Seasonal Demand Modeling

Building a recurring weekly demand curve without assuming every year runs at the same absolute level

STUDY QUESTION

Can the recurring annual demand pattern be represented in a compact, interpretable form that is useful for forward forecasting?

Executive Summary

The first building block of the broader demand-forecasting system was a defensible representation of recurring seasonality. Weekly New Customers showed strong annual structure, persistence, and overdispersion, so the seasonal component needed to capture the shape of the demand cycle without overfitting a small historical sample.

The development design used 2023–2024 only for model selection and preserved 2025 as an untouched holdout. Month controls and Fourier harmonics were evaluated as seasonal representations. The final architecture retained two Fourier harmonics because they produced a compact, smooth annual curve while avoiding a large set of month or week-of-year dummy variables.

Business Problem

A seasonal business needs more than a yearly average. A fixed annual average ignores when demand normally accelerates, peaks, and declines. At the same time, a detailed week-by-week lookup can become unstable when only a few annual cycles are available.

The analytical objective was therefore to estimate the recurring shape of weekly demand with enough flexibility to capture the annual cycle, while keeping the structure parsimonious enough to explain, audit, and reuse in a forecasting system.

Data and Validation Design

Item	Design
Target	Weekly New Customers
Historical data	156 weekly observations across 2023–2025
Development sample	104 weeks from 2023–2024
Holdout	52 weeks from 2025
Chronology	Never shuffled
Internal validation	Rolling-origin / expanding-window forecasting

Seasonal Specification

Fourier terms use sine and cosine waves to describe a smooth repeating annual cycle. Two harmonics were retained in the final model. This provided a compact seasonal curve without requiring 12 separate month coefficients or dozens of week-of-year indicators.

```
eta(w) = 1.66650229 + 0.32560289 sin(2*pi*w/52) - 1.35700057 cos(2*pi*w/52) + 0.07409782
sin(4*pi*w/52) - 0.32840420 cos(4*pi*w/52)
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S(w) = exp(eta(w))
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S(w) is the recurring seasonal demand level for week w.

Benchmark Evidence

The seasonal curve was not treated as a complete forecast by itself. A fixed seasonal model can understand the expected annual shape but cannot automatically adjust when the current year is running above or below historical levels. This limitation is visible in the benchmark results and motivated the later adaptive layer.

2024 development benchmark	MAE	RMSE	Bias	Correlation
Seasonal month mean	5.44	8.48	-1.33	0.478
Recent 4-week mean	5.51	7.82	+0.29	0.559
Adaptive seasonal K2 + 6-week trend	5.22	7.65	-0.51	0.598

Analytical Interpretation

Seasonality is necessary but not sufficient. The annual curve supplies the expected direction and rate of movement through the year, but it should not be forced to determine the current demand level. Separating seasonal shape from adaptive level became the key architectural decision in the final forecasting system.

This study therefore produces a reusable seasonal factor rather than a standalone final forecast.

Key Takeaways

What worked	A two-harmonic Fourier curve provided a compact representation of annual demand seasonality.
What it solves	It establishes when demand should normally rise, peak, and decline.
What it does not solve	It does not by itself know whether the current year is stronger or weaker than historical norms.
Role in system	The seasonal factor becomes the baseline shape used by the adaptive forecast.

Limitations and Next Step

Only two complete annual cycles were available for development, which limits certainty around fine-grained seasonal shape. The seasonal specification should therefore be rechecked as additional full years accumulate.

The next study tests whether environmental conditions add independent predictive information beyond this recurring annual pattern.

Portfolio-Ready Summary

SUGGESTED HEADLINE

Modeling the recurring demand curve before adding external signals

I modeled weekly customer seasonality using chronological development data and Fourier harmonics, producing a compact annual demand curve that could be separated from the current year’s changing demand level. The study established the seasonal backbone for a later adaptive forecast rather than treating seasonality as the entire prediction problem.