



# Stop Using Averages for Safety Stock

*Autonomy Platform · Public Blog*

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# Stop Using Averages for Safety Stock

A supplier with a 10-day average lead time that varies from 5 to 25 days is not the same as one that consistently delivers in 9-11 days. Distribution fitting changes everything.

## The Lie of Averages

Consider two suppliers, both with a **10-day average lead time**:

### Supplier A: Consistent

**9-11**

days delivery range

Normal distribution,  $\sigma = 0.5$  days

**Minimal buffer needed**

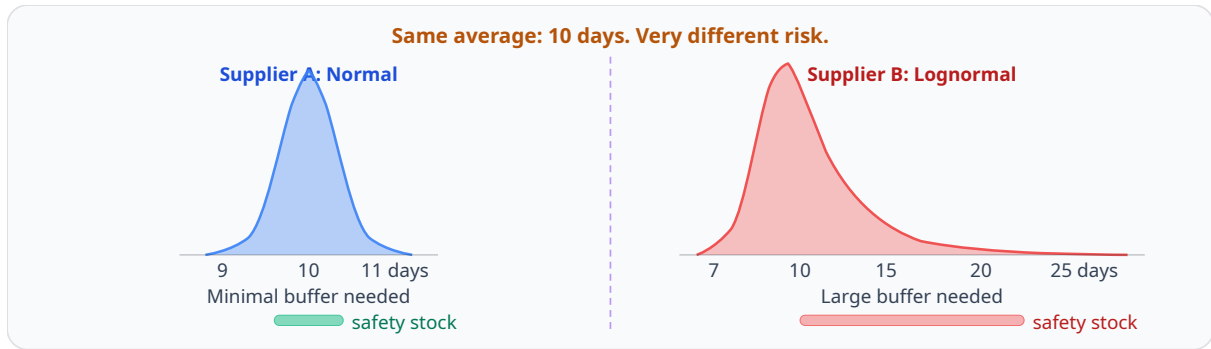
### Supplier B: Volatile

**5-25**

days delivery range

Lognormal distribution, heavy right tail

**Large buffer required**



A traditional planning system treats them identically: average lead time, 10 days. But the safety stock required for 95% service level is dramatically different.

Using the average for both means you're either **over-investing in buffer for Supplier A** or **under-protecting against Supplier B**. Both waste money.

## The Problem with “Safety Stock”

In traditional MRP, safety stock is treated as a **hard demand target**:

### The MRP Safety Stock Trap

1. System generates planned orders to maintain safety stock level
2. These planned orders **compete with real customer demand** for upstream capacity
3. When capacity is constrained, you choose between serving customers and maintaining safety stock
4. **This defeats the entire purpose of having safety stock**

## Inventory Buffers: A Different Concept

What we actually need is an **uncertainty absorber**: a buffer that provides protection against demand and supply variability without generating hard demand signals that distort the planning system.

#### Safety Stock (Traditional)

Hard demand target → generates planned orders → competes with real demand → distorts system

#### Inventory Buffers (Autonomy)

Uncertainty absorber → soft netting → replenishes when capacity allows → protects real demand

The key difference: buffer-replenishment planned orders get **lower priority** than demand-driven orders. Soft-buffer netting means the system replenishes buffers when capacity is available, not at the expense of real demand. Learn more about [inventory buffers](#).

## Distribution Fitting: The Technical Foundation

Autonomy fits actual distributions to operational variables automatically. Instead of assuming one distribution shape fits all, the system identifies the **best-fit distribution** for each variable from your historical data.

#### Why Distribution Shape Matters

If lead times follow a **Weibull distribution** rather than a **Normal distribution**, the buffer calculation changes significantly. Using the wrong distribution leads to either excess inventory or unacceptable stockout risk.

#### Normal

Symmetric, thin tails

#### Lognormal

Right-skewed, heavy tail

#### Weibull

Flexible shape parameter

This changes **every downstream calculation**: safety stock, reorder points, ATP availability, and capacity requirements all become more accurate when they use the right distribution instead of a Normal approximation. See [stochastic planning](#) for the full technical treatment.

## Dynamic Buffer Management

Rather than a fixed safety stock quantity, the Inventory Buffer agent continuously adjusts buffer parameters based on:

### Actual Demand Variability

Not assumptions: real observed patterns from your data

### Realized Lead Time Distributions

Fitted, not averaged: capturing the true shape of variability

### Service Level Targets by Segment

Different customer segments get different service commitments

### Current Inventory Position

Relative to the demand pipeline, not a static target

## From “What’s the Plan?” to “What’s the Probability?”

### Monte Carlo Simulation

Monte Carlo simulation propagates uncertainty through the entire planning engine, generating the scenario data on which agents train and the calibration sets that power [conformal prediction](#).

### Conformal Prediction: Distribution-Free Guarantees

Conformal prediction wraps the simulation output in **distribution-free coverage guarantees**. Instead of raw percentiles, every statement carries a mathematical guarantee:

**P50 cost: \$2.4M, P90 cost: \$2.8M**

with guaranteed 90% coverage

**85% probability OTIF exceeds 95%**

a calibrated bound, not an estimate

**Service level risk: 12% chance of dropping below 90% in Q3**

holds regardless of distribution

This transforms the planning conversation. Instead of debating whether the plan is “right,” you discuss whether the **guaranteed probability distribution of outcomes** is acceptable, and every agent’s likelihood score is trustworthy by construction.

## The Bottom Line

### Stop doing this:

- Using averages for lead time calculations
- Treating safety stock as a hard demand target
- Assuming Normal distributions everywhere
- Debating whether the plan is "right"

### Start doing this:

- Fitting actual distributions to your data
- Using inventory buffers as uncertainty absorbers
- Applying Monte Carlo simulation for scenarios
- Asking "what's the probability the plan works?"

Related reading: [the AIIO operating model](#) · [the shared world model](#) · [the Decision Stream](#).

# See Autonomy in action

Walk through how Autonomy models, executes, monitors, and governs supply chain decisions with autonomous AI agents.

[See It Live](#)