2020

MULTI-ECHELON SUPPLY CHAIN OPTIMISATION WITH TIME SERIES MODELLING

CLIENT: PEPPERL + FUCHS PTE LTD

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Contents

1.0 Executive Summary

Pepperl + Fuchs Pte Ltd (P+F) is a German manufacturer of electronic sensors and interface modules. Serving various regional markets with an enormous product portfolio, the company manages a highly complexed supply chain. To address the numerous concerns of its supply chain, P+F's management has initiated the "Supply Chain Excellence" project (SCE), with the objective of revamping the supply chain operations through a series of cost reduction and performance improvement efforts.

One of the key challenges is to maintain an optimal level of inventory that would keep inventory cost low while still fulfilling customer orders in a timely manner. This project, sponsored by the Supply Chain Department, is thus a part of the SCE initiatives to focus on tackling the above concern.

Through an analysis of current inventory situation, a univariate Time Series predictive model would be built to forecast the future demand of multiple products. This model will be incorporated in the framework of a multi-echelon model to derive the optimal level of safety stock for all inventories in various stages of the supply chain. A network model will be employed at the lower stream to support demand computations. The establishment of this process will enable P&F to maintain an ideal level of inventory with the desired product mix in all warehouses in both the short and the long-term horizon.

The deliverables of this project would be:

1. A predictive model to forecast demand at SKU level
2. A process to define safety stock for make-to-stock products with a multi-echelon model approach
3. A proposal for operational improvements based on insights from the network model

2.0 Introduction

This section will provide an overview of P+F's supply chain structure and associated challenges that this project will attempt to address.

2.1 Client Background

The Supply Chain Structure

The below description is illustrated in Appendix A

P+F is a German manufacturer headquartered (HQ) in Mainheim, with a regional HQ in Singapore. It operates 3 manufacturing plants[1] in South East Asia – Bintan (BT1), Singapore (MF1) and Vietnam (VN1) respectively. Together, these 3 plants accounts for more than 90% of P+F's total production worldwide.

The products produced by the manufacturing plants are stored in the Global Central Warehouse (GDC) located in Singapore. The GDC serves 3 major regional distribution centres (RDC) located in Germany (001), Singapore (AD1) and USA (US1). The RDCs in turn distribute products to other smaller DCs, and at the same time, act as direct contact points to external customers.

As the central warehouse, GDC would be the sole intermediary between manufacturing and RDCs. In practice, however, direct transfer between manufacturing plants and RDCs are not uncommon for all types of products where the cost justifies, complicating the supply chain.

These are the 3 broad categories of products that make up P+F's inventory assets – raw materials (RM), semi-finished goods (SFG)[2] and finished goods (FG). The RM and SFG are primarily stored in the 3 manufacturing warehouses[3], while the FG are stored in GDC. Inventory are kept to a minimum in the RDCs to minimise storage cost.

Current Situation

In recent years, P+F has been challenged by **rising inventory storage cost** resulting from the build-up of **excessive inventories**. Yet P+F has not seen improvements in delivery reliability to external customers but suffered from frequent **delays and failures of service agreements**.

One implication is the **poor inventory mix**, whereby there is insufficient inventory of product in high demand, coupled with an oversupply of products with low demand. The probable cause points to the **lack of a reliable demand forecast process**, and consequently inappropriate safety stock strategy, among others. Therefore, it calls for the necessity to implement a systematic forecast and planning process in order to alleviate the current disequilibrium supply and demand situation and optimise inventory planning.

2.2 Project Objectives

SCE is a company level project involving cross functional teams from several departments.

As shown in Figure 1, one objective of SCE is to **reduce the inventory volume** and affiliated **inventory value** to the targeted amount by 2025, while aspiring to **improve the product mix**

[1] Used interchangeably with the term production warehouse.
[2] Used interchangeably with the term subassemblies.
[3] Some SFG and RMs are sold in 001 as merchandise. They will not be the subject of this project.

to **enhance delivery performance** in RDC warehouses. This objective is to be fulfilled by a task force team in the Supply Chain department, also the sponsor for this internship project.

This project will focus on both the **interim** and **long-term goal** (to be achieved by 2025) to reduce inventory volume and enhance product mix by **developing a predictive models on the SKU level**[4] in a multi-echelon framework to establish a **process to improve planning** in an integrated supply chain.

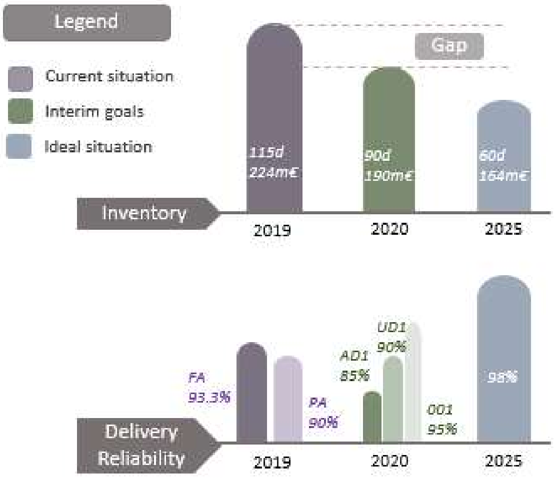

Figure 1 SCE Project goals

2.3 Project Plan

This project is divided into 3 sections:

1) **Data cleaning** – to select a bill of materials (BoM) sample and a representative group of SKUs and clean the historical consumption data to be used for modelling
2) **Predictive modelling** – to develop and select the best performing time series (ts) model (SKU level) amongst machine learning and traditional algorithms
3) **Inventory analysis** – to compute the optimal inventory management parameters in each stages of the supply chain using the multi-echelon model approach. A network model will be employed to calculate materials required in a BoM.

2.4 Success Criteria

The success of the project will be measured as follows:

a) On an aggregated level (i.e. total of all SKUs in the dataset), the outcome of the predictive model must have at least **85% accuracy** on both the test and holdout dataset
b) The integrated inventory management process is **robust** to be extended to **all regular SKUs** in the future with logical calculation process that would be accepted by the sponsor

2.5 Project Deliverables

The project deliverables will be as follows:

a) A **predictive model** to forecast demand at SKU level
b) A **process to define safety stock** for make-to-stock products with a multi-echelon model approach
c) A proposal for **operational improvements** based on insights from the network model

[4] SKU is also known as item numbers in P+F context. The terms will be used interchangeably.

3.0 Data Preparation

There are **two sets of data** required in this project. The first is a set of **historical consumption** data to be used for the **multiple univariate time series predictive modelling**. The second is a set of **aggregated BoMs** to be used for developing the **network model**. Since the preparation process of the latter is a subset of former, this report will address only the cleaning process of the former.

The data preparation process is summarised in Figure 2[5]. It will be referred to and described in detail in the subsections of this topic. The dataset is **internally acquired** from P+F's relational database.

At this stage, two key activities, namely **data cleaning** and **data selection**, are carried out simultaneously. This is due to the sheer size of the number of SKUs produced by P+F that make it infeasible to analyse all SKUs in this project. Thus, this project will focus on using a **smaller subset of SKUs** to build and perform model selection. The subset is selected based on a combination of data exploratory outcome (to be discussed in section 3.1) and business objective considerations (Appendix B documents the selection process).

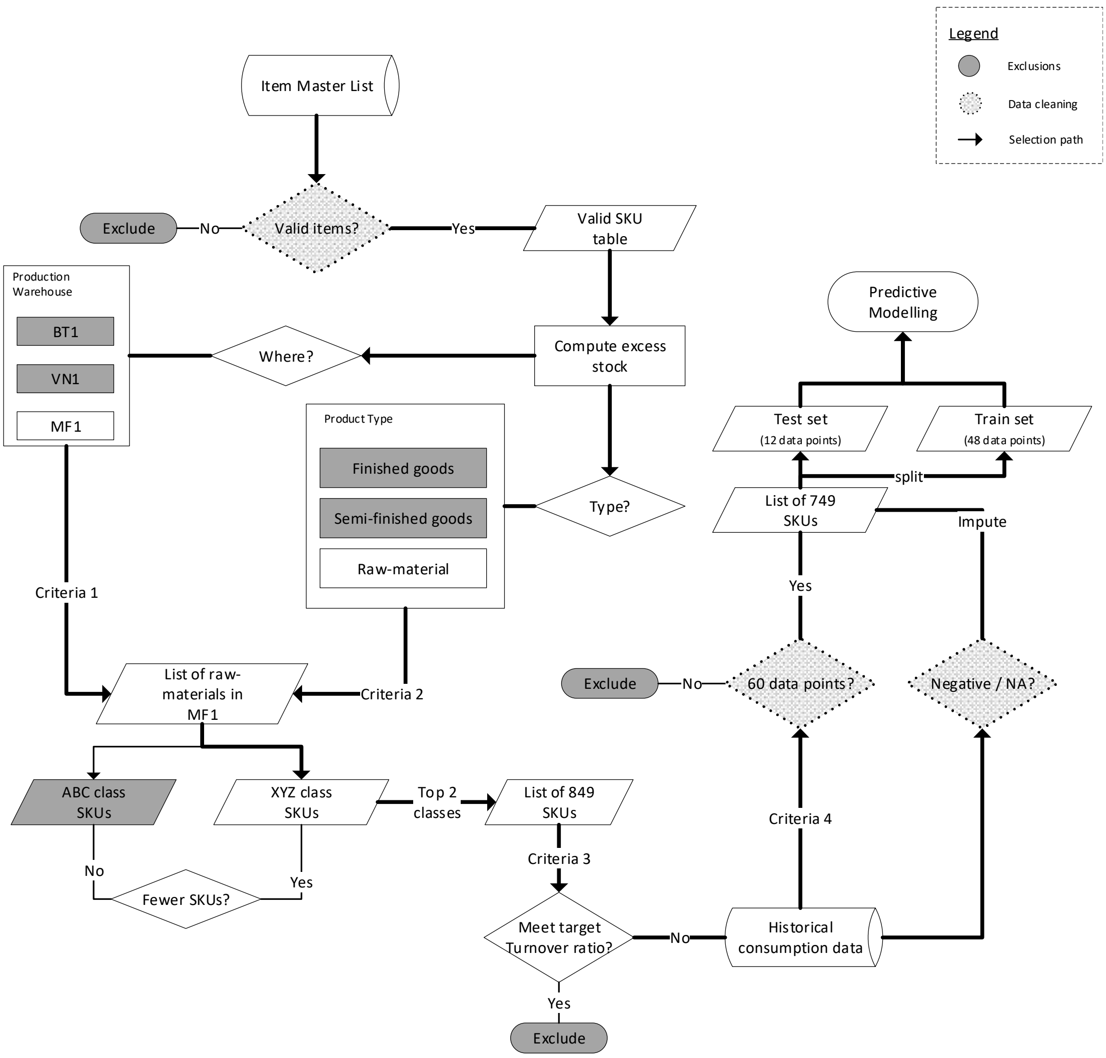

Figure 2 Data preparation process flow

5 The data cleaning process for the BoM will stop at the first step – to remove invalid items.

3.1 Data Exploration

Data exploration is performed with the intention to **highlight outstanding issues** and **identify bottleneck** in the inventory management process.

Findings (1) – lack of demand forecast

There is a general lack of accurate demand forecast as shown in Figure 3, where there is a huge gap between aggregated demand and forecast in the two warehouses. Forecast is available for only a small proportion of products and the current practice is commonly naïve rolling average.

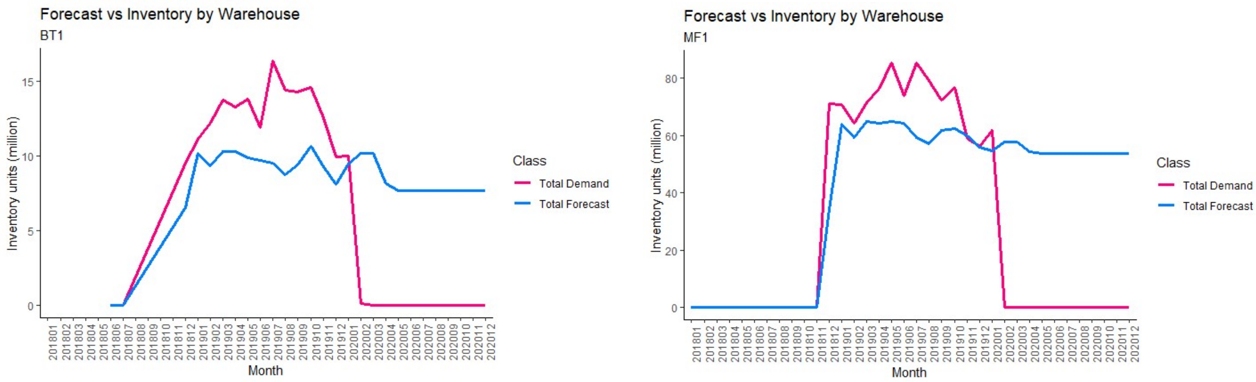

Figure 3 Forecast vs demand for selected periods

Findings (2) – Large number of SKUs per warehouse

As shown in Figure 4, there are more than 10k active SKUs in each warehouse and the same SKU is managed differently in each warehouse, such as different policies guiding safety stock and forecast settings. Therefore, modelling must be done on the warehouse and SKU level to make business sense (i.e. the same SKU should have a separate model per warehouse where it is stored).

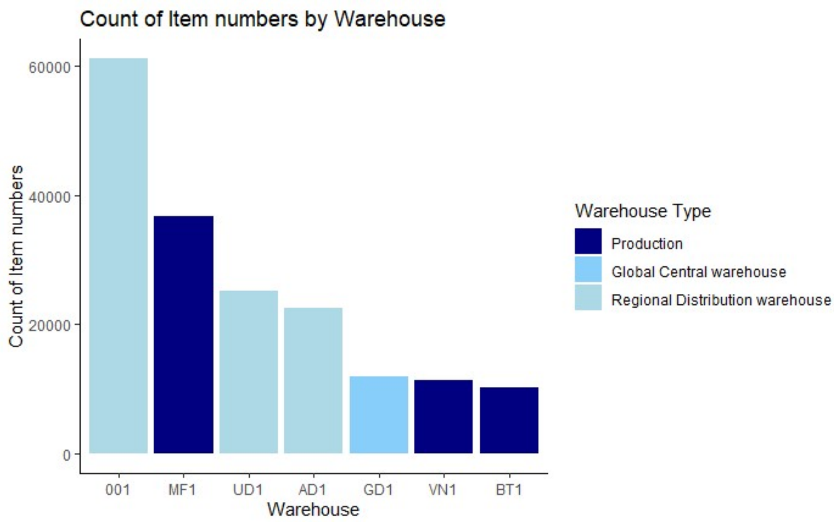

Figure 4 SKUs per warehouse

3.2 Data Cleaning

There are **two levels** of data cleaning.

Firstly, the data is **filtered at the item master level** to select only the **valid SKUs**[6] based on business definitions. SKUs labelled such as customised or pilot products, phase-in (i.e. unreleased) and phase out (i.e. expired) products are not taken into considerations in this project.

Following the initial selection process described in Appendix B, the historical consumption (i.e. demand) data of the 849 SKUs are extracted from the database. The consumption data is cleaned as follows:

a. Filter for **60 data points** from **2015-01 to 2019-12 on monthly basis**[7]. 100 SKUs that are released after 2015-01 are removed. The remaining number of SKUs is **749.**
b. **Missing data** are a result of lack of record (i.e. no consumption in a month). They are replaced with 0.
c. Data points with **negative consumption** value are treated as "NA" and i**mpute** with the time series dedicated *na.Interp()* function from the *forecast* R package[8]. Negative values are a result of business practice for data entry. The same field is used to record both consumption and return for an SKU[9]. It is thus difficult to determine the exact amount of consumption in this scenario. Further, there are a total of 67 incidence out of 44,940 (0.001%) rows, which would not have significant impact on overall data quality.

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[6] Valid is defined as active, standard and fully released make-to-stock products. All subsequent reference to SKUs will solely refer to these products.
[7] Though daily consumption data is available, the monthly data point would better fit the business context since inventory is always reviewed at an aggregated level
[8] This method is found to be the best among available time series imputation methodology according to Moritz et al., 2015
[9] Return refers to such cases whereby units of stock are taken out for quality check or other similar purpose before returning to shelf. The exact transaction cannot be traced due to system limitations.

4.0 Predictive Modelling

The modelling process is conceptualised as shown in Figure 5.

Firstly, the dataset containing 749 SKUs, with 60 data points of monthly consumption from Jan'2015 to Dec'2019 is demarcated sequentially by date into train and test datasets. The train dataset consists of the first 48 data points, while the more recent 12 data points would be the test dataset.

Additionally, 2 data points with the most recent date starting in Jan'2020 would be the holdout set, measured against a 12 step ahead forecast generated by the final selected model predicted using the full dataset.

The train dataset, on SKU level[10], would be analysed using 4 modelling approaches consisting of both **machine learning** and **traditional algorithms** appropriate for time series forecasting (Wagner et al., 2011). The result is validated using the test dataset. A combination of indicators is used to determine both model validity and accuracy to determine the best model for each SKU. With the best approach (i.e. model), a 12-month demand forecast would be generated using the full dataset of 60 data points. The forecast would then be used for further analysis on inventory management that will be discussed in Section 5.0.

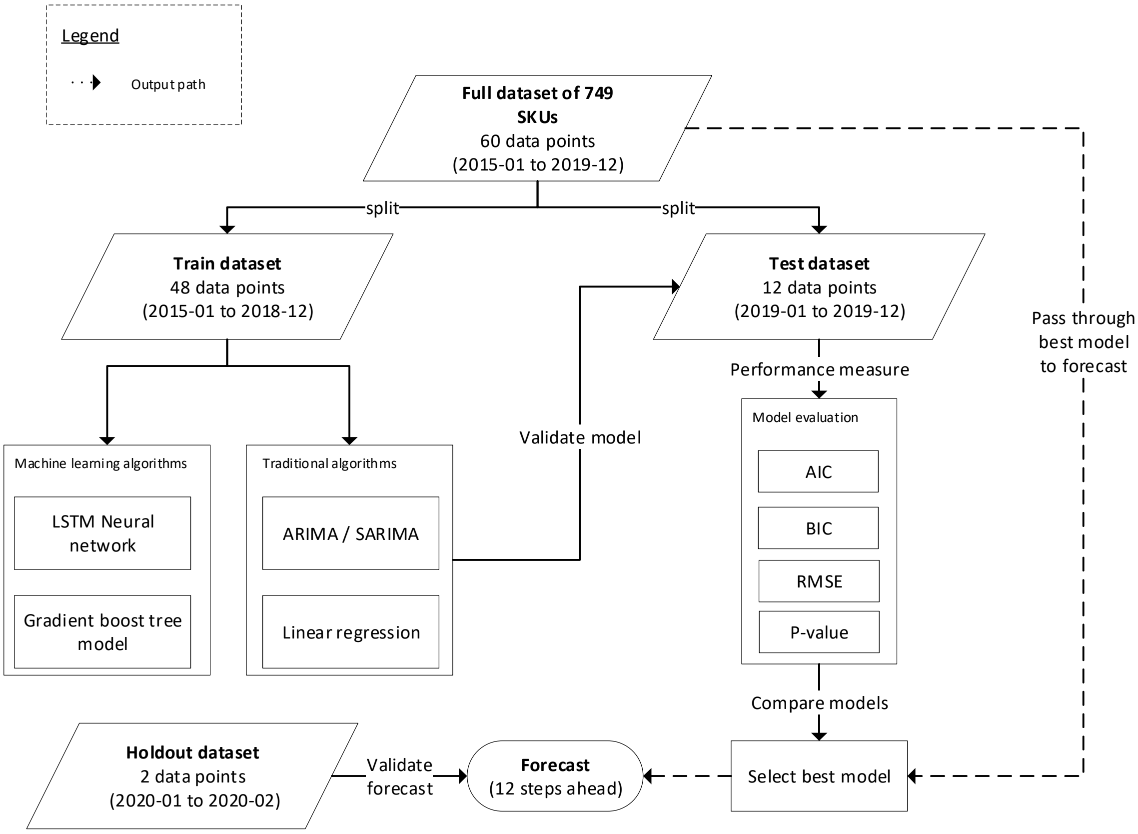


Figure 5 Modelling process

[10] Initially, the idea was to group the SKUs by their statistical characteristic and develop a model for each of the groups. However, upon analyzing the consumption histories of the SKUs as time series, it is difficult to find common ground (in terms of time series characteristics) among the SKUs. Therefore, a customized model will be built for each SKUs with fully automated model evaluation process

4.1 Modelling Objectives

The modelling objective is to develop a **reliable modelling process** to predict the demand at SKU level. Since the model is expected to perform also on datasets that are not studied in this project, rather than accuracy, the **robustness of the process takes priority**. The outcome will be used in two ways:

1. **Standalone model** – the predictive model can be used to forecast individual SKUs at every stage of the supply chain. The outcome is used to compute the inventory management parameters at each stage.
2. **Integrate with multi-echelon model** – the predictive model is used to forecast individual SKUs for FGs at only the upper stream of the supply chain. The outcomes will be the drivers to compute for demand of RM or SFG at the lower streams.

Both approaches will help to prevent overstocking and improve the inventory mix, thus fulfilling business objective of this project as discussed in section 2.2.

As the datasets are univariate time series, it is necessary to adopt **time series specific approaches**. Therefore, 4 typical time series algorithms are considered and will be discussed further in the proceeding sections.

4.2 Time Series Data Analysis

749 ts objects (train set) are analysed. Since it is not feasible to analyse manually, functions from R packages are employed to **extract the relevant components** as shown in Table 1. While the methods may not be 100% reliable[11] and conflicting at times, it could provide some directions towards the modelling approaches.

Dimension	R package	Function	Outcome	
Seasonality	forecast	tbats()	TRUE	20%
			FALSE	80%
Trend	forecast	ets()	A	9%
			N	80%
			M	11%
Stationarity	tseries tseries	kpss.test() adf.test()	difference stationary	10%
			stationary	17%
			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%

Table 1 Components of time series data

[11] Since not all ts objects are normally distributed.

4.3 Machine Learning Algorithms

<u>Algorithms</u>

Two time series specific ML methods are used:

1. Gradient boost linear tree model (GBM) - *xgboost* R package
2. LSTM neural network model - *Tensorflow* and *Keras* R packages

<u>Approach</u>

749 time series objects are **grouped based on similarity in components** analysed in Section 4.2. A customised model for each algorithm will be developed for each group.

<u>Set-up</u>

4 ts objects are selected based on the **seasonality and number of differences**. They are used for an **initial trial run** for developing LSTM models as shown in Table 3. The datasets are **transformed** by differencing accordingly and scaled to fit the model.

The models are tuned for the below parameters on a grid search as shown in

Table 2:

GBM	LSTM
Lag features	Number of layers
Optimiser	Learning rate
Iterations	Optimiser
	Activation function
	Dropout rate

Table 2 ML tuning parameters

<u>Outcome</u>

As can be seen in Table 3, the outcome from the LSTM model is generally **unsatisfactory** as the predictions simply **shift the original curve to the right** by 1 time-unit. A couple more random ts objects with the same features are tested and almost all arrived at similar outcomes. The outcome for GBM model suffers similar problems.

The reasons for this may be due to:

a. **Insufficient data points** – 48 data points on train set is too little for the ML algorithms to learn efficiently and pick up the trend
b. **Sensitivity to dataset** – the algorithms are highly sensitive to changes in datasets. Since the features were rough gauges, transformation may not have produced stationary data and hence affected the output

As such, ML methods are **not appropriate and will not be used** in this project.

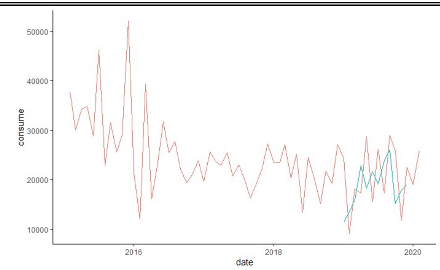
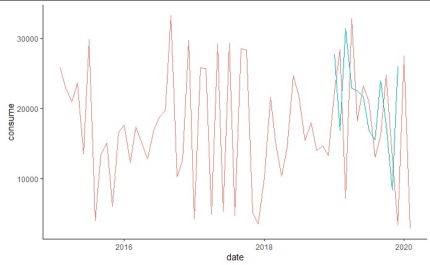
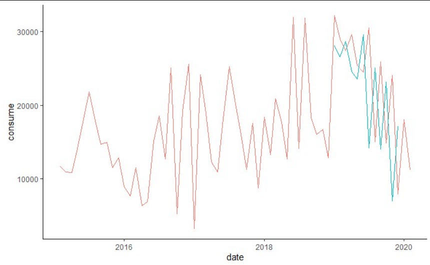
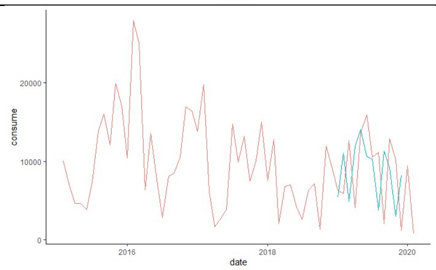
Model	SKU Index	Seasonality	Difference	Outcome
1	31	No	1	
2	94	No	0	
3	601	Yes	1	
4	229	Yes	0	

Table 3 LSTM models

4.4 Statistical Algorithms

<u>Algorithms</u>

Two common statistical methods are used:

1. Autoregressive integrated moving average (ARIMA) with *Arima()* and *auto.arima()* from the *forecast* R package
2. Regression with *tslm()* function from the *forecast* R package

<u>Approach</u>

749 time series objects are put in a **loop** that applies **a respective model on each ts object**. No transformations are made to the datasets[12].

Regression Models

Regressions models **cannot be applied** on all time series. Simple regression produces stationary outcome, while polynomial trend 3 and 4 throw errors on almost all the ts objects. Multiple, Polynomial trend 1 and 2 produced outcomes for a negligible proportion of the ts objects as shown in Table 4. Hence regression model **will not be used** in this project.

Regression	Outcome	Dataset with Outcomes
Simple	Poor fit	
Multiple	Not applicable to all ts	2.7%
Polynomial trend 1	Not applicable to all ts	1.6%
Polynomial trend 2	Not applicable to all ts	6.3%
Polynomial trend 3	Poor fit	
Polynomial trend 4	Poor fit	

Table 4 Regression model outcomes

ARIMA Models

For ARIMA models, **64 models** are considered:

- 63 models of all combinations of p,d,q,P,D,Q with maximum level of 1 using the *Arima()* function. The reason for this is to **avoid complicated models** and most of the ts objects would require a maximum of 1 time difference as shown in Table 1. Examples will be:
  - Arima(1,0,0)(0,1,0)
  - Arima(1,0,0)(1,0,1)
- 1 model using *auto.arima()* function

The ARIMA method proves to be the **best and most robust** method. The outcome will be evaluated in the Section 4.5.

One challenge encountered is that the *Arima()* function tend to produce error due to the fitting method ("CSS-ML", "ML", "CSS")[13]. Some ts object failed at the default method on some models, while others, though very rare, would fail all the methods. Thus, to ensure that the modelling process is able to run without the need for manual intervention and debugging, the *trycatch()* function from the *base* R package is employed to provide alternatives in case of failure of any of the methods. In the event that all methods failed, the *auto.arima()* function will be the last safety measure. A sample code is shown in Figure 6.

[12] See Appendix C for justification for not transforming the datasets in the ARIMA modelling process.
[13] CSS minimizes the sum of squared residuals; ML maximizes the log-likelihood function. the ARIMA model. The default CSS-ML mixes both methods: CSS is run followed by ML (package “forecast” CRAN document).

```
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) })
```

Figure 6 Sample failure prevention code for ARIMA model

4.5 Performance Evaluation

<u>Model Selection</u>

The **best model**, out of 64, is selected for each ts object based on the following criteria:

1. **P-value of residuals**[14] must be **greater than 0.05** (i.e. white noise) – to eliminate insignificant model under a standard 95% confidence level
2. **Top 5 smallest AIC** –a model is closer to the truth
3. From the 5, select **Top 3 smallest BIC**[15]
4. From Top 3, select the option with the **smallest difference** between train and test set **RMSE** – to minimise model overfit

<u>Error Evaluation</u>

Figure 7 show the **error distribution**:

1. **MAPE** – The distributions of train and test sets are very similar. Though there are a few huge outliers for the test data, the chance of severe overfitting is generally small
2. **AIC/BIC** – The distribution of AIC and BIC generally agrees with each other, with the range spreading from ~350-600

Though individual models may suffer from overfitting or poor model fit, the overall outcome is more important in this project since the objective is to establish a reliable process that would work on majority of the products and individual model accuracy is of less concern.

<u>Outcome Evaluation</u>

Figure 8 shows the outcome for all ts objects on an aggregated level. Forecast using the train and test datasets are generally lower than actual consumption with an overall **14.8% error** possibly due to the dip from 2015 to 2016, which meets the project objective. However, the error for the hold out set forecast is way too high as shown in Table 5. The model has **correctly reflected the year on year seasonality and overall pattern** but was not able to catch the rapidly declining trend towards end of 2019. The holdout dataset may also be affected by the impact of COVID-19. Therefore, though the model will still be able to perform in the long run, forecast in the short term for year 2020 may need to be manually adjust towards (~20%) to reflect the current situation.

[14] Lungjung box test using the *Box.test()* function rom the *stats* R package

[15] "a lower AIC means a model is considered closer to the truth" and "a lower BIC means that a model is more likely to be the true model" (Dziak, 2012). In general AIC and BIC should agree with each other, but in case they do not, BIC is prioritised to get closer to the true model.

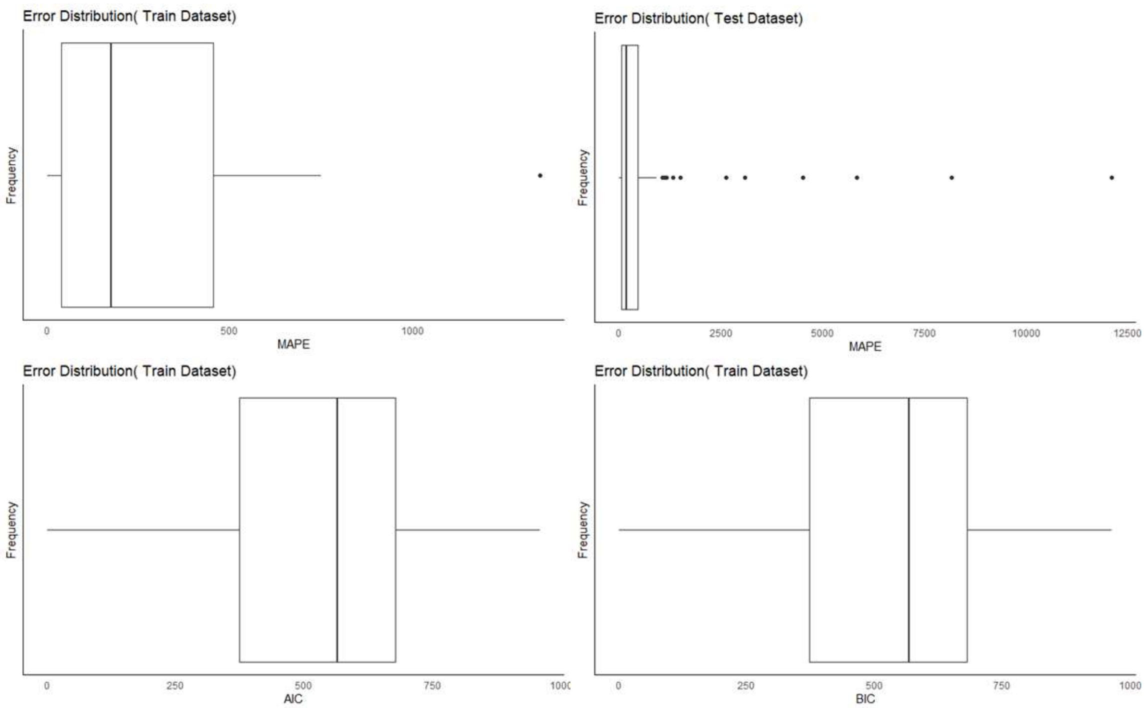


Figure 7 Distribution of error from ARIMA models

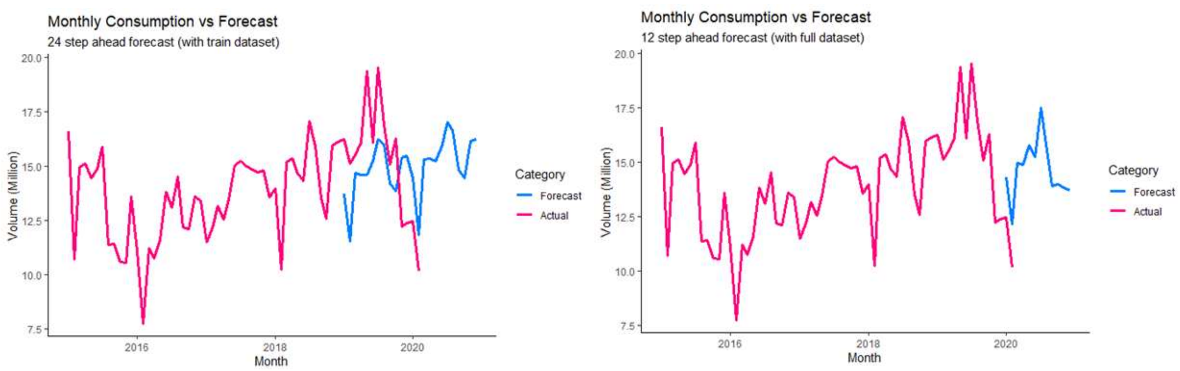


Figure 8 ARIMA modelling outcome

2019 *Test set with train set model*			
Month	**Forecast**	**Actual**	**Accuracy**
1	14	16	-16%
2	12	15	-24%
3	15	15	-5%
4	15	16	-9%
5	15	19	-25%
6	15	16	-5%
7	16	20	-17%
8	16	17	-5%
9	14	15	-6%
10	14	16	-15%
11	15	12	26%
12	15	12	25%
Absolute Average			14.8%

2020 *hold out set with full dataset model*			
Month	**Forecast**	**Actual**	**Accuracy**
1	29	12	131%
2	24	10	136%
Absolute Average			133%

Table 5 ARIMA model error rate (million units)

5.0 Inventory Analysis with Multi-Echelon Model

5.1 Introduction

Some supply chain specific concepts will be introduced in this Section.

A multi-echelon system evolved from single-echelon models, where each stage of the supply chain is grouped as echelons. A stage can be understood as a level in the supply chain where materials are stored and moved (Grob, 2018). In P&F's case, there are 3 stages in the supply chain, consisting of RDC, GDC, and manufacturing warehouses from the upper to the lower stream, thus a **3-echelon distribution network**. It is a **general system** whereby there are no restrictions on material flow from stages to stages as shown in Appendix A. Only the last echelon (RDC) will fulfil external customer demand.

Given the time frame of this project, only the **most basic form** of the multi-echelon model will be studied. In this model, the optimisation of a product in a single echelon is assumed to be an **Economic Order Quantity (EOQ) model** (to be introduced in Section 5.2), given non-perishable inventories. In the multi-echelon system, each stage functions like an EOQ model. The output from the upper level echelon become the input for the lower level echelon.

This concept will be the framework for the proposal of an integrated inventory optimisation solution for P&F. The objective to compute the **optimised level of safety stock** per warehouse for each SKU for all product types (FG, SFG, RM). The predictive model discussed in Section 4.0 and a network model (to be discussed in Section 5.3) will be incorporated into the frame work.

An overview of the framework can be found in Appendix D.

5.2 EOQ Model Assumptions

The EOQ model is a common supply chain optimisation strategy that "prescribes the optimal order quantity for organizations that minimizes the total ordering and holding cost under a relatively restrictive set of assumptions" (Choi , 2014).

The model assumes:

1. A constant deterministic annual demand, D
2. Fixed cost per order, k
3. Known and constant Leadtime for receiving orders, L
4. Unit holding cost, h
5. No stockouts allowed - stocks are always available to fulfil incoming orders

5.3 Model Input – Expected Demand and Other Parameters

An EOQ model is computed **at different levels for different product types** depending on their storage status. SFG and RM are generally kept only in manufacturing warehouse, and their consumptions depends on the demand of FG composed of them. EOQ models for these SKUs will be calculated with the help of a network model. This will be discussed in Section 5.3. The input parameters are summarised in Table 6.

Parameter	Status	Stage	Products	Type
Demand, D	Forecast by predictive model	RDCS	FG	Calculated
	Sum of demand from RDCs	GDC	FG	Calculated
	Demand of FG from GDC	Manufacturing	SFG, RM	Calculated
Standard deviation of demand, sd	3 options: 1) Forecast by predictive model 2) Use system calculated value[16] 3) user defined value	All warehouses	FG, SFG, RM	Depends on user requirement
Fixed cost, k	Assume to be the unit price of each SKU	All warehouses	FG, SFG, RM	Given
Leadtime, L	Available	All warehouses	FG, SFG, RM	Given
Holding cost, h	Assumed to be 10% of k	All warehouses	FG, SFG, RM	Calculated
Service Level, α	Set as 97%[17]	All warehouses	FG, SFG, RM	Given

Table 6 EOQ model input parameters

5.4 Model Output – Optimization Parameters

The model optimises 4 parameters as shown in Table 7 at the SKU level in each stages of the multi-echelon network.

Parameter	Computation Method	Unit	Sponsor Interest
EOQ	$\mathrm{Q} = \sqrt{\frac{2kD}{h}}$	Per order	Good to have
Reorder interval	$u = Q/D$	Days	Good to have
Saftey Stock, ss	*SS()* function in *SCperf* R package	At any instance	Critical
Reorder point	$\mathrm{ROP} = \left(\frac{D}{365} \times L\right) + ss$	Per unit	Good to have

Table 7 EOQ model output parameters

5.5 Role of the Network Analysis Model

While demand for FG in the RDCs can be forecasted by the predictive model, the demand for the SFG and RM are not so straight forward. These types of materials are characterised by very long lead times (i.e. up to a few years), which calls for a long planning horizon. A simple forecast using the predictive model at the manufacturing warehouse based on their past consumption is a quick solution, but accuracy will improve greatly if a **top-down approach** is employed since their demand is driven by the demand for FG for which they produce. By considering only the demand for FG, the forecasting scope can be reduced, which translates to reduction in planning resources. Efforts can be concentrated on model tuning for FG and cascade the external demand down the supply chain.

To compute the demand for SFG and RM, the **Bill of Materials (BoM)**[18] must be considered. In P&F, it is very difficult to analysis the BoM due to system limitations and the **sheer size** and

[16] Monthly standard deviation is available in the inventory management system used by the client company.
[17] Required by sponsor
[18] A BoM or product structure is "a diagram that lists all the components and parts required to produce one unit of a finished product, or end part. It is often represented as a tree structure with hierarchical relationships among different components and materials." (Cinelli et al., 2017)

complexity of the relationships between products. A network model would help to address these concerns by offering benefits such as visualization capability of BoM structure and ease of computation of required quantity of RM and SFG in an aggregate BoM network. The network theories also provide insights and implications for materials planning. These recommendations are attached in Appendix E.

<u>Approach</u>

For demonstration purpose, an aggregated BoM network is constructed using **2 finished goods**, selected based on a randomly selected shared raw material. The **directed** network contains 207 edges and 153 nodes where **each node is a material** and **each edge** are directed from the **high level** (i.e. output material) **to the low level** (i.e. input material). The entire BoM structure is shown in Figure 9.

The *igraph* R package is used for the network construction and *ggraph* and *threejs* R packages are used for visualizations.

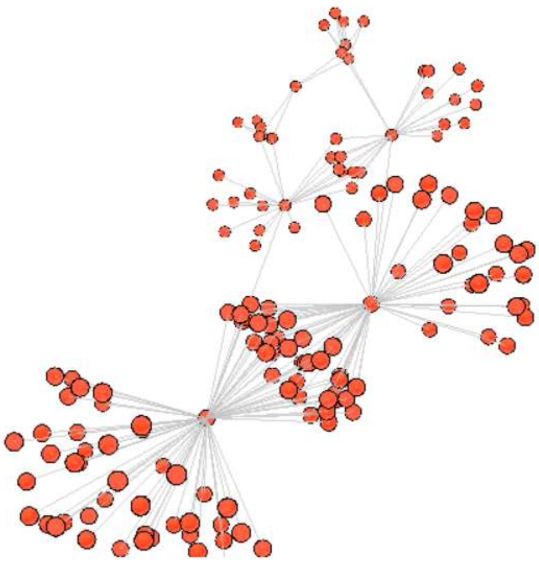


Figure 9 Network structure of sample aggregated BoM

<u>Network Attributes</u>

The edge and node attributes are shown in Table 8. These attributes can be used to make an analysis of the BoM, which will be discussed in Section 5.6.

Edge	**Node**
Qty required	Manufacturing location
BoM level	Inventory type (business definition)
Leadtime	Root Item (i.e. FG, identifier)
Root Item (i.e. FG, identifier)	

Table 8 Network attributes

Network Theories

There are 4 theories that will be useful in this project. The definitions below are taken from (Cinelli et al., 2017):

1. **In-degree** is the number of edges received by or going into a node, represents the number of product (FG or SFG) composing of a specific SFG or RM
2. **Out-degree** is the number edges directed away from a node, represents the number of SFG or RM from which the product is composed of
3. **In-strength** is the sum of weight[19] received by or going into a node, represents the overall participation of a part in the product considering both the occurrence in the BoM network in which it is involved and the required quantities
4. **Betweenness centrality** is the extent to which a node lies in the path between other node, measures the criticality of a product in the aggregated BoM network

Computation

Based on the demand for FG (i.e. root item), which has the highest level in the network, the **quantity required for the SFG and RM** can be calculated with the **in-strength property**. The below steps are taken for the calculation:

1. Create a subgraph for each FG. The materials are identified with the in-degree property:
   - In-degree = 0 → FG
   - In-degree > 0 & out-degree = 0 → RM
   - In-degree > 0 & out-degree > 0 → SFG
2. Compute the quantities required for each SFG and RM used in each subgraph (i.e. a single BoM). This can be done through a loop.
3. Sum quantities per SFG and RM in all subgraphs to obtain the overall respective required amount
4. The quantity required will be the demand for SFG and RM and an EOQ model can be calculated for each material with the same methodology as described in Section 5.2 to 5.4.

5.6 Integrated Model Demonstration

A detailed illustration of how the predictive model and network model can be integrated in the multi-echelon framework can be found in Figure 10. The descriptions are as below:

1. 2 sample FG (185930 and 226028) are selected. Starting at stage 1 (i.e. RDCs), a 12 step ahead forecast is computed using the predictive model. The sum and standard deviation of the forecast are calculated per FG. Together with other necessary input information as discussed in Section 5.3, The output parameters in Section 5.4 can be calculated.
2. The sum of forecast and calculated safety stock from all warehouses containing the respective FG are totalled and become the expected demand for stage 2 (i.e. GDC).
3. The same process for EOQ model computation is repeated for stage 2 to obtain the expected demand per FG[20] for GDC.

[19] The "weight" can be any of the edge attributes, depending on user requirements
[20] The standard deviation in this step is calculated from a forecast using the predictive model for demonstration purpose.

4. At stage 3 (i.e. manufacturing warehouses), the expected demand from GDC is used as the input value in the aggregated BoM network to compute the required quantity for each RM and SFM.
5. The same process for EOQ model computation is repeated for stage 3 to obtain the planning parameters per SFG and RM[21] for the manufacturing warehouses.

[21] The standard deviation in this step is calculated from a forecast using the predictive model for demonstration purpose. In reality, however, it is recommended to use the system calculated standard deviation or user define value for computational efficiency.

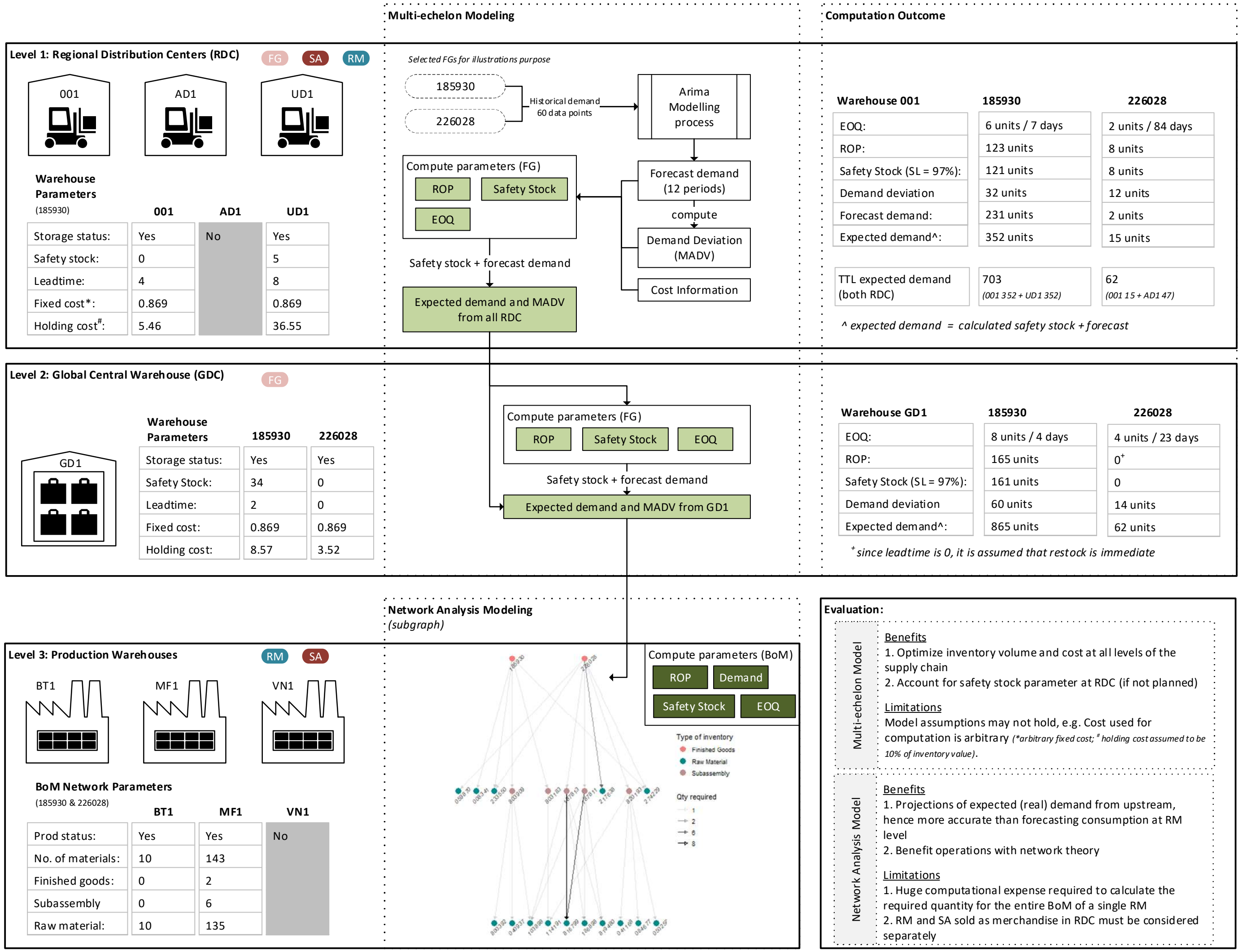


Figure 10 Integrated model demonstration

5.7 Model Evaluation and Recommendations

Benefits

The multi-echelon framework is an integrated solution to manage all levels of supply chain. It offers the benefits as described in Table 9.

Issues	Solutions
High inventory volume	Optimise inventory at all warehouses based on considerations for external customer demand to prevent bullwhip effect at lower levels of the supply chain, thus reducing risk of oversupply.
Poor product mix	Forecast and planning on the SKU level.
Late deliveries	Improve service levels by accounting for safety stock measures in RDCs[22] if no safety stocks are not planned in those warehouses.
Supply shortage	Flexible planning horizon since the predictive model can support both long- and short-term forecast. This is especially useful for RM with very long lead times.
	Operational insights from network theory to optimise resource allocation and take early actions for supply shortages (Appendix E).
Implementation	No additional cost required for implementation since it is built with open source tools and required only existing data.

Table 9 Benefits of the multi-echelon model

Limitations

The limitations of the model are summarised in Table 10.

Issues	Solutions
Model limitations	Model assumptions may not hold • the cost assumption for EOQ model is arbitrary, thus may not reflect the output parameters realistically • The EOQ model also assumes a constant deterministic demand, which may not be applicable to all products
Computational expense	It will take days to run a full-scale analysis due to the large database of the BoM dataset. The predictive model and construction the BoM network will also likely to require high computational effort depending on the number of SKUs involved.
Dataset limitations	Accuracy relies heavily on data integrity which the client company may lack at this moment.
User expertise	Users must be trained to operate the scripts should modifications be required in the future.

Table 10 Limitations of the multi-echelon model

[22] The management of RDCs are not part of the responsibility of the sponsor department

6.0 Conclusion

6.1 Objectives Evaluation

The objectives stated in Section 2.4 are evaluated as such in Table 11. The objectives are **partially met** due to poor performance of the model on the holdout set, likely due to impact by macro-economic factors. Thus, in general, the project is successful.

Objective	Outcome	Evaluation
85% accuracy on test and hold out dataset for predictive model	85 % on test set	Partially met objective
	33% on hold out set	
Robust integrated analytical process for all SKUs	Process is applicable for all SKUs	Met objective

Table 11 Objective Evaluations

6.2 Further research

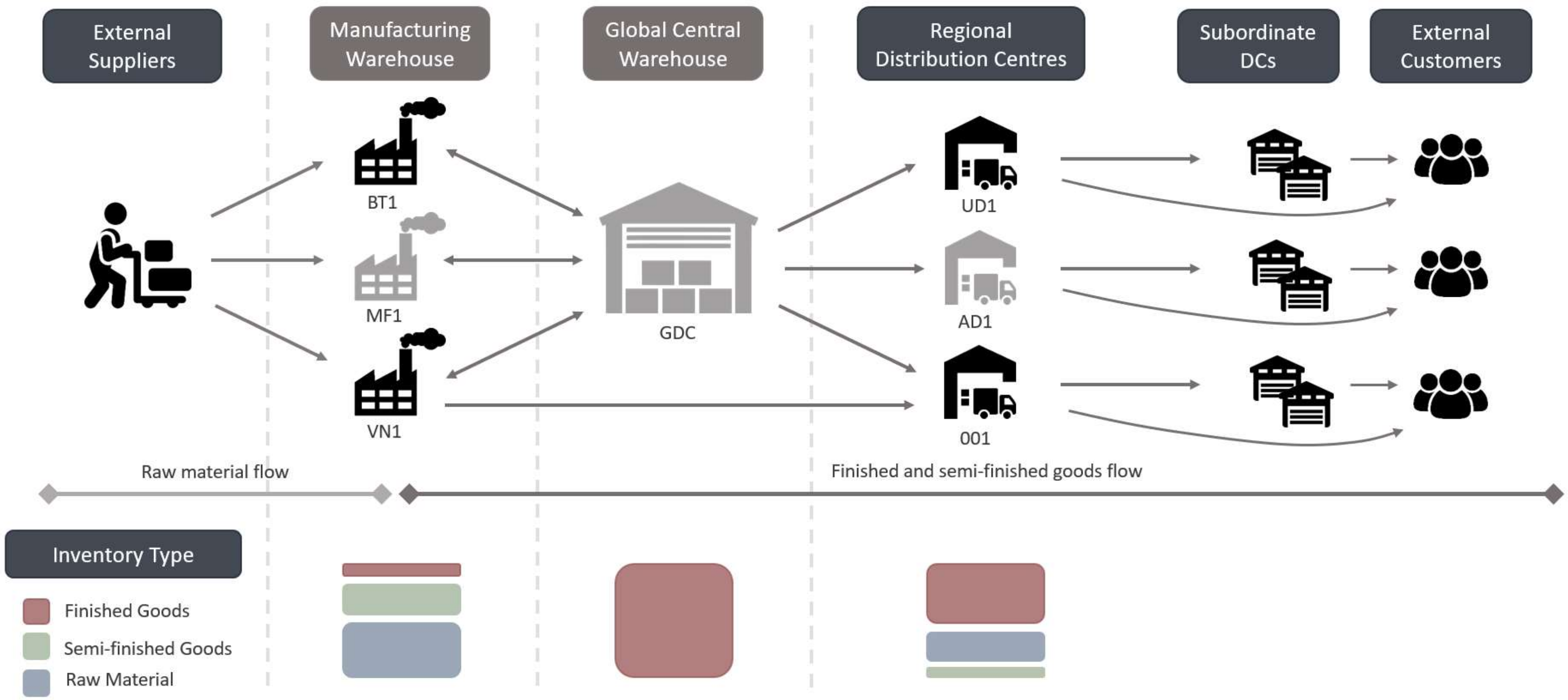
The project provided a generalised framework for both both short- and long-term solutions to optimise P&F's supply chain. Nevertheless, due to the short time span, there are still ample rooms for further improvements to refine the details of the projects. These improvements are summarised in Table 12.

Current Project	Suggested Improvements
Level 1 ARIMA models tested on RM	There may exist a better fit with slightly more complicated models for other types of products (i.e. SFG, FG)
Basic EOQ model that assumes constant and deterministic event	Review model assumptions and consider more complicated models for SKUs with stochastic demand
New released products are not considered	Incorporate forecast for new products based on similarity with existing products

Table 12 Proposals for further improvements

Appendix A

P+F's Supply Chain Structure



Appendix B

SKU Selection Process

Following business requirements, a subset of SKUs will be selected from one of the manufacturing warehouses (BT1/MF1/VN1) to be considered for modelling. The considerations are as follows:

Consideration (1) – Where are the excess inventory?

In the ideal situation, inventory should not exceed the safety stock level. The excess stock, defined as the difference between total stock on hand and safety stock, is primarily contributed by raw materials in MF1, as shown in Figure 11**Error! Reference source not found.**. Therefore, the analysis that follows will be made with reference to this subset of SKUs – **RM in MF1**.

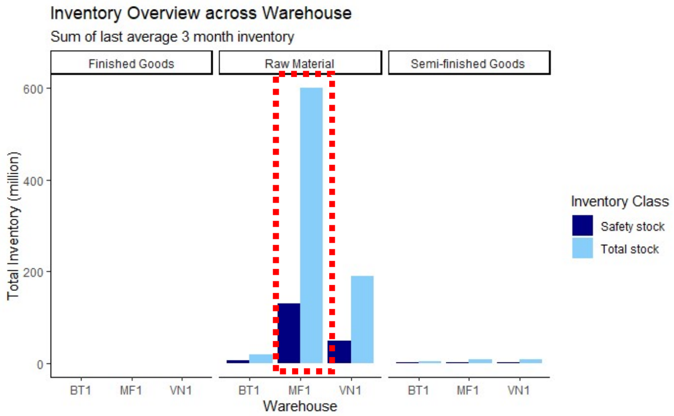


Figure 11 Inventory by type in manufacturing warehouses

Consideration (2) – Which business classification makes more sense?

There are 2 types of classification of SKUs based on business requirements in MF1. The two classifications are dimensions that **guide business decisions** such as the amount of safety stock to set:

1. XYZ class (field name MBABFC) group SKUs according to the demand variability. Measured by values of coefficient variability, X class are SKUs with generally stable demand fluctuations, Y class are SKUs with higher variability and so on.
2. ABC class (field name MBABCD) group SKUs according to the inventory value whereby A class are SKUs with top 20% inventory value, while B class SKUs contribute to the next 40% inventory value and so on.

The same subset of MF1 SKUs is categorised based on the two types of classifications respectively, and the 2 classes from each classification (i.e. B and C class in ABC classification and X and Y class in XYZ classifications) with the highest average excess inventory are chosen for further analysis, as shown in Figure 12**Error! Reference source not found.**.

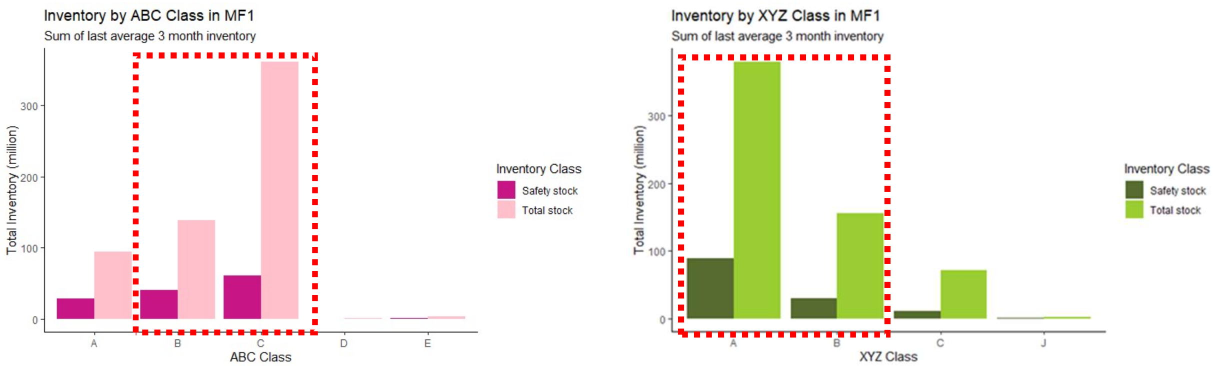


Figure 12 ABC and XYZ classifications

The 2 sets of data, less those that already meet the business objective of 2.0 turnover rate, are then used for comparison based on **volume contribution**, **value contribution**, and **number of qualified SKUs**.

As illustrated in Figure 13**Error! Reference source not found.**, the data set selected based on A and B class (MBABCD) accounted for approximately 19% of the total raw material SKUs in MF1, while that for X and Y (MABBFC) class is 8%. This implies that by looking into 11% more SKUs, we can potential resolve only 5% and 9% additional excess inventory volume and value respectively.

It thus makes more business sense to include only the **8% SKUs** of RM in MF1 in this initial modelling activity.

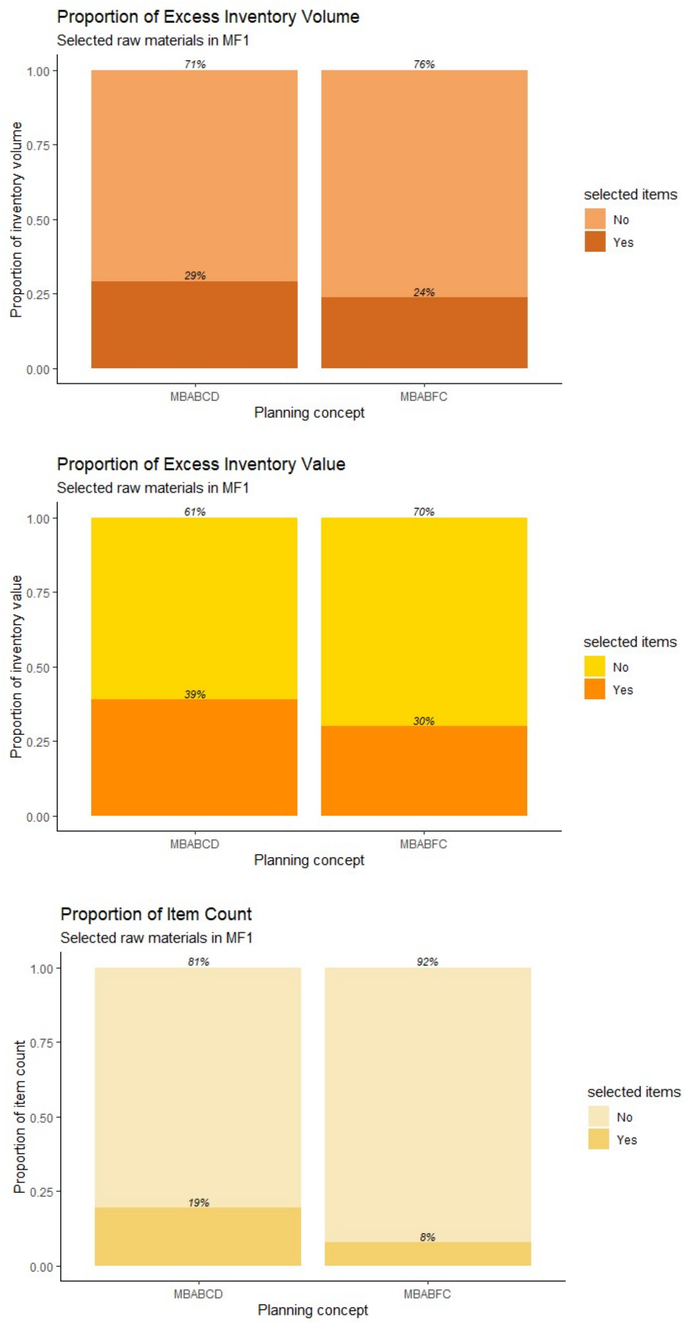


Figure 13 Comparison of ABC and XYZ classification

In terms of number of SKUs, it will be a maximum 849 SKUs (to be reduced to 749 after data cleaning) that this report will be analysing in detail, as shown in Figure 14**Error! Reference source not found.**.

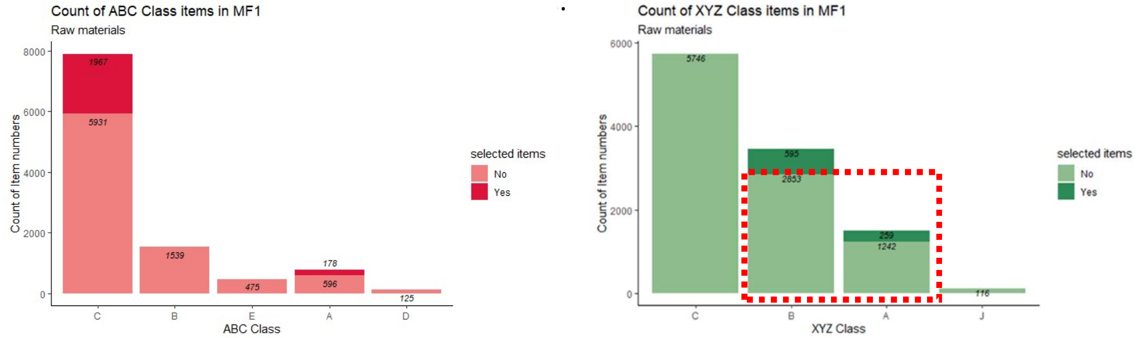


Figure 14 Number of SKUs selected

Appendix C

To transform or not to transform?

It is necessary to transform time series datasets to **make them stationary** before applying a model. In this project, since the 64 ARIMA models will make considerations for seasonality and difference, only trend must be dealt with.

The *ets()* function from the *forecast* R package is used to derive the **trend of each time series** – Addictive (A), Multiplicative (M), None (N). The ts with **multiplicative trends** are the subject of this discussion. To find out whether transformation will improve the outcome, an analysis is done to compare the outcome with set-up as shown in Figure 15. *BoxCox()* and *InvBoxCox()* functions from the *forecast* R package are used to perform a **lambda transformation** on each multiplicative time series.

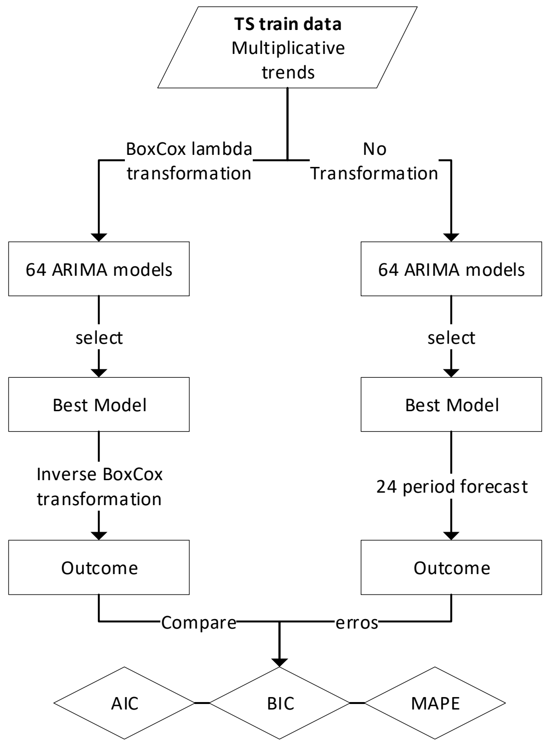


Figure 15 Comparison of with transformation vs without transformation

There findings are as below:

- The error comparison shown in Figure 16 shows that **transformation would reduce MAPE error** in both train and test sets, as well as give **smaller AIC and BIC**
- However, the **transformed forecast tends to produce a stationary forecast** (mostly AR1 models) hovering around the mean, which is unable to reflect the pattern of historical consumption. A random check on 10 ts gives an 80% outcome of such result. Figure 17 shows some examples.

Considering the **unrealistic outcome**, the **uncertainty of the ets()** function in deriving the trend, as well as the **complexity of the data**, the conclusion is to **not use transformed data** in the ARIMA modelling process.

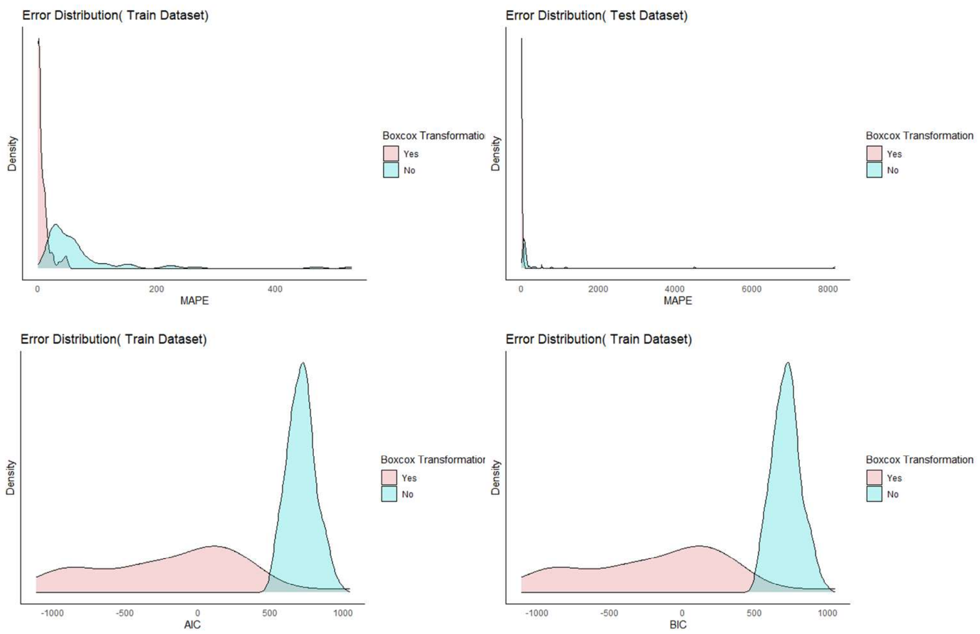


Figure 16 Error Comparison of with and without transformation

Without With

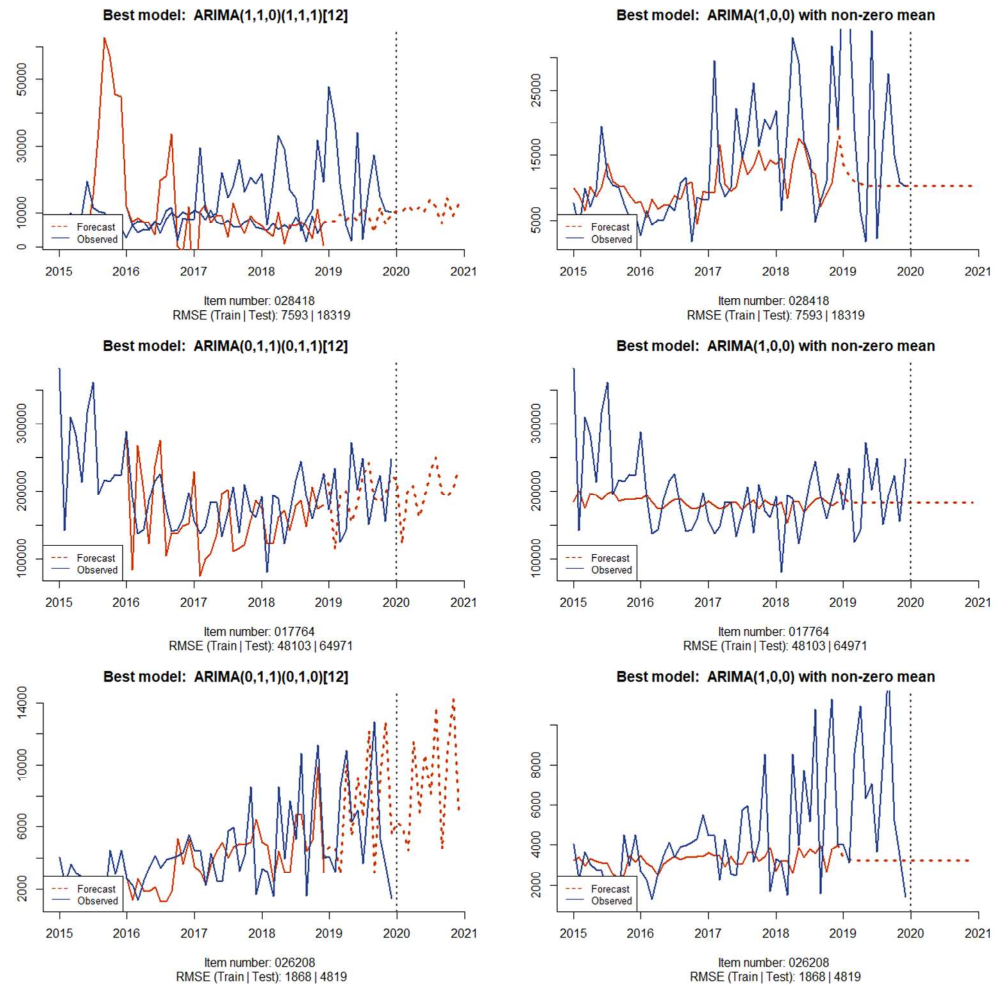
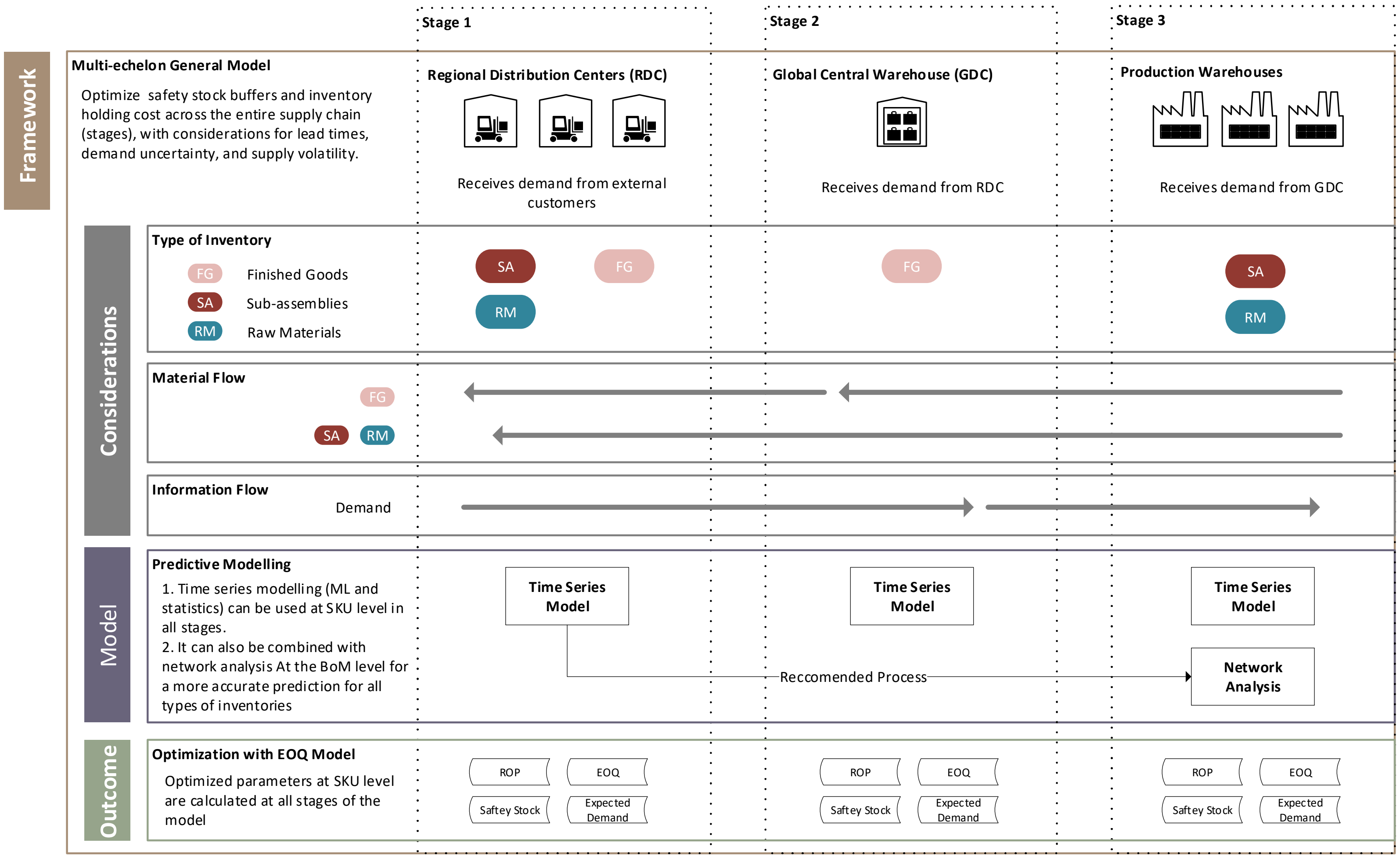


Figure 17 Forecast comparison of with and without transformation

Appendix D

Overview of the Multi-echelon Framework



Appendix E

<u>Operational Insights from Network Theories</u>

These insights can be applied to both a single BoM, as well as aggregated BoM as proposed by from Cinelli et al., 2017 to **identify potential risks** in the material management process. **Resources** should be allocated to these critical products to **ensure their continuous supply**.

1. Identify crucial subassembly products with **betweenness centrality** properties

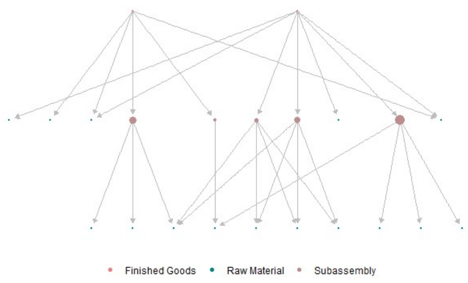


Figure 18 Application - betweenness centrality

2. Identify critical shared raw materials with **In-degree properties**

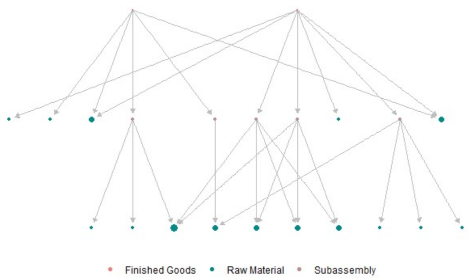


Figure 19 Application - in-degree

3. Identify critical **shared** raw materials with **Strength** properties[23]

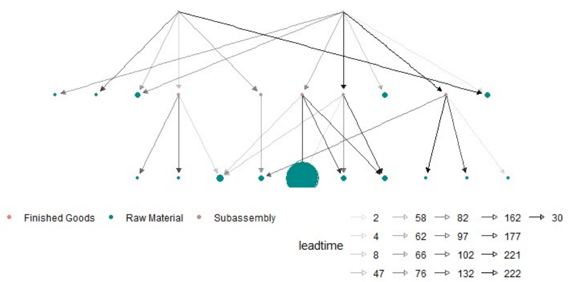


Figure 20 Application - strength

[23] weight can be any edge attributes depending on user requirements

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