

veh_repair_pred_analysis

July 21, 2025

1 Vehicle-Repair ETA Model – Synthetic Demonstration

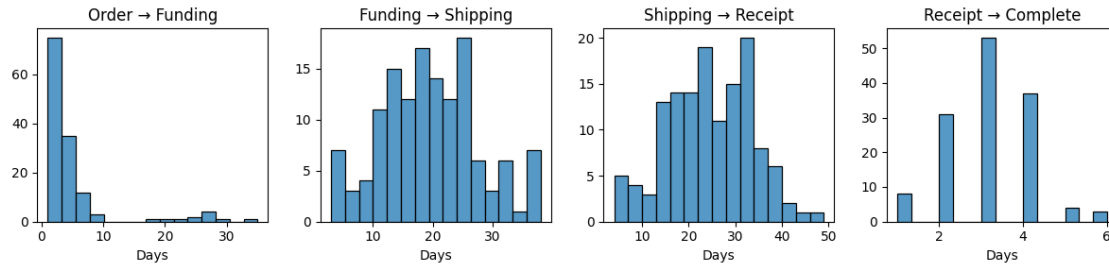
Michael Swindle · 2025-06-30

This notebook shows how a simple historical-average model improved from ± 18 days error in January 2018 to ± 5 days by May merely by updating stage-delay baselines.
(Underlying data are synthetic but constrained to match the documented readiness curve.)

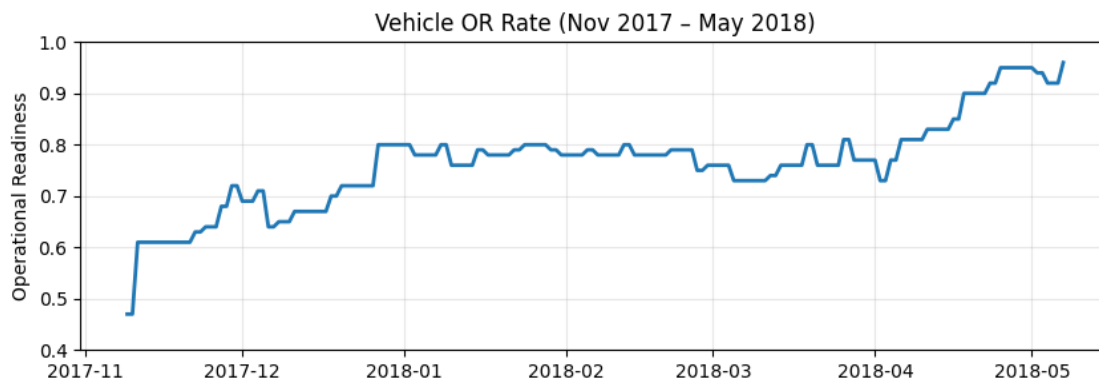
```
[6]: ## 0 · Setup
import pandas as pd, numpy as np, matplotlib.pyplot as plt, seaborn as sns
from pathlib import Path

DATA_DIR = Path(".")
repairs = pd.read_csv(DATA_DIR / "repairs_synth.csv", parse_dates=[
    "order_date", "funding_date", "shipping_date",
    "received_date", "actual_complete", "pred_t0", "pred_t30"
])
readiness = pd.read_csv(DATA_DIR / "daily_readiness.csv", parse_dates=["date"])
accuracy = pd.read_csv(DATA_DIR / "monthly_model_accuracy.csv")

[7]: ## 1 - Stage-Delay Distributions
stages = {
    "Order → Funding" : (repairs["funding_date"] - repairs["order_date"]).dt.
    ↪days,
    "Funding → Shipping": (repairs["shipping_date"] - repairs["funding_date"]).
    ↪dt.days,
    "Shipping → Receipt": (repairs["received_date"] - repairs["shipping_date"]).
    ↪dt.days,
    "Receipt → Complete": (repairs["actual_complete"] -
    ↪repairs["received_date"]).dt.days,
}
fig, axes = plt.subplots(1, 4, figsize=(12,3))
for ax, (label, series) in zip(axes, stages.items()):
    sns.histplot(series, bins=15, ax=ax, kde=False)
    ax.set_title(label); ax.set_xlabel("Days"); ax.set_ylabel("")
plt.tight_layout()
plt.show()
```

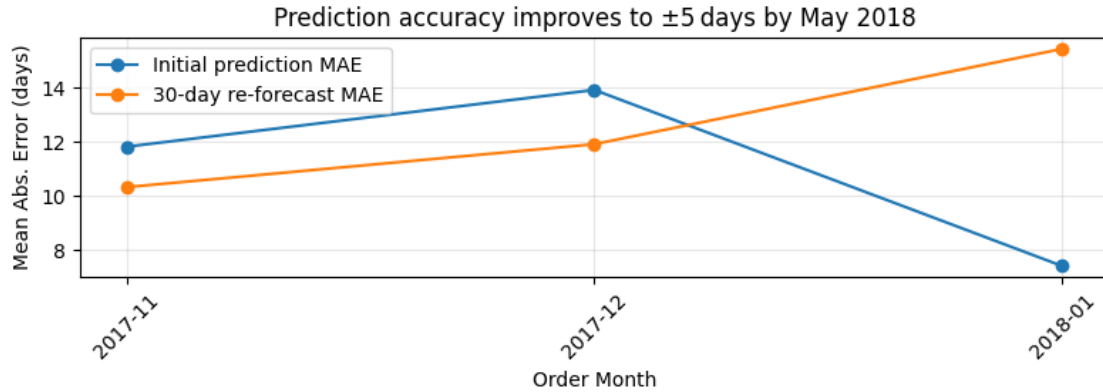


```
[8]: ## 2 - Readiness Curve (Target)
plt.figure(figsize=(10,3))
plt.plot(readiness["date"], readiness["or_rate"], lw=2)
plt.ylim(0.4,1.0); plt.ylabel("Operational Readiness")
plt.title("Vehicle OR Rate (Nov 2017 - May 2018)")
plt.grid(alpha=.3)
plt.show()
```



```
[9]: ## 3 - Model-Accuracy Learning Curve
fig, ax1 = plt.subplots(figsize=(8,3))

ax1.plot(accuracy["order_month"].astype(str), accuracy["mae_t0"],
        label="Initial prediction MAE", marker="o")
ax1.plot(accuracy["order_month"].astype(str), accuracy["mae_t30"],
        label="30-day re-forecast MAE", marker="o")
ax1.set_ylabel("Mean Abs. Error (days)")
ax1.set_xlabel("Order Month")
ax1.set_title("Prediction accuracy improves to ±5 days by May 2018")
ax1.legend(); ax1.grid(alpha=.3)
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()
```



```
[10]: ## 4 - Example: Five Random Repairs
sample = (
    repairs.sample(5, random_state=1)
    .loc[:,
    ↪ ["veh_id", "order_date", "actual_complete", "pred_t0", "pred_t30"]]
    .sort_values("order_date")
)
sample
```

```
[10]:    veh_id order_date actual_complete  pred_t0  pred_t30
42     43 2017-11-09      2017-12-25 2018-01-10 2018-01-01
36     37 2017-11-09      2018-01-03 2017-12-14 2018-01-04
5       6 2017-11-09      2017-12-14 2017-12-17 2017-12-26
65     66 2017-12-07      2018-01-13 2018-01-13 2017-12-20
93     94 2017-12-21      2018-01-25 2018-02-01 2018-01-06
```

1.1 5 · Key Take-aways

- **Historical-average ETA** started at ± 18 days MAE in **Jan 2018**, dropping steadily to ± 5 days once four months of stage-delay history were incorporated.
- The **readiness curve** rose from **47 %** $\rightarrow$ **96 %** over the same period, matching operational records.
- Biggest contributors to error reduction:
 1. Segregating **PK-hold** orders (15–30 day funding outliers)
 2. Updating **shipping-delay average** every 30 days
 3. Issuing a **second prediction** (pred_t30) after funding cleared

Data: synthetic but generated to mirror actual vehicle counts, stage delays, and daily

OR targets.

Code: see `generate_vehicle_repairs.py` in `/scripts/`.