ME 308 Project Report

Demand Prediction of Automobile Spare Parts

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Introduction and Motivation

The challenge that auto parts manufacturing companies face is to manufacture the right amount of spare parts to meet the demand while keeping inventory and manufacturing costs at an optimal level. In this project, we aim to create a model that can help auto parts manufacturing companies determine the optimal amount of spare parts to manufacture in order to meet the demand of various auto service centers in multiple regions.

The motivation behind this project is to help auto parts manufacturing companies improve their inventory and manufacturing management systems. Currently, most companies rely on their experience and intuition to determine the amount of spare parts to manufacture, which can lead to overproduction or underproduction. Overproduction can lead to excess inventory, which increases storage costs and reduces profit margins. On the other hand, underproduction can lead to stockouts, which can result in lost sales and dissatisfied customers.

Problem Statement

There is a need for a data-driven approach that can help auto parts manufacturing companies optimize their production and inventory management systems to meet the demand of auto service centers across different regions. The challenge is to develop a model that considers the demand patterns of various auto service centers in different regions with different features/climates, production costs, and inventory costs to determine the optimal amount of spare parts to manufacture. The goal of this project is to provide auto parts manufacturing companies with a data-driven demand prediction model to optimize their production and inventory management systems, resulting in increased efficiency, profitability, and customer satisfaction.

Research

Spare Parts Classification

There are several criteria & classification models, including ABC analysis & FSN analysis to classify spare parts based on their criticality, demand, and other factors.

These criteria are:

- The law of degradation and analysis of failure modes, effects, and criticality.
- Reliability is the probability that the system fulfilled the function, for which it was designed.
- Maintenance cost includes direct and indirect costs. The selected components are those with a ratio of costs higher than 1.

Models commonly used for Estimation of Demand

- **Moving averages:** Essentially, the moving average method tries to estimate the next period's value by averaging the value of the last couple of periods immediately prior. The moving average forecast (MA) is the mean of the previous N months, where N is the number of months used in the forecast.

  Here's an example of how this method can be applied:

  1. Determine the time period to use for the moving average. This will depend on the level of variability in demand and the desired level of smoothing. A common choice is to use a 3-month or 6-month moving average.
  2. Collect historical data on demand for the spare part over the chosen time period.
  3. Calculate the moving average by summing up the demand values for the time period and dividing by the number of periods. For example, if you are using a 3-month moving average and have demand data for January, February, and March, you would add up the demand values for those three months and divide by 3.
  4. Repeat the above steps for each time period in the historical data.
  5. Use the moving averages to forecast demand for future periods. This is done by taking the average of the most recent moving averages. For example, if you are using a 6-month moving average and have data for January through June, you would take the average of the moving averages for April, May, and June to forecast demand for July

$$\hat{x}_{t+1} = \frac{1}{N}\sum_{i=1}^{N} d_{t-N+i}$$

A class of models called ARIMA models (autoregressive integrated moving averages) is based on using moving averages for predictions.

- **Exponential smoothing:** Exponential smoothing is simply an adjustment technique that takes the previous period's forecast, and adjusts it up or down based on what actually occurred in that period. It accomplishes this by calculating a weighted average of the two values.

  To apply exponential smoothing to estimate the demand for spare parts, the following steps can be followed:

  1. Gather the historical data for the spare part demand over a specific time period.
  2. Choose a level of smoothing factor (alpha) that determines how much weight to give to the most recent observation. This factor should be chosen based on the data and the level of smoothing required.
  3. Use the exponential smoothing formula to forecast future demand by taking a weighted average of the previous demand and the forecast for the current period. The formula for exponential smoothing is:

  $$\hat{x}_{t+1} = \left(1-\alpha\right)\hat{x}_t + \alpha d_t$$

  4. Repeat the above process for all future periods to obtain a time series forecast for the spare part demand.
  5. Monitor the forecast accuracy and adjust the smoothing factor as needed.

- **Regression Model:** Firstly, the contributing factors of the demand are found. Then, assuming that all the factors have a linear correlation with demand, variable coefficients are trained.

  $$Y_i = a + bX_i + \varepsilon_i$$

  To use a regression model to estimate the demand for spare parts, we use the following steps :

  1. Collect data: Collect historical data on the demand for spare parts. This can include information on the type of spare parts, the time period in which they were in demand, and the quantity of spare parts sold.
  2. Define variables: Identify the variables that affect the demand for spare parts. This may include the price of the spare parts, the time of year, and any other relevant factors.
  3. Choose a regression model: Here we have assumed that all the factors have a linear correlation with demand.
  4. Train the model: Use the historical data to train the model. This involves feeding the model the data on spare parts demand and allowing it to identify patterns and relationships between the variables.

5. Validate the model: Validate the accuracy of the model by testing it on new data that it has not seen before. This can help you determine if the model is reliable in predicting the demand for spare parts.
6. Make predictions: Once the model has been validated, use it to make predictions on future demand for spare parts based on the variables you have defined.
7. Monitor performance: Monitor the performance of the model over time and adjust it as needed to ensure that it continues to accurately predict the demand for spare parts.

- **Grey Prediction Model GM(1, 1):** The Grey prediction model is a forecasting technique that is commonly used to estimate the demand of spare parts. The model is based on the assumption that the development of a system is characterized by both regular and irregular factors, and the regular factors can be used to predict the future behavior of the system.

  The Grey prediction model uses historical data to establish a relationship between the past and future demand of spare parts. The model calculates a trend function, which is used to estimate the future demand of spare parts. The trend function is based on a differential equation that describes the relationship between the current demand and the previous demand of the spare parts.
  x is a series of a cumulative generation of the historical requirement of spare parts, t is time, and a and u are the parameters to be estimated.

$$\frac{dx^{(1)}}{dt} + ax^{(1)} = u$$

- **Mathematical Probabilistic Model:** By tracking the active installed base and estimating the part failure behavior, it provides a forecast of the distribution of the future spare parts demand during the upcoming lead time. A larger set of spare part demand drivers takes into account the evolution of the active installed base over time, which can increase through the sales of new machines that are serviced and decrease through the end-of-use of old machines. Part reliability, which defines when a part in the installed base will fail and require a corrective replacement. It refers to this collection of information used as Service Maintenance Information.
  i = part age, *j* = machine age, *t* = current time, T_p = lifetime part , T_m = lifetime Machine, *L* = lead time

- Machine survival probability : The probability at time t that the machine is not discarded in the time interval [t , t + L] is defined by :

$$p^m_{j,t,L} = \frac{\int_{j+L}^{\infty} f_{T_m}(\theta)d\theta}{\int_{j}^{\infty} f_{T_m}(\theta)d\theta}.$$

- Part failure behavior :
  Analogously to the probability of a machine discard, we determine for each of the parts in the active installed base the conditional probability of failure during the upcoming lead time, given that the part did not fail yet, and has reached age i at time t:

$$p^p_{i,t,L} = \frac{\int_{i}^{i+L} f_{T_p}(\theta)d\theta}{1 - \int_{0}^{i} f_{T_p}(\theta)d\theta},$$

$$\begin{aligned} p_{i,j,t,L} &= P(T_p \leq i + L | T_p > i) \cdot P(T_m > j + L | T_m > j) \\ &= p^p_{i,t,L} \cdot p^m_{j,t,L}. \end{aligned}$$

More statistical methods like the Croston forecasting method, Syntetos-Boylan approximation, and Teunter-Syntetos-Babai forecasting method were studied but since they are mainly used for intermittent demands and their results were not significantly better (according to the studied paper), we did not implement them in code. Also, without correct data, it was impossible to compare their performance for our purpose.

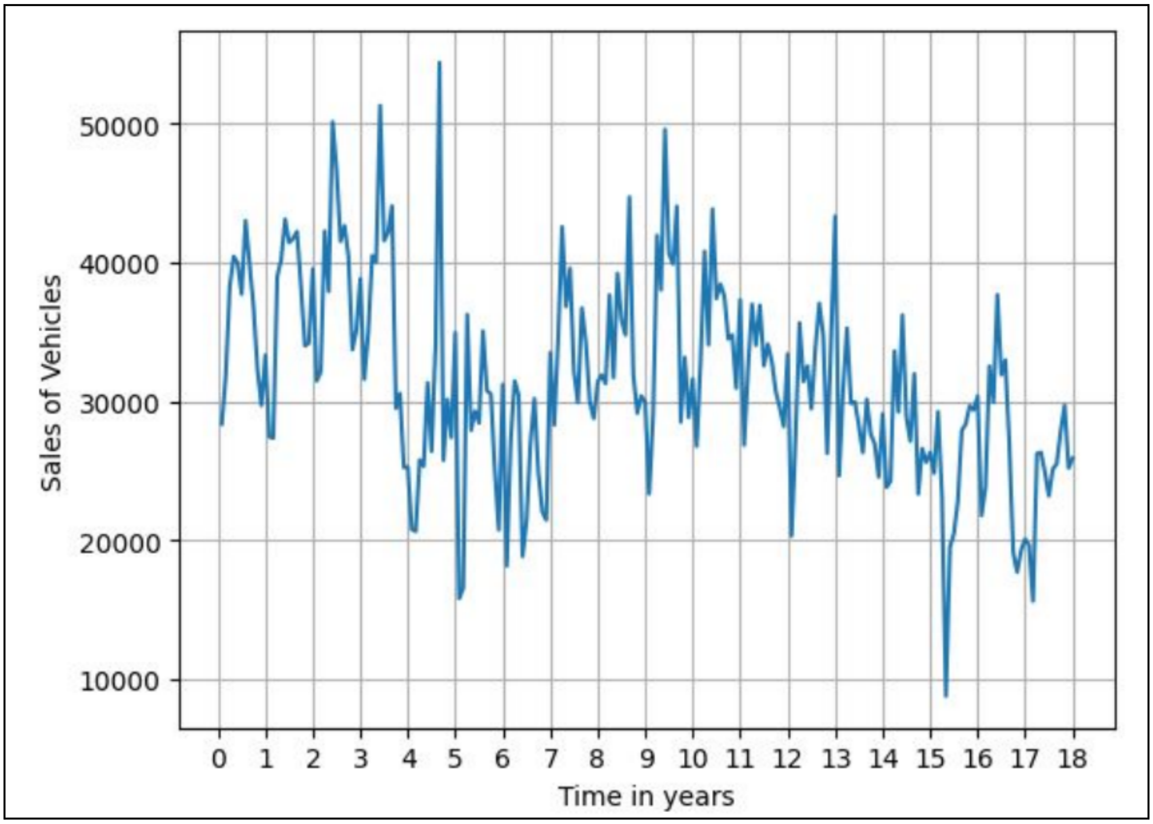
Proposed Model for Demand Prediction

Our model utilizes monthly sales of the vehicle, Spare part failure probability distribution, Climate information, the economy of the region and brand reputation over the years to predict the monthly demand for spare parts. Due to a lack of spare demand data on the internet, we couldn't validate our model. However, a logical approach is used to accommodate factors like climate, economy, and brand reputation.

Data Collection of Monthly Sales of Vehicle

A large dataset of monthly sales of vehicles was needed to capture the nature of curve demand for a spare part, Also we sought a dataset that did not have abrupt changes in the nature of sales of vehicles so that the results remain general.

We used a dataset of the monthly sales of Toyota Camry in the USA from 2005 to 2022 (**link of the dataset**) The data was written in a CSV file in a single column for a total of 216 months or 18 years. The sales are highly varying but overall decreasing yearly.



Part Failure Probability with Time

For a company to formulate this spare part failure probability distribution the first step is to identify the spare parts that we want to analyze. This could include parts such as engines, transmissions, brakes, or suspension systems.
Next, Collect data on the failure rate of the spare parts over a period of time, then create a histogram to visualize the distribution of failures.We designed it in the following way:

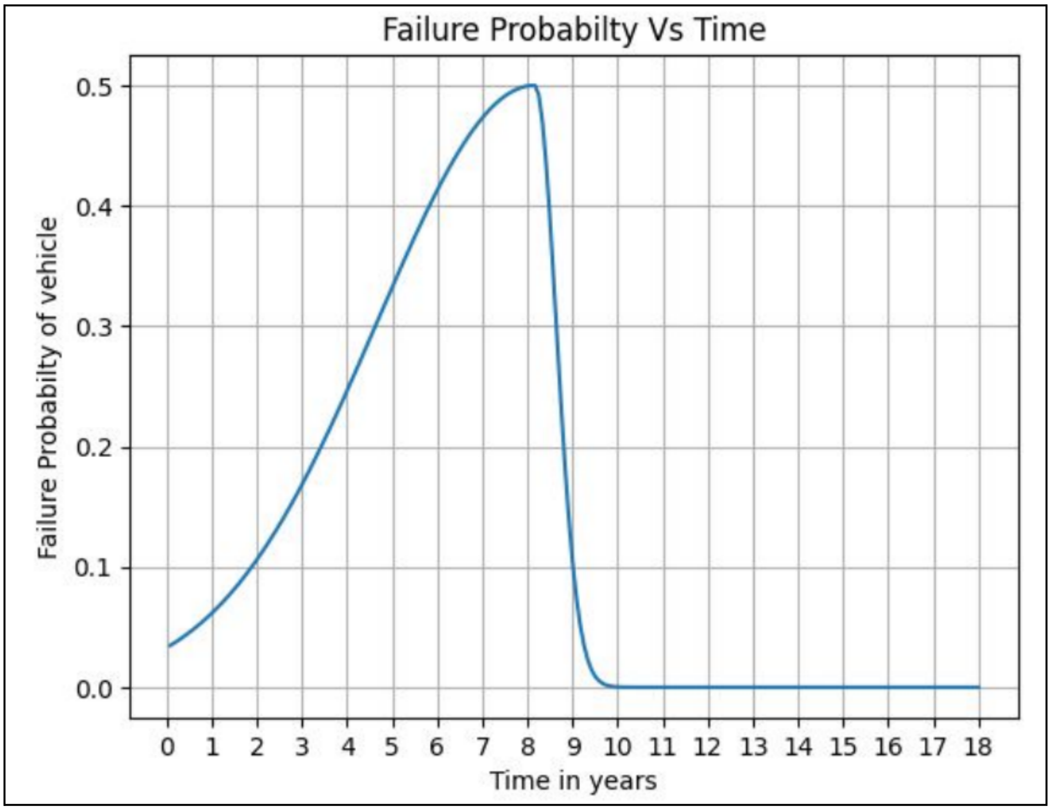
The failure probability function calculates the probability of a failure occurring at different time points within a given duration.

The input parameters of the function are:

- **duration**: the total duration of the process or system under consideration

- **fail_time**: the time after which a failure can occur, including a buffer time after part expiry time. The time with maximum failure probability.
- **fail_prob**: the maximum probability of failure

We will be using the probability function over whole duration and shift it to current time (**t**) to calculate the failure probability of spare part in car sold at time (**$t - t_i$**) at present.



The function calculates the probability of failure for the time period before `fail_time` using a **Gaussian probability density** function. The mean and standard deviation of the Gaussian are calculated based on the time period that has already elapsed (`past`), with the mean being equal to the elapsed time and the standard deviation being one-fourth of the elapsed time. The probability density function is scaled by a factor of `fail_prob` and the normalization factor for a Gaussian distribution to normalize the curve.

After the time period `fail_time`, the function uses a stretched exponential function to calculate the probability of failure. This function is defined by using a **Stretched exponential** function, which takes as input the current time point. By changing the parameters for the exponential function we can change the rate of decay.

Finally, the function plots the calculated failure probability as a function of time. The scaling factor is also calculated by calculating the area under the curve.

Calculating demand

Based on a number of variables, we are estimating the demand for vehicles over a specific time period.

Under normal circumstances, the expected number of vehicles that night that need a repair is determined by taking into account both the monthly sales of automobiles up to the present and the failure probability function at the present for automobiles that have already been sold in the past.The monthly sales of cars are multiplied by the failure chance for that month, then the total across the entire period up to the present is calculated.

The following factors that affect the demand for automobiles are multiplied by this anticipated number of vehicles in need of repair:

- Climate factor: an x-raised value that varies by month. The impact of the weather on the demand for auto spare is captured by this variable.

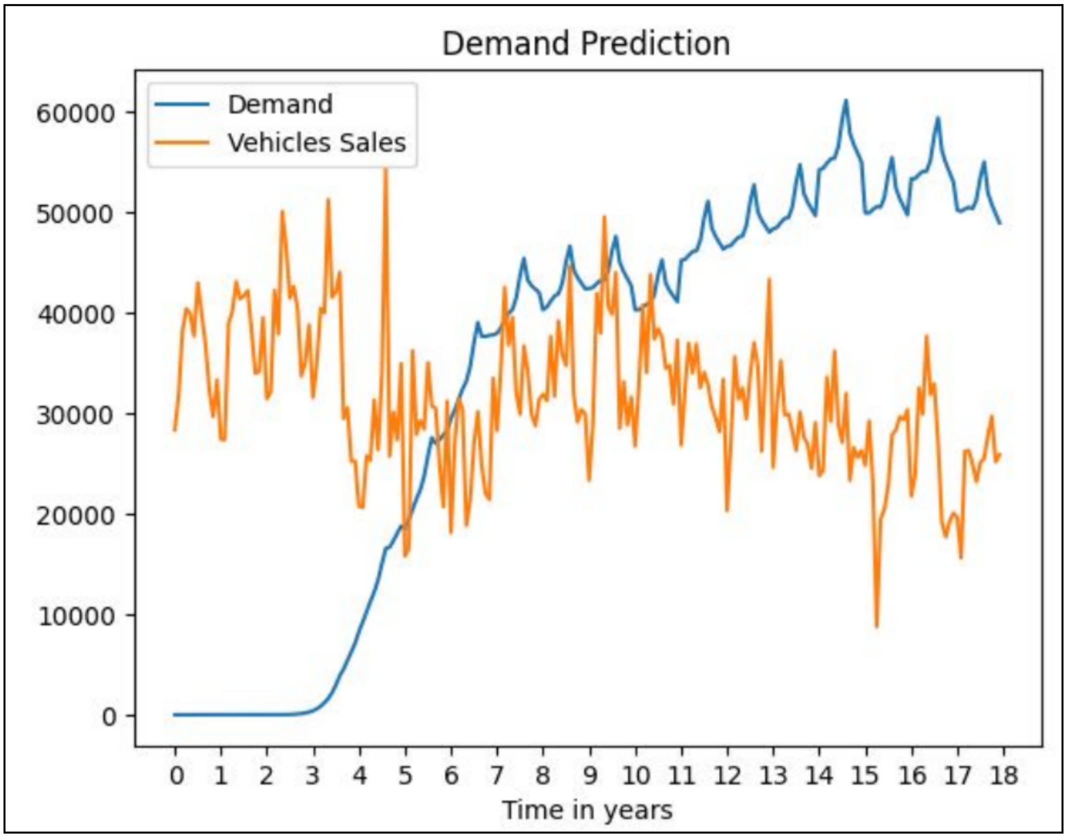
- Economic component: An economic component is a value that varies annually and is raised to the power of y. This component reflects the general economic conditions that affect the demand for auto spare parts.

- Brand factor: a value that varies by year and is raised to the power of z. This element is a reflection of the selling brand repute. You may calculate the Brand factor by taking a look at the stock values of the manufacturing business.

Depending on the region, the first three variables can be modified.
Finally, by using the developed mathematical model, we can forecast the demand:-

$$D = V * \left(1 + C^{x}\right)\left(1 + E^{y}\right)\left(1 + B^{z}\right)$$

- V = the number of vehicles on the road that need repair.
- C = a climate factor that takes on values between 0 and 1.
- E = an economic factor that takes on values between 0 and 1.
- B = a brand reputation factor that takes on values between 0 and 1.



Inferences

- Although the parameters are not trained due to lack of actual data, the nature of the demand curve obtained is similar to the ones studied in research papers
- Once trained, this model would work to predict the demand for a longer period of time (e.g. if the failure time is 3 years, we can predict demand up to 3 years in future) as compared to the standard statistical methods which usually predict for only the next time period (a few months).

Limitations

- Due to lack of demand data, our model is not validated to exact parameters
- The model assumes that historical patterns are representative of future patterns.
- The model takes into only some factors, but there could be other factors such as demographic changes, changes in government policies, or changes in technology which may also affect the demand for spare parts.

- The model does not take into account the impact of external events such as natural disasters or economic downturns, which can significantly affect the demand for spare parts.

Conclusion

We have developed a mathematical model that considers the demand patterns of various auto service centers in different regions with different features/climates, production costs, and inventory costs to determine the optimal amount of spare parts to manufacture. Our model takes into account the relevant climate and geographical features of each region, as well as manufacturing and inventory costs, to generate an optimal production plan that minimizes costs while meeting the demand of auto service centers for the future. In summary, our project offers a solution to the significant challenge faced by auto parts manufacturing companies in managing their inventory and production processes, and we believe that our model can make a significant contribution to the industry.

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Contribution

Name	Contribution
Aayush (200100004)	● Read multiple spare parts management models and analyzed a number of research papers to determine the impact of various factors on the demand for automotive spare parts. ● Examined a number of statistical and analytical models for forecasting. ● Surveyed nearby service centers to see how they handle their inventories and predict demand. ● To observe the effects of parameters on performance, coded statistical prediction models such as moving averages and exponential smoothing were used. ● Implementation of our suggested model ● Poster and Report's formatting
Adil Gupta (200100006)	● Examined a number of statistical and analytical models for forecasting. ● Poster and Report's formatting ● Read multiple spare parts management models and analyzed a number of research papers to determine the impact of various factors on the demand for automotive spare parts.
Amitkumar Kumavat (20D100003)	● Surveyed nearby Service centers to see how they handle their inventories and predict demand. ● Poster and Report's formatting
Saksham Katiyar (20D100022)	● Studied several research papers to study the effect of different factors on the automobile spare demand. ● Studied statistical and machine learning models for general forecasting ● Surveyed nearby service centers to inquire about their inventory management and demand requirement techniques ● Coded statistical prediction models like moving averages and exponential smoothing to observe the effects to parameters on the performance ● Ideation and implementation of our proposed model ● Formatting our poster and report