Multi-echelon Supply Chain Optimisation

with Multiple Time Series Modelling

Client: Pepperl + Fuchs Asia Pte Ltd

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Agenda

Business Background

Topic 1

Project Objectives

Topic 2

Predictive Modelling

Topic 3

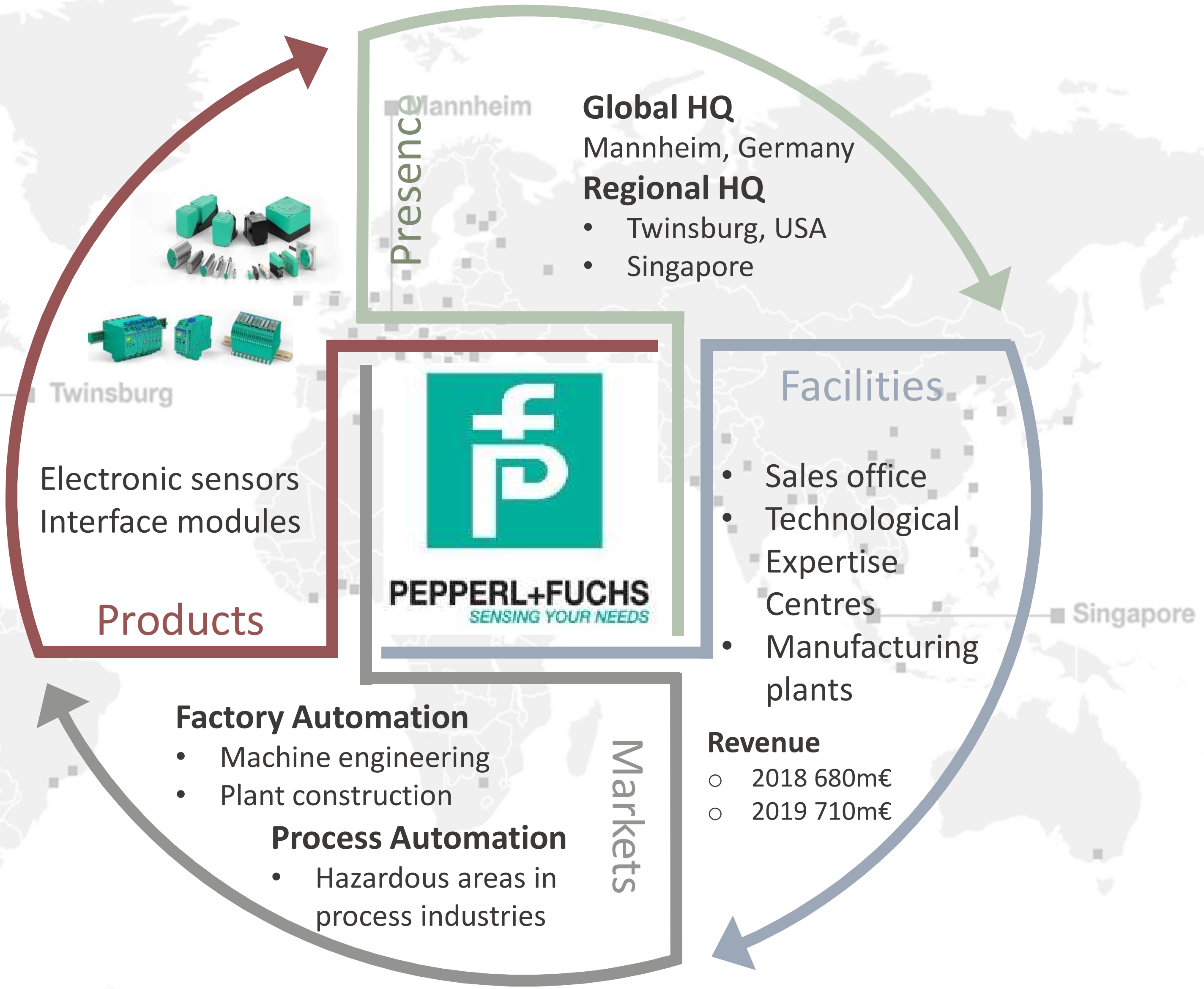
Inventory Analysis

Topic 4

Project Conclusion

Topic 5

Client Introduction



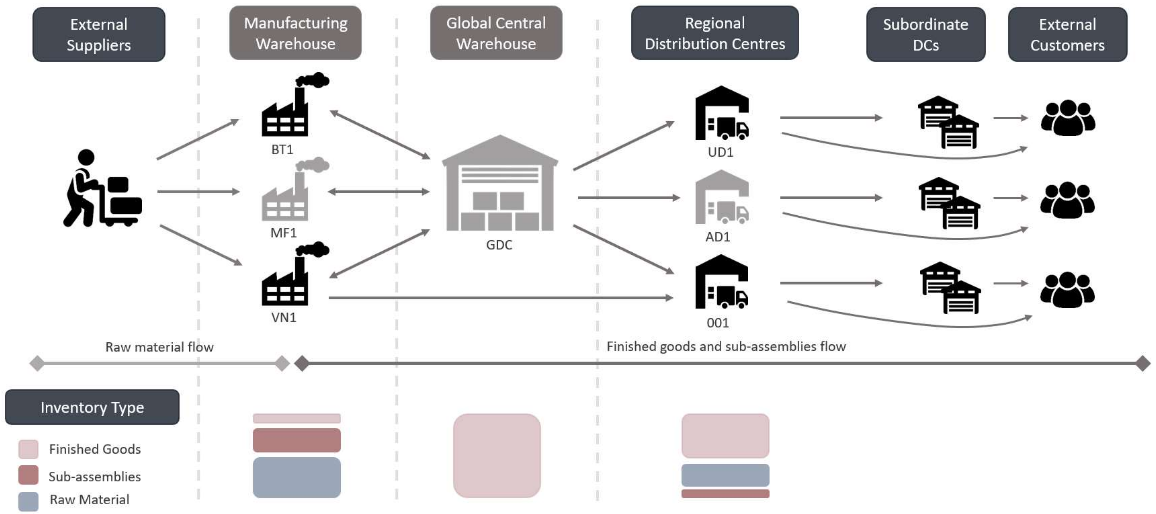
Recap

Data Preparation
- Dataset introduction
- Data selection process
- Data cleaning

Project Planning
- Overall planning
- Project objectives
- Timeframe

Predictive Modelling
- Modelling objectives
- Initial modelling outcome with machine learning algorithms

The P&F Supply Chain



Project Objectives

Challenges

Lack of Reliable Forecast System
No established demand forecast processes. Common practice is simple rolling average for selected products.

Stockpiling & Shortages
224 million Euro worth of excess inventory as of 2019. Yet suffered from frequent shortages and late deliveries.

Safety Stock Management
Lack of an integrated approach for overall Supply Chain.

Success Criteria

1. **Reliable** predictive model with at least **85% accuracy**
2. **Robust process** framework that accounts for **all types of inventory** and is capable of **long and short term solutions**

Solutions

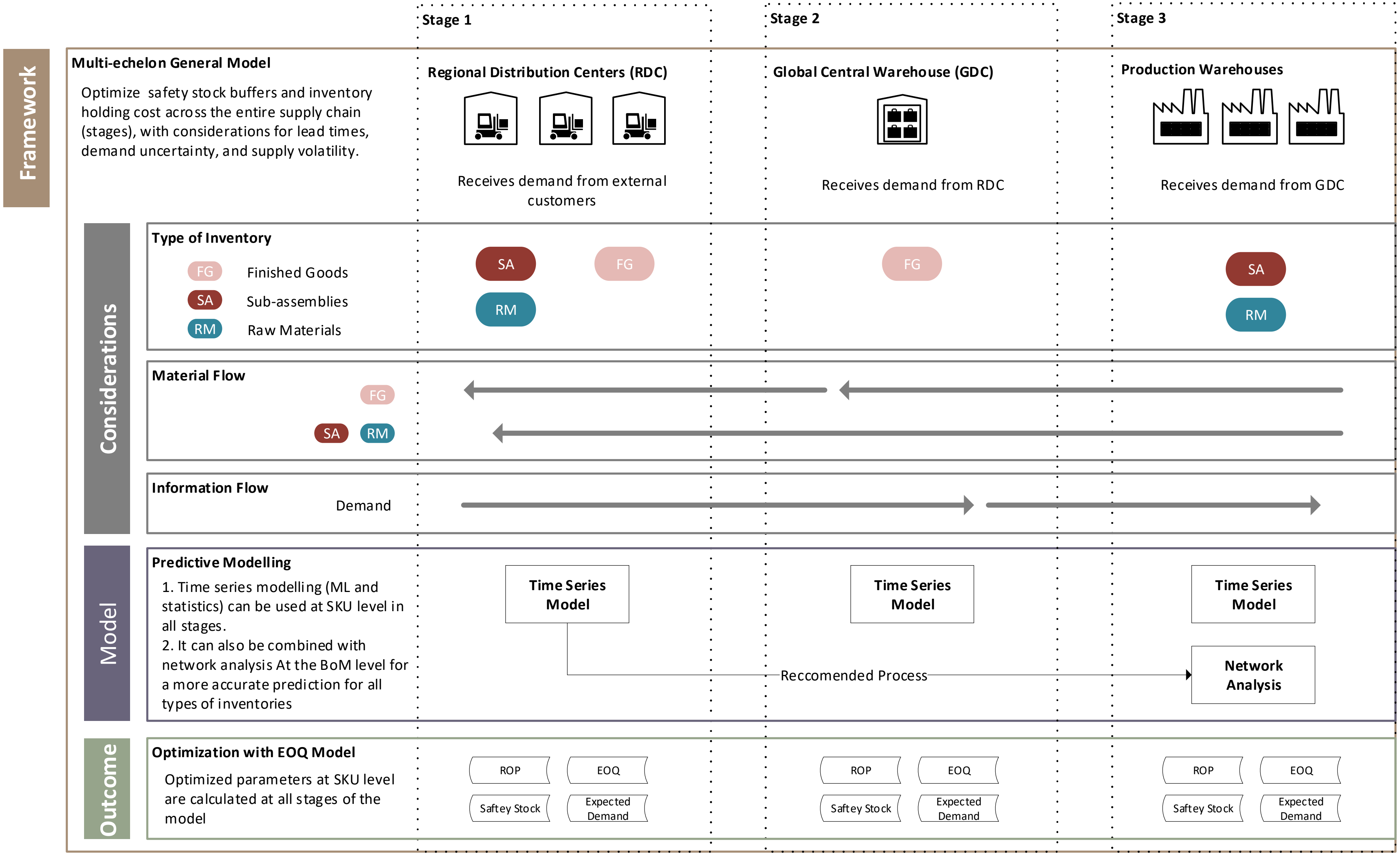
Time Series Model
Allows for systematic forecast of future demand for all standard products*.

**Special products such as customised or modular products are not part of this project*

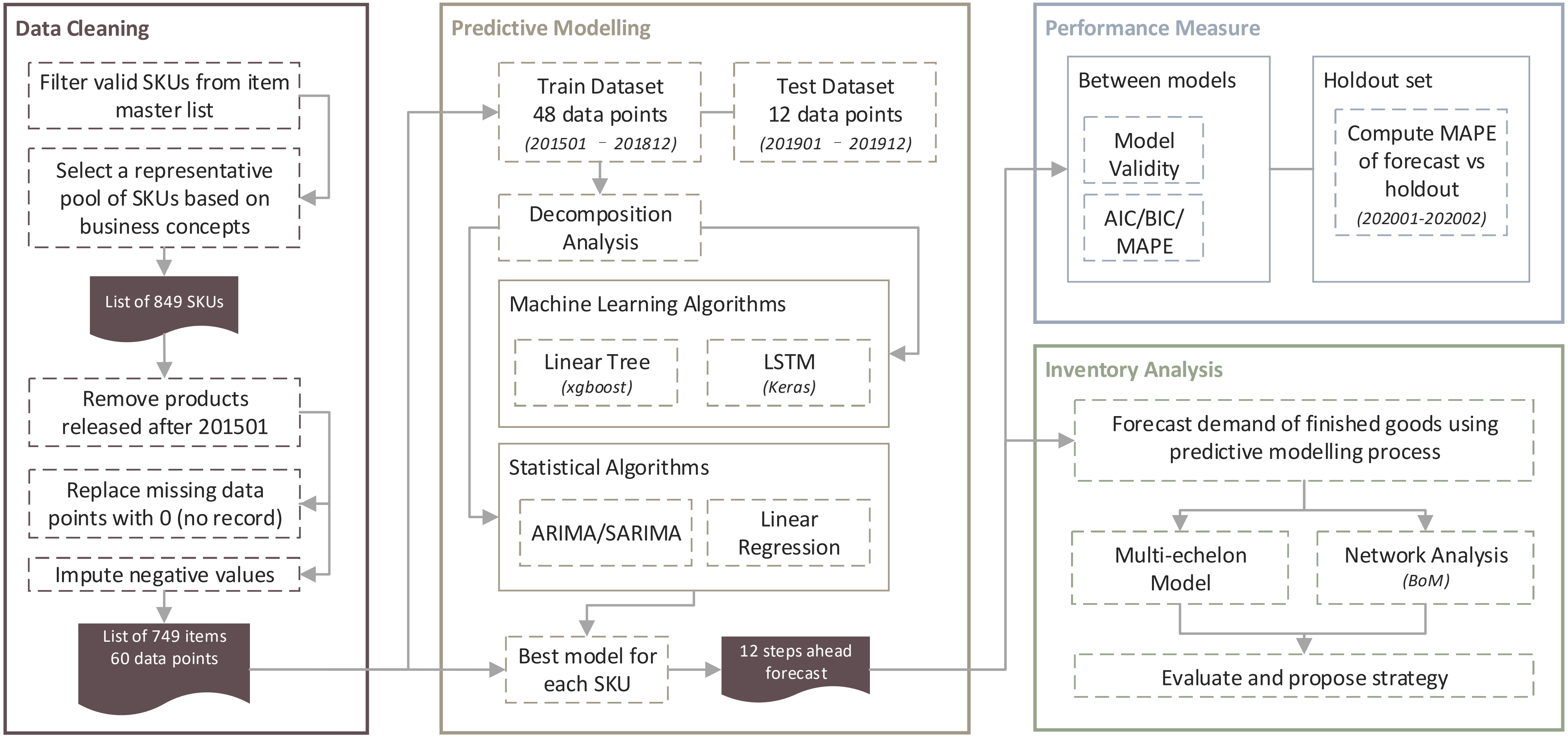
SKU Level Forecast
Forecast at stock keeping unit (SKU) level to optimise the product mix.

Multi-Echelon Model
Optimise inventory as an integrated supply chain

Project Plan



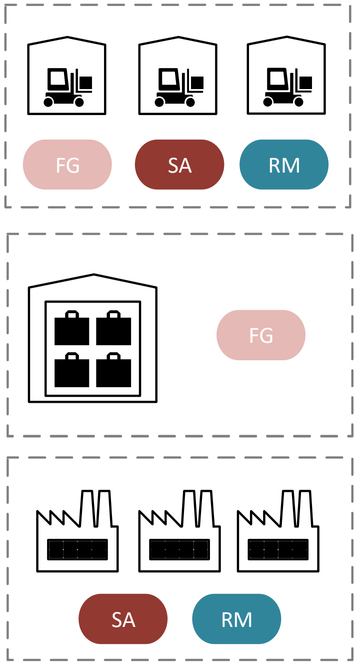
Process Flow



Modelling Objectives

Standalone Solutions

Products are forecasted separately at each stage and parameters are set based on forecast output



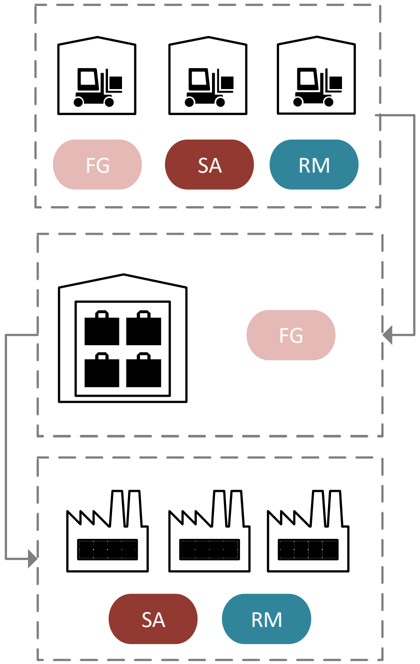
Pros:
- Simple and reliable solution to current void in forecast process
- Cater for administrative separation

Cons:
- Silo processes, may not be optimal solution from company perspective
- High computational expense for the predictive models (~45 sec per time series)

Short Term Solution

Integrated Solutions

Products are forecasted stages by stages, with limited application of model to products in the upper stream

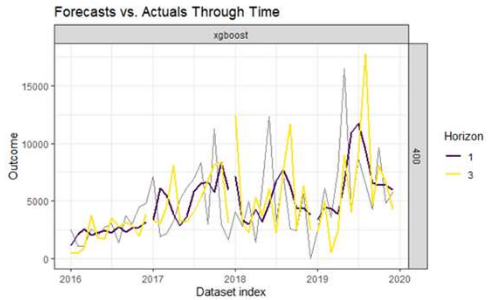


Pros:
- Integrated planning, able to optimize the entire Supply Chain

Cons:
- Complex process involving multiple frameworks and models
- High computational expense to retrieve the entire aggregated BoM
- Required cross-functional collaboration for implementation

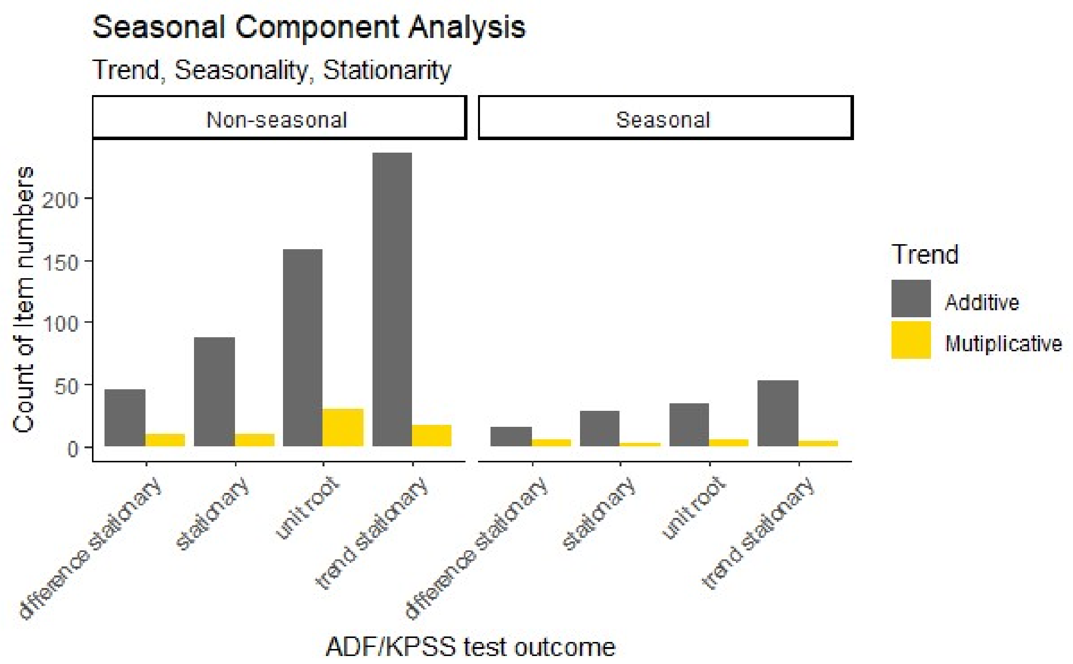
Long Term Solution

Time Series Modelling - Setup

	Machine Learning Models		Statistical Models	
Algorithms	Linear Tree	LSTM	ARIMA	Regression
Package (R)	Xgboost Caret (grid search)	Tensorflow, Keras Caret (grid search)	Forecast Tseries	Forecast Tseries
Hyperparameter Optimization / Method	Features Iterations Optimiser	No. of layers Learning rate Optimiser Activation function Dropout rate	Max p,d,q,P,D,Q = 1	Simple LR Multiple LR Polynomial LR (Trend 1,2,3)
Application	Build a few models with random sampling of time series objects *(diff and scaled data)*		Loop through all 749 time series objects	
Model Outcome	Poor outcome for both algorithms → uses the value at time t to predict time t+1 		Poor outcome for all types of regression methods → Unable to account for trend (flat line) → method not applicable for all objects Good outcome for ARIMA model → best method	
Evaluation	Too few data points to make meaningful prediction → discard		Discard regression method Focus on ARIMA	

Decomposition Analysis

Dimension	R package	Function	Outcome	
Seasonality	forecast	tbats()	TRUE	20%
			FALSE	80%
Trend	forecast	ets()	A	9%
			N	80%
			M	11%
Stationarity	tseries	kpss.test()	difference stationary	10%
			stationary	17%
	tseries	adf.test()	trend stationary	42%
			unit root	31%
Difference	forecast	ndiffs()	0	52.5%
			1	47.4%
			2	0.1%
Seasonal difference	forecast	nsdiffs	0	99.9%
			1	0.1%

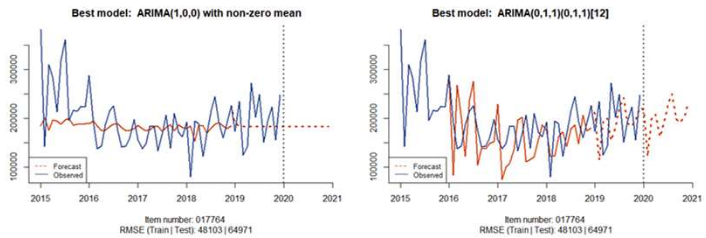


Arima Modelling

	Challenges	**Solution**	**Outcome**
Datasets	Is transformation necessary for non-stationary data?	Compare of Boxcox() lambda vs no transformation *81 TS objects (~11% of total)*	Boxcox transformation tend to produce stationary forecast *7 out of 10 random samples from 81 samples*
Modelling setup	Arima() method error (CSS-ML, CSS, ML)	Use TryCatch() function to run an alternative method in event of an error	

Datasets

- Train: 2015-01 to 2018-12 (48 data points)
- Test: 2019-01 to 2019-12 (12 data points)
- Full: 2015-01 to 2019-12 (60 data points)
- Holdout: 2020-01 to 2020-02 (2 data points)



Modelling setup

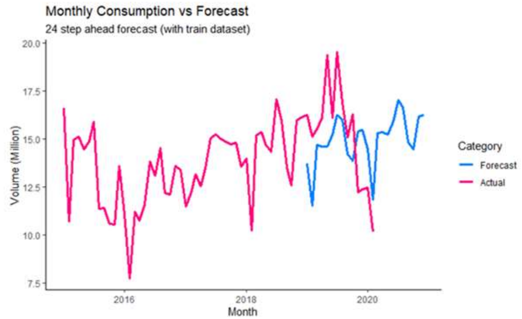
Arima() function → 63 combinations

p = (0,1)	d = (0,1)	q = (0,1)
P = (0,1)	D = (0,1)	Q = (0,1)

auto.arima() function

→ 24-step ahead forecast

```
tryCatch({
mod <- Arima(train)
}, error=function(e){
 tryCatch({
 mod <<- Arima(train,  method = "CSS")
}, error=function(e){
 tryCatch({
 mod <<- Arima(train, method = "ML")
}, error=function(e){
 mod <<- auto.arima(train) })
```



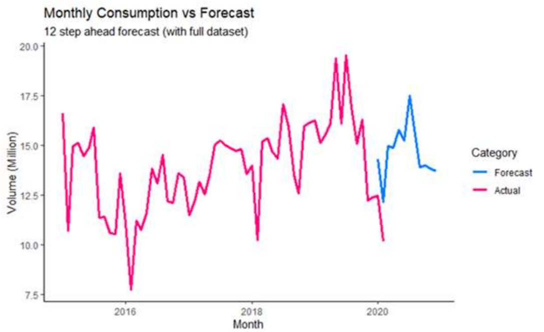
Model Performance

Selection order:

Residual → Top 5 smallest AIC → Top 3 smallest BIC → Smallest RMSE (train-test)

Model Output

Best Model → 12-step ahead forecast



Evaluation

<u>Error distribution</u>

- test set MAPE approx. same range as train set MAPE except for a few large outliers
- AIC/BIC similar with ~350 – 600 range

<u>Model reliability</u>

- 92% accuracy on train set
- 85% accuracy on test set
- 133% on holdout set

Overall reliable and robust but may need manual adjustments according to macro economy outlook

Inventory Analysis

Multi-echelon Modeling

Computation Outcome

Level 1: Regional Distribution Centers (RDC)

FG SA RM

001 AD1 UD1

Warehouse Parameters (185930)

	001	AD1	UD1
Storage status:	Yes	No	Yes
Safety stock:	0		5
Leadtime:	4		8
Fixed cost*:	0.869		0.869
Holding cost#:	5.46		36.55

Selected FGs for illustrations purpose

185930

226028

Historical demand 60 data points → Arima Modelling process → Forecast demand (12 periods) → compute → Demand Deviation (MADV)

Cost Information

Compute parameters (FG): ROP, Safety Stock, EOQ

Safety stock + forecast demand

Expected demand and MADV from all RDC

Warehouse 001	185930	226028
EOQ:	6 units / 7 days	2 units / 84 days
ROP:	123 units	8 units
Safety Stock (SL = 97%):	121 units	8 units
Demand deviation	32 units	12 units
Forecast demand:	231 units	2 units
Expected demand^:	352 units	15 units
TTL expected demand (both RDC)	703 (001 352 + UD1 352)	62 (001 15 + AD1 47)

^ expected demand = calculated safety stock + forecast

Level 2: Global Central Warehouse (GDC)

FG

GD1

Warehouse Parameters	185930	226028
Storage status:	Yes	Yes
Safety Stock:	34	0
Leadtime:	2	0
Fixed cost:	0.869	0.869
Holding cost:	8.57	3.52

Compute parameters (FG): ROP, Safety Stock, EOQ

Safety stock + forecast demand

Expected demand and MADV from GD1

Warehouse GD1	185930	226028
EOQ:	8 units / 4 days	4 units / 23 days
ROP:	165 units	0+
Safety Stock (SL = 97%):	161 units	0
Demand deviation	60 units	14 units
Expected demand^:	865 units	62 units

+ since leadtime is 0, it is assumed that restock is immediate

Network Analysis Modeling *(subgraph)*

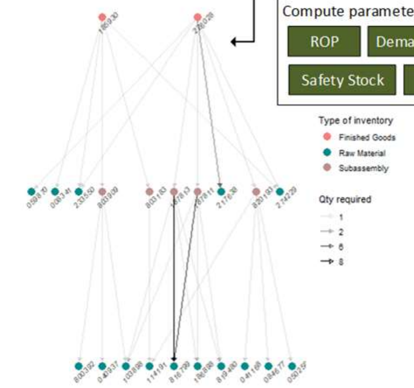
Level 3: Production Warehouses

RM SA

BT1 MF1 VN1

BoM Network Parameters (185930 & 226028)

	BT1	MF1	VN1
Prod status:	Yes	Yes	No
No. of materials:	10	143	
Finished goods:	0	2	
Subassembly	0	6	
Raw material:	10	135	



Compute parameters (BoM): ROP, Demand, Safety Stock, EOQ

Evaluation:

Multi-echelon Model

Benefits
1. Optimize inventory volume and cost at all levels of the supply chain
2. Account for safety stock parameter at RDC (if not planned)

Limitations
Cost used for computation is arbitrary (*arbitrary fixed cost; #holding cost assumed to be 10% of inventory value). Hence, computation may not reflect the real situation

Network Analysis Model

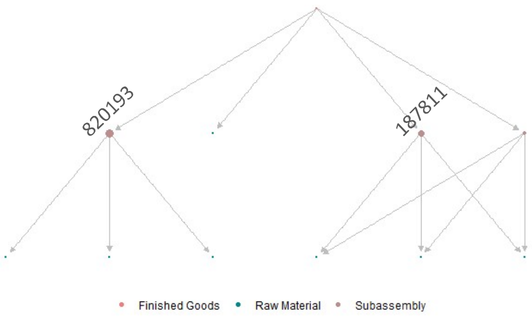
Benefits
1. Projections of expected (real) demand from upstream, hence more accurate than forecasting consumption at RM level
2. Benefit operations with network theory

Limitations
1. Huge computational expense required to calculate the required quantity for the entire BoM of a single RM
2. RM and SA sold as merchandise in RDC must be considered separately

Network Analysis Insights

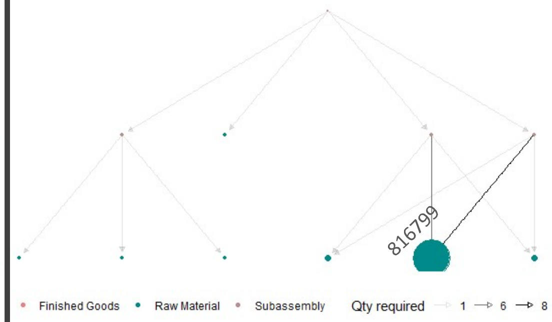
Single BoM

Centrality – Identify critical **subassembly** products



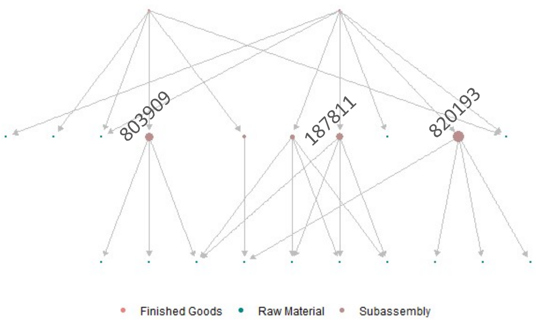
In-degree – Identify critical raw materials (involvement)

Strength – Identify critical **raw materials** in terms of degree of involvement and required quantities

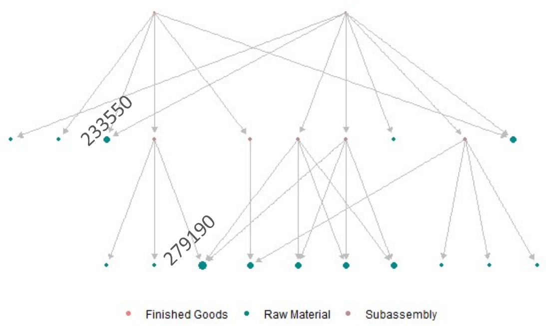


Aggregated BoM

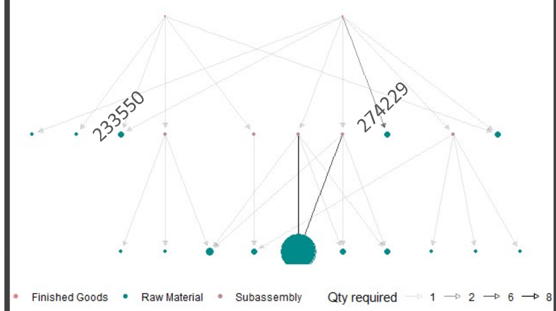
Centrality – Identify critical **shared** subassembly products



In-degree – Identify critical **shared** raw materials (involvement)



Strength – Identify critical **shared** raw materials (involvement + quantity)



Operational Implications

1. Visualization of BoM compositions
2. Priorities material planning on critical components (subassemblies and raw materials)
3. Identify affected high level products given missing raw materials to mitigate risk
4. Incorporate with Multi-echelon model for more accurate planning on the raw materials and subassemblies

Evaluation and Conclusion

Benefits	
Reduce inventory volume	Optimize inventory at all warehouses based on considerations for external demand
Improve product mix	Forecast and planning on the SKU level
Improve service level	Account for safety stock measures in RDCs
Prevent supply shortage	Flexible planning horizon and prevent mitigation with network theory
Low cost implementation	Uses open source tools and internal data

Limitations	
Model limitations	Model assumptions may not hold
High computational expense	Takes time to run full scale analysis on predictive model and network model
Dataset limitations	Accuracy relies on data integrity
User expertise	User must have knowledge on using the tool for modifications in the future

Objectives	
85% accuracy on test and holdout set	**Partial** → 85% on test → 33% on holdout
Robust and integrated analytical process	**Met** → Applicable on all SKUs → Cater for short and long term planning

Further Research
Level 1 Arima model considered for standard raw materials. There better fit with slightly more complicated models for other types of products
Review model assumptions (i.e. EOQ model may not be appropriate for all)
Reviews model for newly released products which are excluded from the scope

End of Phase 2 Presentation