MAKING SENSE OF CHAOS

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I am sure all of you have heard about Chaos theory and Butterfly Effect , the concept introduced by Edward Lorenz when he posed a question “Does the flap of a butterfly’s wing in Brazil set off a tornado in Texas?”. The purpose of his question was to illustrate that complex systems exhibits behavior such that a small variance in initial conditions could have a profound and widely divergent impact on the system’s outcome.

Supply chains are complex systems and changes in customer expectations and Omni-Channel fulfillment have increased the complexity multi-fold. Like any complex system, small fluctuations in some corner of the supply chain, such as port-strike in Bangladesh could cause massive upstream issues. In post COVID world demand volatility and supply uncertainly have lead to revenue and margin volatility and in some industries reduced profitability.

Demand uncertainty leads to challenges in inventory allocation and fulfillment and is an important factor to be considered in designing your supply chain operations. A common way of hedging against demand uncertainty is to use safety stock levels at various locations in the supply chain. Historical methods of estimating safety stock levels based on traditional inventory theory do not provide an effective methodology in todays dynamic environment in which customers could buy from any channel and receive the product at any location.

Over 23% of the customers expect same day delivery and more than 81% don’t want to pay more than $5 for shipping which requires the product to be located closer to the demand. Static rules based allocation, replenishment and purchasing policies cannot address the needs of omni-channel fulfillment. They deliver sub-optimal margins and missed customer service-levels. These inefficiencies can reduce margins by upto 25% and create a negative brand image.

Approaches using Artificial Intelligence and Machine learning can deliver a very agile supply-chain that morphs to support demand volatility thereby significantly improving business outcomes.

However, designing, implementing and integrating these systems into your business processes is expensive and takes time.

Advanced digital technologies and simulators allow comprehensive real-world modeling of the entire supply chain - A Digital Twin - from raw-material suppliers through to customers and run real-world simulations rapidly.Business users can now see and analyze any event which comprises a specific change in the supply chain system's state at a specific point in time.

A typical retail Allocation and Replenishment process has been used to illustrate the use of the Digital Twin. The Digital Twin can be as easily applied to other processes in the value chain.

Digital Twin:

With the advent of Omni-channel retailing, a lot of research is being carried out in the areas of allocation and fulfillment strategies. Increase in number of SKU's, seasonal variations, multitude of fulfillment channels and demanding customers make balancing cost and service levels a complex task.

Simulation tools have been difficult to use in the past because of limited computational and analytical capabilities, complex coding requirements, and lack of data science capabilities available to business decision makers. Now with advanced computing capabilities, ability to process large data volumes quickly and run complex scenarios in minutes, simulation is a useful tool to business decision makers. Decision makers can get AI and data driven predictions in minutes, ask "What if" based questions, run simulations in easy to understand graphical user interfaces and make decisions quickly. Such real time simulation capability enables decision makers to not only make decisions in near time but also respond to changing business conditions leveraging continuous optimization and scenario modeling

A typical business manager responsible for allocation and replenishments may be trying to answer the following questions:

1. Are my initial allocation quantities to fulfillment centers high or low?
2. Are my replenishment rules optimal?
3. Will my allocation and replenishment rules stand the pressures of the real world such as Demand Spikes or Subdued demands?
4. What happens if I add another store or fulfillment center to the network – how does it impact overall inventory requirements in the network?
5. What is my visibility of sales and inventory positions as it relates to expected demand at the SKU level?
6. What sizes should I keep in each location to ensure optimal fulfillment?
7. What is the impact of various business factors like new customer, supplier delays, and weather event on the ability to meet customer service levels?

In a real Omni-channel environment, a customer can purchase products from any channel and can get fulfilled from any channel. With increasing e-commerce demand, issues related to store closures and stores doubling up as fulfillment locations, optimizing inventory at every location and at a very granular level is critical to keeping fulfillment costs low while meeting service levels and delivering a true omni-channel experience and reducing stock-outs.

Current approaches use static rules to fulfill orders and do not take into account factors such as expected demand for a product at a certain location, fulfillment costs, replenishment costs or customer fulfillment preferences especially when converting to an Omni-channel environment.

Introducing Artificial Intelligence (AI) and Machine Learning (ML) approaches to replace the static-rules based approach will allow organizations to use all available data and dynamically adjust and decide on stock-levels by SKU, ideal locations to keep the stock to deliver an efficient Omni-channel service, deliver maximum profits and minimizing stock-outs.

An alternative approach would be to run continuous simulations using AI models and simulators to test these parameters and changes in order to define new allocation and replenishment strategies and optimal inventory policies and replenishment rules.

Simulation uses a valid digital representation of the system – A Digital Twin – and applies AI, ML and optimization algorithms using all available data – external and internal to provide a dynamic environment for analysis of events.

You could add additional demand nodes, supply nodes, new wholesale customers, geographies, shipping methods and various constraints to the Digital Twin of your supply-chain and study impacts of demand changes and supply constraints using all available data, external and internal.

After finding the ideal scenario the rules can be adjusted in existing systems thereby avoiding the need to go through complex implementation of new systems while achieving the desired results. Simulators can also be used to run real-time simulation, historical and future simulation to conduct what-if analysis.

Here is an example of how two fashion retailers used the Digital Twin to analyze and evaluate their replenishment and fulfillment policies:

Global Fashion Jeweler Use Case

An Italian luxury brand known for its jewelry, watches, fragrances, accessories and leather goods, used ORS's simulator for back testing the allocation and replenishment policies for various time-periods, business cycles and product categories.

The back-testing allowed them to:

- Understand the results and the effectiveness of the allocation model
- Test the stability and robustness of the allocation model
- Recalibrate the parameters to ensure robust future allocations

The following data was used for running the back-test:

- Inventory and sales history for 163 jewelry products in 208 stores
- Warehouse inventory history for the same period
- In-transit quantity from distribution centers to stores
- Products sales history used before this experiment

The simulation was run for six months on 7605 store-SKU combinations.

The following KPIs were compared between the actual and simulated values:

- Average Inventory
- Out of Stock Quantity (OOS)
- Lost Sales Estimation and related Service Level
- Number of Shipments

The results of the back-testing were as follows:

For all the store-SKU combinations with more than 10 units marked for intended-to-sell during the back-testing period, the simulator recommended stock units were 15.71% lower than the actual stock units allocated during the period with 44% lower number of out-of-stock weeks and 44% less lost-sales.

	Digital Twin Recommendation	Actual Values from Data	Percentage Difference
Average Stock Units	2840	3369	-15.71%
Number of Weeks out-of-stock	599	1080	-44.54%
Lost Sales Units	1235	2231	-44.64%

For all the store-SKU combinations with more than 50 units marked for intended-to-sell during the back-testing period, the simulator recommended stock units were 29.69% lower than the actual stock units allocated during the period with 47% lower number of out-of-stock weeks and 47% less lost-salesFor all the store-SKU combinations with more than 50 units intended-to-sell in the back-testing period:

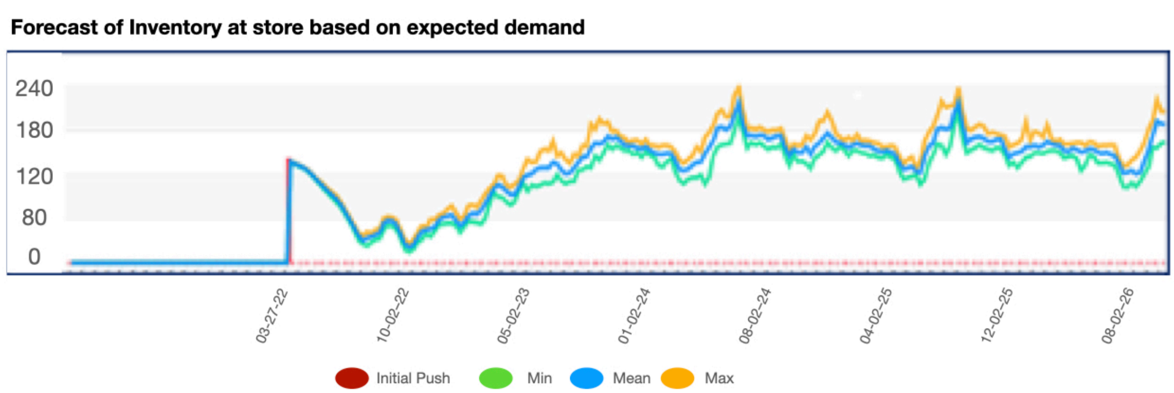
	Digital Twin Recommendation	Actual Values from Data	Percentage Difference
Average Stock Units	1031	1466	-29.69%
Number of Weeks out-of-stock	78	148	-47.30%
Lost Sales Units	384	737	-47.94%

Based on the above simulations, the company reduced the overall inventory at the various point-of-sales locations while lowering number of stock-out units and lowering lost-sales.

These simulations were run on a weekly basis to make the required adjustments in the network.

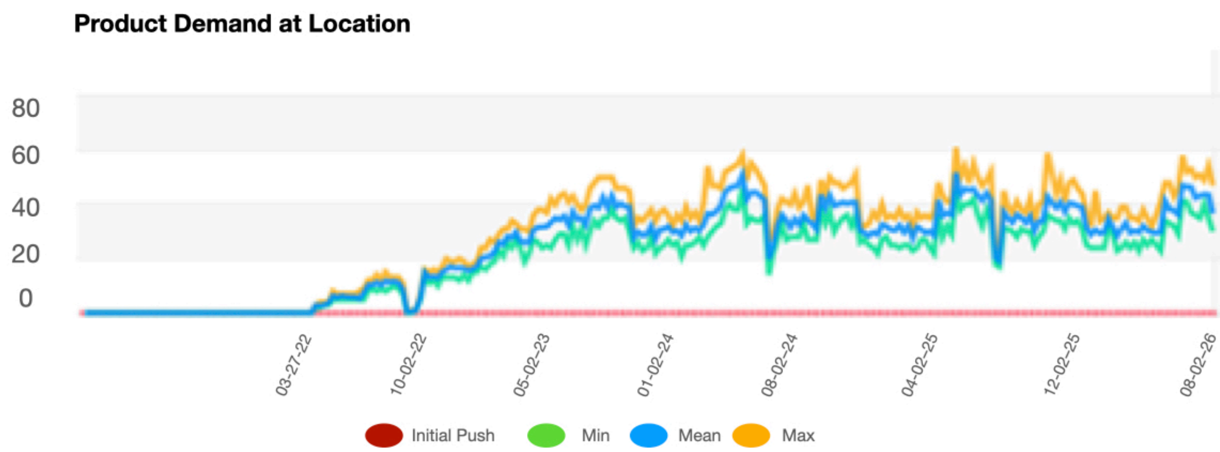
Global Luxury Brand Use Case

A global luxury brand wanted to find optimal quantities for initial allocation and subsequent replenishments for a best-selling product at a best-selling store to meet expected future deman



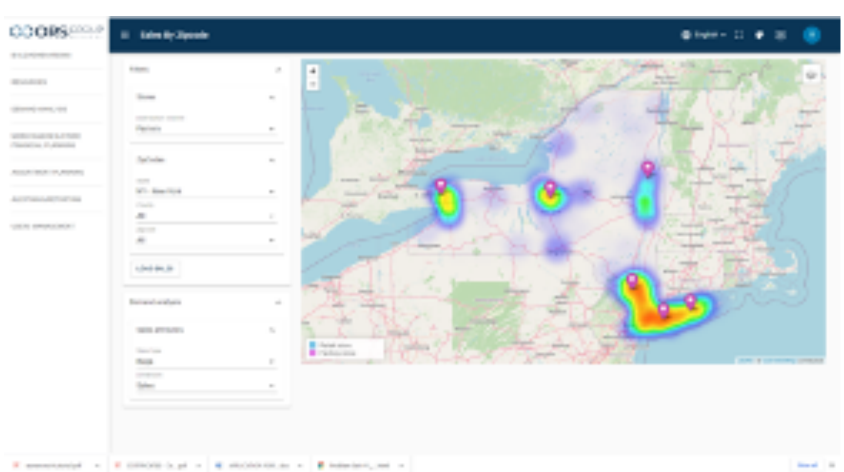
The Simulations show that the initial push, though high, is required to meet the expected future demand for the product in that location

Ten simulations were carried out by forecasting demand for a five year time horizon. The simulation provided values for an optimal initial allocation quantity as well as future replenishments quantities to meet future forecasted demand as sensed by the AI models.



The demand simulations confirm that the the allocation and replenishment policies are optimal.

These decisions were enabled using an easy-to-use intuitive graphical user interface which enables sharing of simulation inputs, outputs and decision across all levels of the organization – from executives, to planners. This capability allows strategic and tactical decisions at the “Speed of Business.”



Conclusion

Using a Digital Twin is a low-cost, low-risk and effective method of introducing AI and ML approaches into decision making process within organizations. In addition to delivering immediate business benefits, the approach also allows fast and easy deployment of AI solutions within an existing technology infrastructure.

About ORS

ORS Group is a leader in Applied Machine Learning and Artificial Intelligence and offers a suite of products that optimize and transform complex business processes in Retail, Manufacturing, Financial Services and Energy verticals. ORS also offers a library of textbook implementations of a few hundred Machine Learning and AI models. The vertically integrated applications and the model library leverage deep knowledge of Risk Management, Advanced Techniques in Finance and Operational Research expertise developed over two decades.

The solutions are offered to large and mid-sized business globally directly and through Systems Integrators, VARs and partnerships with software firms.

ORS's modular software and models have delivered over $10 billion (USD) combined in yearly savings and higher margins to global brands.

Representative list of customers include Brooks Brothers™, Luxottica™, Bulgari™, Benetton, Group™, Dimar SpA™ and Biomin™.