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DEMAND FORECASTING: A COMPARATIVE REVIEW OF CONVENTIONAL TECHNIQUES

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ABSTRACT
Since the inception of competitive markets, demand forecasting has gradually become a fundamental process for all types of industry's decision making mechanisms. Over the years, the bulk of research was focussed on the identification of pattern in previous demand data of the product. However, after the introduction of globalization and era of open markets, demand of any product has witnessed the effect of increasing uncertainty. Academics and practitioners alike have come to understand that probabilistic and artificial intelligence based methods of forecasting are now more important for planning and operations than ever before. With this paper, we offer a comparative review of conventional methods of demand forecasting which helps in understanding the importance of advanced methods in modern competitive scenario.

Keywords*:* Demand Forecasting, Time series.

I. INTRODUCTION
This paper provides comparative review of the literature on various conventional demand forecasting techniques and also identifies various areas where they have been successfully applied. First we deal with the classification of various conventional techniques so that a better understanding can be made.

Demand forecasting is the science of forecasting demand of customer to arrive a conclusion of such demand by different supply chain and business. Demand forecasting includes techniques which are both informal methods, and quantitative methods (the use of historical sales data and statistical techniques or current data from markets). Demand forecasting is used in various fields of industry, production planning, inventory management, and in assessing future capacity requirements.

Demand forecasting is prediction of future demand for the given product. In other words, it gives the prediction of future demand on the basis of the past data and current trends in the market. Demand forecasting Conventional Techniques are shown in below Figure 1.

Conventional Techniques are classified into two categories i.e. survey methods and statistical methods. Survey Methods focuses on the gathering information from various sources and analysing it for predicting the demand. Various survey methods like Delphi's method have proved their worth by giving good results as they take help of industry experts and personals. Other types of method focus on the previous data and their proper analysis. Commonly adopted statistical methods are moving averages, Trend analysis, regression analysis etc. In moving average method, year on year demand data is used for calculating next period demand.

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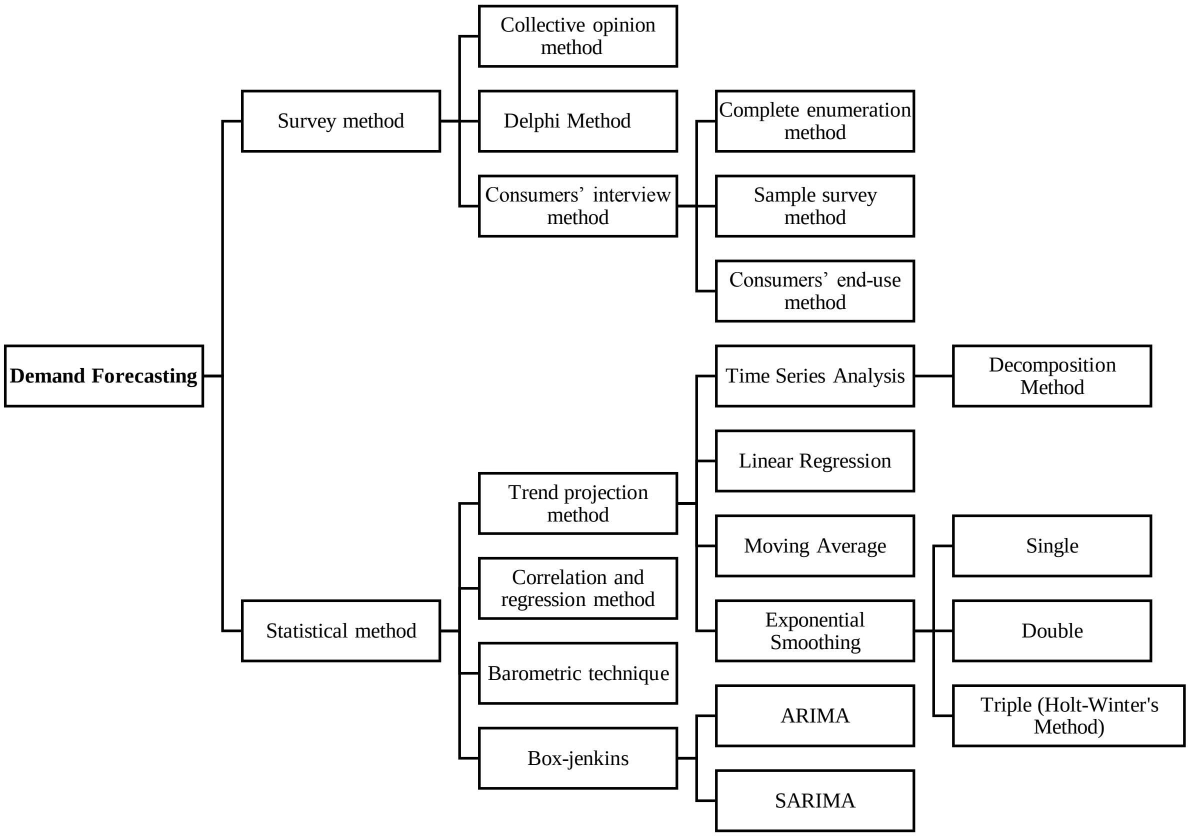

Figure 1: Conventional Techniques of Demand Forecasting

II. LITERATURE REVIEW

Exponential smoothing methods arecommonly used in industry. These methods were first introduced inthe 1950s and 1960s with the work of Brown (1959, 1963), Holt (1957, reprinted 2004), and winters (1960). Pegels (1969) provided a simple but useful and effective classification of the trend and the seasonal patterns. Exponential smoothing methods received a boostin 1985, which formed the foundation for much of the subsequent work in thisfield. Gardner (1985) gave a thoroughreview of techniqueof exponential smoothing and extended Pegels' classification by including damped trend. This paper combined alot of existing work which prompted a substantial amount ofadditional research. Table-1 has been presented below comparing the techniques on basis of different features. Comparison started with finding out the main focus area for each of the demand forecasting technique. Survey methods are basically used for making a rough estimate without taking the help of previous demand data. Whereas in statistical methods, previous demand of each product is taken into account and mathematical analysis is done using the same. Analysis process of each of the methods is different but based upon the complexity and procedural requirement, they have been classified.

Table 1: Comparison of various Demand Forecasting Techniques

Comparison of various Demand Forecasting Techniques								
S. No.	Technique → / Feature ↓	Survey Methods			Statistical Methods			
		Collective opinion method	Delphi Method	Consumer's Interview method	Trend Projection Method	Correlation-Regression Method	Barometric Technique	ARIMA/ SARIMA
1	**Main focus**	Salesman estimates	Expert's views	Consumer's Response	Previous Year Data	Relationship b/w Demand and other variables	Economic Indicators	Previous data
2	**Beneficial for**	New Products	Non-economic Variables	First hand information from Consumer	Previous data available	Measuring effect of other variables	Improving Trend method using indicators	better understanding of data
3	**Analysis process**	Simple	Simple	Simple	Mathematical Analysis	Complex Statistical analysis	Simple	Complex
4	**Nature of Forecast**	Subjective	Subjective	Subjective	Quantitative	Quantitative	Quantitative	Quantitative
5	**Forecast Period**	Long	Long	Short/ Long	Short	Short	Long	Short
6	**Consideration of seasonality?**	Yes	Yes	Yes	Yes (Decomposition Method, Holt Winter's Method)	No	No	Yes (SARIMA)
7	**Cost**	Low	Low	High	Low	Low	Low	Low
8	**Consideration of Factors which may affect demand in future?**	No	No	No	No	Yes	Yes	No

Trend forecasting is one form of quantitative forecasting which is based upon data from the past. It focuses on numerical data available at various point of time in past. This data is plotted on a graph, with the horizontal x-axis being used to plot time e.g. month, and the y-data is used to plot the demand.

There are several different types of patterns that tend to appear on a time-series graph.

a. Constant Pattern

When a constant trend is observed, there is no net increase or decrease in demand over time. The demand may change at specific dates, but the overall average is the same. However, even if the average demand is same within a year, there can be seasonal changes.

b. Linear Patterns

A linear pattern is a steady change in numbers over time. On a graph, this appears as a straight line angled up or down.

c. Exponential Patterns

Replacing the slow or steady increase over time, an exponential pattern represents that data is changing at an increasing rate over time. Instead of a straight, this graph is a curved line where the last point in later years is higher than the first year, if the rate is increasing.

d. More Complicated Patterns

Trend forecasting also deal with patterns that are even more complicated than previous three patterns.

Table 2: Details of various Demand forecasting techniques

Sr. No.	Forecasting Method	Type of Forecasting	Time Horizon	Type of object
1	Expert methods	Any	Any	Any
2	Trend Projection Methods	• Normative, • Operational, • Economic, demographic, social, environmental, etc.	short-term	Unifactor, local, global, Discrete, noncyclic, cyclic
3	ARIMA	• Normative • Economic, demographic, social,	Short-term, medium-term	Multifactor Sublocal, local, subglobal, global

		environmental, etc.		Determinate Discrete, noncyclic, cyclic With full information support
4	Correlation and regression analysis	• Search • normative • Operational, • Variant Interval • Macroeconomic, structural, industrial complexes, regional	short-term, medium-term	
5	Functional hierarchical modeling	• Search • Economic, demographic, social, environmental, etc. • Variant Primary, regional, structural forecast	Medium-term, long-term	Local Deterministic, stochastic Discrete, noncyclic, cyclic With the availability of qualitative variables
6	Matrix modeling	• Normative, search, Operational • Economic, demographic, social, environmental, Macroeconomic	short-, medium-, long-term, very-long-term	Determinate Discrete, noncyclic,With full information support
7	Data Mining (neural networks, pattern recognition)	• Normative, search, Operational • Economic, demographic, social, environmental, etc.	short, medium, long term, very-long-term	Scientific, engineering and-economical, politico-military, natural. Deterministic, stochastic Discrete, noncyclic, cyclic With the availability of qualitative variables

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