

Time Series Algorithms— Appendix



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Time Series Algorithms—Appendix

Fourier Algorithm	
Assumption	Business changes at a constant rate
Best Suitable for	Stable products and seasonal patterns that don't vary a great deal from year to year. This model works by fitting cyclical waves to demand history.
Examples	Light bulbs, paper towels, shampoos, and detergents

MLR Algorithm	
Assumption	Extension of Fourier
Best Suitable for	Products that have multiple causal factors. Causal factors are variables that influence the selling pattern of a product, such as advertising cost, product price, weather, holidays, and promotions. One or more causal factors may affect sales or demand.
Examples	Sunscreen lotion. The seasonal sales pattern remains stable and doesn't vary much from year to year. However, if a region experiences a particularly hot or extended summer, the inclusion of weather-related data into the forecasting process for stores in that area could help explain the higher than anticipated sales levels.

Lewandowski Algorithm	
Assumption	Applies to an array of demand patterns
Best Suitable for	Constant sales pattern shifts during a product's life cycle subject to impacts of data-driven events. Also termed as 'Universal algorithm.'
Examples	Electronic products like cell phones exhibit a specific sales pattern shift in their product lifecycle.

Moving Average Algorithm		
Assumption	Requires less data and uses averages of recent sales history	
Best Suitable for	Scenarios of short lifecycles or new product introduction (NPI).	
Examples	Products such as electronic gadgets and products with a short life cycle such as grocery items	

Holt Winters Algorithm	
Assumption	Produces forecasts using moving averages of systematic components
Best Suitable for	Products with all types of demand patterns
Examples	Bakery and vegetables

Croston Algorithm	
Assumption	Randomly distributed demand with many periods of no sale
Best Suitable for	Products with intermittent demand pattern
Examples	Engines and gears for tankers, propellers for turbines, and spare parts

AVS Graves Algorithm	
Assumption	Updates the forecast after several consecutive periods of zero demand and allows demand planners to include seasonality
Best Suitable for	Targets intermittent demand patterns and slow-moving products
Examples	Snowmobiles and umbrellas