Hotel Demand Forecasting and Revenue Maximization for Short Booking Windows

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ABSTRACT

Forecasting short term demand has always been a problem in the hotel industry. Our study works on the implementation of a robust short-term demand forecasting model which will assist economy hotels in optimizing their price management system and eventually maximize revenue.

INTRODUCTION

The economy hotel chains experience majority of demand within the last 48 hours. This short-term nature of demand realization leads to inaccurate predictions which has an adverse effect on pricing decisions, inventory planning, staffing, and consequentially, the bottom line.

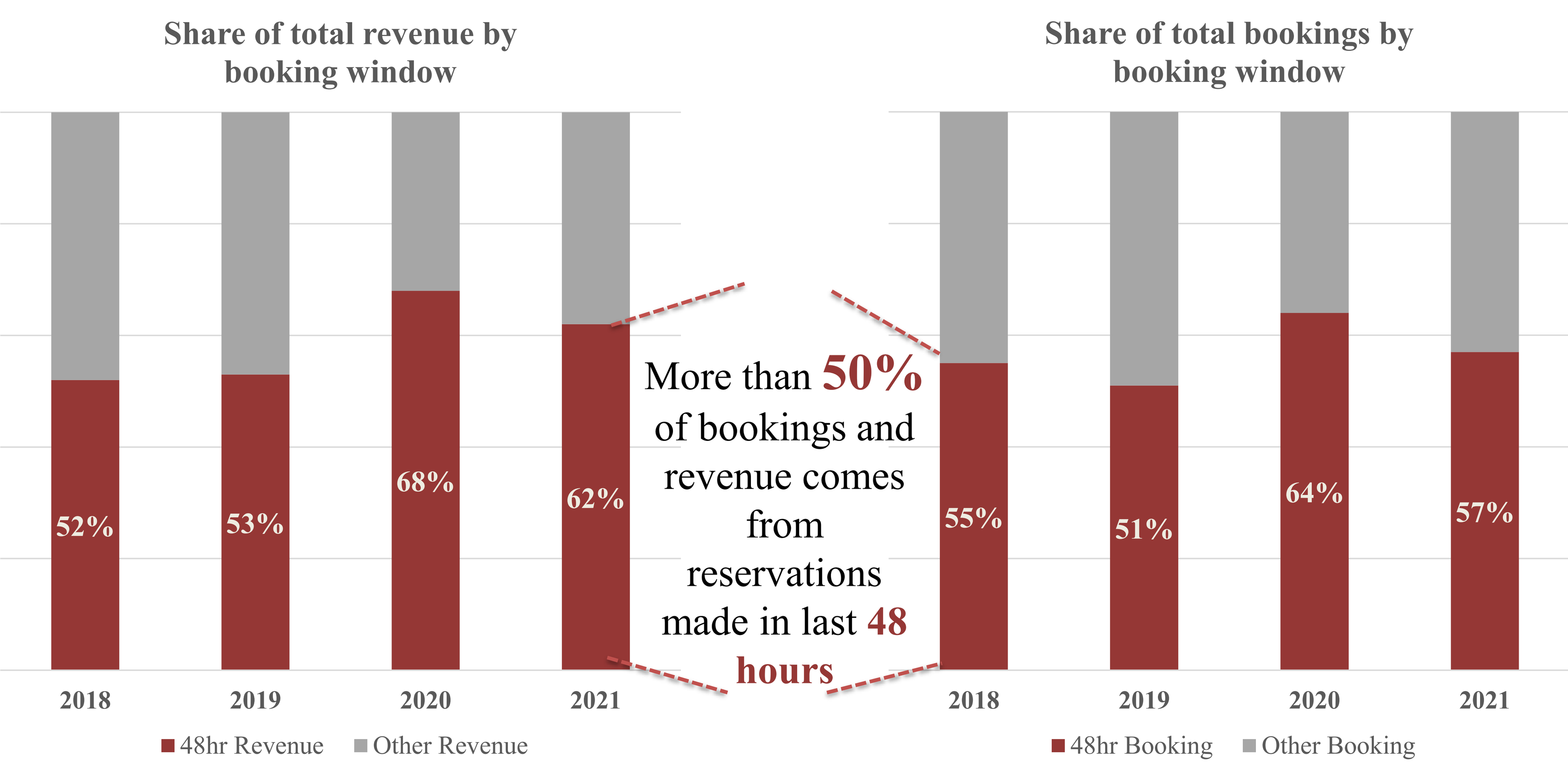

Fig 1. 48hr Revenue and Booking Share

Our study is divided into three main steps:

Demand Forecasting → Price Prediction → Revenue Maximization

RESEARCH QUESTIONS

- What is the best way to accurately forecast hotel bookings for next 48-hours?
- How to utilize the predicted demand to optimize the revenue?

LITERATURE REVIEW

The following studies were reviewed as part of understanding existing solutions available in the demand prediction and revenue optimization space focused on shorter booking windows.

LITERATURE	SARIMA	PROPHET	RNN	LSTM
Lee et. al., 2020	✓			✓
Law et. al., 2019	✓		✓	✓
Abbasimehr et. al,. 2020				✓
Sugiartawan et. al., 2017			✓	✓
Zhang et. al., 2021	✓	✓		
Zvi Schwartz et. al., 2018			✓	
Jiangping Lu et. al., 2021	Impact of Covid-19 on hotel industry.			
Our Study	✓	✓	✓	✓

METHODOLOGY

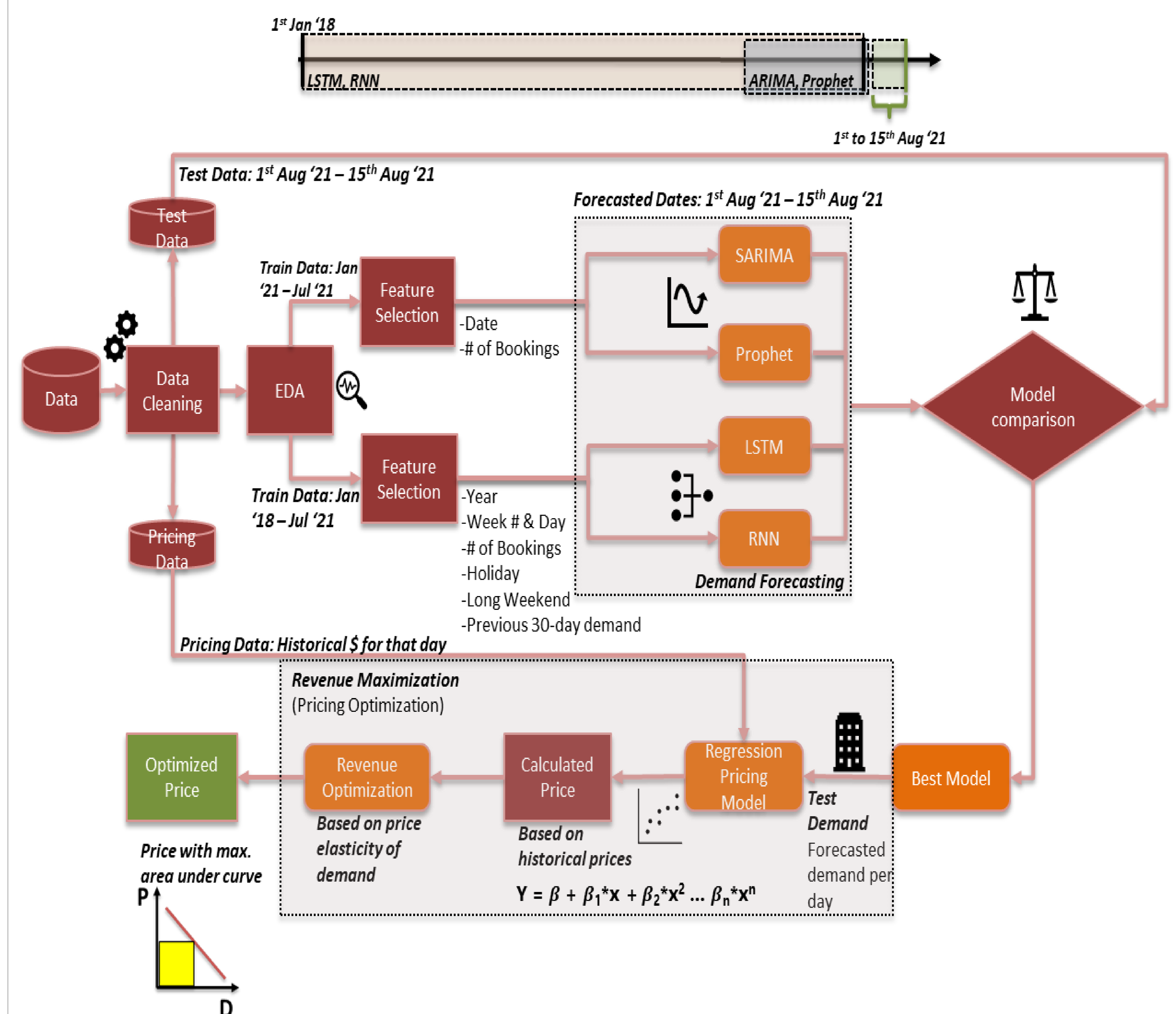

Fig 2. Process Flow Diagram

STATISTICAL RESULTS

Out of all forecasting models tested, LSTM provides the best results with a sample MAPE of 13.48%

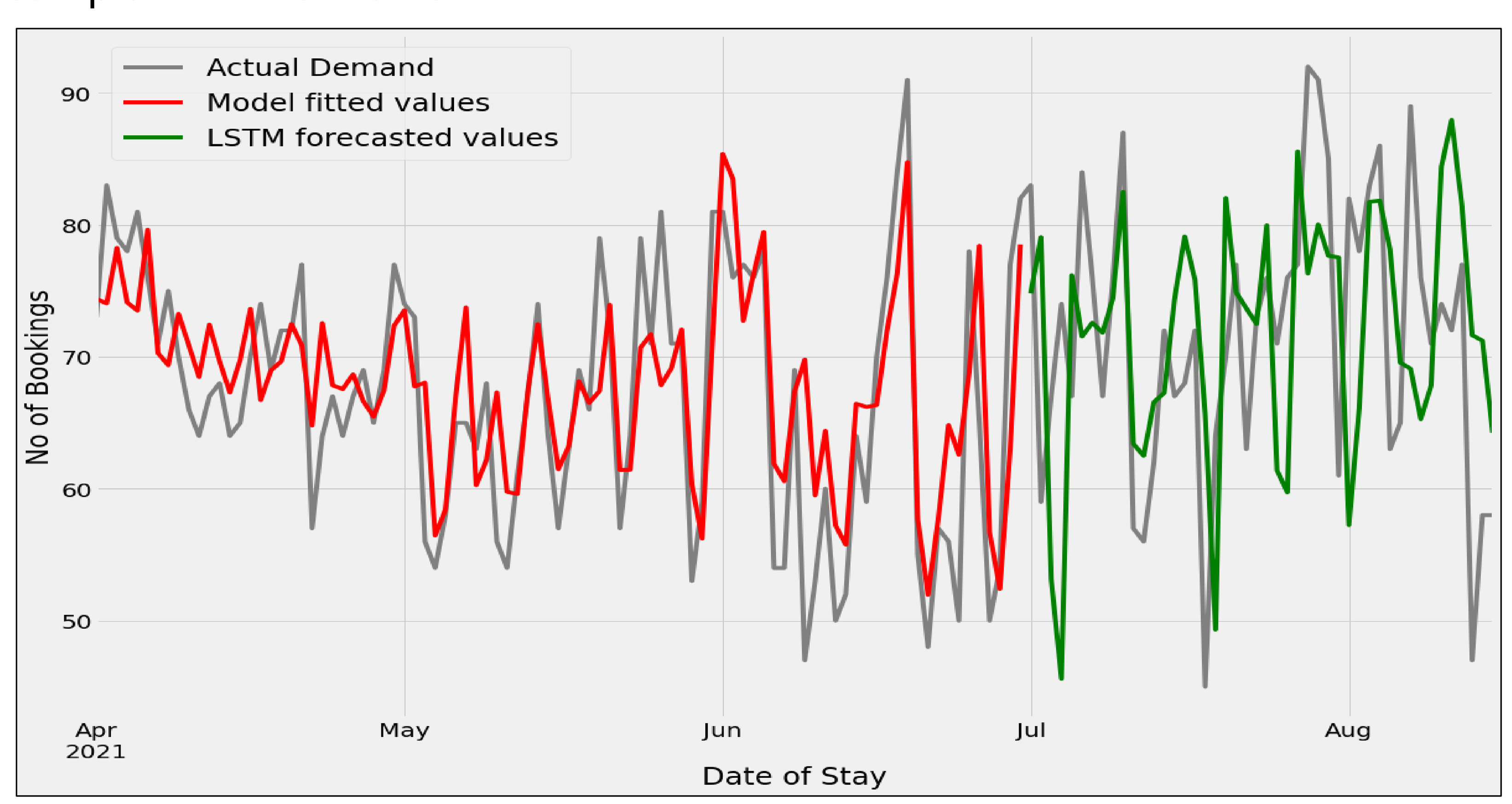

Fig 3. Best Model Performance

BUSINESS IMPACT

For the sample properties analyzed, the optimization model generates a net 3.26% expected revenue. This is a direct result of an improved pricing recommended by the optimization model by considering impact of price on demand. Since both the variables are interdependent, the goal is to maximize for their product and not just one of the variables. In business terms, to maximize for revenue based on price elasticity of demand. This result can be noted by the graphs below. Fig. 4 clearly shows that the historical booked rate was by and large higher than the optimal price. This led to a reduced demand and therefore, reduced revenue generation (Fig. 5).

Following are the additional benefits of this model:

- Improved Staffing – Hotel chains will now be able to better anticipate demand and therefore, provide adequate staffing per property. This will lead to improved customer satisfaction.
- Contracting – Due to increased visibility in future demand, companies can better negotiate contracts for catering, concierge services, etc.
- Inventory Management – Improved room allocation will now lead to increased occupancy rates and therefore higher revenue

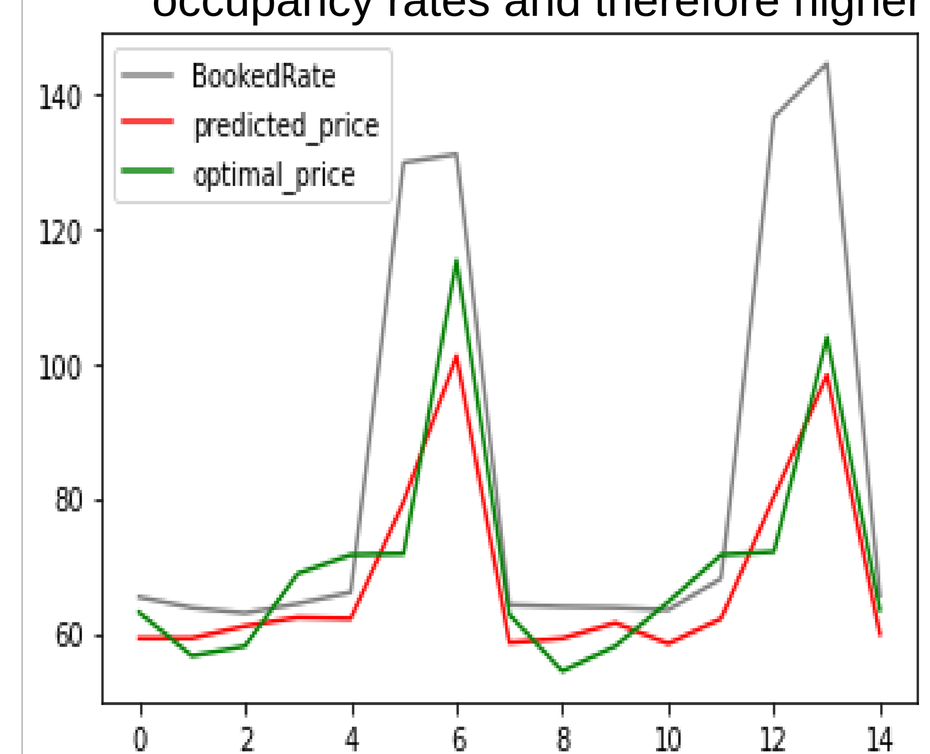

Fig 4. Historical vs. Optimal Price

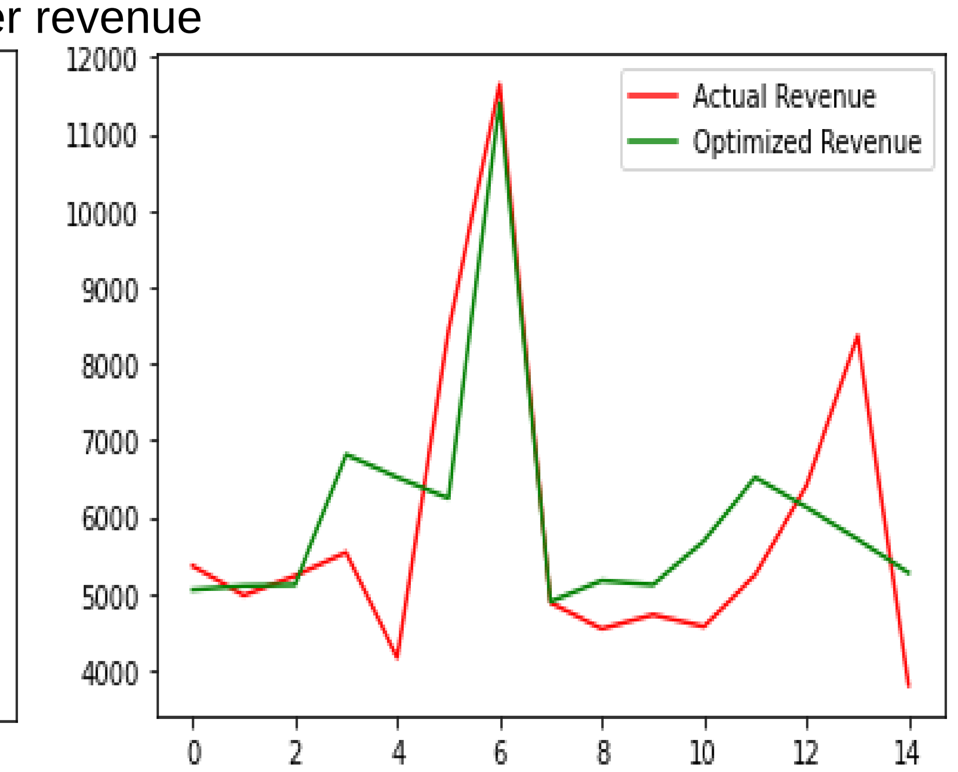

Fig 5. Historical vs. Optimal Revenue

CONCLUSION

- Our experiments revealed that LSTM, out of all the models tested, provides the most accurate hotel room demand forecast over the next 48-hours.
- Additionally, an optimization model which maximizes the area under the curve i.e. revenue by testing for each price point in demand-price curve gives the revenue optimizing price.

However, there is scope for improvement. Additional variables can be added to potentially improve prediction results. For improving price recommendations, more historical data points and other optimization techniques can be tested.

ACKNOWLEDGEMENT

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