Dynamic Selection of Inventory Replenishment Policies for a Fast-changing Supply Chain

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Abstract

Global supply chains suffered considerable impact from the disruptions caused by the pandemic scenario and the need for efficient supply chain management is at an all-time high. Supply chain performance is strongly influenced by the inventory management policy adopted at each echelon. Thus, there is a requirement for an efficient inventory replenishment policy for supply chain environments undergoing frequent changes. The traditional static replenishment policies, omnipresent in industries, prove to be suboptimal in this case as the optimal replenishment policy depends on existing supply chain conditions. This work proposes a dynamic framework, inspired by a similar model identified in literature, which is able to find the optimal replenishment policy for a particular echelon in a three-echelon serial supply chain environment characterised by eight attributes. Supervised machine learning techniques were incorporated for developing the framework which is finally able to select and implement the optimal replenishment policy from four possible alternatives. The dynamic framework is developed using different machine learning algorithms, which further gives an insight into their performance. A comparative analysis of the proposed models is performed under two supply chain environments, namely the chaotic and the fast-changing. The results highlight the improvement obtained by considering the dynamic framework rather than the static alternatives. Additionally, the random forest (RF) based model was found to be the best performing model compared to its counterparts. Finally, the proposed model was observed to outperform the model identified from literature, thus portraying the significance of the work.

Keywords
Machine learning, replenishment policy, serial supply chain, supervised learning, supply chain management

1. Introduction
Supply chains across the globe were exposed to unprecedented disruptions resulting in huge economic losses due to the present pandemic scenario. The COVID 19 associated disruptions have created a major global crisis by damaging global supply chains (Araz et al. 2020). The effect ranges from the development of a volatile market environment to an unpredictable economic system. Further, Handfield et al. (2020) reported an increase in bullwhip effect to an ever maximum in the manufacturing sector due to the pandemic situation. Lockdowns gave rise to labour force shortage and logistic disruptions and finally, a supply-side shock in food supply chains (Hobbs 2021). Thus, supply chain environments across the globe have suffered significant changes in recent

years. Reacting to these changes is a possible way of reducing the impact of such disruptions. As Lancioni (2000) pointed out, inventory-related costs cover nearly 50% of the supply chain costs which suggests the importance of a proper inventory management system for better performance. This idea is visible in Zimon et al. (2021), where a change in inventory management policy was reported for Poland-based SMEs (small and medium-sized enterprises) during the pandemic time, possibly incorporated as a measure to avoid huge economic losses. This highlights the need for an inventory replenishment policy in consistency with the supply chain environment for better management of the system. The traditional inventory policies, which are static in nature, may result in sub-optimal performance due to the dynamic nature of the environment. Priore et al. (2019) has confirmed this idea and has proposed a dynamic alternative for a single echelon, wherein a framework identifies the best policy for a particular environment.

The present work is inspired by Priore et al. (2019) and the proposed model is applied to chaotic and fast-changing supply chain scenarios. For each of these scenarios, the model identifies the optimal policy for the echelon in focus after considering its state and environment. The applicability and effectiveness of various supervised learning algorithms are also considered in the work. The evaluation metric considered in Priore et al. (2019) is used here. The metric is the weighted sum of order variance ratio and inventory variance ratio and hence considers the effect of both inventory and order variation. The cost structure of the supply chain decides the weight assigned for each term which is again dependent on the existing supply chain conditions.

The paper is structured as follows. Section 2 reviews the literature that has been thoroughly studied for the purpose of this work. Section 3 contains the problem description where the basic idea about the outline of the problem is described alongside the underlying supply chain assumptions. Section 4 delves into the details of the methodology followed which includes the structure of the simulation model used, an explanation of the example generator and details about the developed ML models. Section 5 reports the steps followed to create the labelled data required for training the ML models. Section 6 contains analyses of the results from the decision tree and a comparative analysis of the ML model and the static alternatives along with a discussion on the performance of various ML algorithms. Finally, Section 7 provides the conclusions and the scope of future work with references in Section 8.

1.1 Objectives

The study aims to develop a dynamic machine learning model which can predict the optimal policy for a wholesaler in a serial three-echelon supply chain subjected to changes in the operating environment. The machine learning model is an updated version of the model identified in literature, to be developed after careful consideration of the parameters involved and the existing supply chain environment. The model thus developed should be able to choose the replenishment policies in such a way that the performance of the echelon is improved compared to the traditional static approach. Different machine learning techniques, ubiquitous in this field of study, are considered for developing machine learning models and thus the model corresponding to the best performing algorithm should give better results.

2. Literature Review

Performance of a supply chain depends on a couple of factors whose values and mutual interactions decide the state of a supply chain. It could also be observed that significant research was on the effect of inventory replenishment policies in managing supply chains efficiently. OUT policy, a type of periodic inventory policy, being simple and less expensive compared to continuous review policy was found to be widely used in industries. Literature was further investigated to identify the optimal replenishment policy for a particular supply chain structure. Further, a review on machine learning algorithms was performed to identify the best algorithm suited for the problem considered in this work. Algorithms that have appreciable interpretability were considered and hence unsupervised learning algorithms were ruled out as they are considered as black-boxes (Priore et al. 2019). Major works that have been reviewed in these directions are given below.

A number of factors were identified from literature that affects the performance of a given supply chain. Chopra et al. (2004) and Song et al. (2010) stressed the importance of the replenishment lead time, which when reduced causes an associated decrease in safety stock and hence the inventory cost. He et al. (2011) and Heydari et al. (2009) demonstrated that not only the actual lead time, but the variation of lead times also has a significant effect on supply chain performance. The former reported the relation safety stock has, with lead time standard deviation under constant demand and the latter highlighted the effect of lead time variation on the amount of inventory and the corresponding effect on holding costs and stockouts. On the other hand, Acar et al. (2010) assessed the relative impact of demand, supply and transportation lead-time uncertainty for a global speciality chemical manufacturer. The demand uncertainty showed the most damaging impact on both cost and customer service performance out of the considered parameters. Also, a simulation-based study done by Yan and Woo. (2004) concluded that the changes in end consumers' demand patterns will affect the performance of the supply chain, which could be improved by adjusting the information-sharing strategy according to the changes in demand. Information sharing is yet another relevant factor that has an impact on inventory level and cos (Yu et al. 2001). It has also been identified as a parameter that can enhance the effective supply chain practice (Zhou et al. 2007). These factors, which influence the performance of a supply chain, could be used for characterising the state of a supply chain.

Given the state of a supply chain, the next relevant parameter to be considered is the optimum inventory policy to be used for an echelon. Li and Disney (2017) considered a two-stage supply chain structure with a single retailer and a single manufacturer and concluded that the MRP nervousness and inventory costs of the manufacturer were reduced when the retailer adopted either of the two POUT strategies considered. The work also highlighted the importance of the feedback controller (associated with the proportional controller of POUT policy) which when properly tuned, reduces the bullwhip effect at both echelons. Disney et al. (2016) did a comparative study on the effectiveness of POUT and OUT policy for a supply chain with open orders with stochastic lead time and order crossover. POUT policy was identified as the best strategy under the specified environment due to a significant reduction in inventory costs, however, for the case with constant lead time, the OUT policy resulted in reduced inventory cost. Dejonckheere et al. (2003) employed a control system approach for understanding the response of OUT and POUT policies under real-life demand patterns. OUT policy, though it is accompanied by increased order variance, was reported to offer better response to a rapid increase in demand than the POUT policies. A major conclusion that could be drawn from these works is that the notion of optimal policy for a particular supply chain structure largely depends on its operating conditions. As already mentioned, Priore et al. (2019) addressed the question of optimality by developing a dynamic framework which identifies and implements one among four replenishment policies considering the operating conditions of the supply chain node. The work considered POUT policies (with three different controller values) and OUT policy as the possible inventory replenishment policies for the node. The idea of a static replenishment policy was thus proven to be less effective as those systems don't react to the changes in external conditions. The dynamic framework uses a classification algorithm to obtain the optimum policy under a given supply chain environment.

Supervised machine learning algorithms are frequently used classification algorithms. There are a number of supervised learning algorithms that are used in similar classification problems as the present one. Zhou et al. (2021) applied the XGBoost algorithm for the prediction of fraudulent products and performed a comparison with Logistic Regression and Gaussian Naive Bayes algorithms and outperformed both of them. Ni et al. (2020) conducted a literature review to identify frequently used ML algorithms in the field of supply chain management. The review shortlisted a total of 10 algorithms and further found increasing use of neural networks and SVM (Support Vector Machine) in the field of supply chain management. Major reasons for this trend can be associated with the ability of neural networks to identify complicated input/output relations and the strong generalisability and interpretability of SVM. Osisanwo et al. (2017) did a detailed comparison between various supervised learning algorithms based on parameters like size of dataset, number of instances, accuracy, time for learning etc. SVM, RF (Random Forest) and Naive Bayes were identified as delivering high precision and accuracy irrespective of the number of the attributes and instances. Singh et al. (2016) compared various supervised machine learning algorithms based on the speed of learning, complexity, accuracy and risk of over-fitting. Complex algorithms like KNN, SVM and ANN were reported to have underperformed for the dataset considered. A major reason being the necessity of choosing various hyperparameters associated with the algorithm. The work also reported better performance of RF compared to decision tree as the former is able to eliminate the possibility of overfitting.

Though there are a number of works discussing the effect of a particular policy on a supply chain structure, the notion of an optimal inventory replenishment policy for supply chains under changing conditions hasn't been analysed much. The machine learning algorithms such as SVM, RF, Naive Bayes and XG Boost were identified as potential algorithms that could be considered for the study as they were reported as having considerable accuracy and appreciable interpretability.

3. Problem Description

A single product three-echelon linear supply chain structure consisting of a retailer, a wholesaler and a factory along with its production floor is considered in this study. All the nodes are assumed to follow the POUT (proportionate order up to) policy for replenishing their respective inventory with a review period of one day.

Specifically, POUT policy with matched controllers (Disney et al. 2007) is considered here, which is represented mathematically by the equation:

Inventory replenishment order $= O_t = D_t + [SS_t - NS_t] + [DW_t - AW_t]$

Here $D_t$is the forecasted demand, SS_t is the safety stock considered, NS_t is the net stock on the wholesaler node at the review period and finally D_t and AW_t are the desired and actual work in progress inventory. The parameter β is referred to as a proportionate controller which could be adjusted to regulate the variability associated with the replenishment order placed.

The supply chain is further associated with three lead times, namely-production lead time of the factory (L_f), the shipping lead time from factory to wholesaler (L_w) and shipping lead time from wholesaler to retailer (L_r). Due to the dynamic nature of the supply chain environment, there is a certain degree of uncertainty associated with the supply chain. Thus, the lead time is considered to be stochastic and the consumer demand to follow a normal distribution. The order policies of the retailer and the factory occur independent of each other and also the wholesaler.

Thus, for the wholesaler node, a total of eight parameters were identified that characterise its state and the supply chain environment, these includes the three lead times, proportional controller values of retailer and factory, COV (coefficient of variation), cost structure of the node (in this case, the wholesaler), and the IP (inventory position) at the considered instant. In order to optimise the performance of the wholesaler, the inventory replenishment policy of the wholesaler should consider the values of these eight parameters. The dynamic framework proposed, aids the wholesaler node to identify the optimal policy.

The dynamic framework analyses the state of the supply chain and decides the optimal replenishment policy to be taken under that specific condition. The optimal policy should be able to reduce the total cost incurred due to inventory variation and order variation of the wholesaler node. Hence a combined metric which gives an idea about the net effect of inventory variation and order variation is considered here. The metric consists of two entities, namely: Order variance ratio (OVR) and inventory variance ratio (IVR), mathematically

$$OVR = \frac{\sigma_O^2}{\sigma_D^2}$$

$$IVR = \frac{\sigma_{NS}^2}{\sigma_D^2}$$

σ_O^2 , σ_{NS}^2 and σ_D^2 corresponds to the variance of order placed, net stock and the consumer demand respectively. The combined metric draws a balance between order variations and inventory variations which in most cases are opposing entities. The metric is represented by *J*, and mathematically by the equation

$$J = c_o\sqrt{OVR} + c_i\sqrt{IVR}$$

Here $c_o$and c_i ($c_o, c_i \geq 0, c_o + c_i = 1$) depend on the cost associated with each source of variability and represent the relative importance of each indicator. The change in the cost structure of the wholesaler is achieved by changing the value of c_o (thus changing c_i automatically). Situation where $c_i < c_o$ implies order variation is more damaging than inventory variation, while $c_i > c_o$ represents the other alternative.

As mentioned earlier, the order policy taken up by the wholesaler node is decided by considering the state of the supply chain, assessed using the eight attributes. In order to reduce computational complexity, the choice of order policies for the wholesaler is restricted to four, where each policy has a different β value. For a set of values of the attribute, the proposed model should be able to predict the policy that offers the least *J* metric value compared to its counterparts. The wholesaler then works with this optimal policy till the supply chain conditions undergo a change.

4. Methods

The dynamic model is developed using the application of various supervised ML (machine learning) techniques and it hence demands sufficient label data for training. This data is developed using an example generator which consists of a simulation model coupled with a parameter value generator. The simulation model matches with the structure of the supply chain considered and the parameter value generator is able to produce different values for the seven independent parameters according to their assigned ranges (explained later). The generated label data is then used for developing dynamic models with different ML algorithms.

4.1 Simulation Model and Example Generator

The data required for developing the dynamic model is obtained from a simulation model architectured according to the supply chain structure. The four-step sequence of events considered in Priore et al. (2019) is used for the model with a review period of one day. The working of the simulation model is strictly based on the above-mentioned sequence of events.

For the simulation model, the consumer demand is considered to follow a normal distribution$N\ (\mu, \sigma^2)$, where the coefficient of variation $COV\ =\ \sigma/\mu$, quantifies the uncertainty in demand with μ and σ^2as the mean and variance of the consumer demand. A total of four decision points are incorporated in the considered POUT Models: controller setting, safety stock, forecast, and work-in-progress policy. The nodes are assumed to employ static forecasts $\hat{D}_t\ =\ \mu$ with the work-in-progress (DW_t) following the equation $DW_t\ =\ L_x\ \mu$ (where $L_x\ =\ \{L_r,\ L_w,\ L_f\}$ according to the echelon). Safety stock is considered to be 3 times the mean consumer demand i.e., $SS_t\ =\ 3\mu$. Thus, the remaining decision point which are the proportional controllers, act as the main decision variables (for retailer β_r; for wholesaler β_w ; for factory β_f). This simulation model is coupled with the parameter value generator, where the values of relevant parameters could be changed to obtain different working environments. The attributes and their corresponding ranges are as follows

1. The coefficient of variation of consumer demand (COV) can vary within the interval of 10% to 50%.
2. Lead times (L_r, L_w, L_f) can take values from 1 to 4 days
3. β_r, β_f both are generated randomly from the interval [0,1].
4. The cost structure of the wholesaler, represented by the relative importance of minimising order variability (c_o), is generated randomly from the interval [0,1].

The value of the eighth attribute, namely the inventory position, is extracted from the simulation run as the system progresses. The wholesaler node is modelled such that it can have a policy from a set of four different alternatives namely:

1. OUT represents the classic Order Up to policy (i.e., the controller value, $\beta_w\ =\ 1$)
2. POUT_H refers to a Proportionate Order Up to policy with the controller regulated at a high level (i.e., the controller value, $\beta_w =\ 0.7$ is selected)
3. POUT_M represents a Proportionate Order Up to model with the controller regulated at a moderate level (i.e., the controller value, $\beta_w\ =\ 0.4$ is selected)
4. POUT_L refers to a Proportionate Order Up to model with the controller regulated at a low level (i.e., the controller value, $\beta_w =\ 0.1$ is selected).

The inventory position for the first run is taken as 1000 products with the mean consumer demand being 100 products per day. The simulation model is then run for the required number of days after setting a particular set of parameter values to obtain the performance of each of the four alternative order policies of the wholesaler node.

4.2 Machine Learning Models

Once the training data is extracted using the example generator coupled with the simulation model, the data is used for developing machine learning models. A detailed literature review on common and frequently used machine learning algorithms yielded a list of possible algorithms that could be used to perform the analysis (mentioned in literature review). Among the shortlisted algorithms, RF and SVM (Support Vector Machine) were considered for developing ML models for the problem statement, mainly due to the interpretability and accuracy of the algorithms. The optimal values of parameters for all the three algorithms (Decision tree, RF and SVM) were evaluated using the grid search method from the sklearn library. Grid search is mainly used for hyperparameter tuning, but the same method is capable of evaluating the optimum number and depth of decision trees. The method also includes cross-validation which is implemented internally. The accuracies for each algorithm were observed as 66% for decision tree, 73% for SVM and 74% for RF.

5. Labelled Data Generation

The example generator randomly generates values for the seven independent parameters which are fed to the simulation model. The simulation model works with this set of parameters for a month (considered as 30 days). The wholesaler node then takes up each of the four possible replenishment policies and the corresponding *J* metric values for each policy and the inventory position at the end of the month is noted (which will be equal to the inventory position at the beginning of the next month). The policy giving the lowest *J* metric value is considered as the class policy for that particular set of attributes which includes the seven independent parameters and the inventory position at the beginning of the month. Thus, for a set of eight attributes, we would obtain the class policy which is considered as the optimum policy for the present supply chain condition.

The simulation then runs with the class policy corresponding to the attributes and moves to the second month. Again, the values for the seven independent parameters are generated randomly and the beginning inventory position is taken as the inventory position at the end of the previous month. The whole process is repeated again, that is, the class policy is determined for the set of attributes for the second month as discussed above. The process is continued to generate a set of 2000 examples and this data is used as the training data set for creating ML models (machine learning models). A portion of the generated labelled data which has the attributes and the corresponding class policy is shown in Table 1. It is evident from this dataset that the changing conditions of the supply chain, which are represented by changing values of the attributes, result in different optimal class policies for the wholesaler.

Table 1. An extract of the training data

S.no	L_r	L_w	L_f	**COV**	β_r	β_f	c_o	**IP**	**Class Policy**
1	3	4	3	32	0.4741	0.4789	0.0798	587	POUT_H
2	4	2	4	15	0.5979	0.0408	0.8824	678	POUT_L
3	1	1	3	38	0.9561	0.3793	0.5734	510	POUT_L
4	4	2	1	34	0.8157	0.8959	0.164	527	POUT_H
5	3	4	2	49	0.682	0.7103	0.3306	435	POUT_L
6	3	4	2	44	0.4277	0.2206	0.2081	603	OUT
7	2	1	2	10	0.7454	0.6209	0.1238	708	OUT
8	2	1	3	21	0.2732	0.6044	0.0157	396	OUT
9	4	3	2	38	0.7938	0.2643	0.7952	386	POUT_L
10	4	1	3	42	0.851	0.0751	0.0986	430	POUT_L

6. Results

6.1 Decision tree model and impact of attributes

Out of the three ML models developed, the decision tree-based dynamic model can provide valuable insights as it uses a tree representation to effectively classify the given data. The tree-based model, after training, is capable of giving proper knowledge about the learning process, that is, the logic behind the classification. This allows the decision-makers to understand the relation between the attribute values and the optimal policy (Priore et al. 2019).

The trained ML models also yield the relevance of each attribute in the classification process. Figure 1 represents the relevance of attributes obtained from the decision tree model. The most relevant attribute was found to be the weight c_o followed by β_r . This underscores the importance of the cost structure of the node and the fact that the order policy of an echelon (here, the retailer) greatly affects the inventory decision of the preceding upper echelon (in this case, the wholesaler). The result goes in line with the conclusions obtained in Priore et al. (2019). Inventory position, which was incorporated as the eighth attribute, also showed significant relevance. Order of relevance of attributes obtained from other two ML models also follows the same trend and hence their individual analysis is avoided.

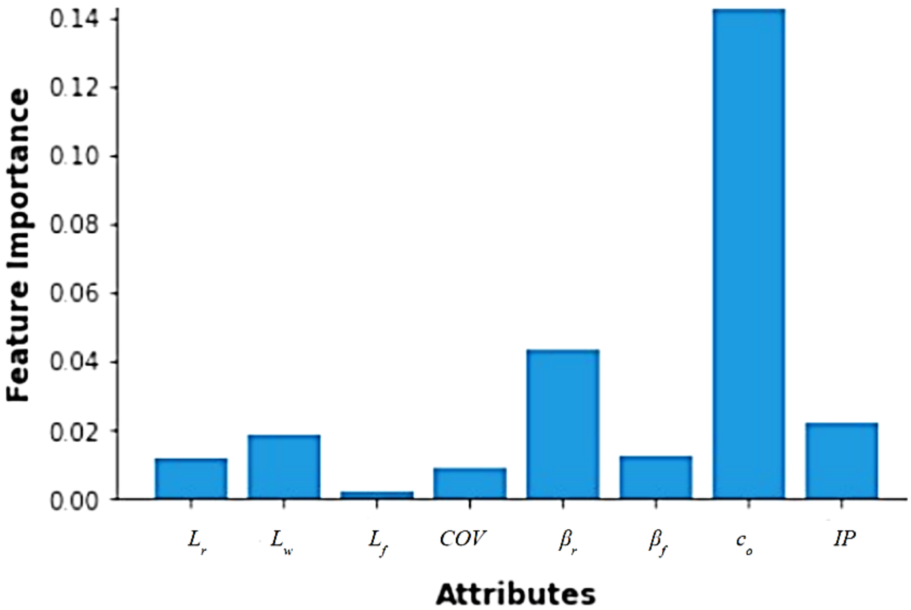

Figure 1. Feature importance (here IP represents inventory position)

6.2 Comparative analysis and validation

To compare the performance of the proposed models with the model identified from literature and the static alternatives, a separate simulation model of 1000 months is considered (again, one month has 30 days). The attribute values of the environment are assumed to vary from one month to the next in two different ways, each identified as a scenario. The first scenario is a fast-changing environment, in which the values of the independent attributes are generated randomly using the example generator. The subsequent months will have their independent attribute values dependent on the previous month's conditions. The discrete variables e.g., lead times of a month will be $\pm$ 1 of the previous month's attribute value whereas, for the continuous attributes e.g., COV of consumer demand, the value will be within the interval $\pm$ 10%. The second scenario is a chaotic environment where the values of the independent attributes of each month are generated randomly (Priore et al. 2019).

The simulation is run for three times and the values from each case are noted. The mean *J* metric value for each considered model for the two scenarios is tabulated in Table 2 and Table 3 and represented graphically using Figure 2 and Figure 3. The tables represent *J* metric values relative to the lowest possible *J* metric value for that particular month. For each of the three runs, all the ML models performed better than the static alternatives, clearly indicating the advantage of a dynamic model where the replenishment policies are changed according to the supply chain conditions.

Table 2. Evaluation metric value for fast-changing scenario

Policy	**Run 1**	**Run 2**	**Run 3**	**Average**
POUT_L (static)	1.2764	1.2607	1.2488	1.2619
POUT_M (static)	1.1693	1.1595	1.1665	*1.1651*
POUT_H (static)	1.1744	1.1708	1.1820	1.1757
OUT (static)	1.2370	1.2375	1.2488	1.2411
ML model (based on Priore et al. 2019)	1.1138	1.1138	1.1238	1.1171

ML model (Decision tree)	1.0961	1.0907	1.0920	1.0929
ML model (RF)	1.0874	1.0793	1.1038	*1.0902*
ML model (SVM)	1.0982	1.0886	1.0863	1.0910

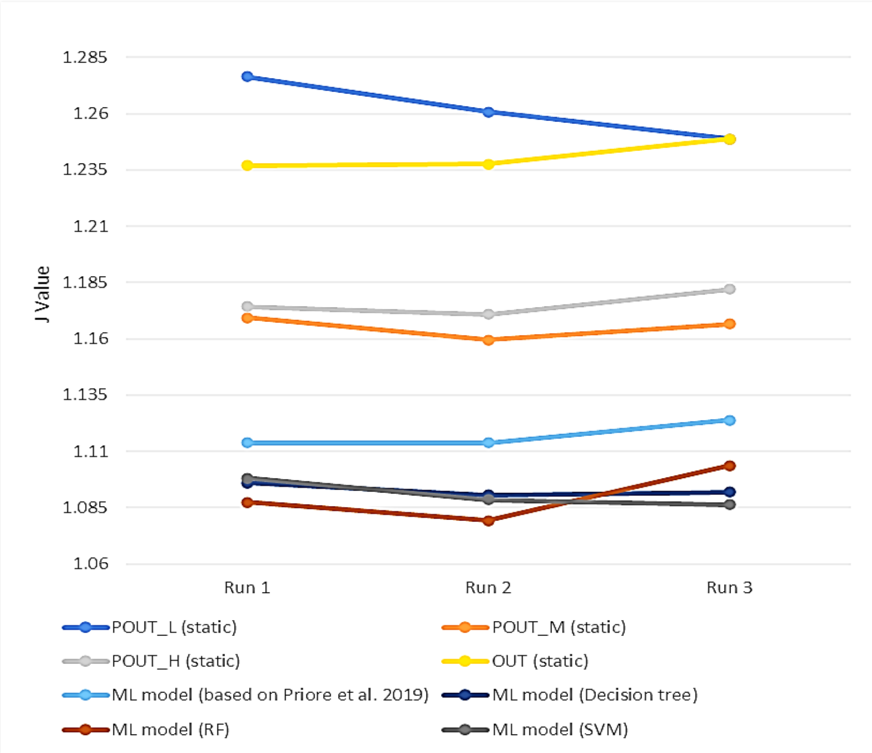

Figure 2. Graphical representation of evaluation metric value for fast-changing scenario

Table 3. Evaluation metric value for chaotic scenario

Policy	**Run 1**	**Run 2**	**Run 3**	**Average**
POUT_L (static)	1.2011	1.2055	1.1967	1.2011
POUT_M (static)	1.1807	1.1713	1.1815	*1.1778*
POUT_H (static)	1.2247	1.2087	1.2199	1.2177
OUT (static)	1.3185	1.3000	1.3131	1.3105
ML model (based on Priore et al. 2019)	1.1690	1.1622	1.1806	1.1706
ML model (Decision tree)	1.1145	1.1120	1.1037	1.1100
ML model	1.0815	1.0848	1.0758	*1.0807*

(RF)				
ML model (SVM)	1.0997	1.1152	1.0895	1.1014

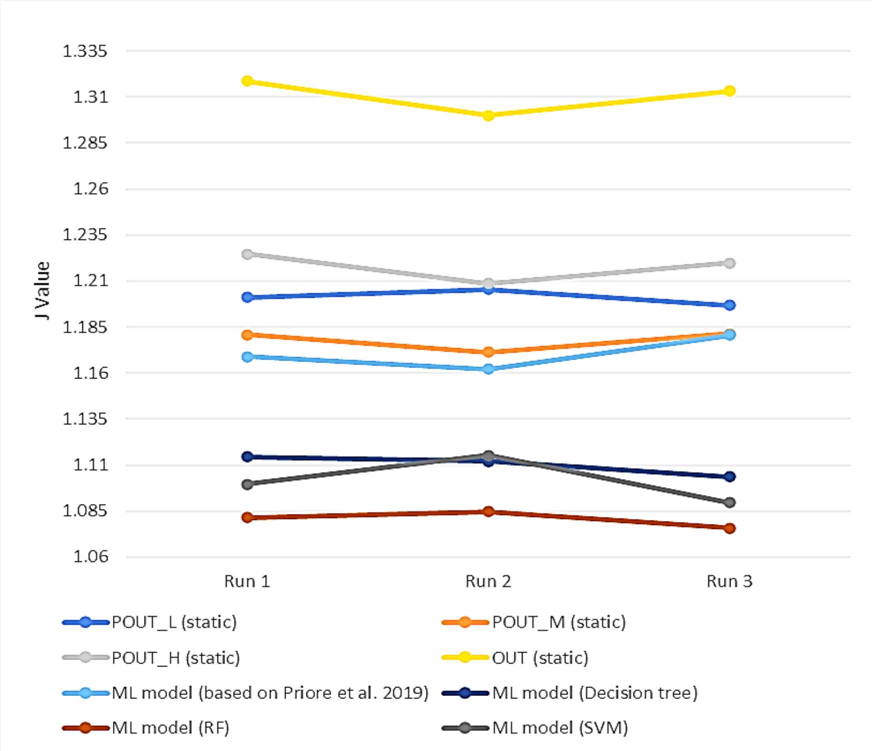

Figure 3. Graphical representation of evaluation metric value for chaotic scenario

In Figure 2 and Figure 3, the J values for each implementation are plotted respectively for 3 separate runs and the average J values for each implementation are calculated across the runs. After comparing these values it can be observed that the proposed dynamic approach-based ML models performed better than the model identified from literature in both the dynamic and the fast-changing environments. This could be due to the similarity of the comparative environment and the training dataset generation of the proposed model. In addition to that, the present work also considered the effect of inventory position as an attribute for the ML model which was not considered by Priore et al. (2019). Moreover as depicted in Figure 4, the best proposed dynamic model outperforms the best considered static approach in both Fast-Changing and Chaotic Environments by 8.2% and 6.4% respectively.

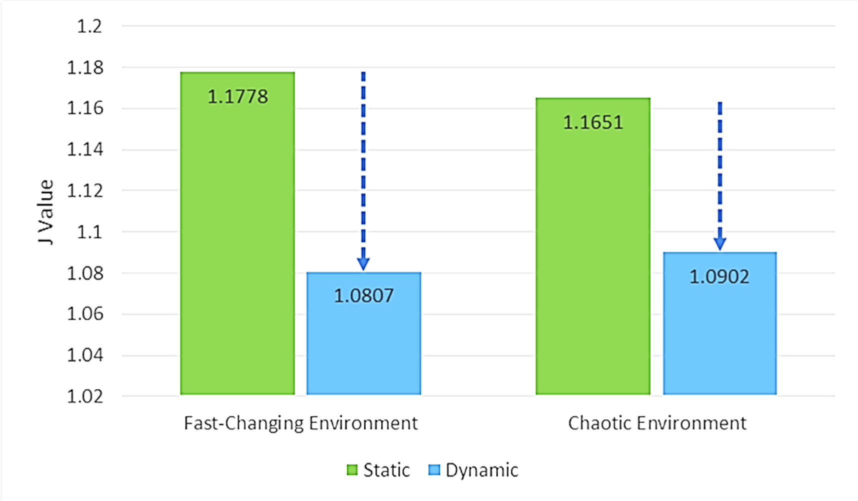

Figure 4. Performance comparison between best static and dynamic models

In the proposed dynamic model, the performances of the algorithms in both scenarios are quite intuitive. The RF model outperformed its counterparts which could be associated with the efficiency of ensemble machine learning algorithms. Though works like Ni et al. (2020) reported of SVM having better accuracy and performance than other supervised ML algorithms (including RF), the RF model outperformed the SVM model for the present problem. The reason for this deviation could be associated to the fact that the performance of an algorithm on a dataset is affected by the kind of variables and number of instances of that dataset, which means that there can be no single algorithm that can outperform other algorithms in all datasets (Osisanwo et al. 2017).

The robustness of the proposed model was verified using ANOVA techniques where the statistical significance of the proposed model was compared to the model identified from literature (Priore et al. 2019). The significance of the difference between the means was confirmed by the p value which was identified to be lower than 10%.

7. Conclusions and Scope of Future Work

The pandemic scenario has created a volatile market environment characterised by frequent changes in the supply chain environment which have forced industries to better manage their inventory. The traditional static alternatives would prove to be suboptimal under such changing conditions, which is attained by changing the values of eight attributes considered in this study. As shown in Figure 1, the lowest value of the J metrics (evaluation metrics) is observed in different order policies according to the varying conditions. Lowering the J metric value directly corresponds to a reduction in operating costs. Thus, a dynamic framework which is able to identify the best policy considering the varying conditions of the operating environment will perform better than a static policy applied throughout without considering various internal and external factors. This concept was successfully proven by the study conducted in this work.

Further, the proposed dynamic framework for a three-echelon supply chain was compared with a similar model by Priore et al. (2019) from literature and with the traditional static order policies. The result proved the success of the proposed model in managing the echelon under consideration compared to the alternatives. All the dynamic models outperformed the static alternatives which again cements the argument that a dynamic model offers better performance. The proposed model surpassed the similar model from literature as the former bears more similarity between its training dataset and the comparing environment. In addition to that, the proposed model also considered the inventory position as an attribute, which was not accounted for in Priore et al. (2019). Among the models implemented using different ML algorithms, RF model outperformed the models developed using decision tree and SVM. This could be due to the efficiency of ensemble models and the characteristics of the training dataset.

In real-life scenarios, the conditions are probably more dynamic which can result in the obsolescence of extracted knowledge. This point towards the need for careful examination and updating of the existing knowledge acquired through the decision tree model. In this direction, using dynamic knowledge refinement techniques is a suggested future work (Park et al. 2001). Also incorporating the network structure of the supply chain into the analysis is another direction for future research.

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