SEDGE THE SOLUTIONS EDGE

LINER SHIPPING

Predicting the container repair costs based on repair estimates received from depots

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OBJECTIVE

PORT COST REDUCTION

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CHALLENGE

Port costs exceptionally high for certain vessel services in some locations

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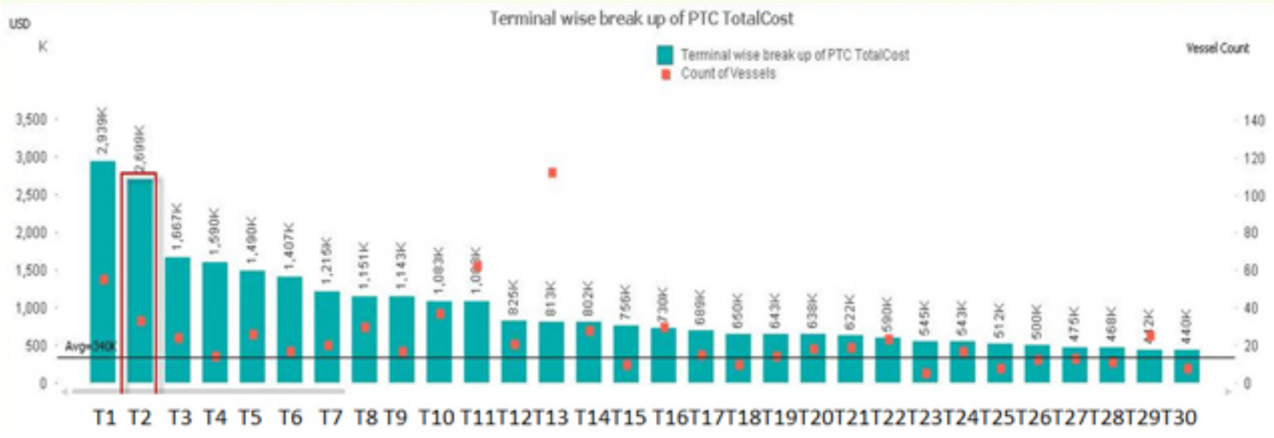
World's leading Liner company



Liner	Total Vessel Count	Count of vessels calling on a weekend (Sat or Sun)	%age of vsls calling high Overtime cost Ports on Weekend
Liner 1	20	13	65%
Liner 2	40	25	63%
Liner 3	125	69	55%
Liner 4	830	406	49%
Liner 5	1,276	518	41%
Liner 6	2,211	853	39%
Liner 7	333	128	38%
Liner 8	355	105	30%
Liner 9	2,325	583	25%
Grand Total	**7,515**	**2,700**	**36%**

Using data analytics tools found, following key reasons for this cost aberration:

- Due to chronic vessel schedule delay, 49% of vessels arriving port on weekends, causing levy of expensive weekend overtime charges by port
- Port anchorage charges were high, more than 25% of port dues were anchorage charges due to vessel delay
- Benchmarked clients port cost with the competitors port cost, Found client was way above the industry average

Outcome:

- Client renegotiated the weekend call rates with the terminal
- Conscious decision to move the calls from high weekend overtime ports to calls on weekdays

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OBJECTIVE

REDUCTION OF HIGH REEFER COST

CHALLENGE

Reefer monitoring costs, exceptionally high at some locations as compared to other ports with similar cargo volumes !

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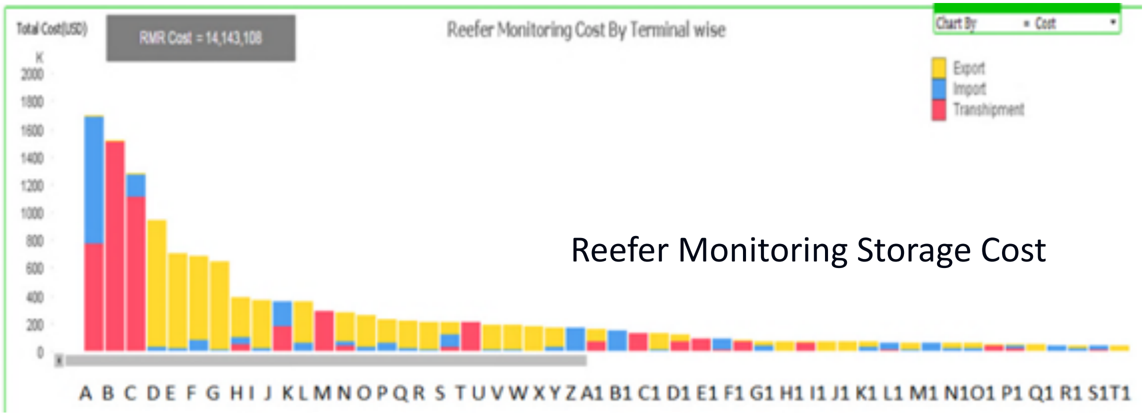
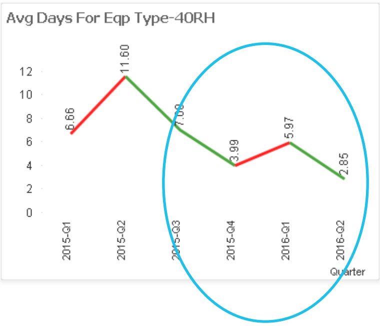


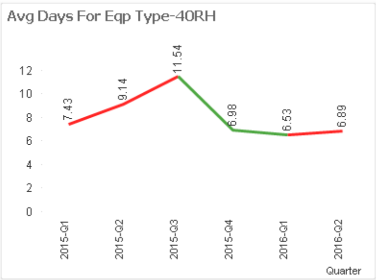
Transhipment

Transhipment		
Type		40RH
Average Qtly Volumes	217	217
Total Volumes	867	867
Avg Ageing	6.3	6.3



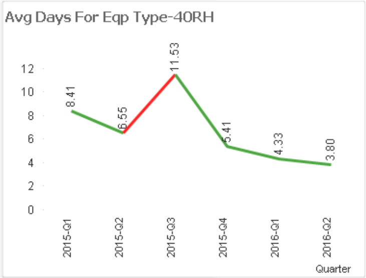
Import

Import		
Type		40RH
Average Qtly Volumes	3,901	3,901
Total Volumes	15,604	15,604
Avg Ageing	7.9	7.9



Export

Export		
Type		40RH
Average Qtly Volumes	111	111
Total Volumes	445	445
Avg Ageing	7.2	7.2



Using data analytics tools found, following key reasons for this cost aberration:

- 26.5% of all reefer monitoring charges coming from one location!
- Increase in the transhipment reefer monitoring cost at certain location, due to erratic schedules of vessels
- In our data analytics, we found 'type of cargo commodity' had a pronounced impact on increasing Reefer monitoring days!

Outcome:

- Client improved the schedule reliability and also negotiated reefer monitoring rates with terminals

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OBJECTIVE

REDUCTION OF STORAGE COST

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CHALLENGE

Storage cost of laden container, exceptionally high at some locations as compared to other ports with similar cargo volumes

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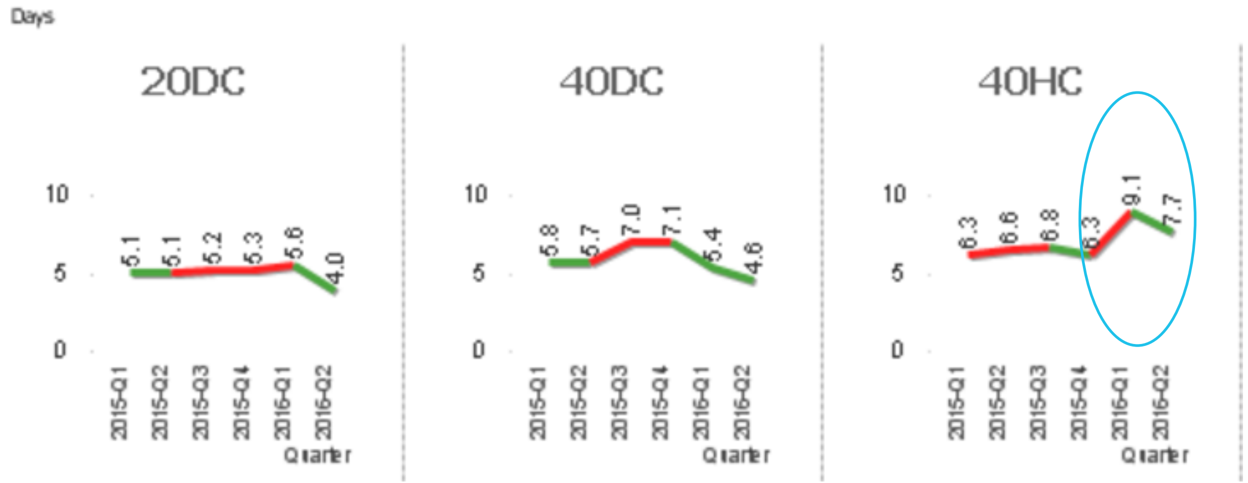
Type		40HC	20DC	40DC
Average Qtly Volumes	**2,990**	2,624	263	104
Total Volumes	**11,960**	10,496	1,050	414
Avg Ageing	**6.9**	7.1	5.0	5.8
Total Cost(USD)	**1,235,787**	1,157,861	41,901	36,025



Using data analytics tools found, following key reasons for this cost aberration:

- Most of the containers were scrap or waste paper shipments
- Most of the BL's where Hitchment BL
- Waste paper gave negative contribution with additional average storage cost
- Identified that empty repositioning would incur less cost than carrying waste paper shipment from this location
- Space not a constraint for increase in export days (66 – 74% utilized)
- Vessel delay accounted for 16% for increase in export storage cost

Outcome:

- Client renegotiated contract with terminal and also negotiated with customer, improving the contribution and also the storage cost.

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EQUIPMENT MAINTENENACE & REPAIR

OBJECTIVE

PREDICTING REPAIR COST FROM DEPOTS

CHALLENGE

Equipment repair cost as received from the depot was high, and monitoring each and every repair estimate was difficult due to complexity of multi country, currency, repair type, and labor rules.

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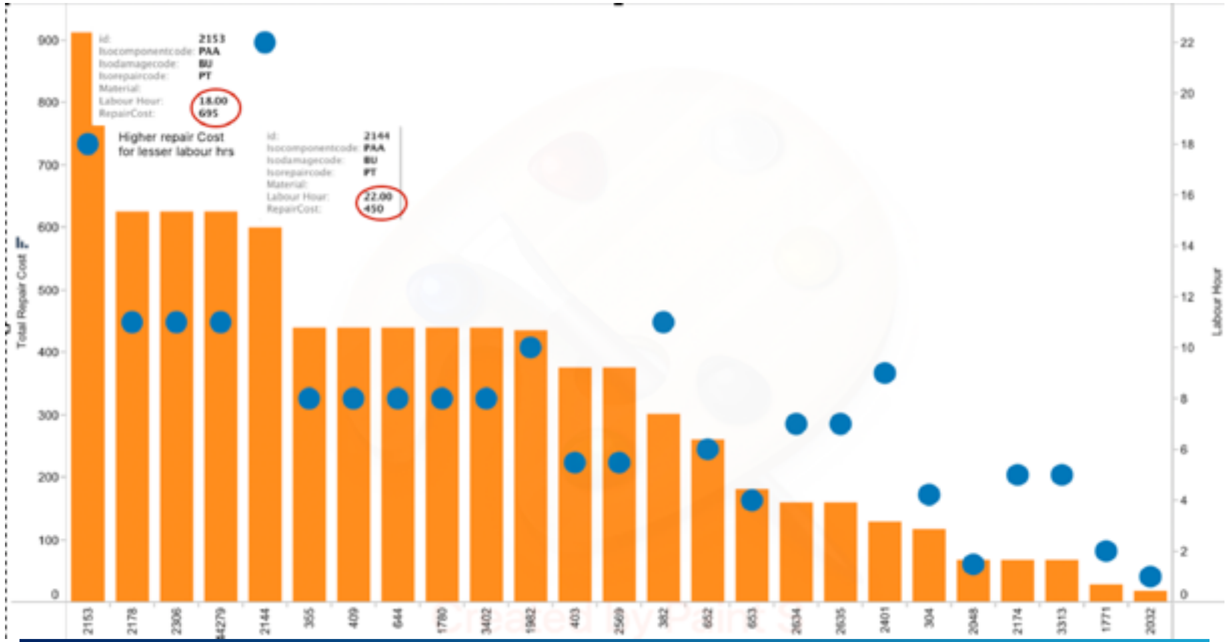

Outcome:

- Client reduced the equipment repair cost by 20% and was able to monitor equipment repair cost effectively.

Challenge

Client a shipping company would manually estimate the repair cost and approve the repair request as received from depot.

- Client is a shipping company and receives estimated cost of repairs from various container repair depots
- There are various repair depots around the globe, and the repair cost varies on various factors such as
  - Component to be repaired
  - Cost of labor, and hours utilized
  - Repair Location
  - Currency
  - Repair type
  - Material used for repair
- Too many repair components and the depots are numerous across the globe.

Implemented

Client implemented the regression model and compared the repair estimate as received from depot and was able to reduce the repair cost based on the past learnings.

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OBJECTIVE

DEMAND FORECASTING USING DEEP LEARNING (LSTM)

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Data Imputation

- Sample data over a period was used for 1500 port pair combination
- Each port pair was grouped on a period basis (Weekly).
- Excluded data which had more than 70% missing data
- Missing data were imputed by Quadratic Interpolation.
- Sample demo - one of the port pair with 30% missing data and interpolated.

Data Pre-Processing & Feature Engineering

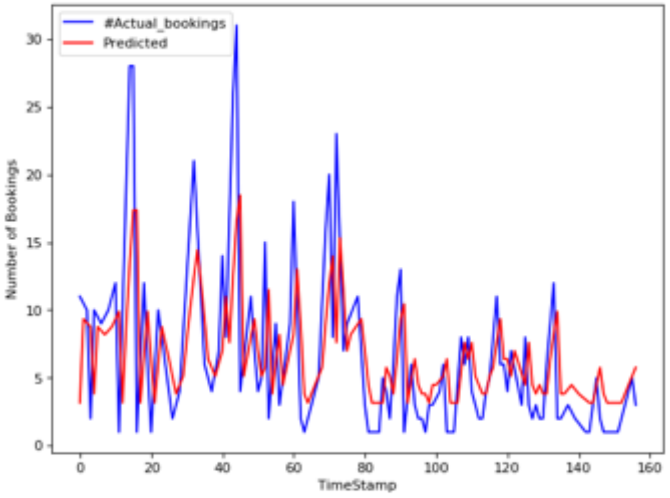
- Created the dataset, with data as float
- Normalized the features
- Split into training and test sets
- Converted array of values into a dataset matrix
- Reshaped into X=t and Y=t+1
- Reshaped input to be 3D
  - (num_samples, num_timesteps, num_features)

Applied Multi-layered Long Short-Tem Memory (LSTM) recurrent neural network to predict the sequence of weekly values.

LSTM Architecture

```
Model: "sequential_15"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
unified_lstm_15 (UnifiedLSTM (None, 100)               40800
_________________________________________________________________
dropout_2 (Dropout)          (None, 100)               0
_________________________________________________________________
dense_14 (Dense)             (None, 1)                 101
=================================================================
Total params: 40,901
Trainable params: 40,901
Non-trainable params: 0
_________________________________________________________________
Test Score: 4.49 RMSE
```

Training actual vs Prediction LSTM model



- Created LSTM with 100 neurons in the first hidden layer and 1 neuron in the output layer for predicting Cargo quantity
- Dropout 20%, Optimiser – Adam version stochastic gradient descent, MSE loss function
- The model was fit for 100 training epochs with a batch size of 1
- Total Observations were 184 data points, 80/20 split – Training / Testing

Compared LSTM vs ARIMA

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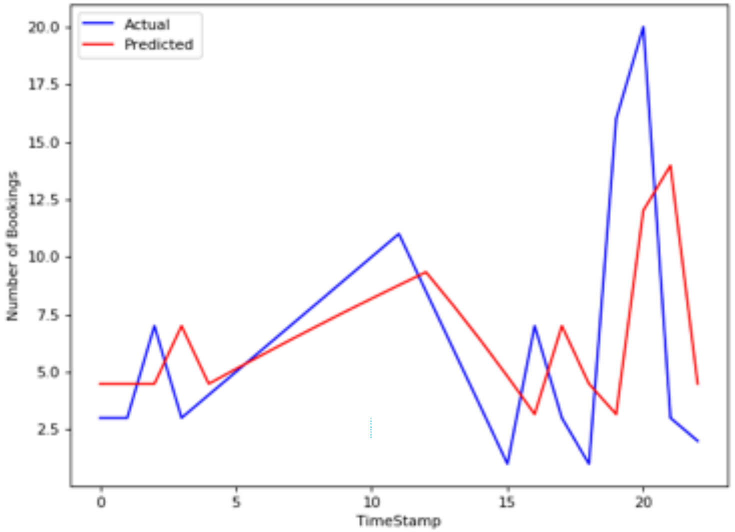
Testing actual vs Prediction LSTM

Total RMSE

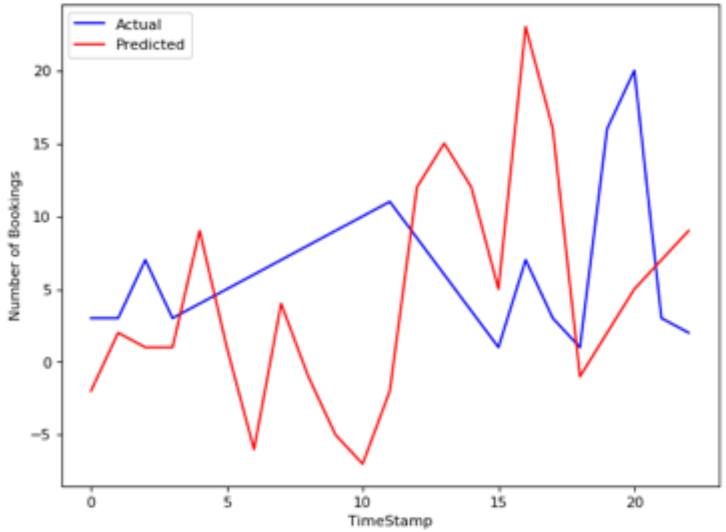
4.49



Testing actual vs Prediction ARIMA

Total RMSE

9.53



Data for other port pair using rolling ARIMA and LSTM, and the RMSE values indicate that LSTM based models outperform ARIMA-based models with a high margin

Port Pair	RMSE		% Reduction in RMSE
	ARIMA	LSTM	
Port A to B	76.6	10.5	-86.2
Port A to C	28.7	3.61	-87.4
Port C to D	30.23	3.17	-89.5
Port D to F	135.6	22	-83.7

Outcome:

Forecast data generated using LSTM, with minimal Root Mean Square Error (RMSE) for each port pair and equipment type. The forecast of the customer improved substantially using the LSTM Architecture.