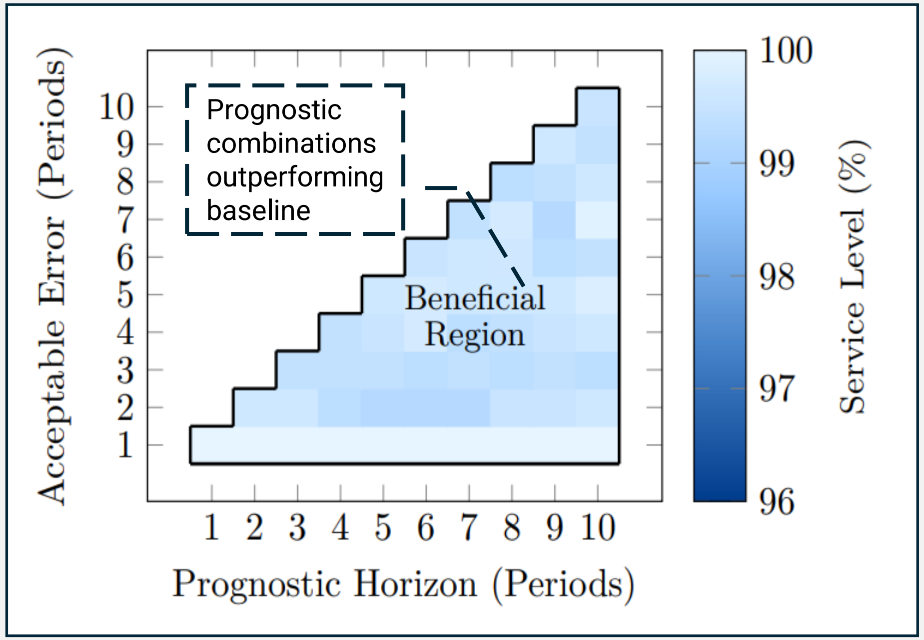
Holding Cost is Dominant

PA is the dominant cause of total cost variation

- High holding costs discourage excessive inventory buildup.
- PA variability can drive costly early replenishment.
- Higher PH reinforces this effect through earlier predictions by allowing higher PA.

Results: Effect on Service Level

The **service level comparison** between **reliability (baseline – 96%)** and **prognostics** means of demand generation is represented in heatmap



Impact of PH

Increment in PH has no impact on Service Level

- Since, WW assumes 0 lead time, delayed predictions do not affect the service level
- Sometimes, having lower PH is better to reduce faulty predictions

Impact of PA

PA improves service level, but the effect is very low

- Early Predictions help service level → further facilitated by WW lot sizing

The improper or unstructured incorporation of external shocks**, such as lead time variability and false alarms,** can bias system behavior and lead to misleading or unreliable observations.

Conclusion

The framework demonstrates that **prognostics-driven inventory strategies** can **outperform reliability-based** approaches by leveraging **dynamic, component-specific information**.

Inventory performance depends on **ordering strategy**, while benefits from **higher prediction accuracy and prognostic horizon diminish beyond a threshold**.

Inventory outcomes are highly sensitive to **uncertainty** and **external variability**, requiring **rigorous modeling** to avoid **biased conclusions**

Thank You

Questions ?

Please feel free to connect on LinkedIn

Imprint

Topic: **Analyzing the Effects of Failure Prognosis on Spare Part Inventory Management**

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