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Original Research

Improving Parts Availability and Forecasting in Global Operations Through Advanced Data Analytics

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Abstract
Global production and service networks depend on reliable availability of spare parts to maintain equipment uptime and customer service levels across distributed geographies. The complexity of these networks has increased with product differentiation, shorter life cycles, and heterogeneous usage profiles, while organizations continue to operate under cost and capital constraints. Planning processes must reconcile intermittent and highly skewed demand signals, stochastic transport and procurement lead times, and varying criticality of parts across applications. Conventional deterministic or aggregate forecasting approaches are often insufficient to capture these dynamics and to distinguish uncertainty that is structural from noise that arises from data quality issues or rare events. At the same time, transactional, sensor, and contextual data are increasingly available at scale, creating opportunities for more granular modeling of demand and supply processes. This paper develops an integrated framework for improving parts availability and forecasting in global operations using advanced data analytics. It combines a data architecture tailored to multi-echelon service networks with probabilistic models for demand and lead times and with optimization formulations for inventory and replenishment policies. The study emphasizes the representation of uncertainty, the propagation of predictive distributions into decision models, and the evaluation of policy robustness through simulation. The proposed concepts are discussed with respect to their algorithmic properties, information requirements, and practical implementation aspects within existing planning systems, with attention to both potential benefits and limitations.

1. Introduction

The management of spare parts in global operations combines characteristics of supply chains for both make-to-stock and make-to-order systems, while introducing additional challenges related to asset criticality and uncertainty [1]. Parts demand often originates from failure processes that depend on equipment age, operating conditions, and maintenance strategies. Such demand tends to be intermittent, highly skewed, and subject to structural breaks caused by design modifications, supplier changes, or regulatory interventions. Service level requirements are typically specified not only in terms of fill rates but also in terms of downtime risk for critical assets. At the same time, financial constraints limit the amount of capital that can be committed to slow moving and long tail parts. These factors create a setting in which forecasting and inventory decisions are tightly coupled, and errors in one layer propagate nonlinearly to others.

Classical aggregate forecasting methods, such as exponential smoothing or simple time series models calibrated on historical shipments, are often insufficient for such environments. They treat demand as a univariate stochastic process and do not directly leverage information about installed base, operating profiles, or sensor-derived health metrics. They also tend to provide point forecasts rather than full predictive distributions, which complicates the calibration of safety stocks for specified service levels. In contrast, modern data analytics opens the possibility of modeling the conditional demand distribution at the level of part, location, and time period, conditioned on explanatory variables that capture both local and global effects. Machine learning methods can extract nonlinear relationships, while probabilistic frameworks ensure coherent uncertainty quantification.

However, advanced models introduce their own complexities. They require careful feature engineering, regularization, and governance to avoid overfitting and to maintain interpretability for operational users. They must be aligned with the structure of optimization models used to derive stocking and replenishment policies. In multi-echelon networks, decisions at local warehouses interact with policies at regional distribution centers and central hubs. Lead times, procurement constraints, and capacity limitations create further couplings. As a result, the design of an analytics pipeline for global parts operations should be guided not only by predictive accuracy but also by the requirements of downstream planning algorithms and the characteristics of the decision environment.

Feature	Type	Source	Purpose
Demand history	Numeric	ERP	Forecast driver
Installed base	Numeric	Asset DB	Exposure measure
Utilization	Numeric	Sensor	Failure intensity proxy
Lead time samples	Numeric	Logistics	Supply uncertainty
Location attributes	Categorical	Master data	Context encoding

Table 1. *Key features used in probabilistic demand modeling..*

Model	Target	Output	Notes
Poisson GLM	Demand	Mean rate	Hierarchical effects
Zero-inflated	Demand	Activation/intensity	Sparse series
Quantile model	Demand	Quantiles	Risk-driven use
Log-normal model	Lead time	Mean/variance	Parametric form
Ensemble	Both	Samples	Distributional view

Table 2. *Model structures used across demand and lead-time forecasting..*

Variable	Unit	Layer	Role
$D_{i,j,t}$	Units	Demand	Target variable
$L_{i,j}$	Days	Supply	Lead-time input
$S_{i,j}$	Units	Inventory	Base-stock level
$c^h_{i,j}$	Cost	Cost	Holding cost
$c^b_{i,j}$	Cost	Cost	Backorder cost

Table 3. *Core variables appearing in the optimization formulation..*

This paper develops a modeling and analytics framework that connects the data layer, the forecasting layer, and the optimization layer in a coherent way [2]. The focus is on spare parts networks with multiple stocking locations, a mixture of critical and noncritical items, and heterogeneous demand patterns. The proposed framework integrates hierarchical probabilistic models for demand and lead times with inventory optimization formulations that incorporate predictive distributions rather than point forecasts. To evaluate the behavior of resulting policies under uncertainty and model misspecification, the framework embeds a simulation layer that can emulate network operations over extended horizons. The modeling choices are discussed in terms of their algorithmic structure, data requirements, and scalability to large part portfolios typical of global operations.

The remainder of the paper is structured as follows. After a discussion of the operational context of global parts networks, the paper specifies a data architecture and feature space suitable for analytics-driven forecasting. It then presents probabilistic models for demand and supply processes, followed by an optimization formulation for inventory and replenishment that uses these models as inputs. A simulation component for numerical experiments is described to examine policy behavior. The paper concludes by discussing implementation considerations and limitations of the proposed approach in practice.

2. Global Parts Operations and Problem Context

A global parts network typically consists of a set of central hubs, regional distribution centers, and local warehouses that support installed equipment across multiple countries and industries. Let the set of parts be indexed by $i \in \{1, \ldots, N\}$, the set of stocking locations by $j \in \{1, \ldots, M\}$, and discrete time periods by $t \in \{1, \ldots, T\}$. Demand for part i at location j during period t is represented by a random variable $D_{i,j,t}$. This demand may correspond to a combination of corrective maintenance, preventive replacement, and project-related consumption. The distribution of $D_{i,j,t}$ can differ substantially across parts and locations, with many combinations being zero in most periods.

Lead times in such networks arise from multiple sources. For a given upstream location k and downstream location j, the replenishment lead time for part i can be represented as a random variable $L_{i,j,k}$ capturing procurement processing, transportation, customs, and internal handling. Lead time distributions can differ significantly across lanes and parts, and may exhibit heavy tails due to disruptions or capacity constraints. These stochastic lead times interact with demand variability to determine the probability of stockouts under a given inventory policy. Because forecast errors and lead time variability accumulate over the replenishment horizon, policy design must be based on probabilistic characterizations rather than single estimates.

Another layer of complexity comes from heterogeneity in criticality and service targets. Critical parts may be associated with stringent availability requirements and contractual service level agreements, while noncritical parts may allow for more flexible response times [3]. Let $\phi_{i,j}$ denote a service metric such as the probability that a demand for part i at location j is filled immediately from stock. Different thresholds $\bar{\phi}_{i,j}$ may be specified across the portfolio, and planning processes must respect these thresholds while managing limited budget and capacity. In practice, constraints on storage, transportation, and working capital create tradeoffs between service levels across parts and locations.

Operational data in global networks is distributed across systems such as enterprise resource planning, transportation management, warehouse management, and condition monitoring platforms. These systems differ in granularity, latency, and data quality. Demand is often recorded at order line level, while installed base and operating conditions are captured at asset or site level. Sensor data may be available at high frequency but only for subsets of the fleet. Joining these data sources in a way that supports part-level forecasting and decision making across the network requires a structured data architecture. Without such an architecture, advanced modeling may rely on incomplete or biased data and may not deliver reliable insights.

The planning horizon for spare parts decisions is another important characteristic [4]. For many items, replenishment lead times are on the order of weeks or months, and design or supplier changes can alter demand and lead time patterns during this horizon. For others, local replenishment may be rapid but subject to transportation capacity limits or regulatory constraints. As a result, decision makers operate on multiple timescales, with strategic, tactical, and operational planning cycles. The analytics framework must therefore support forecasts and decisions at different aggregation levels and with varying planning cadences, while maintaining consistency in the representation of uncertainty across horizons.

The cost structure associated with spare parts includes holding costs, order processing costs, penalty costs for stockouts or delayed service, and obsolescence costs for parts whose demand declines or ceases. Let $c^h_{i,j}$ denote the per period holding cost for part i at location j, and $c^b_{i,j}$ a cost parameter reflecting the impact of backorders or lost sales. These parameters may incorporate not only financial elements but also implicit valuation of downtime risk. The optimization models developed later use such cost parameters as inputs, but their calibration depends on organizational preferences, risk attitudes, and contract structures. The realism of any analytics-based decision support tool critically depends on alignment between these parameters and the actual objectives of the organization.

In summary, the problem context for improving parts availability and forecasting in global operations is characterized by networked structure, stochastic demand and lead times, heterogeneous service targets, and multiple cost components [5]. These characteristics motivate the development of an analytics framework that can integrate diverse data sources, represent uncertainty in a coherent manner, and support decision models that reflect operational reality. The next section describes a data architecture and feature engineering approach tailored to these requirements [6].

3. Data Architecture and Feature Engineering

Effective use of advanced data analytics for parts availability requires a data architecture that maps raw transactional and contextual data into a structured feature space. The objective is to represent, for each part i, location j, and time period t, a set of explanatory variables $x_{i,j,t}$ capturing demand drivers, supply conditions, and network context. These features are then used in probabilistic models to characterize the conditional distribution of $D_{i,j,t}$ and associated quantities.

A central component of the architecture is a time indexed panel structure that aggregates events at an appropriate granularity. Let Δt denote a base time bucket, such as one week. For each triple (i, j, t), the architecture maintains measures of historical demand, current inventory, open orders, and lead time observations. Additional attributes capture the installed base of equipment at location j that uses part i. If $B_{i,j,t}$ denotes the count of active assets requiring part i at time t, and $U_{i,j,t}$ denotes a measure of utilization such as operating hours per asset, then the feature vector may include $B_{i,j,t}$ and $B_{i,j,t}U_{i,j,t}$ as proxies for exposure.

External and contextual variables can also be integrated. Examples include climate indicators, market segment classifications, maintenance regimes, and macroeconomic variables. Let $w_{j,t}$ represent a vector of location time features and a_i a vector of static attributes for part i. The combined feature vector can then be expressed as

$$x_{i,j,t} = g(a_i, B_{i,j,t}, U_{i,j,t}, w_{j,t}),$$

where g denotes a transformation that may include interactions, lags, and nonlinearities. The transformation can be designed explicitly or learned as part of a representation learning stage using embedding or neural network techniques.

Lead time data requires particular attention. For each replenishment order of part i from location k to location j, the architecture records the realized lead time and associated attributes such as carrier, route, mode, and shipping conditions. Let $\ell_{i,j,k,n}$ denote the realized lead time for the nth order on the lane from k to j. The feature vector for lead time modeling, denoted $z_{i,j,k,n}$, may include order size, seasonality indicators, and congestion metrics. These observations form the basis for probabilistic models of $L_{i,j,k}$ as a function of $z_{i,j,k,n}$.

Data quality is a central concern in such architectures. Missing values, inconsistent identifiers, and occasional measurement errors can introduce biases in downstream models. The architecture therefore integrates data validation and imputation steps [7]. For example, if installed base records for some assets are incomplete, approximate values of $B_{i,j,t}$ can be inferred from commissioning histories or replacement patterns. Similarly, extreme values of lead times can be flagged and treated separately, either as genuine disruptions or as data anomalies. These steps are implemented as transformations on the panel, producing both cleaned features and quality indicators that can be used as additional variables in predictive models.

Another important aspect is the representation of network relationships. Parts may be shared across multiple product families or platforms, and substitution relationships may exist between parts. Locations may be connected through multiple replenishment paths, and transshipment policies may allow lateral movement of inventory. To capture such structure, the architecture can incorporate graph derived features. For example, define an adjacency matrix A for the location network, where $A_{j,k}$ reflects connectivity or effective distance between locations. For each part i, features can be derived that summarize demand in the neighborhood of location j, such as lagged averages of $D_{i,k,t}$ for locations k with high $A_{j,k}$. Such features can help models exploit spatial correlations in demand.

Finally, the architecture must support the generation of training, validation, and test sets for predictive modeling that respect temporal ordering [8]. For time period t, features are constructed using information available up to time t, and the target variable is demand or lead time realized in a future period. Rolling origin schemes can be used to evaluate predictive performance under realistic deployment scenarios. The architecture should provide efficient mechanisms for generating such datasets across millions of (i, j, t) combinations, which often requires distributed data processing and storage systems. With this data foundation, advanced probabilistic models can be developed to characterize demand and supply uncertainty.

4. Probabilistic Modeling of Demand and Supply

The forecasting layer of the framework aims to estimate the joint distribution of future demand and lead times for each part and location, conditioned on the feature vectors derived from the data architecture. Rather than focusing solely on point forecasts, the modeling approach emphasizes predictive distributions to support decision making under uncertainty. This section presents probabilistic models for demand and supply processes that are suitable for intermittent and heterogeneous patterns.

Demand for part i at location j in period t is represented by $D_{i,j,t}$. A flexible starting point is a hierarchical generalized linear model where the conditional distribution of $D_{i,j,t}$ given features $x_{i,j,t}$ is Poisson with log link. Formally, one may assume

$$D_{i,j,t} \mid \lambda_{i,j,t} \sim \text{Poisson}(\lambda_{i,j,t}),$$

with intensity [9]

$$\log \lambda_{i,j,t} = \alpha_i + \gamma_j + u_{i,j} + \beta^\top x_{i,j,t}.$$

Here, α_i and γ_j capture part and location specific effects, $u_{i,j}$ captures part location interaction, and β is a parameter vector for global feature effects. Hierarchical priors or regularization penalties can be imposed to prevent overfitting and to share strength across sparse combinations.

Intermittent demand with many zero observations motivates extensions beyond the simple Poisson specification. A zero inflated model introduces a binary latent variable indicating whether a period is active. Let

$$Z_{i,j,t} \sim \text{Bernoulli}(p_{i,j,t}),$$

$$Y_{i,j,t} \sim \text{Poisson}(\mu_{i,j,t}),$$

$$D_{i,j,t} = Z_{i,j,t} Y_{i,j,t}.$$

The activation probability $p_{i,j,t}$ and mean $\mu_{i,j,t}$ can each be modeled as functions of features, for example

$$\operatorname{logit} p_{i,j,t} = a_i + b_j + \theta^\top x_{i,j,t},$$

$$\log \mu_{i,j,t} = c_i + d_j + \eta^\top x_{i,j,t}.$$

This structure allows the model to distinguish between parts that rarely experience demand and parts that frequently experience demand but with variable magnitude. It also supports separate interpretation of activation and intensity drivers.

Machine learning models can be embedded in the intensity or activation functions to capture nonlinearities. For instance, a gradient boosted tree model or a neural network can be used to approximate the mapping

$$\lambda_{i,j,t} = f_\theta(x_{i,j,t}),$$

where θ denotes model parameters [10]. To obtain predictive distributions rather than point estimates, methods such as quantile regression, Bayesian neural networks, or ensemble approaches can be employed. For example, in quantile regression the model estimates conditional quantiles $q_\tau(D_{i,j,t} \mid x_{i,j,t})$ for multiple τ values in $(0, 1)$, with loss based on the pinball function

$$\rho_\tau(u) = u(\tau - \mathbf{1}_{\{u<0\}}).$$

These quantiles can then be used directly in inventory calculations or approximated by parametric distributions.

Lead time modeling follows similar principles. For each lane from location k to location j, realized lead time samples $\ell_{i,j,k,n}$ with features $z_{i,j,k,n}$ are observed. A parametric model might assume that the logarithm of lead time is Gaussian,

$$\log L_{i,j,k} \sim \mathcal{N}(m_{i,j,k}, s^2_{i,j,k}),$$

with

$$m_{i,j,k} = \delta^\top_{i,j,k} z_{i,j,k},$$

where $\delta_{i,j,k}$ is a parameter vector that can be regularized or partially pooled. Alternatively, nonparametric methods such as kernel density estimation conditional on features can be used where sufficient data is available. The choice between parametric and nonparametric forms depends on data volume and the need for computational efficiency in downstream optimization.

The joint distribution of demand and lead times influences inventory dynamics because demand during the replenishment period is driven by both processes. A simplified assumption treats $D_{i,j,t}$ and $L_{i,j,k}$ as conditionally independent given their respective features. Under this assumption, the distribution of cumulative demand over a random lead time can be approximated via convolution. For example, if $D_{i,j,t}$ is approximated as Poisson with rate $\lambda_{i,j}$ per period and $L_{i,j,k}$ has expectation $\bar{L}_{i,j,k}$, then cumulative demand during lead time has mean $\lambda_{i,j}\bar{L}_{i,j,k}$. When predictive distributions with higher resolution are available, numerical methods or Monte Carlo simulation can be used to approximate the distribution of demand during lead time more accurately [11].

In large part portfolios, models must be scalable and robust to sparse data. One strategy is to adopt global models that operate on all parts and locations simultaneously, with the identity of part and location encoded as categorical features or embeddings. Such models can capture cross sectional patterns and share information, allowing rare parts to benefit from structure learned on more common parts. Another strategy combines simple baseline models for the long tail with more complex models for parts that meet data volume thresholds. For example, a Croston style method may be used for extremely sparse series, while probabilistic machine learning models are reserved for parts with sufficient history and feature richness.

Finally, the outputs of the probabilistic models must be calibrated and monitored over time. Calibration refers to the alignment between predicted probabilities and observed frequencies. For example, if a predictive distribution assigns 10% probability to an event, that event should occur in roughly 10% of cases in the long run [12]. Techniques such as probability integral transform diagnostics, reliability diagrams, and scoring rules like the continuous ranked probability score can be used to assess calibration. Feedback from these diagnostics informs model retraining, feature updates, and potential structural changes in response to shifts in the operating environment.

5. Inventory and Replenishment Optimization

The optimization layer translates probabilistic forecasts of demand and lead times into stocking and replenishment policies for each part and location across the network. A common policy structure in multi echelon service parts systems is the base stock policy. Under such a policy, each stocking location j maintains a base stock level $S_{i,j}$ for each part i. Whenever the inventory position, defined as on hand inventory plus on order inventory minus backorders, falls below $S_{i,j}$, a replenishment order is placed to restore the position to $S_{i,j}$. The objective is to determine $S_{i,j}$ values that balance holding costs and service level requirements given the probabilistic models.

Metric	Definition	Scale	Usage
Fill rate	Immediate service probability	0–1	SLA target
Avg. inventory	Mean on-hand	Units	Cost analysis
Backorders	Mean delayed units	Units	Risk indicator
Total cost	Holding + penalty	Cost	Objective measure

Table 4. *Simulation output metrics used to evaluate policies..*

Category	Example	Frequency	Impact
Demand spikes	Failure clusters	Occasional	High
Lead-time shocks	Port delays	Rare	High
Data gaps	Missing installs	Common	Medium
Forecast drift	Feature shifts	Gradual	Medium

Table 5. *Common sources of uncertainty in parts networks..*

Layer	Input	Output	Function
Data	Raw events	Features	Structuring
Modeling	Features	Distributions	Prediction
Optimization	Distributions	Policies	Decision support
Simulation	Policies	KPIs	Evaluation

Table 6. *High-level pipeline structure in the analytics framework..*

Approach	Complexity	Scalability	Notes
Base-stock rules	Low	High	Widely used
Quantile policies	Low–Medium	High	Distribution-based
Stochastic DP	High	Low	Detailed but costly
RL-based policy	High	Medium	Requires simulation

Table 7. *Comparison of inventory policy types..*

Consider a single location j supplied from an upstream source with stochastic lead time $L_{i,j}$. Let $D_{i,j}(L)$ denote the cumulative demand for part i during a lead time of length L. Under a base stock policy $S_{i,j}$, a stockout occurs during the lead time when $D_{i,j}(L)$ exceeds $S_{i,j}$. A fill rate based service level metric can be written as

$$\phi_{i,j} = \mathbb{P}\big(D_{i,j}(L_{i,j}) \le S_{i,j}\big).$$

Scenario	Demand shift	Lead-time shift	Purpose
Baseline	None	None	Calibration
High-demand	Moderate	None	Stress test
Disruption	None	Strong	Robustness check
Combined	Strong	Strong	Worst-case exploration

Table 8. *Representative simulation scenarios..*

To achieve a target service level $\bar{\phi}_{i,j}$, one can choose $S_{i,j}$ such that

$$S_{i,j} = F_{i,j}^{-1}(\bar{\phi}_{i,j}),$$

where $F_{i,j}^{-1}$ denotes the quantile function of $D_{i,j}(L_{i,j})$. When $D_{i,j}(L_{i,j})$ is approximately normal with mean $\mu_{i,j}$ and standard deviation $\sigma_{i,j}$, this quantile can be expressed as

$$S_{i,j} = \mu_{i,j} + z_{\bar{\phi}_{i,j}} \sigma_{i,j},$$

where $z_{\bar{\phi}_{i,j}}$ is the standard normal quantile. In practice, the distribution of $D_{i,j}(L_{i,j})$ may deviate from normality, so quantiles can be estimated numerically using predictive samples from the probabilistic models.

The cost perspective can be represented by an expected cost function that depends on $S_{i,j}$. Let $I_{i,j,t}$ denote on hand inventory at time t, and $B_{i,j,t}$ denote backorders. Under stationarity assumptions, one can focus on a steady state distribution of $I_{i,j}$ and $B_{i,j}$. An approximate expected per period cost for part i at location j can be written as

$$C_{i,j}(S_{i,j}) = c_{i,j}^{h}\, \mathbb{E}[I_{i,j}] + c_{i,j}^{b}\, \mathbb{E}[B_{i,j}],$$

where $\mathbb{E}[I_{i,j}]$ and $\mathbb{E}[B_{i,j}]$ depend on the distribution of $D_{i,j}(L_{i,j})$ and the chosen base stock level. The optimization problem at the portfolio level is

$$\min_{S} \sum_{i,j} C_{i,j}(S_{i,j})$$

subject to service constraints

$$\phi_{i,j}(S_{i,j}) \geq \bar{\phi}_{i,j}$$

and possible budget constraints of the form [13]

$$\sum_{i,j} v_i S_{i,j} \leq B,$$

where v_i denotes the unit value of part i and B a budget limit on inventory investment. This yields a nonlinear constrained optimization problem, typically separable across parts for fixed service levels but coupled via budget or capacity constraints.

In multi echelon networks, inventory decisions at upstream and downstream locations interact. A common strategy is to adopt a guaranteed service time approach, where each upstream location commits to delivering parts to downstream locations within a specified time. Let $T_{j,k}$ denote the guaranteed service time from location k to location j. Downstream locations then treat this time as the effective lead time and set base stock levels accordingly. Upstream locations hold inventory to buffer uncertainty in external supply and in aggregate demand from downstream locations. Analytical results exist for certain assumptions, but in practical settings approximations and heuristics are used.

The optimization can be framed as a stochastic program or a Markov decision process. Let s_t denote the state vector at time t, including inventory positions across locations, outstanding orders, and possibly estimates of latent variables in the demand models [14]. Let a_t denote the vector of replenishment decisions. The system evolves according to a state transition function $s_{t+1} = f(s_t, a_t, \xi_t)$, where ξ_t represents realizations of demand and lead times. The long run average or discounted cost is

$$J(\pi) = \mathbb{E}\left[\sum_{t=0}^{\infty} \gamma^t c(s_t, a_t)\right],$$

where π denotes a policy mapping states to actions, $c(s_t, a_t)$ is the cost in period t, and γ is a discount factor in $(0, 1)$. The optimal value function satisfies the Bellman equation

$$V(s) = \min_a \Big(c(s, a) + \gamma\, \mathbb{E}[V(f(s, a, \xi))]\Big).$$

Exact solutions are infeasible for large systems, so approximate dynamic programming or reinforcement learning methods can be employed. In such approaches, the probabilistic forecasts serve as models for ξ_t, and function approximators parameterized by vectors θ approximate the value function, for example

$$V(s) \approx \hat{V}(s; \theta).$$

Policies can then be derived via policy iteration or direct policy search.

From a practical standpoint, organizations often prefer policies with simple structure and interpretable parameters. The framework therefore supports optimization of base stock or order up to policies using probabilistic forecasts, while leaving open the possibility of more complex policies when the decision environment and data support them [15]. The complexity of optimization must also be aligned with computational constraints, as large portfolios may include hundreds of thousands of part location combinations. Techniques such as decomposition, aggregation of similar items, and precomputation of lookup tables for quantiles are important for tractability.

6. Simulation and Numerical Experimentation

Simulation plays a central role in evaluating the performance of forecasting and optimization approaches in global parts operations. Even when analytical approximations for costs and service levels exist, simulation can reveal interactions and nonlinear effects that are difficult to capture otherwise. The framework therefore includes a simulation component that uses the probabilistic models of demand and lead times to generate synthetic operational histories under candidate policies.

Consider a discrete event simulation over a horizon of T periods. For each period t, the simulation draws demand realizations $D_{i,j,t}$ from the predictive distributions conditioned on features available at time t. Lead times for replenishment orders are drawn from the modeled distributions of $L_{i,j,k}$. The inventory system is updated according to the policy rules. The simulation tracks metrics such as fill rates, backorders, average inventory, and costs [16]. Let $\hat{\phi}_{i,j}$ denote the simulated fill rate for part i at location j, and let $\hat{C}_{i,j}$ denote the simulated average cost. Aggregated metrics such as network wide service levels and total cost can be computed as

$$\hat{\Phi} = \frac{1}{NM} \sum_{i,j} \hat{\phi}_{i,j},$$

$$\hat{C} = \sum_{i,j} \hat{C}_{i,j}.$$

These metrics provide empirical estimates of performance for a given policy under the modeled uncertainty.

Simulation can also be used to study the sensitivity of policies to model misspecification and to external shocks. For example, suppose that the true demand process undergoes a structural change not captured by the training data. This can be represented in simulation by altering the demand generation process after a certain time index. One can then observe how quickly forecasting models detect the change and how policy performance degrades during the adaptation period. Similarly, disruptions in supply can be simulated by temporarily inflating lead time distributions or introducing capacity caps on certain lanes, allowing evaluation of policy robustness.

In practice, simulation scenarios may be constructed based on historical events, hypothetical stress conditions, or combinations of both. Calibration to historical data ensures that typical operating patterns are reproduced, while hypothetical scenarios explore the range of plausible futures [17]. The probabilistic models described earlier provide a flexible tool for such scenario generation because they can be conditioned on synthetic or counterfactual feature trajectories. For instance, changes in installed base or maintenance strategies can be represented through modifications to $B_{i,j,t}$ and $U_{i,j,t}$, which propagate through the demand models to affect simulated demand.

An important methodological issue is the treatment of feedback between decisions and future demand or lead times. For many spare parts, demand is exogenous to inventory decisions, but there are cases where availability influences behavior, for example when maintenance is advanced or deferred based on stock levels. Lead times can also be affected by order quantities and congestion effects. While the basic simulation framework assumes exogenous demand and lead times conditioned on features, extensions are possible where decision variables enter the feature space, creating endogenous dynamics. In such cases, simulation becomes a tool not only for evaluation but also for policy optimization through methods such as simulation based optimization.

Simulation results can be summarized through distributions of key performance indicators rather than single estimates. For example, instead of reporting a point estimate of total cost, one can estimate its empirical distribution and derive quantiles that reflect risk [18]. If $\{\hat{C}^{(s)}\}$ denotes simulated cost outcomes across independent replication runs indexed by s, then the empirical τ quantile q_τ of cost can be computed and used in risk aware decision making. Such perspectives align with organizational preferences that consider not only expected outcomes but also downside risk and variability.

Finally, simulation models require validation against observed operational data. Validation involves comparing simulated and historical distributions of quantities such as demand, lead times, inventory levels, and service metrics. If discrepancies are observed, they can point to deficiencies in the probabilistic models, in the representation of policy rules, or in assumptions about exogeneity. Iterative refinement of models based on such feedback is essential for maintaining the relevance of the simulation framework as the operating environment evolves.

7. Implementation Considerations and Limitations

Translating an analytics driven framework for parts availability into operational practice involves organizational, technical, and governance considerations. One fundamental requirement is integration with existing planning systems such as enterprise resource planning and advanced planning and scheduling tools. Forecasts and policy recommendations must be delivered in formats and frequencies that align with current processes, such as monthly demand review cycles, weekly replenishment planning, or daily exception management. This often requires development of interfaces, data pipelines, and orchestration mechanisms to ensure that data flows and computations occur reliably and at appropriate times [19].

Another consideration is model explainability and user acceptance. While probabilistic machine learning models can provide flexible representations of demand and lead time distributions, their internal structure may be complex. Operational planners often need to understand why a model suggests a certain stocking level or why forecasts for a part changed between planning cycles. Methods such as feature importance analysis, partial dependence plots, or local surrogate models can provide qualitative explanations of model behavior. These methods can help identify violations of domain knowledge or counterintuitive patterns that warrant further investigation.

Model lifecycle management is critical in dynamic environments where demand patterns, supply conditions, and product portfolios change over time. A systematic process for monitoring model performance, triggering retraining, and evaluating candidate models before deployment is necessary. Performance metrics include predictive accuracy, calibration, and the impact of decisions on service levels and costs [20]. When a model is retrained, its implications for downstream optimization and operational processes should be assessed through backtesting and simulation before full deployment.

Data governance and quality management are inherent limitations and enablers of any analytics framework. The reliability of probabilistic models depends on the consistency and completeness of data across systems and time. Governance structures should define ownership of key data elements, procedures for handling missing or inconsistent values, and versioning of feature engineering pipelines. Although advanced modeling techniques can sometimes compensate for noise or sparsity, they cannot fully overcome systematic errors or biases in source data. As such, improvements in data acquisition and quality are often necessary complements to modeling improvements.

Scalability is both a technical and a methodological challenge. Global parts portfolios can include hundreds of thousands of distinct items across many locations, leading to very high dimensional feature spaces and large volumes of transactional data. Efficient training and prediction require distributed computing frameworks and optimized storage architectures [21]. At the same time, model complexity must be balanced against computational budgets for forecasting and optimization. For example, a highly complex model that yields marginal gains in accuracy but requires prohibitive computation may not be appropriate for daily operations, whereas a simpler model with reasonable performance can be deployed across the full portfolio.

The framework also faces limitations related to structural assumptions. Many of the probabilistic models assume conditional independence of demand across parts and locations given features, or independence between demand and lead times. In reality, correlated shocks, macroeconomic effects, and network congestion can create dependencies that are not fully captured by observable features. Likewise, inventory optimization models often approximate costs and service levels under simplifying assumptions about stationarity and policy structure. These assumptions may be violated during product introductions, phase outs, or periods of severe disruption, limiting the accuracy of model based recommendations.

By design, the framework focuses on quantitative, data driven aspects of parts availability and does not fully incorporate qualitative factors such as supplier relationships, regulatory constraints, or strategic considerations that may influence stocking decisions [22]. In some cases, organizational policies may dictate minimum or maximum stock levels that override analytics based recommendations. Additionally, contracts with customers or suppliers may include clauses that cannot be easily translated into the cost and constraint parameters of the optimization models, requiring manual adjustments or additional rule based layers.

Despite these limitations, the framework provides a structured way to integrate data, probabilistic models, optimization, and simulation in global parts operations. Its effectiveness in practice depends on careful design of the technical architecture, thoughtful calibration of models and parameters, alignment with organizational processes, and ongoing monitoring and adaptation. These aspects are crucial for ensuring that analytics supports rather than disrupts operational decision making and that it can evolve alongside changes in the business environment.

8. Conclusion

This paper has presented a structured framework for improving parts availability and forecasting in global operations through advanced data analytics. The framework links a data architecture that integrates transactional, contextual, and network information with probabilistic models of demand and lead times, optimization formulations for inventory and replenishment policies, and a simulation component for performance evaluation. The discussion has emphasized the importance of representing uncertainty explicitly, leveraging hierarchical and machine learning models for heterogeneous and intermittent demand, and translating predictive distributions into stocking decisions via cost and service level based criteria.

The probabilistic modeling layer provides a means to move beyond point forecasts and to quantify uncertainty at the level of part, location, and time period [23]. By conditioning on features that describe installed base, utilization, and external context, the models can capture structural drivers of demand and lead times. Inventory optimization models can then use these predictive distributions to compute base stock levels or other policy parameters that balance holding costs, stockout risks, and budget constraints, while multi echelon extensions account for interactions across network tiers. Simulation serves as a bridge between theory and practice by enabling evaluation of candidate policies under modeled uncertainty, exploration of sensitivity to shocks, and validation of model assumptions against observed behavior.

Implementation of such a framework in real organizations requires attention to integration with existing planning processes, explainability of models, lifecycle management, and data governance. Limitations arise from structural assumptions, data quality issues, and the need to maintain scalability across large part portfolios. These limitations suggest directions for refinement, including richer dependence structures in probabilistic models, enhanced representation of behavioral and contractual aspects in optimization, and closer coupling between analytics and domain expertise in decision making.

Overall, the framework discussed here offers a coherent approach for using advanced data analytics to support parts availability decisions in complex global settings. It delineates the main components and their interactions rather than prescribing a single solution, allowing adaptation to different industries, network structures, and organizational contexts. Future work may extend the modeling to incorporate dynamic pricing, conditional maintenance strategies, or joint optimization of parts and workforce capacity, thereby broadening the scope of analytics supported decision making in service operations [24].

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