Inventory and Warehousing Optimisation in the Current Global Economy

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Abstract

The Water Corporation is the largest water utility by geographical area in the world, and maintaining operations is critical as they are the principal supplier of water, wastewater, drainage, and bulk irrigation services in Western Australia. The pandemic has highlighted vulnerabilities within the organisation's supply chain, and disruptions have threatened stock-outs of assets required to continue providing essential services to the state. This project aims to model the chlorine supply chain at the organisation using mathematical optimisation techniques and simulation. First, a comparison of time-series forecasting methods will be evaluated using Python, then the appropriate levels of safety-stock for each storage site will be determined using Palisade's @risk simulation software. Lastly, these results will be used to generate a simulation model in anyLogistix for the trialling and testing of different contingency measures against "what if" disruption scenarios.

1. Introduction

The Water Corporation of Western Australia is the world's largest water utility by geographical area serving over one million business and properties. In $\mathbf{2021}$, $\mathbf{360\ 000}\ \boldsymbol{ML}$ of water was supplied to the state, and an average of $\mathbf{450}\ \boldsymbol{ML}$ of wastewater was treated per day. Liquified chlorine gas is the primary disinfectant method for water and wastewater, and it is added to all the organisation's water supply schemes to inactivate pathogenic microorganisms that can cause disease (Water Corporation, 2021). The chemical has been deemed a 'high risk' asset, as stocking out would seriously impact the state's access to safe and clean water. In early $\mathbf{2022}$, the Trans-Australian railway line was damaged by floods (Wood, 2022), halting the delivery of chlorine into WA. Interstate travel regulations, tied with a shortage of truck drivers, and chlorine being classified as a dangerous good made it difficult to arrange alternate modes of transport.

Successful inventory management is vital because it ensures that there is rarely too little or too much stock on hand, to limit holding costs and limit the risk of stock-outs. At the beginning of each year the price of the chemical is negotiated with suppliers, and a standing order is placed to cover demand for this period. Currently, the Water Corporation does not forecast to anticipate this demand, instead relying on experience learned over years. Demand forecasting lays the groundwork for most planning and control activities. Without forecasts, organisations will risk placing inaccurate inventory orders, arranging inappropriate transportation, or failing to ensure adequate safety-stock (Boylan, & Syntetos, 2021). An obvious way to handle uncertainty is through increased levels of safety-stock i.e., the amount of extra stock available to withstand fluctuations in demand and lead-time. To cope with levels of uncertainty, inventory models can be tested through simulation and optimisation modelling (Abo-Hamad & Arisha, 2011).

Analytical optimisation and dynamic simulation are the most widely used analytical techniques used support complex supply chain decisions (Abo-Hamad & Arisha, 2011). While optimisation techniques dominate research within this field, the potential benefits of supply chain simulation remain underexplored (Ivanov, 2017). Although optimisation techniques offer high levels of computational efficiency, they become impractical due to their limitations in capturing real supply chain dynamics (Abo-Hamad & Arisha, 2011). In contrast, simulation modelling brings the advantage of being able to handle complex problems, capturing stochastic real-world elements where situational behaviour changes over time (Dolgui et al., 2018).

2. Process

2.1. Supply Chain Simulation Model

This study applies mathematical optimisation and simulation modelling to the portion of the chlorine supply chain covered by the Victorian based company, IXOM, for the upcoming financial year ($2022 - 2023$). IXOM supplies chlorine drums of three sizes: $33\ kg$, $70\ kg$ and $920\ kg$. There are forty-six major sites that store/ use $920\ kg$ chlorine drums across six regions of the state, and forty-one of these are supplied by IXOM (Water Corporation, 2021). These drums are transported via the Trans-Australian railway into Western Australia to a distribution centre located in Welshpool. Qube Logistics, the organisations preferred logistics freight forwarder, then transports drums directly to sites via road.

For modelling, we consider a single product, four-stage supply chain (see Figure 1.) that consists of IXOM's manufacturing plant in Laverton, Victoria, IXOM's central distribution centre in Welshpool, Perth, regional distribution centres for each site across Western Australia, and a single 'customer' at each site to simulate demand.

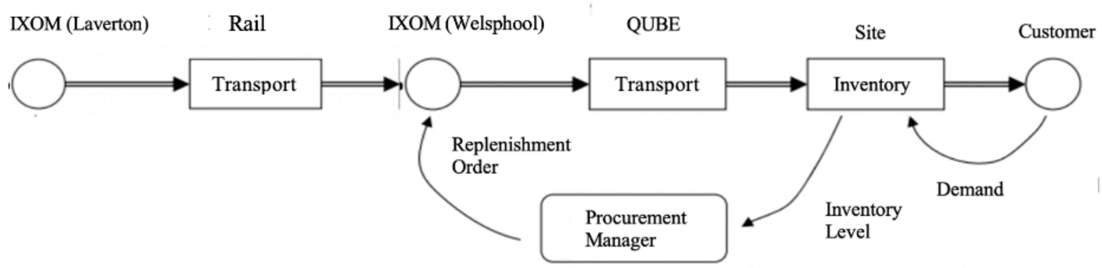

Figure 1 Simulation model abstraction

2.2. Data Collection and Cleaning

Site addresses have been obtrained from Water Corporation documents and converted to coordinates for input into the anyLogistix model. Demand from July $\mathbf{2017}$ through June $\mathbf{2022}$ have been pulled from SAP (procurement software) by the client to generate the forecasts for the upcoming financial year. Information regarding lead times have been obtained through contacts at Qube and IXOM, as well as staff within the Water Corporation's procurement team. The majority of sites utilise a continuous review inventory policy, with drums being ordered on demand once one has run empty. Maximum inventory levels for each site were sourced from the organisation's procurement plan for chlorine and are dictated by the dangerous goods licence issued for that location.

2.2. Demand Forecasting

A comparison of different time-series forecasting models has been conducted using the statsmodels and pmdarima packages in Python to determine which is the best fit for the data set. Time-series methods rely on historical demand data (Meindl & Chopra, 2015). The observed demand for a period can be split into two components, systematic (expected demand) and random (unpredictable part of the forecast arising from fluctuations in demand) used to determine the standard deviation. The systematic component can be further broken down and consists of three elements, level (current de-seasonalized demand), trend (growth or decline in demand) and seasonality (seasonal fluctuations in demand) (Meindl & Chopra, 2015). To begin, demand for the whole state has been forecasted using time-series methods, followed by each of the state's regions. Then high-volume sites such as those within the metro area will be forecasted. For sites with lower/ more constant usage (such as those in regional areas), a qualitative forecast relying on judgment is more appropriate.

2.2.1. Exponential Smoothing Models

The expected demand F_{t+l} from exponential smoothing forecasting methods in the period $t + l$ rely on estimates of the level and trend present within Period t, giving:

$$F_{t+l} = (L_t + lT_t)S_{t+l} \qquad 2.2.1$$

Where L_t, T_t, and S_t are the estimates of the level, trend, and seasonality at the end of Period t (Meindl & Chopra, 2015). These different methods can be implemented based on the presence or lack of trend or seasonality within the data set for forecasting using statsmodels.

Forecasting Method	Applicability
Single Exponential Smoothing	No trend or seasonality
Double Exponential Smoothing (Holt's model)	Trend but no seasonality
Triple Exponential Smoothing (Holt-Winter's model)	Trend and seasonality

Table 1 Exponential smoothing forecasting method's applicability

2.2.2. ARIMA and SARIMA Models

The ARIMA (autoregressive integrated moving average) and SARIMA (seasonal ARIMA) models take several inputs derived from the time-series data set to predict future values. Each model takes the form $ARIMA(p, d, q)$ and $SARIMA(p, d, q)(P, D, Q)_s$, where p is the order of the nonseasonal autoregressive component, d is the order of differencing required to make the data set stationary (i.e., remove trend), q is the order of the nonseasonal moving-average process. For the SARIMA model: P is the order of the seasonal autoregressive component, D is the order of the seasonal differencing (i.e., remove seasonality), Q is the order of the seasonal moving-average process, and s is the length of the seasonal cycle (Shih & Rajendran, 2019). The model parameters can be determined using the pmdarima package's auto ARIMA function, and then fit to the data set using statsmodels for forecasting the expected demand.

2.2.3 Forecast Errors

The forecast error (E_t) is defined as the difference between the forecasted demand and the actual demand for a period. Forecast errors are examined to determine whether one of the above models is a good fit for the data and can accurately predict the demand for each period. Errors are used as the estimate for the random component (standard deviation) of demand. The size of this error can be determined by calculating different statistics, the most common being the Mean Square Error ($\boldsymbol{MSE}$), the Root Mean Squared Error $(\boldsymbol{RMSE})$, the Mean Absolute Error ($\boldsymbol{MAE}$), and the Mean Absolute Percentage Error ($\boldsymbol{MAPE}$) (Meindl & Chopra, 2015).

$$MSE = \frac{1}{n}\sum_{t-1}^{n} E_t^2 \qquad 2.2.2 \qquad\qquad RMSE = \sqrt{MSE} \qquad 2.2.3$$

$$MAE = \frac{1}{n}\sum_{t-1}^{n} |E_t| \qquad 2.2.3 \qquad\qquad MAPE = \frac{1}{n}\sum_{t-1}^{n} \left|\frac{E_t}{D_t}\right| 100 \qquad 2.2.4$$

2.3. Safety Stock and Lead Times

With uncertainties surrounding the forecasted demand, simulation can provide valuable insight when determining the appropriate levels of safety stock to carry at each site. Safety-stock levels for each site will be calculated using Palisade's @RISK monte-carlo simulation software within Excel. Safety-stock (SS) for a period with variable demand and lead-time is calculated as:

$$SS = Z \times \sqrt{\left(\frac{PC}{T_1} \times \sigma_D^2\right) + \left(\sigma_{LT} \times D_{avg}\right)^2} \qquad 2.3.1$$

Where Z is the Z-score for the desired service level, PC is the performance cycle (total lead-time), T_1 is the time increment for the standard deviation of demand calculation, σ_D and σ_{LT} are the standard deviation of demand and lead time respecitvely, and D_{avg} is the average demand (Meindl & Chopra, 2015).

Operating under ideal conditions, the lead time for an order placed by IXOM (Welshpool) to IXOM (Laverton) is five days, for sites ordering from IXOM (Welshpool), the lead time is typically $5-7$ days for within the metropolitan area, and $7-10$ days for other regions. Assuming a uniform distribution, this yields a mean and standard deviation of 6 and 0.577 respectively for the $5-7$ day lead times, and a mean and standard deviation of 8.5 and 0.866 respectively for the $7-10$ day lead time.

3. Preliminary Results and Discussion

Taking the drum usage for the whole of Western Australia as an example, we partition the data set into a training set of the first four years, and testing set in the final year. Each forecast model is fit to the training set and a forecast is produced for the final year. Due to the railway disruption at the beginning of $\mathbf{2022}$ that impacted sourcing, the ordering data for the final year is not an accurate depiction of the number of drums used during that period. Instead of a replenishment order being placed when drums ran empty, safety-stock at each site was utilised to keep up with demand. This can be seen in *Figure 2*, where the peaks are significantly lower for our test set than in previous years. For this reason, instead of comparing the errors between the testing set against the forecast, we will compare the training set against the fitted model. For our final model, we will replace the final years' worth of data with the forecasted values to produce a more accurate depiction of what usage would've been in the absence of disruption.

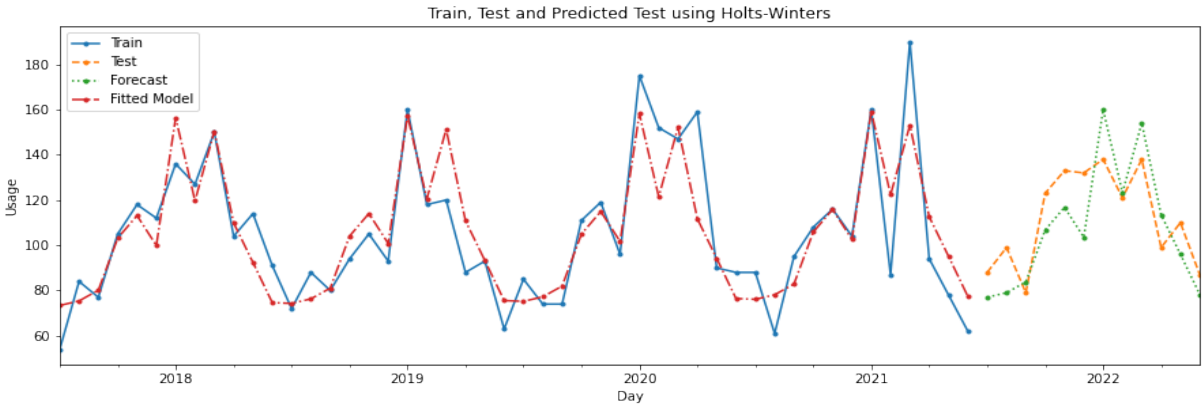

Figure 2 Fitting forecast model using Holt-Winters as example

Error	ARIMA	SARIMA	Single exp.	Holt (additive)	Holt (multiplicative)	Holt-Winters
MAE	22.11	14.87	25.28	24.28	24.06	11.61
MAPE	0.22	0.14	0.25	0.24	0.23	0.12
MSE	769.09	366.38	998.61	988.89	983.25	247.72
RMSE	28.22	19.14	31.6	31.45	31.36	15.74

Table 2 Western Australia error statistics for each fitted forecast model

As expected, due to the presence of seasonality within the data set the SARIMA and Holt-Winter's models produce the lowest errors across all measures. In *Table 2,* with the Holt-Winter's model providing the best fit. To forecast the upcoming $\mathbf{2022-2023}$ period, the best performing model is fit to the full data set $(\mathbf{2017-2022})$. The expected usage for each forecasted month is the forecasted value for that month, and the standard deviation is the $\boldsymbol{RMSE}$ obtained for the model.

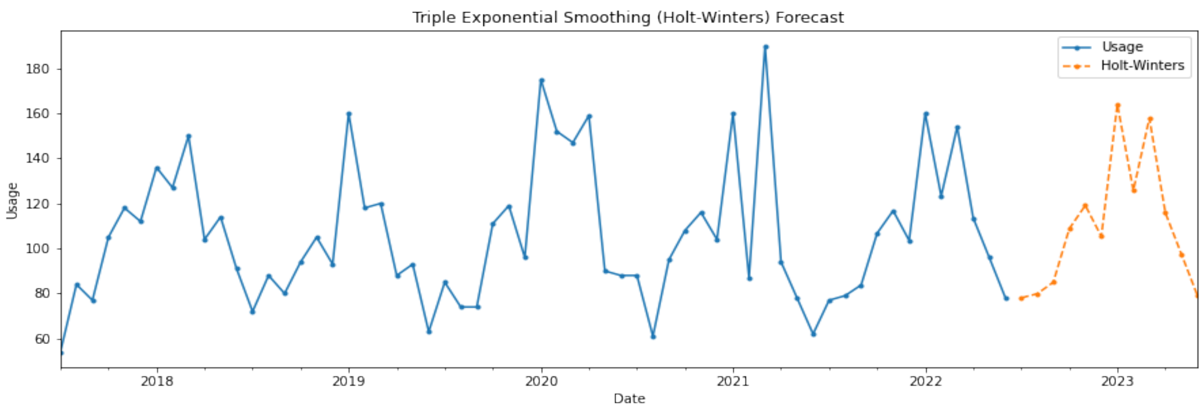

Figure 3 Forecast of Western Australia usage using Holt-Winters

Repeating this process for each of the state regions and high-volume sites we can determine the best model to fit to the data and the respective forecast.

4. Conclusions and Next Steps

The results for forecasting have enabled the future demand for the July 2022 – June 2023 period to be calculated with the expected monthly demand being obtained directly from the forecast, and the standard deviation from the forecast errors. This can enable the procurement team to accurately assess demand for upcoming periods to ensure the optimal amount of chlorine is purchased. The next steps will be to collect the rest of the forecasting data for each site and take this information as inputs for our @risk safety-stock simulation.

Data will then be uploaded to the anyLogistix simulation software to complete the supply chain model. To test possible contingency plans, disruption events such as the railway closure will be introduced into our model, and we will monitor the effect on lead-times and service levels. Analysis of recent literature and plans at the Water Corporation have identified the following possible contingency measures: Alternate supply arrangements including importation from ChemXpress in the Northern Territory and local production from Coogee Chemicals, increased safety-stock levels at existing sites, and increasing storage downstream of disruptions to introduce between site sharing.

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