Session III
Innovations in use of water transport for Oil and Gas industry

Dynamic allocation of vessels on services and schedule creation based on cargo demand
Model built using Optimization and LSTM

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In Tandem 2.0
Opti Chain
Intelligent Supply Chain

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Presentation Agenda

1. Motivation
2. Current Day Challenges - Oil & Gas Industry
3. Overcoming Challenges through technology
4. Challenges in Demand forecasting, Vessel allocation & Scheduling
5. Methodology – Vessel Allocation & Scheduling
6. Stage 1 - Demand Forecasting
7. Stage 2 - Pre-Solver
8. Stage 3 Optimization
9. Stage 4 Scheduling
10. Conclusion - Value Creation
Motivation

Innovations in use of water transport for Oil and Gas industry

- Minimizing Cost / Maximizing profit
- Smarter Vessel
- Scheduling
- Satisfying the Cargo Demand
Current Day Challenges - Oil & Gas Industry

- Extreme Competition
- Geopolitical Uncertainty
- Economic Instability
- Disruptive Technologies
- Changing consumer behavior
- Demand for continuous innovation
Overcoming Challenges through technology

Survive, Adapt and Evolve to create a Competitive Edge

Survive / Adapt / Evolve

- Artificial Intelligence
- Out of box-Analytics
- Optimization Models
- Forecasting Model
- Internet of Things (IOT)
- Benchmarking Process

- Machine Learning
- Deep Learning
- LSTM- RNN
Dynamic Vessel allocation & Schedule creation based on cargo demand

Supply

Grade A1
Grade A2
Grade A3
Ras Laffan

Grade B1
Grade B2
Grade B3
Ras Tanurah

Grade C1
Grade C2
Grade C3
Fujairah terminal

...........m Load Ports

............x vessels

Demand

Kandla Port

JNPT Port

Hazira Port

Vizag Port

...........n Discharge Ports
Challenges in demand forecasting, vessel allocation, satisfying cargo demands and schedule generation - Case Study of Liner Ship

- 1500 Port Pairs
- 60 Ships
- 10 cargo type
- 6 Equipment Type
- Daily Fluctuating Demand
- Multiple Port Discharge
- Port Depth Restrictions / Varying draft

Variables
- Which Ship ?
- On what Service ?
- Loading what Port Pair ?
- What cargo ?
- What Quantity in Teus / Tons ?
- What Equipment Types ?

Variables - 5.4 million
Methodology

4 Stage approach

Forecasting
- Demand for Cargo
- Lower / Upper Bound
- Delivery by X days

Pre-Solver
- Hard Constraint
- Soft Constraints

Optimization
- Satisfying Demand
- Selecting Vessel
- Port-Pair
- Maximizing Profit

Scheduling
- Arr/Dep Date Time
- Tidal Window
- Day Time
- Time Window
Methodology

Stage 1 - Forecasting

Forecasting
• Demand for Cargo
• Lower / Upper Bound
• Delivery by X days

Pre-Solver
• Hard Constraint
• Soft Constraint

Optimization
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Motivation for demand forecasting

- A good forecast is needed for identifying the cargo demand
- With a good forecast the vessel optimization is built on strong foundation

Forecasting the cargo demand using Artificial Neural Networks (ANNs)

- ANNs are data-driven, self-adaptive methods with few assumptions.
- ANN's challenging the traditional techniques - time series forecast, -
  - ARIMA (Auto Regressive Integrated moving average) / SARIMA / Kalman assume Linear relationship
  - ANN's are efficient in solving non linear problems
- In this use case, the performance of ANN and ARIMA models are compared for a cargo demand scenario.
Cargo demand forecast – Imputing the missing data

**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-Term Memory (LSTM) recurrent neural network to predict the sequence of weekly values.
LSTM Architecture

- 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

Result

![Training actual vs Prediction LSTM model](image.png)

<table>
<thead>
<tr>
<th>Model: &quot;sequential_15&quot;</th>
</tr>
</thead>
<tbody>
<tr>
<td>Layer (type)</td>
</tr>
<tr>
<td>----------------</td>
</tr>
<tr>
<td>unified_lstm_15 (UnifiedLSTM (None, 100))</td>
</tr>
<tr>
<td>dropout_2 (Dropout)</td>
</tr>
<tr>
<td>dense_14 (Dense)</td>
</tr>
</tbody>
</table>

Total params: 40,901
Trainable params: 40,901
Non-trainable params: 0

Test Score: 4.49 RMSE
Compared LSTM vs ARIMA

Total RMSE: 4.49

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

<table>
<thead>
<tr>
<th>Port Pair</th>
<th>ARIMA RMSE</th>
<th>LSTM RMSE</th>
<th>% Reduction in RMSE</th>
</tr>
</thead>
<tbody>
<tr>
<td>Port A to B</td>
<td>76.6</td>
<td>10.5</td>
<td>-86.2</td>
</tr>
<tr>
<td>Port A to C</td>
<td>28.7</td>
<td>3.61</td>
<td>-87.4</td>
</tr>
<tr>
<td>Port C to D</td>
<td>30.23</td>
<td>3.17</td>
<td>-89.5</td>
</tr>
<tr>
<td>Port D to F</td>
<td>135.6</td>
<td>22</td>
<td>-83.7</td>
</tr>
</tbody>
</table>
Methodology

Stage 2- Pre-Solver

Forecasting
• Demand for Commodity
• Lower / Upper Bound
• Delivery by X days

Pre-Solver
• Hard Constraint
• Soft Constraint

Optimization
• Satisfying Demand
• Selecting Vessel
• Port-Pair
• Maximizing Profit

Scheduling
• Arr/Dep Date Time
• Tidal Window
• Day Time
• Time Window
Input parameters to the Pre-solver

- Vessels with cost information
- Vessel with Technical details
- Ports with details
- Port Pair with cargo demand data – With Lower and Upper Bound Constraints
  * Data from forecasting
- Port Pair with Profit Contribution for each Service / commodity / Equipment Type
- Service information with the order of ports of call and the round voyage days
- Costs related to Cargo handling
- Freight Charges related to Cargo
Pre-Solver

HARD CONSTRAINTS
- Services contain ports. Ports in a service do not allow certain vessels
- The port constraints in a service that vessels have to satisfy are:
  - Length Overall (LOA)
  - Cranes (some ports do not have cranes and need vessels with cranes)
  - Beam
  - WLTHC (Water Line to Hatch Coaming)
  - Flag Restriction
  - Vessel Age restriction
  - Vessels on Time Charter or Voyage Charter
  - Hold Type / Previous loaded cargo
  - Oil major ratings (Vetting Inspection)

SOFT CONSTRAINTS
- Vessel Draft – Draft adjusted based on the available depth at port
- Adjusting Draft also implies that vessel fuel consumption varies. Cost needs to be recalculated
- Adjustment of speed due to draft adjustment
- Adjustment of speed of vessel to achieve a round voyage of X days.
- Air draft of vessel (Adjusted by ballasting)
Methodology
Stage 3 - Optimization

Forecasting
• Demand for Commodity
• Lower / Upper Bound
• Delivery by X days

Pre-Solver
• Hard Constraint
• Vessel Constraint
• Port Constraint

Optimization
• Satisfying Demand
• Selecting Vessel
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Scheduling
• Arr/Dep Date Time
• Tidal Window
• Day Time
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Optimization Model (Problem Statement)

Objective function
- Minimize the cost
- Or
- Maximize the profit

Variables to determine
- Allocation of vessel on service / Port pair combination
- Quantity of cargo to be carried between each port pair
- Between multiple Load Port and multiple discharge ports
- By the vessel, with load dates and discharge dates

Port based Constraints
- Demand at the Discharge ports
- Multiple cargo type loading and discharge
- Lower bound and Upper bound
- Daily consumption at the discharge port
- Supply side restrictions at the load port
- Loading and Discharging time
- Port restriction (Load and Discharge)
- Seasonality / Port Congestion / Port Holidays / Strikes
- Weather / Tidal restrictions
- Day time arrival only / Time Windows for port arrival

Vessel based Constraints
- Vessel capacity / Tank Capacity restriction
- No of vessels parallel loading and discharge restriction
- Draft / Air draft restriction
- Vessel LOA / Beam restriction
- Flag restriction (Indian Flag – Cabotage Rules)
- Time Charter / Voyage Charter / COA
- Oil major inspection / audit (Approved vessels)
- Age of vessel restriction
- Planned off-hire / drydocking periods
- Vessel Speed and Fuel Oil consumption
- Charter Hire and Port Cost
Methodology

Stage 4 - Scheduling

Forecasting
• Demand for Commodity
• Lower / Upper Bound
• Delivery by X days

Pre-Solver
• Hard Constraint
• Soft Constraint

Optimization
• Satisfying Demand
• Selecting Vessel
• Port-Pair
• Maximizing Profit

Scheduling
• Arr/Dep Date Time
• Tidal Window
• Day Time
• Time Window
Parameters needed for Schedule creation

- Demand of cargo at each Port / terminal
- Details of Ports & Terminals
- Vessel / Voyage Details
- Distances between Ports (Sea Time)
- Pilot Station to Berth distance (Pilotage Time)
- Port rotation order
- Rate of Loading / Rate of discharge at Ports
- Vessel Speed & Fuel consumption
- Charter Hire Cost
- Port / Canal Cost
- Date of Loading / Laycan dates

Data from optimizer fed into the Vessel Scheduler. Allocated vessel on the respective service and port pair is used for creating Vessel Schedule
Vessel Scheduling

Schedule of vessel with voyage details

- Date and Time of arrival of the vessel at the Pilot Station
- Date and Time of arrival of the vessel at the Berth in the port
- Date and Time of departure of the vessel from the Pilot Station
- Date and Time of departure of the vessel from the Berth
View of Vessels on map with ETA / ETD and position data

- Position updated through Automatic Identification System (AIS) / Noon report
Conclusion - Value creation

**Forecasting**
- Deep Learning models - LSTM can generate good forecast (pillars for optimization to run on)
- Reduction in the vessel detention time

**Pre-Solver**
- Pre-Solver functions can reduce the variables substantially leading to faster optimization

**Optimization**
- Demand from each port able to be satisfied
- Larger sized ship allocated with port pairs with greater demand
- Maximize the profitability
- Excess Vessels identified were off-hired (reduced charter hire)
- Maximized the lifting (Teus / Tons) on board the vessel within draft limits
- Negative Contribution services /port pairs identified, and excluded

**Schedule creation**
- Vessel schedule planned to arrive at port to satisfy demand within time constraint
- Ability to dynamically change schedule in shorter period