

CDM Forecasting and Arbitration

FAURECIA CLEAN MOBILITY



24.Feb.2023 Jiaxue LI



- 01 Introduction
- O2 Forecasting Example of Division and Plant
- O3 Accuracy & Statistical Conclusion
- 04 Future Questions



1. Introduction of CDM Forecasting

Objective:



Proposal a forecasting rate based on relationship between history Customer Demand and Actual Sales, to direct the future short—term and long-term sales for certain OEM and below Plants





- Be able to compare the different customer behavior in a better way
- 2. Be able to have a short—term and long-term way to arbitrate customer demand and improve production plan arbitration process (PIC and PDP)





1. Introduction of CDM Forecasting

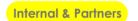
Available potential Data Source:

		Detail Level	Time horizon		Sources	
Forecast	EDI (Customer)	BG/ Div/ Plant/ Material/ Customer (Ship-to)	Weekly and Monthly	L37 BI report (Sunday)	Palantir (up -to-date data)	SAP (zppcd)
	Magritte (Finance)	BG/ Div/ Plant	Monthly	Sarah		
	IHS	Market Research	Monthly	IHS Web		
Actual Sales	Controlling	BG/ Div/ Plant/ Material/ Customer (Ship-to)	Weekly and Monthly	C35 BI report/ S10 BI report	Palantir (up -to-date data)	SAP (zqsd01)
	Magritte (Finance)	BG/ Div/ Plant	Monthly	Sarah		

Available potential Model:

- Linear regression model Y = m X + b
- Time series forecasting model (Useful for ordered time series data) AR, MA, ARIMA, SARIMA, SES, HWES
- Relevant machine learning model LSTM ...





1. Introduction of CDM Forecasting

Introduction of available potential Model:

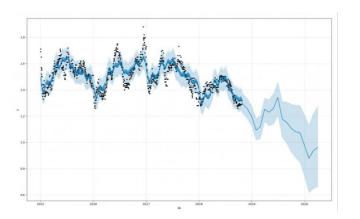
• Time series forecasting model – AR, MA, ARIMA, SARIMA, SES, HWES

1) Definition:

Use historical data feature of seasonality or trend to make future observations

2) Applications:

Weather forecasting, stock price forecasting, retail forecasting



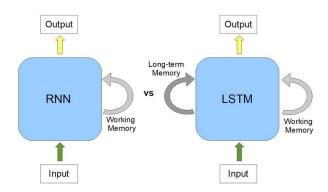
Possible machine learning model – LSTM

1) Definition:

- Long short-term memory (LSTM) is an artificial neural network used in deep learning, which can learn long-term dependencies between time steps of data
- It's a better traditional machine learning model (RNN model)

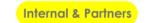
2) Applications:

Sentiment analysis, language modeling, speech recognition, and video analysis





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2.1 Selected Data Scope & Data Source for Division and Plant

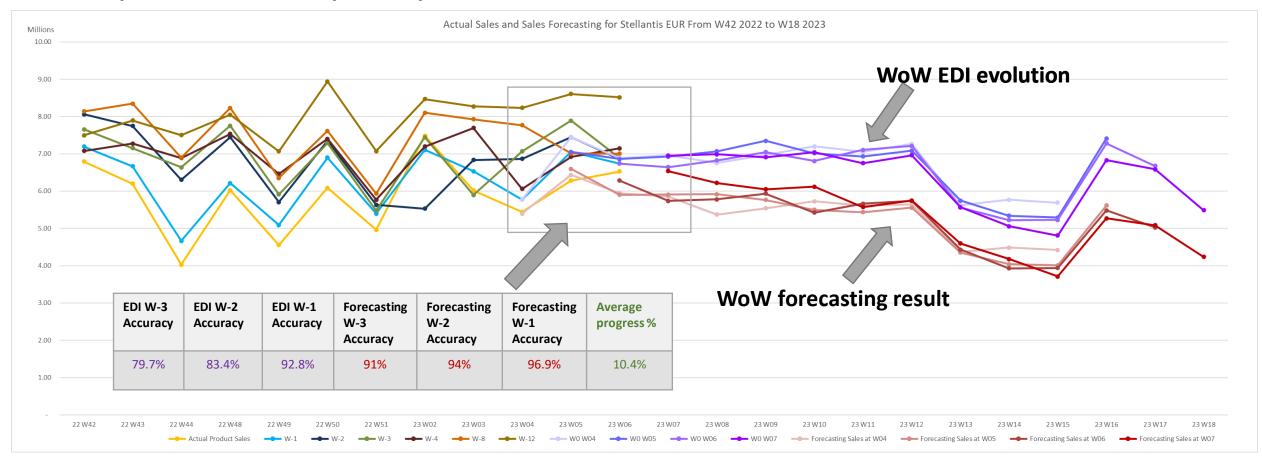
BG Scope	FCM
Customer Scope	Stellantis
Division Scope	Europe Division
Data Source & Time Scope	S10: 2021 W48 – 2023 W07 (64 weeks) L37/EDI: 2021 W48 – 2023 W07 (64 weeks)
Forecasting & Arbitration level	Upper level: Per Customer/Division, for example Stellantis Europe Lower level: Per Customer/Plant, for example Stellantis Terni, Stellantis Pisek





2.2 Forecasting results for Stellantis Europe Division

Example for Stellantis Europe Sales prediction in 2023 W04, W05, W06, and W07



- Principle: Apply on future EDI the historical customer demand behavior
- The Actual Sales value is closer the Red Forecasting results than EDI week by week





2.3 Logic for Stellantis Europe Division Forecasting

1. Delete the regular drops in a year, January and August, so exclude W30 W31 W32 and W52 W01 for each of years.



Data clean is mandatory

Methodologies: dropping detection (Sales is -50% vs. Sales W-2/W+2)



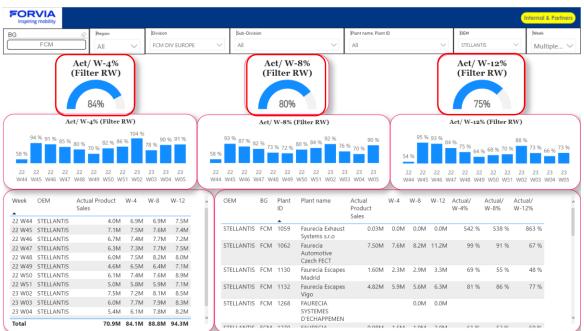


2.3 Logic for Stellantis Europe Division Forecasting

2. Principle:

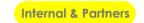
- Based on average of previous rolling weeks (12), EDI accuracy is defined, called "customer demand behavior"
- Apply the customer demand behavior defined per plant/ship-to on corresponding future EDI





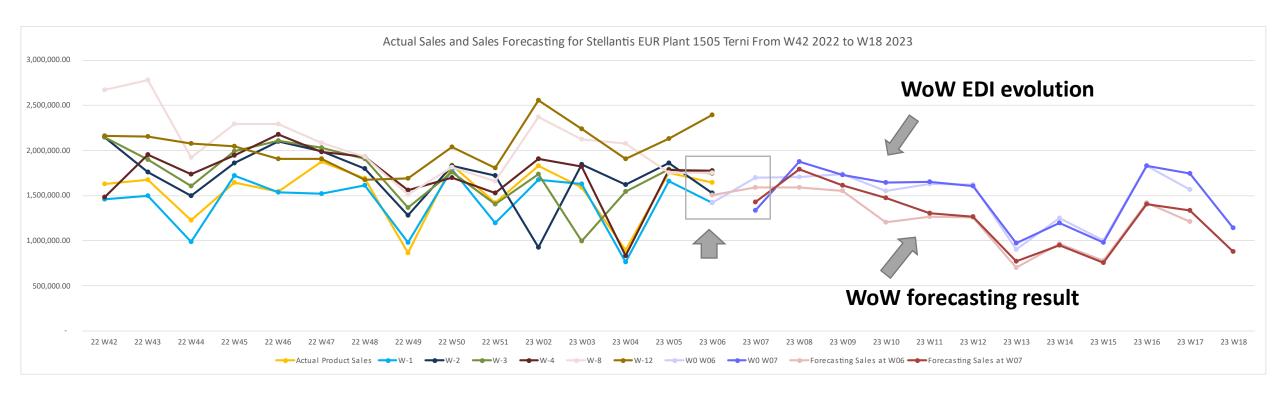
Weekly EDI Accuracy in Power Bi





2.4 Forecasting results for Stellantis Plant example #1

Apply the same logic for the Plant level: Example for Stellantis Plant 1505 Terni Sales prediction in W06 and W07



The Red Forecasting accuracy is better than EDI (91.3% vs. 86.2%)

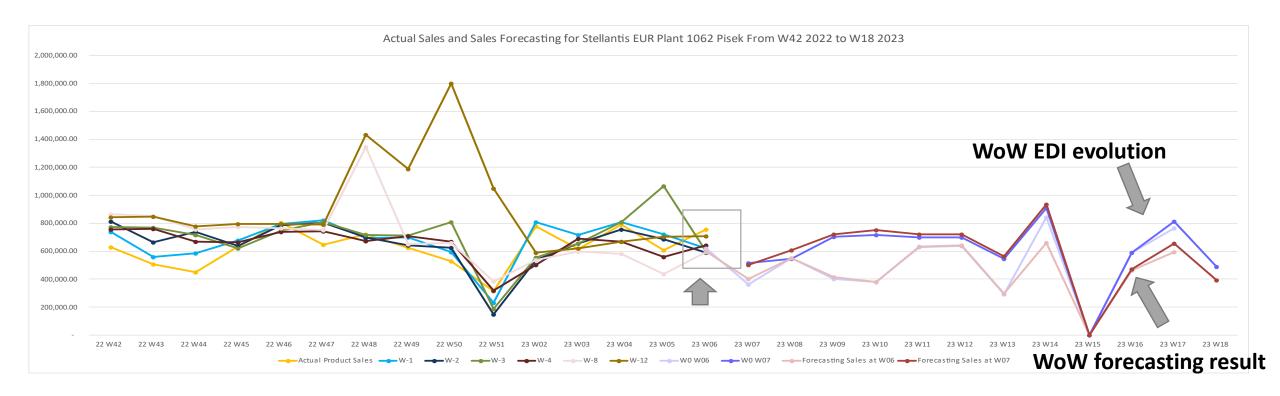




2.4 Forecasting results for Stellantis Plant example #2

Apply the same logic for the Plant level:

Example for Stellantis Plant 1062 Pisek Sales prediction in W06, and W07



The Red Forecasting accuracy is worse than EDI accuracy (78.7% vs 82.1%)

In the logic for the Plant Level, the model performance need to be tested more times

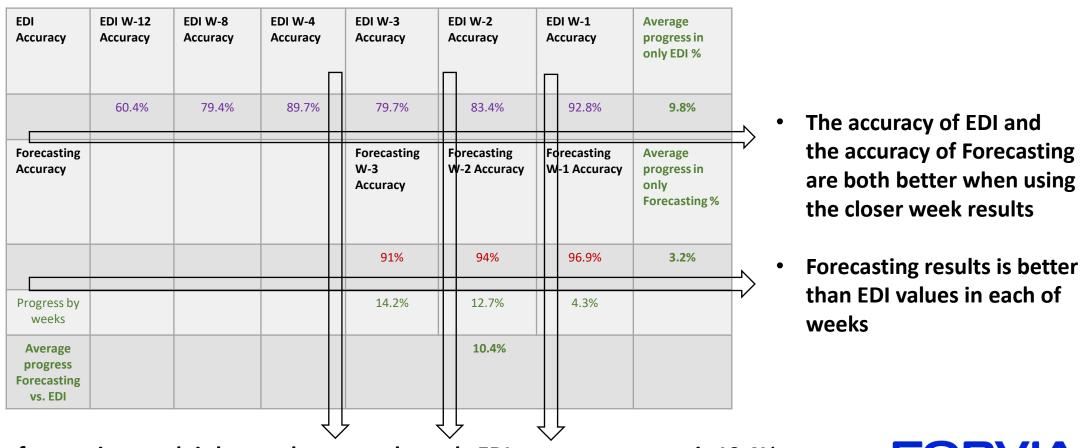


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3.1 Accuracy for Stellantis Europe Division Forecasting

Accuracy comparation for the Forecasting of W04, W05, W06 examples



The forecasting result is better than we only apply EDI, average progress is 10.4%





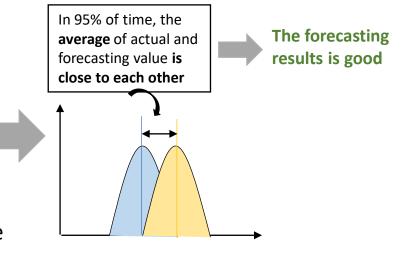
3. Statistical test for Stellantis Europe Division Forecasting

In order to validate the accuracy of the model, Z-test done on 42 past weeks data

Z-Test: Compare the error of averages (Actual and Forecasting)

ZTest		
Z W-1	0.00346	
Z W-2	0.01155	
ZW-3	0.00587	
Z W-4	0.00995	
Z W-8	0.13892	
ZW-12	(3.58715)	

Z < 1.96 means The correct rate of "the two means are not significantly different" is higher than 95%



RMSE (Root-mean-square deviation): Compare the error of extreme value



Average of weekly Stellantis EUR Sales is €5,397,739, But the extreme error are under € 900,000 and far smaller than €5,397,738.7, Then, the extreme error are acceptable,

The forecasting results is good

After Z-test and comparation of RMSE, the forecasting logic is confident enough to be used



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Future Work Plan

- Testing different division sales for Stellantis, and different OEM sales for Europe to compare the results. (need to be transferred to Adam and Samir)
- 2. Apply the same logic or develop another one for the Plant Level, remember there will be 0 sales in plant on some weeks
- 3. Starting use IHS to combine with EDI prediction result

The optimization direction is determined by the results of the above 3 points

