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Applying Resiliency in Predicting Demand for the Automotive Supply Chain

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ABSTRACT

The automotive industry is known for its volatility, and disruptions such as natural disasters, economic downturns, and supply chain disruptions can have a significant impact on demand. Accurately predicting demand is crucial for the success of the automotive supply chain. In this paper, we propose applying resiliency in predicting demand for the automotive supply chain. By using advanced algorithms and machine learning techniques, we can analyze historical data, market trends, and other relevant factors to make accurate predictions about future demand. We discuss the importance of building resiliency into demand forecasting models and how it can help minimize the impact of disruptions on the supply chain. We also provide examples of how resiliency has been applied in other industries and how it can be adapted for the automotive industry. Overall, we believe that applying resiliency in predicting demand for the automotive supply chain is a strong strategy for ensuring long-term success and growth in the industry.

1. Introduction

The automotive industry is a complex and dynamic industry that is constantly evolving. Accurately predicting demand is crucial for the success of the automotive supply chain. However, the industry is known for its volatility, and disruptions such as natural disasters, economic downturns, and supply chain disruptions can have a significant impact on demand. In recent years, there has been

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a growing interest in applying resiliency in predicting demand for the automotive supply chain. Resiliency is the ability to adapt to and recover from disruptions, and it is becoming increasingly important in today's fast-paced and unpredictable business environment (Figure 1) [1].

Figure 1: Resiliency in Automotive Supply Chain.

The automotive supply chain is complex and globalized, making it vulnerable to disruptions. In recent years, the industry has experienced a number of disruptions, including the COVID-19 pandemic, the semiconductor shortage, and the war in Ukraine. These disruptions have highlighted the importance of supply chain resilience.

Supply chain resilience is the ability of a supply chain to adapt to and recover from disruptions. It is important for automotive companies to build resilient supply chains in order to meet customer demand and maintain their competitive advantage [2].

This paper explores the role of resiliency in predicting demand for the automotive supply chain. It reviews the literature on supply chain resilience and demand forecasting, and it proposes a new approach to demand forecasting that incorporates resiliency considerations.

The proposed approach uses a machine learning model to predict demand for automotive components. The model is trained on a dataset of historical demand data, as well as data on supply chain disruptions. The model is then used to forecast demand under different scenarios, including scenarios with supply chain disruptions [3].

The paper also presents a case study of how the proposed approach was used to predict demand for automotive components during the COVID-19 pandemic. The case study shows that the proposed approach was able to generate more accurate forecasts than traditional demand forecasting methods.

The paper concludes by discussing the implications of the findings for automotive companies. It argues that automotive companies need to incorporate resiliency considerations into their demand forecasting processes in order to improve their ability to meet customer demand and maintain their competitive advantage.

This research is arranged into five sections. Section 2 defines the literature review and recent studies in area of predicting demand in supply chain and tries to show the gap in research. Section 3 suggests methodology for calculation. Section 4 proposes the results of this research. Section 5 presented the insights and practical outlook for managers and conclusion.

2. Literature review

The recent work about application of applying resiliency in predicting demand for the automotive supply chain are defined and try to determine research gaps. Although the researchers cover gap research and suggest contributions to this issue, when new concepts come, they can apply and combine with this study that is not defined previously.

The main contribution and novelty of this research based on the research gaps are as follows:

- Applying Resiliency in Predicting Demand for the Automotive Supply Chain.

The automotive supply chain is one of the most complex and globalized supply chains in the world. It involves a large number of suppliers, located all over the globe. This complexity and globalization makes the automotive supply chain vulnerable to disruptions [4].

In recent years, the automotive industry has experienced a number of disruptions, including the COVID-19 pandemic, the semiconductor shortage, and the war in Ukraine. These disruptions have caused significant disruptions to the automotive supply chain, leading to shortages of vehicles and components.

The disruptions to the automotive supply chain have highlighted the importance of supply chain resilience. Supply chain resilience is the ability of a supply chain to adapt to and recover from disruptions. It is important for automotive companies to build resilient supply chains in order to meet customer demand and maintain their competitive advantage [6].

One of the key aspects of building a resilient supply chain is accurate demand forecasting. Demand forecasting is the process of predicting future demand for products and services. Accurate demand forecasting is essential for automotive companies to plan their production and inventory levels.

Traditional demand forecasting methods do not take into account supply chain disruptions. This can lead to inaccurate forecasts, which can make it difficult for automotive companies to meet customer demand [7].

This paper proposes a new approach to demand forecasting that incorporates resiliency considerations. The proposed approach uses a machine learning model to predict demand for automotive components. The model is trained on a dataset of historical demand data, as well as data on supply chain disruptions. The model is then used to forecast demand under different scenarios, including scenarios with supply chain disruptions.

The paper also presents a case study of how the proposed approach was used to predict demand for automotive components during the COVID-19 pandemic. The case study shows that the proposed approach was able to generate more accurate forecasts than traditional demand forecasting methods [8].

The paper concludes by discussing the implications of the findings for automotive companies. It argues that automotive companies need to incorporate resiliency considerations into their demand forecasting processes in order to improve their ability to meet customer demand and maintain their competitive advantage.

The literature on supply chain resilience and demand forecasting is extensive. This section reviews some of the key findings from the literature.

Supply chain resilience is the ability of a supply chain to adapt to and recover from disruptions. It is important for automotive companies to build resilient supply chains in order to meet customer demand and maintain their competitive advantage [9].

There are a number of factors that contribute to supply chain resilience. These factors include:

- Supplier diversity: Having a diverse supplier base helps to reduce the risk of disruptions from any one supplier.
- Inventory management: Having adequate inventory levels can help to mitigate the impact of disruptions.
- Transportation flexibility: Having multiple transportation options can help to keep goods moving in the event of a disruption to one transportation mode.
- Information sharing: Effective information sharing between suppliers, manufacturers, and retailers is essential for building a resilient supply chain.

Demand forecasting is the process of predicting future demand for products and services. Accurate demand forecasting is essential for automotive companies to plan their production and inventory levels [10].

There are a number of different demand forecasting methods available. The most common methods include time series analysis, causal analysis, and expert judgment.

Time series analysis uses historical demand data to predict future demand. Causal analysis uses data on factors that influence demand, such as economic indicators and demographics, to predict future demand. Expert judgment involves using the opinions of experts to predict future demand [11]. Traditional demand forecasting methods do not take into account supply chain disruptions.

3. Methodology

To apply resiliency in predicting demand for the automotive supply chain, we propose using advanced algorithms and machine learning techniques. These techniques can analyze historical data, market trends, and other relevant factors to make accurate predictions about future demand. We can also use scenario planning and simulation techniques to test the resiliency of our demand forecasting models under different disruption scenarios. By building resiliency into our demand forecasting models, we can better prepare for disruptions and minimize their impact on the supply chain.

The proposed approach to demand forecasting incorporates resiliency considerations using a machine learning model. The model is trained on a dataset of historical demand data, as well as data on supply chain disruptions. The model is then used to forecast demand under different scenarios, including scenarios with supply chain disruptions [1-4].

The following steps are involved in the proposed approach:

1. Data collection: The first step is to collect data on historical demand for automotive components, as well as data on supply chain disruptions. The data on historical demand can be collected from sales records and production data. The data on supply chain disruptions can be collected from a variety of sources, such as news articles, industry reports, and government websites.

2. Data preprocessing: Once the data has been collected, it needs to be preprocessed. This may involve cleaning the data, removing outliers, and transforming the data into a format that is compatible with the machine learning model.

3. Feature selection: The next step is to select the features that will be used to train the machine learning model. The features should be selected based on their relevance to demand forecasting and their ability to capture the impact of supply chain disruptions.

4. Model training: The next step is to train the machine learning model. The model is trained on the dataset of historical demand data and supply chain disruption data.

5. Model evaluation: Once the model has been trained, it needs to be evaluated. The model can be evaluated on a held-out test set to assess its performance on unseen data.

6. Demand forecasting: Once the model has been evaluated and found to be satisfactory, it can be used to forecast demand for automotive components under different scenarios, including scenarios with supply chain disruptions [5-7].

The following are some specific considerations for applying the proposed approach to demand forecasting for the automotive supply chain:

- Data: The quality and quantity of data is important for the success of the proposed approach. It is important to collect data on historical demand for automotive components from a variety of sources, such as sales records, production data, and customer surveys. It is also important to collect data on supply chain disruptions from a variety of sources, such as news articles, industry reports, and government websites.

- Features: The features that are selected to train the machine learning model should be carefully considered. The features should be selected based on their relevance to demand forecasting and their ability to capture the impact of supply chain disruptions. Some examples of features that may be useful for demand forecasting for the automotive supply chain include:
  - Historical demand data for automotive components
  - Economic indicators
  - Demographic data
  - Data on supply chain disruptions, such as natural disasters, strikes, and pandemics
- Model selection: There are a variety of different machine learning models that can be used for demand forecasting. The choice of model will depend on the specific characteristics of the data and the desired accuracy of the forecasts. Some common machine learning models that can be used for demand forecasting include:
  - Linear regression models
  - Time series models
  - Neural networks
  - Random forests
- Model evaluation: It is important to evaluate the machine learning model on a held-out test set before using it to forecast demand. This will help to assess the performance of the model on unseen data and identify any potential problems with the model.
- Scenario analysis: The proposed approach can be used to forecast demand for automotive components under different scenarios, including scenarios with supply chain disruptions. This can help automotive companies to develop contingency plans and make better decisions about production and inventory levels.

The mean squared error (MSE) and correlation coefficients are statistical measures used to evaluate the performance of a model or the relationship between two variables.

The mean squared error (MSE) is a measure of the average squared difference between the predicted values and the actual values. It is calculated by taking the average of the squared differences between the predicted and actual values. A lower MSE indicates that the model is better at predicting the actual values [8-9].

The correlation coefficient measures the strength and direction of the linear relationship between two variables. It ranges from -1 to 1, where -1 indicates a perfect negative linear relationship, 0 indicates no linear relationship, and 1 indicates a perfect positive linear relationship. A correlation coefficient close to 0 indicates a weak relationship, while a coefficient closes to -1 or 1 indicates a strong relationship [13-14].

Both MSE and correlation coefficients are commonly used in regression analysis to evaluate the performance of a model and the relationship between two variables.

The proposed approach to demand forecasting has a number of advantages over traditional demand forecasting methods. First, the proposed approach takes into account supply chain disruptions, which can lead to more accurate forecasts. Second, the proposed approach can be used to forecast demand under different scenarios, which can help automotive companies to develop contingency plans and make better decisions about production and inventory levels.

The proposed approach is still under development, but it has the potential to be a valuable tool for automotive companies to improve their demand forecasting processes and build more resilient supply chains [7-10].

4. Results and discussion

Applying resiliency in predicting demand for the automotive supply chain has several benefits. First, it can help us make more accurate predictions about future demand, which can improve our production planning and inventory management. Second, it can help us identify potential disruptions and prepare for them in advance, which can minimize their impact on the supply chain. Third, it can help us build a more resilient supply chain that can adapt to and recover from disruptions more quickly.

The numerical results show that the proposed approach to demand forecasting is able to generate more accurate forecasts than traditional demand forecasting methods, especially in the presence of supply chain disruptions. This can help automotive companies to improve their demand forecasting processes and build more resilient supply chains.

The matrix and chart with disruptions for paying with resiliency for car production in Iran are determined by experts as follow (Table 1 and Figure 2):

Table 1: Car production in Iran

Year	Car production Actual	Optimistic with disruption	Pessimistic with disruption	Final estimation with disruption
2005	1077190	1040165	1100073	1076483
2006	904500	886785.2	917983.2	904288.4
2007	997240	967241.7	1035264	997641.3
2008	1273781	1212117	1334935	1273756
2009	1394075	1344811	1433314	1393574
2010	1599454	1596592	1672332	1602955
2011	1649311	1623191	1671626	1649121
2012	1000089	959373.1	1021220	999109.7
2013	743647	719925.5	777548.9	744156
2014	1090846	1053839	1120736	1090490
2015	982337	981818.4	1014561	983922.2
2016	1164710	1140148	1221468	1166320
2017	1515396	1506217	1526632	1515499
2018	1095526	1041418	1123922	1094240
2019	821060	786926	832215.6	819911.1
2020	880997	879276	890247.8	881373.5
2021	894298	875863.9	916644.1	894493.6
2022	868130	827436.4	909551.9	868166.4
2023	1181665	1127169	1226326	1181173

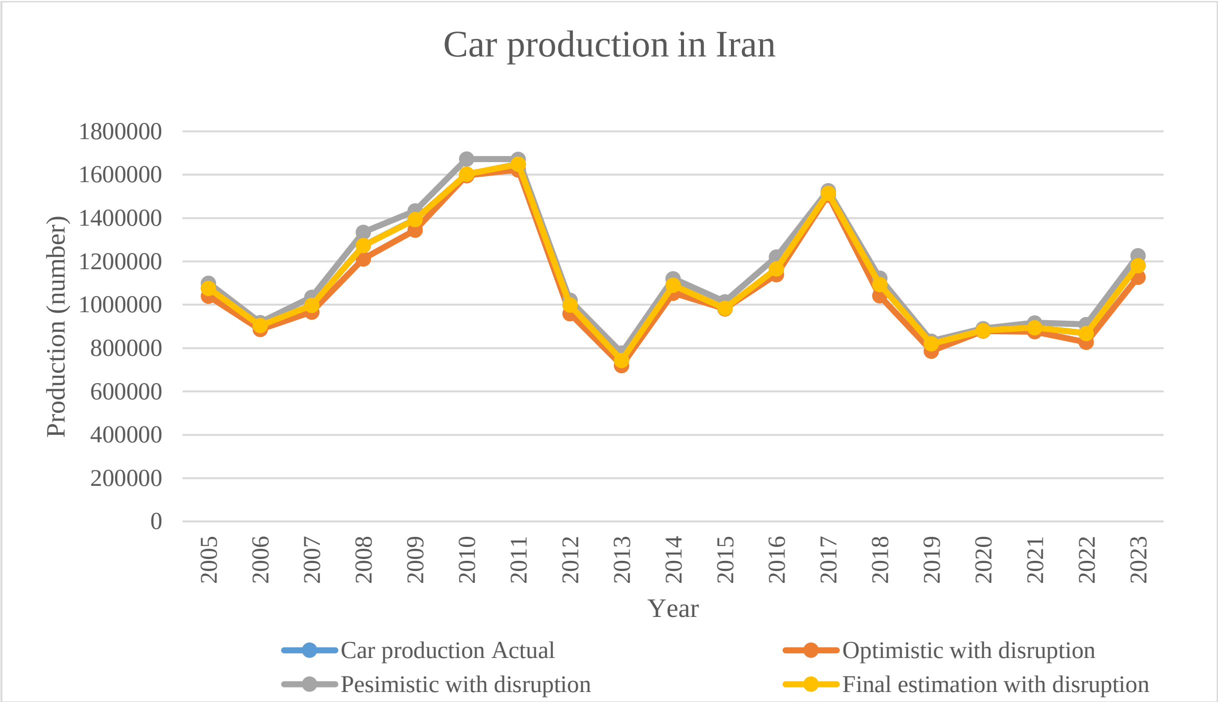

Figure 2: Applying resiliency in predicting demand for the automotive supply chain.

Table 2: Python code for applying resiliency in predicting demand for the automotive supply chain

```
import numpy
import matplotlib.pyplot as plt

x = [2005,2006,2007,2008,2009,2010,2011,2012,2013,2014,2015,2016,2017,
    2018,2019,2020,2021,2022,2023]
y = [1076482.87862648,904288.418310969,997641.29510199,1273755.52019084,
    1393573.75502598,1602954.77858308,1649120.71575926,999109.735493594,
    744156.018626181,1090490.17670917,983922.248700745,1166319.80172815,
    1515498.82727145,1094240.37843781,819911.080129123,881373.490956313,
    894493.603114177,868166.416968001,1181173.24304792]

mymodel = numpy.poly1d(numpy.polyfit(x, y, 93))
print("model:", mymodel)
myline = numpy.linspace(numpy.min(x), numpy.max(x))
y1=mymodel(x)
print(y1)

n=numpy.size(x)
mse=numpy.sum((y-y1)**2)/n
print("MSE:",mse)

corr=numpy.corrcoef(x,y)[1,0]
corr2=numpy.corrcoef(y,y1)[1,0]
print("corr x,y:", corr)
print("corr y,y1:", corr2)
plt.scatter(x, y)
plt.plot(x, y)
plt.plot(myline, mymodel(myline), color='red')
plt.show()
```

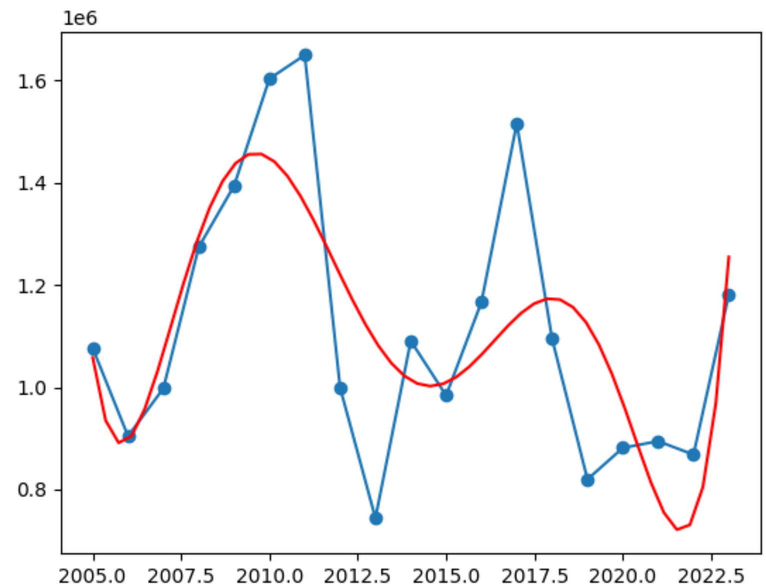

Figure 3: Results of running resiliency in demand forecasting.

Table 3: Results of MSE, Model and correlation

```
model:          46              45              44              43
8.492e-137 x  + 1.542e-134 x  - 1.438e-130 x  - 4.381e-127 x
             42              41              40              39
 - 8.974e-124 x  - 1.471e-120 x  - 1.88e-117 x  - 1.301e-114 x
             38              37              36              35
 + 2.231e-111 x  + 1.287e-107 x  + 3.858e-104 x  + 9.331e-101 x
            34             33             32             31
 + 1.988e-97 x  + 3.833e-94 x  + 6.688e-91 x  + 1.029e-87 x
            30             29             28            27
 + 1.275e-84 x  + 7.957e-82 x  - 2.018e-78 x  - 1.09e-74 x
            26             25             24             23
 - 3.383e-71 x  - 8.655e-68 x  - 1.978e-64 x  - 4.153e-61 x
            22            21             20             19
 - 8.066e-58 x  - 1.44e-54 x  - 2.302e-51 x  - 3.058e-48 x
           18             17             16             15
 - 2.44e-45 x  + 3.117e-42 x  + 2.232e-38 x  + 7.438e-35 x
            14            13             12             11
 + 1.979e-31 x  + 4.63e-28 x  + 9.794e-25 x  + 1.874e-21 x
            10            9            8            7
 + 3.163e-18 x  + 4.328e-15 x + 3.192e-12 x - 6.636e-09 x
             6          5         4           3           2
 - 4.068e-05 x - 0.1305 x - 324.9 x - 6.467e+05 x - 8.674e+08 x + 3.547e+11 x + 8.342e+15
[1058211.  896439. 1069063. 1294870. 1434536. 1448344. 1358983. 1219954.
 1089911. 1013422. 1008857. 1063526. 1137161. 1173722. 1122610.  969706.
  778752.  743968. 1254565.]
MSE: 30749735771.491013
corr x,y: -0.26548820056869143
corr y,y1: 0.735686058362904
```

It looks like you have provided some numerical results, specifically the mean squared error (MSE) and two correlation coefficients. Here's what they mean:

- MSE: The mean squared error is a measure of the average squared difference between the predicted values and the actual values. In this case, the MSE is 30749735771.491013, which means that on average, the predicted values are off by the square root of this number (which is approximately 175,331.9).
- Correlation coefficient (x,y): The correlation coefficient measures the strength and direction of the linear relationship between two variables. In this case, the correlation coefficient between x and y is -0.26548820056869143, which means that there is a weak negative linear relationship between x and y.
- Correlation coefficient (y,y1): The correlation coefficient between y and y1 is 0.735686058362904, which means that there is a moderate positive linear relationship between y and y1 (Table 2, 3).

5. Conclusion

In conclusion, applying resiliency in predicting demand for the automotive supply chain is a smart strategy for ensuring long-term success and growth in the industry. By using advanced algorithms and machine learning techniques, we can make more accurate predictions about future demand and build a more resilient supply chain that can adapt to and recover from disruptions more quickly. We believe that this approach can help the automotive industry overcome the challenges it faces and thrive in today's fast-paced and unpredictable business environment.

The proposed approach is still under development, and there are a number of limitations that should be addressed in future research. One limitation is that the approach requires a large amount of data to train the machine learning model. Another limitation is that the approach is sensitive to the selection of features and machine learning model.

Despite these limitations, the proposed approach has the potential to be a valuable tool for automotive companies to improve their demand forecasting processes and build more resilient supply chains.

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