**8 -KEY FEATURES OF ARRIVAL PROCESSES.**

**1. The arrival rate varies (sometimes considerably) with the time of day and exhibits daily, weekly, yearly, and other types of seasonality’s.**

A modeling hypothesis that may appear natural is that calls arrive according to a **Poisson process** with time dependent arrival rates. For sure, the arrival rate in queues is not constant. In typical business-related queues, there is a peak period just before lunch and another one just after lunch, with a lower arrival rate during lunch, and even lower in the early morning and late afternoon; Moreover, different shapes of arrival rate patterns are often observed over different days of the week, in different periods of the year, or on certain particular days (e.g., the first Monday of the month), in a given Process. This leads to our first key feature (or property) of call arrival processes

**2. The total number of incoming calls over any given time period has over dispersion relative to the Poisson distribution (the variance is significantly greater than the mean).**

A Poisson process assumption with a deterministic arrival rate function implies that the number of arrivals over any given time period is a Poisson random variable, whose variance is equal to its expectation. However, empirical evidence invalidates this assumption; the observed variance of arrival counts is typically much larger than the mean.

**3. There is significant (strong) positive dependence between arrivals rates (or counts) in different time periods of the same day, and this positive dependence usually decreases when the considered time periods are taken farther apart.**

**4. After correcting for detectable seasonalities, noticeable correlations remain between arrival counts over successive days.**

**5. After accounting for the dependence between total daily volumes in two successive days, the dependence that remains between the last period(s) of the first day and the first period(s) of the second day could be significant in call centers that operate 24 hours a day (such as for emergency services, police, etc.), and negligible in centers that close during the night.**

For 24-hour-a-day Process, it may then seem natural to state the model of arrival rates (counts) per period as a single univariate time series after removing seasonalities and perhaps daily random effects For other Process, it would be more fitting to use a multivariate time series for the sequence of vectors of arrival rates (counts).

**6. In certain types of Process, the arrival rate has sometimes unexpected high peaks over short periods of time.**

**7. In Process with multiple call types, there is sometimes strong dependence between arrival rates (and counts) of certain call types during the same time period.**

When incoming calls are classified into multiple types, arrival rates (and counts) of certain pairs of call types are sometimes correlated (usually positively), while other pairs are approximately independent. Positive correlations may arise, for example, in multilingual Process where certain service requests are handled in different languages. Neglecting this positive dependence can lead to serious overloads, particularly when some agents handle calls in multiple languages.

**8. External knowledge can often be used to improve forecasting accuracy (and reduce the variance of distributional forecasts) by introducing covariates in models.**

Auxiliary information is often available in call centers to improve point or distributional forecasts considerably. For example, when a company sends notification letters to customers, or makes advertisements, this may trigger a larger volume of Also, the number of abandonments in recent periods could be used as a covariate in a forecasting model for forthcoming hours, to account for retrials.

Ideally, we want arrival models to be as realistic as possible and to account for the above-named Properties Their number of parameters should remain reasonably small to avoid overfitting, and these parameters should be easy to estimate from available data. Moreover, these estimates should not be too hard to update (e.g., via Bayesian methods) to obtain distributional forecasts when new information becomes available at the end of any given time period.