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Research Article

A Hybrid DDMRP-OUTL Inventory Policy with Defect Prediction for Resilient Supply Chains

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ABSTRACT

The high variability of consumer demand makes the development of inventory strategies crucial, especially regarding operational inventory resilience. Combining defect prediction with inventory strategies is crucial amidst uncertainty related to quality. Conventional Demand-Driven Material Requirements Planning (DDMRP) strategies are sensitive to shifts in consumer demand based on buffers for replenishment. However, this strategy has the disadvantage of not considering losses due to defective production output quality. This study develops a hybrid inventory model by combining DDMRP with Order-Up-To-Level (OUTL) replenishment management, and defect rate prediction. Production output is assessed from estimated defect rates converted into yield factors. OUTL is used for conditional quantity setting by determining the amount of excess replenishment. Defect rate prediction uses a manufacturing defect dataset along with production volume, supplier quality, maintenance hours, time percentage, and worker productivity. The initial predictive element in inventory simulation using a random forest regressor configuration achieved an R^2 value of 0.7208. Numerical experiments to evaluate the inventory model used 24 scenarios over a 200-day daily review period. Scenarios were conducted by integrating various demand patterns, production process conditions, and production capacity limitations. The DDMRP-OUTL hybrid strategy model can reduce the Bullwhip Effect Ratio (Ratio of Echelon Logistics - REL) compared to conventional DDMRP for various scenarios, and the most significant reduction is close to 24% under intermittent demand. Furthermore, it demonstrates a higher average inventory increase as a trade-off between replenishment stability and inventory load. Stockout events are not consistently reduced across all scenarios, although the integration of defect rate prediction and the DDMRP-OUTL hybrid model leads to replenishment stability, and inventory load and service reliability must be balanced when implementing this policy.

Keywords: Hybrid inventory model, DDMRP, OUTL, defect prediction, inventory strategy, random forest regressor

INTRODUCTION

Modern supply chains address not only uncertainty due to demand variability but also replenishment uncertainty and quality uncertainty, which can impact service reliability and replenishment stability. This highlights the challenges associated with adaptive and responsive supply chain reliability [1],[2]. Reliability here refers to supply chain resilience related to operational inventory, including replenishment stability, inventory load, and service reliability. It should be noted that the dimensions evaluated are the Bullwhip Effect Ratio (REL), Average Inventory on Hand, and Stockout Events.

This study develops a hybrid DDMRP–OUTL inventory policy with defect prediction to address uncertainty. DDMRP determines the buffer-based replenishment logic through Net Flow Inventory (NFE) allowing replenishment decisions to respond to replenishment signals., while OUTL is used as a conditional quantity setting mechanism at replenishment decision to limit excessive replenishment quantities when its decision condition is satisfied. Defect prediction adjusts the expected usable production output based on predicted defect rate. This coupling enables replenishment decisions to consider not only demand signals and inventory position, but also quality related yield rate.

DDMRP supports demand-driven replenishment through buffer positioning and NFE signals, thereby supporting more responsive replenishment decisions under demand variability [3],[4]. However, its performance remains sensitive to buffer parameterization and does not explicitly account for quality-related uncertainty. OUTL can support replenishment by providing a reference inventory level for determining order quantities under assumptions regarding review interval, lead time, service targets, and cost parameters [5],[6]. In this study, OUTL is not treated as a stand-alone inventory policy, but as a conditional quantity-setting mechanism applied after the DDMRP replenishment trigger is activated. The OUTL rule is used only when the predefined decision condition is satisfied.

In parallel, predictive quality models can estimate defect rate in manufacturing processes and support earlier identification of potential quality problems [7]. However, these predictions are commonly used for process monitoring rather than being translated into replenishment decisions. Hybrid machine learning models have also been applied to improve demand and inventory forecasting accuracy [8], but such forecasting-oriented approaches generally do not incorporate quality related defect rate information into replenishment decision policies. Based on previous research, this indicates that there are three related streams: DDMRP and replenishment strategies that focus on demand, OUTL inventory policies with periodic reviews, and predictive quality analytics. These streams are typically developed separately and are not integrated into replenishment decisions to assess demand signals, inventory positions, and quality-related defect rate information.

This indicates that development related to these streams is still very limited, especially the integration of DDMRP, OUTL, and defect rate prediction is still limited. Azzamouri et al. [9] study related DDMRP strategies to demand variability but did not consider quality-related defect rates as input for replenishment. Seyedan et al. [10] developed an OUTL-based inventory model centered on the cost-service trade-off under uncertain demand, but did not include defect-rate prediction as an input to replenishment decisions. Meanwhile, machine learning-based defect prediction studies [7] demonstrate the ability of predictive models to estimate quality-related production outcomes, but they are generally positioned in quality prediction or process monitoring rather than inventory replenishment policies. Ivanov [1] emphasized the importance of digital integration for resilient supply chains, but did not operationalize a shared inventory decision logic linking buffer-based replenishment, OUTL quantity control, and predicted defect-rate information.

Therefore, this study addresses the gap by proposing a hybrid DDMRP–OUTL inventory policy with defect prediction. The novelty lies in the operational coupling of three decision components within a single daily review procedure. Within the proposed decision flow, DDMRP first determines the buffer-based replenishment zones and uses NFE to activate replenishment trigger. Once the trigger is activated, the framework selects the replenishment quantity determination method based on a predefined decision condition. The quantity is calculated using either the DDMRP logic or the OUTL rule. The estimated defect rate is subsequently converted into a yield factor to determine the expected usable production output. By integrating these elements, demand, buffer level, replenishment quantity alternative choices, and expected defect rate data are incorporated into an integrated replenishment decision process.

METHODS

This research applies a quantitative and applied approach focused on exploring and assessing a demand-driven inventory control framework that incorporates defect rate prediction into inventory policy. The developed model

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remains demand-driven because replenishment policy is activated by demand, Qualified Demand (QD), and Net Flow Inventory Position. The study utilizes a mixed computational method that integrates predictions of defect rates into replenishment decision making.

During the predictive modeling phase, the defect rate is predicted using a Random Forest regressor approaches that has been trained on manufacturing process data. The expected defect rate is subsequently integrated into the inventory management system by converting it into an expected yield factor to gauge usable production results. This integration is appropriate as yield uncertainty can affect production and inventory planning when the released production amounts do not entirely convert into usable output due to defects [11]. The proposed model is tested through numerical experiments consider multiple scenarios and simulated on a daily inventory review, with inventory levels, observed demand, incoming supply, usable production output, and replenishment decisions being updated in sequence at every time step. This framework enables the proposed structure to assess how fluctuations in demand and forecasted defect rates influence replenishment choices and inventory outcomes.

To overcome the limitations, the suggested framework is designed as a modular yet synchronized system, where defect rate estimation and inventory control procedure run under the same reorder mechanism logic. The computational experiments were conducted using Python within a Linux environment based on Ubuntu. A machine learning model was developed and the inventory simulation was executed using Python version 3.14.4. Its support for libraries like scikit-learn, pandas, NumPy, and SciPy facilitates effective development and management of data-driven supply chain models [12]. The primary libraries utilized in this research included scikit-learn version 1.8.0, Pandas version 3.0.2, NumPy version 2.4.4, and SciPy. The development of the Random Forest Regressor model was carried out using the scikit-learn library.

To enhance reproducibility, a fixed random seed of 42 was utilized during the entire experiment. The global random seed was configured with `random.seed(42)` and `numpy.random.seed(42)`, while the Random Forest was set up with `random_state=42`. The identical random state was used for data partitioning and shuffling in 10-fold cross-validation when relevant. The hyperparameter grid was predefined before model evaluation and was evaluated consistently without introducing additional stochastic procedures. No containerization was used; the required libraries were installed in the Python environment with the versions reported above.

After the demand scenarios and defect-related inputs were generated, the inventory simulation layer was deterministic because the same replenishment logic, lead time, capacity settings, parameter values, and decision rules were applied consistently across runs. Therefore, the reported numerical outputs can be reproduced under the same dataset, Ubuntu-based computational environment, package versions, parameter settings, and random seed configuration.

Data Description and Defect Prediction Modeling

The dataset used in this study is the Predicting Manufacturing Defects Dataset obtained from Kaggle [13]. The dataset was retrieved from the Kaggle source (https://www.kaggle.com/datasets/rabieelkharoua/predicting-manufacturing-defects-dataset). The dataset version used in this study is Version 1 and was accessed on Jun 24, 2025. The file used for the analysis was manufacturing_defect_dataset.csv.

The dataset contains 1000 production period observations and 17 variables. In this study, six variables were retained for defect rate prediction: five input features, namely Production Volume, Supplier Quality, Maintenance Hours, Downtime Percentage and Worker Productivity, and one target variable, namely Defect Rate. Production Volume represents the number of units produced in a single production period. Supplier Quality represents the supplier quality rating. Maintenance Hours represents the number of hours allocated to maintenance activities. Downtime Percentage represents the proportion of production downtime, while Worker Productivity represents the productivity level of the workforce.

During data preprocessing, the chosen variables were analyzed for missing values. No missing values were found in the selected variables; consequently, neither imputation for missing values nor deletion of rows was necessary. As all the kept input variables were numerical, categorical encoding was not utilized. Variables not used in the predictive model, such as the binary Defect Status variable, were removed from the input feature set as they were unnecessary for the defect-rate regression task or the inventory simulation framework.

No rows were removed from the dataset. Summary statistics of the retained variables, including count, mean, standard deviation, minimum, and maximum values, are reported in Table X to support dataset verification and reproducibility. The source dataset is interpreted at the production-period level. One row represents a production-period observation rather than a production unit, or customer-demand transaction. The Defect Rate variable is therefore treated as a period-level quality measure associated with the production-related variables in the same record.

Prior to model training, data preprocessing was performed to improve data consistency and reduce the influence of extreme values. The dataset is then divided into training and testing subsets using an 80:20 split, where 80% of the data are used for model training and 20% are used for testing. A random state of 42 is applied to ensure reproducibility of the data partitioning process. Since the selected variables numerical, no categorical encoding was required. Outlier treatment was conducted using Winsorization based on the interquartile range. For each numerical feature, the first quartile (Q1), third quartile (Q3), and interquartile range (IQR) are calculated. The lower bound is defined as Q1 - 1,5 x IQR, while the upper bound is defined as Q3 + 1,5 x IQR. This procedure is intended to reduce the effect of extreme values without removing observations from dataset.

After outlier treatment, missing values are handled using median imputation. To prevent data leakage, the Winsorization bounds and median imputation values were estimated only from training subset and then applied to the testing subset using the same parameters. The target variable, defect rate, was excluded from the input feature set and used only as the prediction target.

To evaluate the stability of the defect rate prediction model, a 10-fold cross validation procedure was applied on the training subset. The dataset was shuffled and divided into 10 folds using KFold with `n_splits=10`, `shuffle=True`, and `random_state=42`. Since the prediction task is formulated as a regression problem with Defect Rate as a continues target variable, stratified cross validation was not applied. No repeated cross-validation was conducted.

In each iteration, nine folds were used for model training and one fold was used for validation. All preprocessing steps, including Winsorization, were fitted only on the training folds and then applied to the corresponding validation fold to prevent data leakage. Four performance metrics were documented on every validation fold: Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and coefficient of determination (R2). Upon finishing the iteration process, the average and standard deviation for each metric were determined. This method was employed to evaluate the reliability of the defect rate prediction model prior to utilizing its predicted defect rates as inputs in the inventory management simulation.

In the predictive modelling stage, a Random Forest regressor model is used to estimate the defect rate based on the selected manufacturing process variables. The predicted defect rate was subsequently transformed into a yield factor, where the yield factor is calculated as one minus the predicted defect rate. This yield factor is used as a quality-

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adjustment mechanism in the inventory control simulation to estimate the usable finished product. Therefore, the predictive model does not forecast demand; rather, it estimates quality-related uncertainty that affects the usable quantity of replenishment received in the inventory system.

The defect rate prediction serves as a key input in the integrated demand-driven inventory control framework. Demand information is incorporated through historical and observed demand values, including average daily usage, qualified demand, and net flow position. Meanwhile, the predicted defect rate is incorporated to account for quality losses in received or pending inventory. In this way, the proposed framework combines data-driven defect rate prediction with simulation-based demand-driven replenishment control.

Integrated Defect Prediction and Demand-Driven Inventory Control Framework

This study proposes a quality-aware demand-driven inventory control framework that builds upon the conventional Demand-Driven Material Requirements Planning (DDMRP) framework, initially introduced by Ptak and Smith [14], and incorporates two key enhancements to address quality-related uncertainties in manufacturing. Figure 1 illustrates the overall workflow of the proposed framework, which integrates defect rate prediction, quality-adjusted inventory calculation, DDMRP replenishment logic, production constraint and performance evaluation.

First, the model integrates predictive defect information derived from a Random Forest Regressor model based on production-related variables. The predicted defect rate is transformed into a quality adjustment factor to estimate effective inventory availability by considering only usable units. Yueli, et al. [15] affirmed that by adjusting the demand and inventory planning parameters based on the estimated proportion of defective products, the model ensures that replenishment decisions are based solely on usable inventory rather than total physical inventory.

Secondly, the Order-Up-To-Level (OUTL) policy is incorporated into the DDMRP execution logic as a control mechanism that sets an upper limit for replenishment amounts. Instead of functioning as an independent policy, the OUTL is incorporated to limit the highest inventory level allowed by the DDMRP buffer signals, avoiding excessive stock buildup during times of significant demand fluctuations or inflated buffer adjustments. OUTL sets a maximum threshold for inventory, aiding in the management of excessive purchasing in environments with significant demand fluctuations.This policy acts as a complement to the adaptive nature of DDMRP by introducing a strategic boundary informed by safety stock and historical usage patterns [15]. The predicted proportion of defective units, is incorporated into the net flow inventory calculation to reflect usable inventory more accurately. Iseri, et al. [16] believed that by synchronizing predictive analytics with operational constraints, the model aims to deliver a more realistic, adaptive, and resilient inventory control mechanism tailored to the challenges of the manufacturing sector.

The stepwise in proposed framework begins with the preparation of demand data and production-related variables, including supplier quality, maintenance hours, downtime percentage, worker productivity, production capacity, minimal production, lead time, and initial inventory. The buffer levels are calculated once at the beginning of each simulation scenario using the demand historical data. The buffer parameters, including ADU, DLT, LTF, VF, BRZ, TOR, TOY, and TOG, are treated as fixed parameters during the daily simulation. This setting is used to isolate the effect of daily inventory dynamics, quality-adjusted receipts, and replenishment decisions without recalibrating the buffer at every time step.

Although the buffer levels remain fixed within one simulation run, the inventory state is updated on a daily review basis. The demand-driven component calculates, qualified demand, buffer zones, and net flow inventory. At the same time, the predictive quality component estimates the defect rate and adjusts the effective quantity of incoming supply and pending orders. The replenishment quantity decision is established by merging DDMRP replenishment indicators, minimum production levels, and production capacity limitations. The expected defect rate is included in the inventory estimation to better represent usable stock. Consequently, the suggested framework intends to deliver a more practical, flexible, and quality-conscious inventory control system for manufacturing settings where defect rates affect usable stock availability and service performance.

Computational Procedure and Model Formulation

In the context supply chain management, uncertainty comes from both, external factors such as demand and lead time uncertainty and internal factors such as uncertainty in product quality, aspects frequently neglected in inventory planning system. Unusable product in the supply chain network can lead to financial damage, disrupt distribution process and decrease customer trust and satisfaction [17]. Although inventory planning frameworks like DDMRP have developed to face demand fluctuations using buffer-oriented inventory techniques [2], they usually assume that all existing inventory meets quality standards. This assumption states a significant weakness in manufacturers where product quality is a key factor in deliverability. The failure to distinguish between usable and defective stock in DDMRP's calculations can lead to overestimated availability, inaccurate replenishment signals, and poor service performance [18]. Hence, the integration of data-driven predictive quality mechanisms into inventory planning has become a necessary evolution for risk-sensitive sectors, particularly manufacturing.

The mathematical model developed in this study introduces key enhancements and integrations to the foundational framework of Demand-Driven Material Requirements Planning (DDMRP) that initially introduced by Ptak and Smith [14]. For comparison purposes, the baseline DDMRP model is formulated using the same core DDMRP parameters as the proposed hybrid model, including *ADU, DLT, LTF, VF, OST, OSH*, buffer calculation rules. The baseline model follows the conventional DDMRP replenishment logic, where net flow inventory is calculated based on physical on-hand inventory and pending orders, assuming that all inventory units are usable.

The proposed hybrid model retains the same DDMRP buffer structure and demand-driven replenishment logic but modifies the inventory availability calculation by incorporating predicted defect rate information. The predicted defect rate is used to adjust usable finished product then treated as incoming supply in the model. In addition, the proposed model incorporates the OUTL policy as a strategic inventory control constraint within the DDMRP framework. The OUTL establishes a maximum limit for acceptable inventory levels, thus avoiding excessive restocking. In this concept, the order quantity is established after replenishment signal triggered then selects either the DDMRP or OUTL method based on the threshold. This adjustment allows for a more cautions and regulated ordering approach, especially in unstable market situations where conventional DDMRP could lead to overstocking [19]. The OUTL constraint improves system responsiveness by matching order quantities to past consumption trends and safety stock amounts, as also recommended by Reddy and Rajendran [20].

Step 1. Set the DDMRP parameters and compute the buffer

The DDMRP parameters include Average Daily Usage (*ADU*), Decoupled Lead Time (*DLT*), Lead Time Factor (*LTF*), and Variability Factor (*VF*). These parameters are set before the daily execution of the inventory control process. *ADU* is calculated from historical demand data, while *DLT* represents the total time from placing an order to the point the item is ready for use. *LTF* adjusts for differences in lead time, and *VF* accounts for demand variability by providing additional buffer, especially within the red zone under highly fluctuating conditions. A higher *VF* increases the red zone coverage, thereby improving buffer responsiveness under fluctuating demand conditions.

Based on these parameters, the buffer levels, including Base Red Zone (*BRZ*), Top of Red (*TOR*), Top of Yellow (*TOY*), and Top of Green (*TOG*) are illustrated in Figure 1. *BRZ* is used as the starting point for calculating the red

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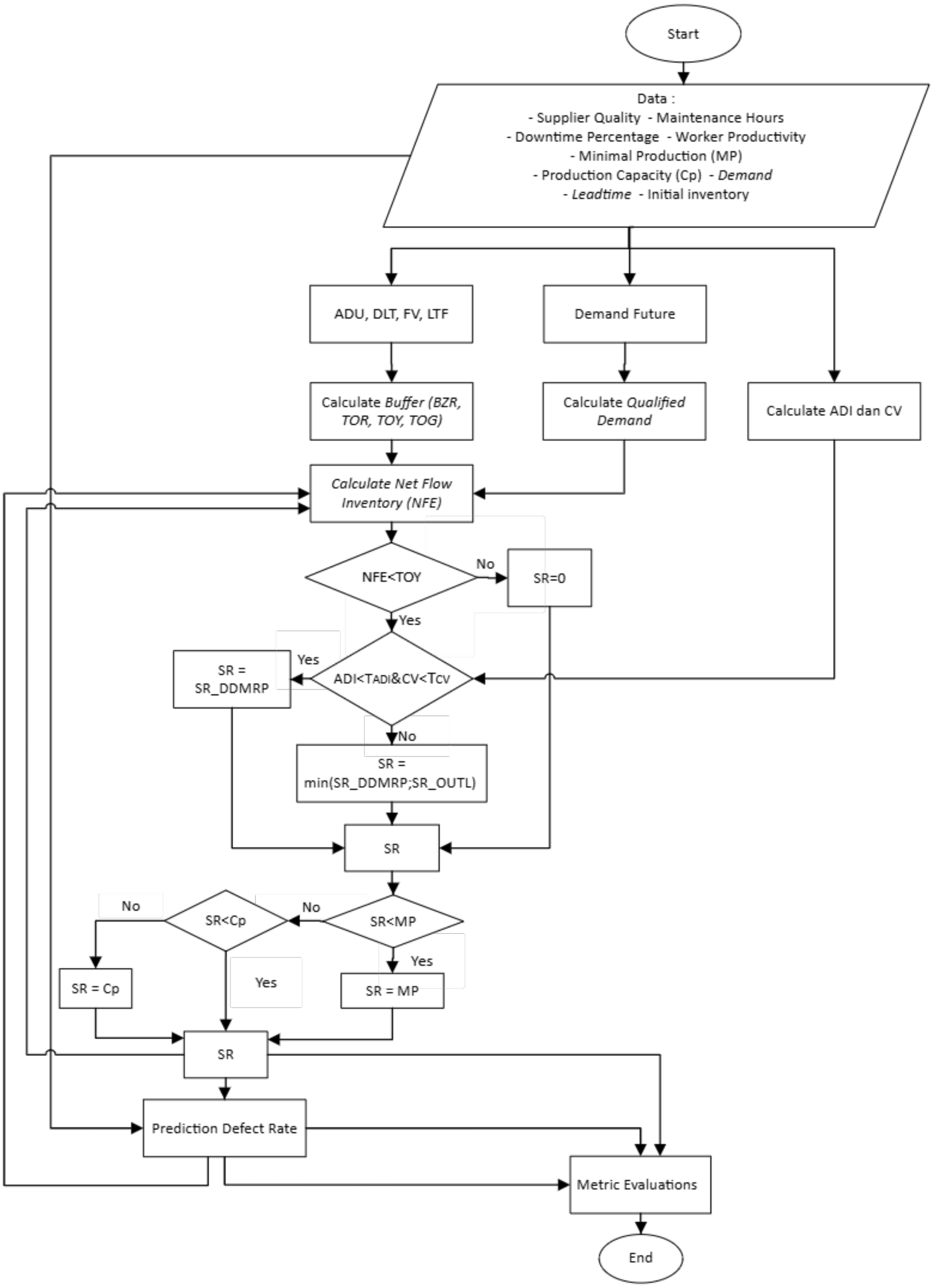

Figure 1. Demand-Driven Inventory Control with Defect Prediction Framework

zone, which is then adjusted based on lead time to obtain the final red zone. *BRZ* is calculated by multiplying the *ADU*, *DLT*, and *LTF*.

$$BRZ = ADU \times DLT \times LTF \tag{1}$$

The second component within the red zone is Top of Red (TOR). TOR is designed to address uncertainties such as demand fluctuations. It is calculated by multiplying the adjusted *BRZ* with *FV*, which provides additional flexibility within the red zone under uncertain demand conditions. *TOR* formula represented in Equation (2).

$$TOR = BRZ \times FV \times LTF \tag{2}$$

The Top of Yellow (*TOY*) represents the upper boundary of the yellow zone in DDMRP buffer structure. It is calculated by adding the yellow zone component to the *TOR*, as shown in equation (3). Therefore, *TOY* indicates the replenishment threshold above which the inventory position is considered sufficient within the yellow zone.

$$TOY = TOR + (ADU \times DLT) \tag{3}$$

The Top of Green (*TOG*) represents the upper boundary of the green zone in DDMRP buffer structure. It is obtained by adding *TOY* to the maximum value of Desired Order Cycle (*DOC*), *BRZ* and Minimum Batch production (MBP) from which the result is then added to *TOY*. The Top of Green (*TOG*) is calculated using the following Equation (4). DOC represents the inventory quantity required to cover the desired order cycle, *BRZ* reflects the minimum replenishment protection based on average demand and lead time, and MBP denotes the minimum production quantity that must be released in a single production batch. By taking the maximum of these three values, the mode ensures that the green zone is sufficiently sized to satisfy replenishment cycle requirements, minimum protection needs, and production batch constraints.

$$TOG = TOY + \max(DOC, BRZ, MBP) \tag{4}$$

Step 2. Observe realized demand and calculated qualified demand

For each daily review period, the demand realized in period t is recorded as D_t. Subsequently, qualified demand QD_t is calculated according to the DDMRP logic by combining the current demand with future known demand that fall within the Order Spike Horizon (*OSH*) and exceeding the Order Spike Threshold (*OST*). In this study, *OST* is set equal to *ADU*, so that the demand is classified as a spike when it exceeds the normal daily consumption level. While *OSH* represents the future time window used to detect significant short-term demand spikes. In this study, *OSH* is set equal to *DLT*, so that only demand spikes occurring within the relevant replenishment horizon are included in the qualified demand calculation. The qualified demand is expressed as

$$QD_t = D_t + \sum_{i=1}^{OSH} D_{t+1} \mathbf{1}(D_{t+1} > OST) \tag{5}$$

D_t denotes the realized demand in period t, D_{t+1} denotes the known demand for period $t+1$ that is already available at the beginning of review period t. While, $\mathbf{1}(.)$ is an indicator function that takes the value of 1 when known demand exceeds the thresholds and 0 otherwise. This mechanism allows the model to incorporate exceptional short-term demand into the replenishment. In this formulation, the demand values within the OST are interpreted as known customer orders available at review period. They do not represent future realized demand observed ex post. Therefore, the replenishment decision uses only current demand and known demand information available at the time of decision making, thereby avoiding look ahead bias in the simulation.

Step 3. Receive Scheduled Receipt and Determine Pending Order

At each daily review period t, the system first receives ani scheduled receipt that becomes available in current period. The scheduled receipt received in period t represents the usable finished product generated from production released in previous periods. Therefore, this receipt has already been adjusted for predicted yield when it was scheduled at the earlier production released period.

After receiving the scheduled receipt due in period t, the pending order ({PO}_t) is calculated as the total quantity of scheduled receipts that are still expected to arrive within OSH. It is calculated as

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$$PO_t = \sum_{u=t}^{t+OSH-1} SR_u \tag{6}$$

$$PO_t^{eff} = \sum_{u=t}^{t+OSH-1} SR_u^{eff} \tag{7}$$

SR_u denotes the scheduled receipt expected to arrive in period u. This formulation ensures that PO_t includes only open replenishment orders that have not yet arrived but are expected to become available within the relevant execution horizon. To account for production induced quality loss, each scheduled receipt is determined at the time of production release. If production releases in period r, the predicted defect rate and predicted yield are computed in that period, and the resulting usable finished product is scheduled to arrive at period $r + DLT$. Therefore, the predicted yield computed in the current period affects future scheduled receipts, not the scheduled receipt already received in the current period.

In this step, the predicted yield computed in the current period is not used to adjust the scheduled receipt already received in the current period. Instead, the predicted defect rate and predicted yield computed in Step 6 and Step 7 are used to estimate the usable finished product from the current released production quantity and to schedule the corresponding defect adjusted receipt for a future period.

Step 4. Compute net flow inventory

Net Flow Inventory (NFE) is used to represent the effective inventory position available for the replenishment decision at each review period. In the proposed model, NFE is calculated by combining the on-hand inventory, the effective pending order and then subtracting the qualified demand. Accordingly, NFE is expressed as

$$NFE_t = OH_{t-1} + PO_t^{eff} - QD_t \tag{8}$$

OH_{t-1} denotes the on-hand inventory before replenishment decision at period t, PO_t^{eff} represents the effective pending order adjusted by the predicted yield and QD_t is the qualified demand.

Since back orders are not considered in this study, unmet demand is treated as stockout, and on-hand inventory is not allowed to become negative after fulfillment demand. Therefore, the inventory balance is updated as follows:

$$OH_t = \max(0, OH_{t-1} + SR_t - QD_t) \tag{9}$$

SR_t denotes the scheduled receipt arriving at period t, and D_t is the demand at period t. Any unmet demand is recorded as stockout and is not carried forward to the next period.

Step 5. Calculate ADI and CV²

Demand pattern classification was used as a decision support mechanism for selecting the replenishment quantity calculation logic. The classification was conducted using Average Demand Interval (*ADI*) and squared coefficient of variant (CV^2), following the demand categorization approach proposed by Syntetos, Boylan, and Croston [21]. *ADI* is used to represent the frequency of demand occurrence, while CV^2 is used represent the variability of demand size. *ADI* is calculated by comparing the total number of observation periods with the number of periods in which positive demand occurs, so it reflects how frequently demand appears over simulation horizon. Meanwhile, CV^2 is calculated from the variability of positive demand values by comparing the standard deviation of demand with its mean and then squaring the result. Thus, ADI captures demand occurrence frequency, while CV^2 captures demand size variability.

The threshold values of $ADI = 1{,}32$ and $CV^2 = 0{,}49$ were used to support the selection of replenishment logic. When $ADI < 1{,}32$ and $CV^2 < 0{,}49$, the standard DDMRP logic was applied to calculate the replenishment quantity. Otherwise, the hybrid DDMRP-OUTL logic was applied. The actual replenishment trigger remained based on *NFE*, while ADI and CV^2 were used only to select the replenishment logic after the trigger condition was met.

Step 6. Generate the replenishment signal

In this study, the replenishment quantity is determined by integrating the DDMRP replenishment signal with the $OUTL$ constraint. The DDMRP logic provides the primary replenishment signal based on the buffer status, while the $OUTL$ rule acts as an upper-bound control to prevent excessive replenishment. Accordingly, the final order quantity is determined by combining these two control rules, so that the system remains responsive to demand while limiting the inventory position to predefined maximum level.

First, the replenishment signal is generated by comparing the NFE with the predefined DDMRP buffer threshold. Since the buffer levels are fixed during each simulation run, the replenishment decision is based on the previously computed values of the TOY and the TOG. If the net flow inventory is less than or equal to the TOY, a replenishment signal is triggered. The reorder quantity is then calculated as the difference between the TOG and the current NFE, as follows:

$$Q_t^{DDMRP} = TOG - NFE_t \tag{10}$$

Second, the OUTL defines the maximum allowable reorder quantity required to restore the inventory toward the target inventory position. In this model, the target inventory position is established by ADU, DLT, and safety stock. The OUTL is calculated as follows:

$$Q_t^{OUTL} = max(0, (ADU * DLT + SS) - OH_t) \tag{11}$$

The OUTL represents the positive difference between the target inventory level and the current on-hand inventory. If the current on-hand inventory is greater than or equal to the target inventory position, the OUTL is set to zero.

The integration of the OUTL into the DDMRP framework is implemented through a conditional reorder logic based on demand type. In the proposed framework, the demand pattern is evaluated using *ADI* and the coefficient of variation (CV^2). When the demand pattern satisfies the predefined *ADI* and *CV* thresholds, the DDMRP is used as the replenishment quantity. Otherwise, the replenishment quantity is controlled by comparing the DDMRP with the OUTL, and the smaller value is selected to avoid excessive ordering. The mechanism is expressed as

$$Q_{calc} = \begin{cases} \min(Q_{DDMRP}, Q_{OUTL}) & \text{if } CV > T_{CV} \; and \; ADI > T_{ADI} \\ Q_{DDMRP} & \text{otherwise} \end{cases} \tag{12}$$

The system evaluation compares the performance of the conventional DDMRP model with the proposed quality-aware modified DDMRP model. In the modified model, product quality information is incorporated only through the predicted defect rate generated by the Random Forest Regressor. The predicted defect rate is then converted into predicted yield and used to estimate the usable finished product and defect adjusted scheduled receipt in the daily replenishment simulation. This mechanism allows the model to account for quality related supply loss when evaluating inventory availability and replenishment performance.

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This evaluation follows the approach of Cuartas and Aguilar [22], who emphasize the importance of adaptive buffer formulation to address variability in the supply chain, including fluctuations in demand and lead time. In this study, defect rate information is treated as an additional risk factor that affects the availability of usable inventory. Therefore, the predicted defect rate is incorporated into the estimation of usable finished product and defect adjusted scheduled receipt, which subsequently affects the inventory position used in the replenishment evaluation.

After the initial supply request is determined, the replenishment quantity is further adjusted according to operational production constraints. If the supply request is positive but lower than the Minimum Production (MP), the order quantity is increased to meet the minimum production requirement. If the supply request exceeds the available production capacity (CP), the order quantity is capped at the production capacity. Therefore, the final supply request is not only demand-driven and quality-aware, but also operationally feasible within the production system.

Step 7. Predict the defect rate and compute the prediction performance

At each daily review period, the defect rate is estimated using a trained Random Forest Regressor based on production-related variables obtained from the manufacturing defect dataset. Since the defect information in the dataset is reported as the number of defective units, it is first transformed into a defect rate by dividing the defect quantity by the corresponding production volume. The resulting defect rate is then used as the continues target variable for training the Random Forest Regressor.

In this study, the input features include production volume, supplier quality rating, maintenance hours, downtime percentage, and workforce productivity. The production volume used in the defect prediction stage is derived from the replenishment decision generated by the inventory control model. Specifically, the replenishment decision determines the released production quantity after considering the minimum production requirement and the available production capacity. This feasible released quantity is treated as the production volume variable for defect rate prediction. At each period t, the feature vector for defect rate prediction is constructed as

$$x_t = [PV_t, SQ_s, MH_s, DT_s, WP_s] \tag{13}$$

where PV_t represents the production volume released at period t, which is obtained from the feasible replenishment quantity generated by the inventory control model. Meanwhile, SQ_s denotes supplier quality under scenario s, MH_s denotes maintenance hours under scenario s, DT_s denotes downtime percentage under scenario s, and WP_s denotes workforce productivity under scenario s. These variables are determined based on defined production process scenario.

The Random Forest Regressor does not use demand directly as its input. Instead, it uses the production related feature vector (x_t) consisting of $PV_t, SQ_s, MH_s, DT_s, WP_s$. This formulation allows the predicted defect rate to represent the expected quality risk associated with the feasible production quantity released by the replenishment decision. Meanwhile, the remaining input variables are adopted from the manufacturing defect dataset and used as scenario parameters in the defect prediction model. Given the feature vector x_t, the raw defect rate prediction generated by the Random Forest Regressor is expressed as

$$\hat{p}_t = f_{RF}(x_t) = \frac{1}{B}\sum_{b=1}^{B} T_b(x_t)\,, 0 \le \hat{p}_t \le 1 \tag{14}$$

where $\hat{p}_t$ denotes the raw predicted defect rate at period t, x_t represents the vector of production-related input features, and $f_{RF}(.)$ denotes the trained Random Forest Regressor function. In its detailed form, B represents the number of regression trees in the Random Forest, while $T_b(x_t)$ denotes the prediction generated by the b-th decision tree for the input vector x_t. The final predicted defect rate is obtained by averaging the predictions from all regression trees.

The predicted defect rate is generated at the daily review period or release-batch level. It is not fixed at the scenario level and is not randomly sampled in each period. Instead, it is deterministically estimated by the trained Random Forest Regressor based on the feasible production volume released in period t and the production process condition assigned to the scenario. The predicted defect rate is then used in the subsequent step to calculate predicted yield and the defect-adjusted scheduled receipt.

The Random Forest Regressor model is evaluated using regression-based performance metrics, including Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and the coefficient of determination (R^2). These performance metrics are employed because the prediction approach in this model is framed as a continues defect rate estimation case instead of a classification case. MAE calculates the average absolute gap between estimated and actual defect rates, whereas MSE and RMSE highlight larger prediction inaccuracies. R^2 indicates the proportion of variance in the actual defect rate that can be explained by the model. These metrics are appropriate because the model estimates a continuous defect rate rather than assigning observations to discrete defect classes.

Lower MAE, MSE, and RMSE values and higher R^2 indicate better predictive accuracy. Since the defect rate is treated as a continues variable, these regression-based metrics are used to evaluate the performance of the Random Forest Regressor before its output is incorporated into the inventory simulation. The use of machine learning models for predicting manufacturing-related quality characteristic has been reported in previous manufacturing studies [24]. However, the evaluation of the proposed defect rate prediction model in this study relies on regression- based performance metrics. MAE provides a direct measure of the average magnitude of errors in a set of predictions, without considering their direction, making it an intuitive indicator of overall prediction accuracy. MSE and RMSE extend this by emphasizing larger errors through squaring, with RMSE offering interpretability in the same units as the predicted variable, thus reflecting the typical deviation from actual values [25]. A lower value of MAE, MSE, or RMSE indicates that the model effectively captures the defect patterns in the data. Simultaneously, R^2 functions as an indicator of goodness-of-fit, reflecting the proportion of variability in the observed data; R^2 value near 1.0 implies strong explanatory capability [26]. The linkage of these performance metrics delivers a comprehensive mechanism for validating the predictive ability, guaranteeing that only reliable defect rate forecasts are used to estimate the usable finished products, which are then incorporated into the suggested reorder mechanism.

Step 8. Compute the predicted yield

The predicted yield represents the expected proportion of usable finished product obtained from the released production volume. It is calculated as the complement of the predicted defect rate generated by the Random Forest Regressor. Since the defect rate is defined as the ratio of defective units to total production quantity, it is expressed as a portion within the interval [0,1]. Therefore, the predicted yield at period t is calculated as

$$y_t = 1 - \hat{p}_t \tag{15}$$

where y_t denotes the predicted yield at period t. Because $\hat{p}_t$ is expressed as a proportional value between 0 and 1, the resulting predicted yield also falls within the feasible proportional range of 0 and 1. Thus, y_t can be interpreted as the expected usable fraction of the released production volume. The predicted yield is then used to estimate the usable finished product. The usable finished product will be completed at period $t + DLT - 1$, it means that, if the production volume is released at period t, the corresponding finished product becomes available at period $t + DLT - 1$. Therefore, the usable finished product is formulated as

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$$UFP_{t+DLT-1} = y_t \, x \, PV_t = (1 - \hat{p}_t)PV_t \tag{16}$$

where UFP_t denotes the usable finished product available at the completion period, PV_t denotes the production volume released at period t. The value of $UFP_{t+DLT-1}$ represents the expected number of good units completed after considering the predicted defect rate. This value is then recorded as the scheduled receipt at period $t + DLT - 1$ as expressed as

$$SR_{t+DLT-1} = UFP_{t+DLT-1} \tag{17}$$

Thus, the predicted defect rate affects the scheduled receipt available after the lead time completion period, rather than directly changing demand or immediately increasing on-hand inventory at period t.

Step 9. Update inventory state

At the end of each daily review period, the inventory state is updated by considering the scheduled receipts arriving at period t and the realized demand during the same period. Since back-orders are not allowed in this study, on-hand inventory is not permitted to take negative values. Accordingly, the inventory balance is updated as

$$OH_t = \max(0, OH_{t-1} + SR_t - D_t) \tag{18}$$

Any unmet demand is recorded as stockout calculated as

$$SO_t = \max\big(0, DT_t - (OH_{t-1} + SR_t)\big) \tag{19}$$

where SO_t denotes the stockout quantity at period t. The updated value of OH_t is then carried forward as the opening inventory to the next review period.

Step 10. Repeat for each daily review period

Step 2 through 8 are carried out in order for each daily review period across the simulation dataset. During each period, the inventory condition updated from the previous day serves as the opening inventory for the subsequent review period. This repetitive step allows the model to grasp the evolving interaction between demand fulfilment, adjusted incoming supply defect rates, and restocking choices

Step 11. Calculated the inventory performance

After finishing the simulation throughout all day review intervals, the proposed inventory model effectiveness is tested using the selected inventory performance metrics. In this research, to assess the efficiency, inventory performance metrics from Cuartas and Aguilar [22], including Bullwhip Effect Ratio (REL), which captures amplification of order variability; number of stockout events (BS), which reflects service reliability; and Average on-hand inventory, which indicates the trade-off between inventory availability and the potential risk of overstock. Together, these metrics propose a multidimensional view of inventory performance, emphasizing the model's ability to maintain a balance between responsiveness and inventory efficiency.

Performance Evaluation

To evaluate the effectiveness of the proposed model, this research applies a performance evaluation framework based on established logistic metric. According to Cuartas and Aguilar [22], reliable inventory performance evaluation should include some indicators that reflect demand fluctuation, service level reliability, and inventory balance. These metrics hold particular importance in manufacturing settings sensitive to quality, where faulty stock evaluations stemming from untracked defective products can greatly hinder supply chain efficiency. The following subsections describe three performance metrics used to evaluate the enhanced DDMRP system: REL, BS, and Average On-hand Inventory.

Bullwhip Effect Ratio

Bullwhip Effect Ratio (Ratio of Echelon Logistics - REL) is used to measure the degree of demand distortion that occurs along the supply chain. This indicator is calculated as the ratio between the variance of order quantities and the variance of actual demand, shown in Equation (16). In this study, REL is computed at the scenario level using the full 200-day simulation horizon. The order quantity used in the calculation is the final replenishment quantity after applying DDMRP logic, minimum production, and production capacity constraints. The variance is calculated as an aggregate variance over all daily periods, not as a rolling-window measure. No additional filtering or centering is applied. For intermittent demand scenarios, the REL value is interpreted with caution because variance-based measures may be unstable when the demand series contains many zero-demand periods. If demand variance is zero, REL is treated as undefined. Therefore, REL is evaluated together with stockout, and average on hand inventory.

$$REL = \frac{\sigma^2_{order}}{\sigma^2_{demand}} \tag{20}$$

REL value of 1 indicates no distortion, implying that variability in order reflects true demand. While, a REL exceeding 1 indicates the existence of the bullwhip, where order fluctuations surpass demand variability, which may lead to inefficiencies like overstock, underused capacity, and misaligned purchasing strategies [27]. This issue is frequently exacerbated by misleading inventory planning, long lead times, and insufficient demand estimations. In this study, integrating defect rate predictions into DDMRP framework seeks to diminish these distortions by enhancing the precision of inventory availability evaluations. By excluding the defect items from usable inventory calculations, the system improves the accuracy of replenishment alerts, thus aiding in reducing false order variations and ensuring higher stability across the supply chain [28].

Stockout Event (BS)

Stockout Events (BS) are used to calculate how often stockout occurrences throughout the simulation period. In this study, BS is explained at the daily period level. A stockout happens in period t when the actual demand exceeds the available inventory on hand, leading to unmet demand that is greater than zero. Partial fulfilment is regarded as a stockout event when any part of the demand goes unsatisfied. The stockout indicator is expressed as follow:

$$BS_t = \begin{cases} 1 & \text{if } CV > T_{CV} \text{ } and \text{ } ADI > T_{ADI} \\ 0 & \text{otherwise} \end{cases} \tag{21}$$

where D_unmet_t represents the unmet demand in period t. The total number of stockout events is calculated as

$$BS = \sum_{t=1,2,\dots T} BS_t \tag{22}$$

where T denotes the number of daily simulation periods. In this study, T = 200 for each scenario. Backorders are not considered in this study, while unfulfilled demand is noted as lost demand. To facilitate comparison across scenario, the raw count of stockout events is additionally presented as a normalized stockout event rate. This rate is calculated by dividing the overall count of stockout events by the total number of daily simulation periods. As each scenario is

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assessed over a 200-day period, the normalized value indicates the fraction of simulation days during which stockouts take place. When represented as a percentage, it shows the portion of daily review intervals encountering stockout. A normalized stockout event rate of 5% indicates that stockouts happen in 5% of the simulated daily periods.

The stockout event rate is used to assess the robust of the proposed model in fulfilling customer orders. Smaller values suggest improved product availability and greater consistency in service level performance. Incorrect calculation of available stock, especially when defective items are factored into inventory counts, can result in unforeseen shortages and unmet orders. Incorporating projected defect rates into inventory planning addresses this problem by differentiating between usable and faulty stock, thereby offering a more precise depiction of what is genuinely available to fulfill customer orders.

This integration allows for more accurate restocking decisions and minimizes the risk of overrating inventory amounts that could be unsellable. According to Selepe and Makinde [29], misaligned between inventory with real demand, particularly in the presence of quality problems, can greatly diminish customer satisfaction and enhance the risk of service disruptions. Moreover, Huo, et al. [30] highlight that quality driven stockouts not just immediate fulfillment but can also lead to affect customer loyalty and supply chain robustness. Thus, integrating quality factors like defect prediction into the inventory planning model is crucial for decrease BS rate and boosting service reliability.

Average On-hand Inventory

Average On-Hand Inventory is used to calculate the average inventory throughout the simulation period. It is determined by averaging the final on-hand inventory throughout all daily review periods. This performance metric does not aim to reflect an optimality gap, but instead, serves as a direct gauge of inventory buildup in each scenario.

Defect Rate prediction Metrics

The Random Forest Regressor model is assessed using common performance indicators such as Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and R-squared (R^2) to confirm its reliability in continues defect rate prediction [23]. Smaller MAE, MSE, and RMSE values along with increased R^2 suggest enhanced predictive accuracy. These metrics are well acknowledged in the literature for evaluating the accuracy and robustness of predictive models, particularly in quality prediction within manufacturing contexts [24]. MAE offers a straightforward assessment of the average size of errors in a group of predictions, disregarding their direction, thus serving as an intuitive gauge of overall prediction accuracy. MSE and RMSE build on this by highlighting larger errors via squaring, with RMSE providing clarity in the same units as the predicted variable, thereby indicating the standard deviation from actual data [25]. A smaller MAE, MSE, or RMSE illustrates that the model successfully identifies the defect patterns present in the data. At the same time, R^2 acts as an indicator of goodness-of-fit, reflecting the fraction of variance in the observed data that the model accounts for; an R^2 value near 1.0 implies strong explanatory capability [26]. The integration of these metrics provides a thorough framework for confirming the predictive ability of the Random Forest algorithm, guaranteeing that solely reliable defect predictions inform inventory modifications in the suggested hybrid planning model.

Assumptions

To ensure the integrity and applicability of the proposed hybrid inventory model, a number of assumptions were formulated. These assumptions establish the operational limits and data conditions in which the model assessed.

Similar to earlier inventory optimization research [31], such foundational premises are needed to maintain computational tractability and clarity of simulation outcomes. The assumptions are:

- Defect Rate Prediction: The defect rate applied in the suggested model is estimated through a Random Forest Regressor trained on past product quality data. As the defect rate is regarded as a continuous variable, the prediction task is defined as a regression problem instead of a classification issue. Therefore, the predictive performance of the model is evaluated separately using regression-based metrics, including MAE, MSE, RMSE, and R^2. For the purpose of the inventory simulation, the predicted defect rate generated by the trained model to calculate predicted yield, usable finished product, and defect adjusted scheduled receipt.
- Stability of Operational Parameters: Key parameters such as Average Daily Usage (ADU), Lead Time Factor (LTF), and Demand Variability (FV) are considered constant within a single buffer recalculation cycle. This assumption allows the simulation to maintain consistency in buffer evaluation and simplifies sensitivity analysis without changing the operational logic of the model [32].
- Known Future Demand within the OSH: in the QD calculation, the future demand component within the OSH is assumed to represent known customer orders that are already available at the beginning of review period. Therefore, the model does not use future realized demand that would only be observed after the replenishment decision is made. This assumption ensures that the daily replenishment decision based only on information available at the time of decision making and avoids look ahead bias in the simulation.
- Supply Chain Continuity: The model assumes no disruptions in the supply of raw materials or distribution processes, except for supply availability changes caused by predicted quality loss in finished products. This assumption allows the study to isolate the effect of defect related quality risk on inventory performance and is consistent with studies focusing on internal quality related supply uncertainty [33].

These assumptions enable the model to focus on the integration of defect prediction and adaptive inventory control under conditions that reflect typical, yet controlled, manufacturing environments.

Experimental Design and Scenario Configuration

This study evaluates the proposed hybrid inventory planning model using a scenario-based numerical experiment, following recommended practices for simulation-based studies [34]. Scenario-based experimentation has been widely recognized in supply chain research for its effectiveness in capturing system behavior under complex uncertainties. This experiment combines secondary-data defect rate prediction and discrete time inventory simulations. The design is intended to examine the behavior of the baseline DDMRP and the proposed hybrid DDMRP-OUTL model under different demand patterns, defect-related production process conditions, and capacity settings. In this study, defect related production process conditions represent different quality risk environments that influence the predicted defect rate trough variations in supplier quality, maintenance hours, downtime percentage, workforce productivity, and production volume. Therefore, the experiment is positioned as a controlled scenario-based evaluation of model behavior, rather than as direct operational validation in a specific manufacturing firm. This approach allows the study to examine how predicted defect rates affect usable incoming supply, replenishment decisions, and the inventory performance under different operational scenarios.

To assess the adaptability and performance of the proposed model, 24 simulation scenarios were constructed, as illustrated in Table 1. These scenarios were generated from the combination of four demand scenarios, three production process conditions, and two production capacity settings. The demand scenarios include baseline demand, seasonal demand, intermittent demand, and highly fluctuating demand. The production process conditions consist of baseline, improved, and deteriorated production conditions. The minimum production is fixed at 500

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Table 1. Parameter configuration of simulation scenarios

Demand Pattern	Production Condition	Capacity 750 unit	Capacity 1000 unit
Baseline	Baseline	Scenario 1	Scenario 2
	Improved	Scenario 3	Scenario 4
	Deteriorated	Scenario 5	Scenario 6
Seasonal	Baseline	Scenario 7	Scenario 8
	Improved	Scenario 9	Scenario 10
	Deteriorated	Scenario 11	Scenario 12
Intermittent	Baseline	Scenario 13	Scenario 14
	Improved	Scenario 15	Scenario 16
	Deteriorated	Scenario 17	Scenario 18
Highly Fluctuation	Baseline	Scenario 19	Scenario 20
	Improved	Scenario 21	Scenario 22
	Deteriorated	Scenario 23	Scenario 24

units, while two maximum production capacity levels are considered, namely 750 and 1,000 units. The decoupled lead time is set to 14 days across all scenarios.

Since the Kaggle manufacturing defect dataset does not provide direct customer demand records, the baseline demand scenario is constructed using the production volume variable as an operational-scale proxy for demand. This proxy is used to generate controlled numerical demand inputs for the discrete-time inventory simulation, not to claim empirical equivalence between production volume and actual customer demand. Therefore, the simulation results should be interpreted as scenario-based evidence of model behavior rather than direct validation of real customer-demand dynamics in specific manufacturing firm. The baseline demand series is then used as the reference input for generating the seasonal, intermittent, and highly fluctuating demand scenarios.

The other demand scenarios are generated by transforming the baseline demand series using explicitly defined demand generation rules. This transformation-based scenario design follows the logic of simulation-based experimentation, in which controlled input conditions are varied to examine system behavior under uncertainty [25],[34]. The seasonal demand scenario was generated by applying a periodic seasonal multiplier to the baseline demand as

$$D_t^{seasonal} = max\left(0, round\left[D_t^{baseline}\left(1 + Asin\left(\frac{2\pi t}{L}\right)\right)\right]\right) \tag{23}$$

where $D_t^{baseline}$ denotes the baseline demand at period t, A denotes the seasonal amplitude, and L denotes the seasonal cycle length. Meanwhile, $D_t^{seasonal}$ denotes the seasonal demand at period t.

The intermittent demand scenario was generated by introducing zero-demand periods into the baseline demand series using a Bernoulli demand-occurrence mechanism. This representation is consistent with intermittent demand settings, where demand occurs sporadically and some periods may have no demand [35].

$$Z_t \sim Bernoulli\ (q) \tag{24}$$

$$D_t^{intermittent} = Z_t \times D_t^{baseline} \tag{25}$$

where $Z_t = 1$ indicates that demand occurs in period t, $Z_t = 0$ indicates a zero-demand period, and q denotes the probability of demand occurrence.

The highly fluctuating demand scenario was generated by applying a stochastic variability multiplier to the baseline demand. This scenario reflects unstable demand conditions in which demand size varies substantially across periods a characteristic often associated with highly variable demand environments as

$$\epsilon_t \sim Normal\ (0, \sigma) \tag{26}$$

$$D_t^{fluctuating} = max(0, round[D_t^{base}(1 + \epsilon_t)]) \tag{27}$$

where ϵ_t denotes the random demand fluctuation factor, and σ controls the variability level. In this study, σ = [0,3] was used. All stochastic components in the intermittent and highly fluctuating demand scenarios were generated using a fixed random seed of 42 to ensure reproducibility. In all scenarios, demand is not forecasted. The generated demand series is treated as realized demand input for the simulation. Average daily usage is calculated from the demand history, while qualified demand and Net Flow Inventory are computed according to the information assumed to be available at each daily review period.

In the scenario design, production process conditions are used to represent different defect-related quality-risk environment. Three production process conditions are considered namely: baseline, improved, and deteriorated. These conditions determine the scenario values of supplier quality rating, maintenance hours, downtime percentage, and workforce productivity. The improve condition represents a lower quality-risk environment, characterized by higher supplier quality and workforce productivity, as well as lower maintenance hours and downtime percentage. In contrast, the deteriorated condition represents a higher quality-risk environment, characterized by lower supplier quality and workforce productivity, as well as higher maintenance hours and downtime percentage.

Within each scenario, supplier quality rating, maintenance hours, downtime percentage, and workforce productivity are treated as scenario level parameters and are held constant throughout the simulation horizon, unless otherwise specified in Table 1. In contrast, the production volume is updated at each daily review period because it is derived from the feasible replenishment quantity generated by the inventory control model after considering the minimum production requirement and the maximum production capacity. Therefore, the feature vector used for defect rate prediction consists of one period level variable and four scenario level production process variables.

The detailed formulation of the defect rate prediction is provided in Step 6. In brief, the Random Forest Regressor does not use demand directly as its input. Instead, it estimates the defect rate at the daily review period or released batch level based on the production related feature vector. The predicted defect rate is therefore deterministic conditional on the released production volume and the assigned production process condition; it is not fixed at the scenario level and is not randomly sampled at each period.

The predicted defect rate is subsequently converted into predicted yield and usable finished product, as described in Step 7. Since the finishing process requires finish at $t + DLT - 1$, the usable finished product generated from production released at period t becomes available as schedule receipt at period $t + DLT - 1$. This defect rate prediction model will provide evidence regarding the potential number of defective products. Estimates based on production process conditions can be used to represent production conditions that will influence the defect rate of the resulting product. Therefore, these estimates can be used as a reference for determining usable finished products. The estimated number of usable finished products will be used as a reference for scheduling receipts and will influence replenishment plans. This estimation is one strategy for improving inventory system performance. Several studies have examined supply chain systems considering demand and quality uncertainty. Leithner and Fikar [36] emphasize that the resilience of supply chain systems needs to be tested by considering various demand and quality uncertainty scenarios. Additionally, Table 1 above combines variations in demand types and production process

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conditions that influence defect rates, thus being considered sufficiently representative for testing the resilience of the developed model.

RESULTS AND DISCUSSION

The results presented in this section are based on simulation-based numerical experiments rather than direct field deployment. Both the baseline DDMRP model and the proposed hybrid model are evaluated under the same scenario settings. The evaluation consists of 24 scenarios generated from the combination of four demand patterns, three production process conditions, and two production capacity settings.

At each daily review period, observed demand, quality-adjusted incoming supply, on-hand inventory, qualified demand, Net Flow Inventory Position, replenishment signals, and final order quantities are updated sequentially. The DDMRP buffer levels are calculated once at the beginning of each scenario and remain fixed throughout the simulation horizon. The proposed hybrid model incorporates predicted defect rate information from the Random Forest Regressor to adjust usable inventory and incoming supply. The simulation results are evaluated using stockout events, bullwhip effect, and average on-hand inventory. These indicators are used to compare the baseline and proposed models in terms of service reliability, replenishment stability, and inventory burden.

Defect Rate Prediction

Evaluating the performance of the defect rate prediction model involved testing several Random Forest Regressor configurations through 10-fold cross-validation. In this study, defect rate prediction is formulated as a regression problem because the target variable, Defect Rate, is represented as a continuous numerical value. Although defect rate conceptually ranges from 0% to 100%, the observed values in the dataset range from 0.5% to 5%. Therefore, the Random Forest Regressor is used to estimate the continuous defect rate value based on production-related variables.

Several hyperparameters of the Random Forest Regressor were tuned to identify a model configuration that balances prediction accuracy and generalization ability. The number of estimators specifies how many trees are in the ensemble, whereas maximum depth regulates the intricacy of each single tree. The maximum features parameter controls the number of predictors considered at every split, thus affecting the diversity of the model. The minimum samples split parameter indicates the least number of observations needed to divide an internal node, while the minimum samples leaf parameter determines the minimum number of observations permitted in each terminal node.

Each configuration's performance was tested using regression-based metrics such as MAE, MSE, RMSE, or R^2 Score [37]. To increase the evaluation's robustness and decrease the risk of choosing a configuration from just one data split, a 10-fold cross-validation method was employed, as suggested by Malakouti [38]. The results shown in Table 2 reflect the average performance over validation folds, accompanied by the standard deviation to demonstrate the variability of performance across the folds.

The most effective configuration was chosen mainly due to the smallest mean MAE, as MAE directly indicates the average absolute error in predicting the defect rate. R^2 was utilized as a supplementary measure to test the percentage of variance clarified by the model, whereas RMSE was used as a conditional error-related metric. When configurations exhibited comparable error values, the one with greater stability in performance across folds, as demonstrated by the standard deviation, was favored.

Based on the cross-validation results in Table 2, the configuration with `max_depth = 15, max_features = auto, min_samples_leaf = 2, min_samples_split = 2, and n_estimators = 200` was selected as the final

Table 2. Cross-validation performance of Random Forest Regressor hyperparameter configurations

Hyperparameters						**Metric value**			
max_ depth	**max_ features**	**min_ samples_leaf**	**min_ samples_split**	**n_ estimators**	**k value**	**MAE (mean±std)**	**MSE (mean±std)**	**RMSE (mean±std)**	**R^2 Score (mean±std)**
15	auto	2	2	200	10	0.0267 ±0.0137	0.0113 ±0.06881	0.1065 ±0.04188	0.7208 ±0.04584
None	sqrt	4	5	200	10	0.0432 ±0.0126	0.0132 ±0.07545	0.1120 ±0.03984	0.6727 ±0.03726
5	auto	1	2	300	10	0.0351 ±0.0137	0.0120 ±0.07450	0.1080 ±0.04066	0.6737 ±0.04733
None	sqrt	4	10	300	10	0.0437 ±0.0129	0.0135 ±0.07629	0.1130 ±0.03959	0.6676 ±0.03743
5	auto	1	5	100	10	0.0350 ±0.0137	0.0119 ±0.07399	0.1007 ±0.04062	0.6783 ±0.04469

Random Forest Regressor configuration. This parameter setting reached the smallest average MAE of 0.0267±0.0137 and the best average R^2 0.7208±0.04584 among all configurations evaluated. These findings illustrate that the chosen configuration yielded the lowest average absolute prediction error and the highest explanatory performance throughout the validation folds. Although the configuration with `max_depth = 5, max_features = auto, min_samples_leaf = 1, min_samples_split = 5, and n_estimators = 100` produced the lowest mean RMSE of 0.1007 ± 0.0406, its MAE and R^2 values were less favorable than those of the selected configuration. Because the selection criteria emphasizing the minimum mean MAE, alongside R^2, RMSE, and cross-fold variability as auxiliary metrics, the scenario of `max_depth = 15 and n_estimators = 200` was chosen as the final model.

In general, the chosen configuration was selected based on its overall performance across the reported regression metrics instead of relying on a single hyperparameter influence. In a Random Forest, the quantity of estimators needs to be adequately high to ensure stable ensemble predictions; nevertheless, beyond a specific threshold, incorporating additional trees might yield minimal performance enhancement while raising computational cost [39]. Thus, the best configuration was chosen by evaluating its predictive ability using MAE, MSE, RMSE, and R^2, along with the model complexity within the tested hyperparameter conditions.

The chosen Random Forest Regressor was then utilized as the predictive mechanism in the suggested inventory model. During each daily review, the estimated defect rate was converted into an expected yield factor to assess usable production output prior to the inventory simulation determining the NFE status and restocking decision.

Performance Evaluation of Hybrid DDMRP-OUTL

This section conducts a performance evaluation to assess the resilience of the proposed model when implemented. To analyze model resilience, several demand type scenarios are designed, each with conditions that impact the inventory system. This allows for a better understanding of the model's robustness. Different demand types will respond differently to procurement triggers, particularly when demand is rare and the quantity demanded varies. Possible risks in these situations include stockouts or overstocks. In addition to demand types, product quality scenarios are also developed, including production process conditions that influence the presence of defects. This factor cannot be ignored, as it always impacts the quantity supplied. Using defect rate estimation information as a reference for estimating supply quantities, which takes into account the presence of defects, is expected to accommodate real-world systems, and inventory planning estimates will be more responsive and stable.

The demand types are illustrated in Figure 2. There are four types of demand, each consisting of 200 periods. The four types of demand include baseline demand, which tends to be stable; demand A, which reflects seasonal demand;

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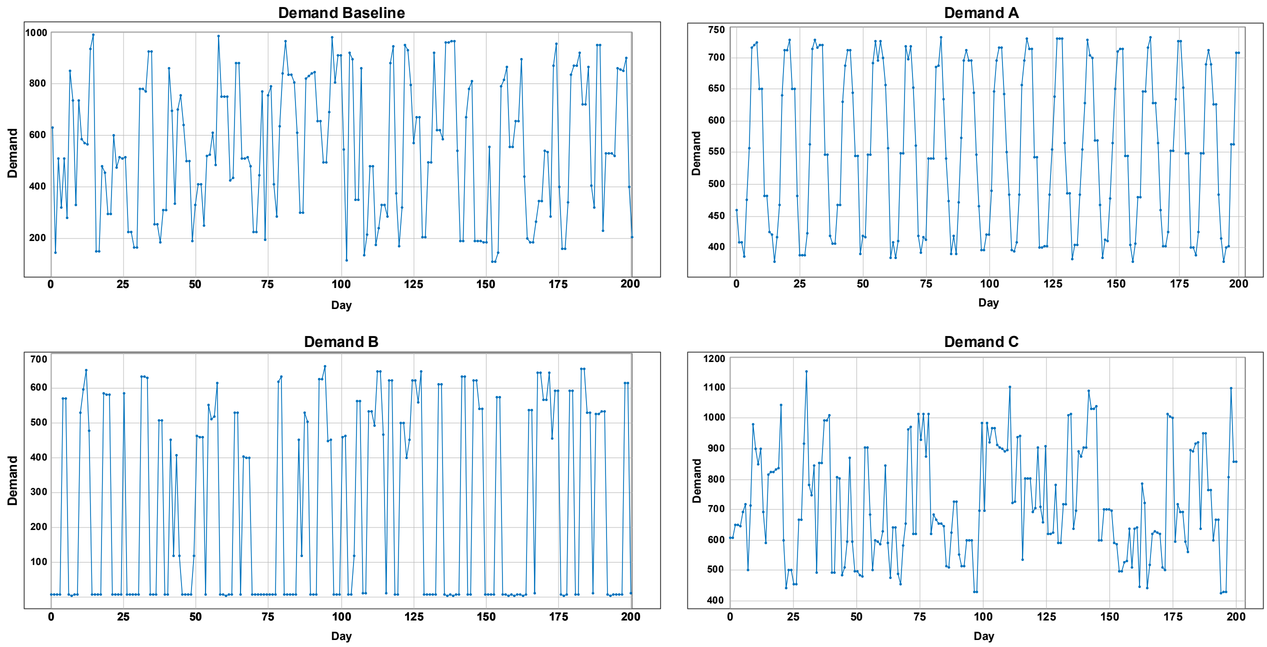

Figure 2. Daily demand patterns used in the simulation: Baseline, Demand A, Demand B, and Demand C

demand B, which reflects infrequent demand; and demand C, which reflects highly volatile demand. This request data is then used as a reference for determining buffers and as test material for periodic simulations.

Table 3 displays a comparison based performance assessment between the baseline DDMRP model approach and the suggested hybrid DDMRP-OUTL model over 24 simulation scenarios. Three logistic metrics were examined: REL, Average On-Hand Inventory, and Stockout Events.

The findings indicate that the hybrid DDMRP–OUTL model typically lowers REL in comparison to the baseline DDMRP model. A smaller REL signifies that the hybrid model can lessen the variability of replenishment orders compared to the variability of demand. This decrease can be seen in multiple cases, like Scenario 8, where REL drops from 17.20 with DDMRP to 16.65 with the hybrid model, and Scenario 12, where REL falls from 16.13 to 15.49. Comparable decreases are noted in Scenarios 13–18, suggesting that the OUTL control system helps stabilize replenishment signals amidst fluctuating demand conditions. Nonetheless, in certain situations, like Scenarios 1, 5, 19, 21, and 23, the REL values do not differ between the two models. This suggests that the hybrid mechanism does not consistently change order variability when the replenishment pattern is stable or when the variance-based REL value is near zero.

Average on-hand inventory simulation results perform a distinct trade-off in inventory. In many situations, the hybrid DDMRP–OUTL model leads to greater average on-hand inventory than the baseline DDMRP model. For instance, in Scenario 3, the average climbs from 2146 units with DDMRP to 4257 units with the hybrid model, whereas in Scenario 18 it rises from 467 units to 1024 units. This indicates that while the hybrid model might decrease variability in replenishment, it could also sustain a greater inventory level. Consequently, the decrease in REL should be viewed in conjunction with the average inventory on hand, as enhanced replenishment stability could come with a higher inventory load.

As indicated in Table 3, instances of stockouts differ based on demand patterns and production environments, with increased levels noted in more difficult situations like highly fluctuation demand. Consequently, stockout effectiveness is analyzed alongside REL and average on-hand inventory to assess the balance between replenishment consistency, inventory load, and service dependability.

Table 3. Inventory stability vs. responsiveness: DDMRP vs. hybrid DDMRP-OUTL under demand variability

Scenario	REL		Average OH Distance		Stockout Rate (%)	
	DDMRP	DDMRP & OUTL	DDMRP	DDMRP & OUTL	DDMRP	DDMRP & OUTL
1	1,26	1,26	3488	3488	1	1
2	3,25	3,07	2037	3283	1	1
3	1,17	1,09	2146	4257	1	1
4	3,22	3,05	2035	3344	1	1
5	0,00	0,00	2303	4272	1	1
6	3,09	2,91	2010	3721	1	1
7	6,42	6,12	2144	4099	1	2
8	17,20	16,65	1970	3419	1	2
9	5,92	5,51	2206	4156	1	1,5
10	16,98	16,56	2008	3503	1	1,5
11	4,09	3,29	2786	3709	1	1
12	16,13	15,49	1986	3655	1	2,5
13	1,34	1,13	396	955	0	0,5
14	1,91	1,40	493	940	0	0
15	1,36	1,07	404	820	0	0,5
16	1,91	1,38	515	963	0	1
17	1,43	1,08	349	741	0	0
18	2,01	1,46	467	1024	0	0,5
19	0,00	0,00	10527	10527	8,5	8,5
20	3,42	3,26	2767	5286	2	2
21	0,00	0,00	11005	11005	1,7	1,7
22	3,23	2,98	2931	4948	2	2
23	0,00	0,00	11299	11299	41,5	41,5
24	2,25	2,07	3731	5906	2	2

As an example, Scenarios 19, 21, and 23 illustrate considerably high stockout occurrences in both models, suggesting that demand variability exerts greater service pressure. In various situations, the hybrid model results in the same count of stockout incidents as the traditional DDMRP model, whereas in certain intermittent and seasonal cases, the hybrid model yields a marginally increased number of stockout events. This indicates that the OUTL control mechanism might lessen replenishment variability but could also limit replenishment amounts in specific situations, resulting in a trade-off among order stability, inventory levels, and service performance.

In general, Table 3 shows that the suggested hybrid DDMRP–OUTL model delivers a more regulated replenishment approach by decreasing REL in various situations. Nonetheless, this advantage is not consistent throughout all performance measures. The hybrid model generally raises the average inventory on hand and does not consistently minimize stockout occurrences. Thus, the suggested model ought to be seen as a method for balancing replenishment stability with inventory availability, instead of as an overall superior solution for every situation. The success of the hybrid model relies on the demand trends, state of the production process, and configuration of production capacity. Expanding on the trade-offs found between inventory stability and responsiveness, Table 4 methodically explores how demand pattern traits and defect rate levels collectively affect system performance. Table 4 enhances the scenario-level analysis by categorizing 24 simulation scenarios based on demand pattern and defect rate level. Baseline demand consists of Scenarios 1-6, Demand A consists of Scenarios 7-12, Demand B consists of Scenarios 13-18, and Demand C consists of Scenarios 19-24. Each demand pattern group contains six scenarios, representing three defect rate conditions and two production capacity settings. These grouping helps clarify how demand patterns and defect rate levels jointly affect REL, DAOH, and Stockout under the standard DDMRP and hybrid DDMRP-OUTL models.

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Table 4. Comparative Average Performance Evaluation by Demand Pattern

Demand pattern	REL DDMRP	REL DDMRP & OUTL	Average On hand Inventory DDMRP	Average On hand Inventory DDMRP & OUTL	Stockout Rate (%) DDMRP	Stockout Rate (%) DDMRP & OUTL
Baseline	2.00	1.90	2,336	3,727	1	0
Demand A	11.12	10.60	2,183	3,757	1	2
Demand B	1.66	1.25	4378	907	0	0,5
Demand C	1.48	1.38	7,043	8,162	12,5	12,5

Table 5. Comparative Average Performance Evaluation by Production Process Condition

.Production Conditions	REL DDMRP	REL DDMRP & OUTL	Average On hand Inventory DDMRP	Average On hand Inventory DDMRP & OUTL	Stockout Rate (%) DDMRP	Stockout Rate (%) DDMRP&OUTL
Baseline Production	4.35	4.11	2978	4000	1	1
Improved Production	4.22	3.95	2907	4125	3	3
Deteriorated Production	3.62	3.29	3116	4291	6	6

Based on defect rate level, the scenarios are grouped into baseline, improved and deteriorated production conditions. Each defect rate group contains eight scenarios, representing four demand patterns and two production capacity settings. The baseline production condition consists of Scenarios 1, 2, 7, 8, 13, 14, 19, and 20. The improved production condition consists of Scenarios 3, 4, 9, 10, 15, 16, 21, and 22, and the deteriorated production condition consists of Scenarios 5, 6, 11, 12, 17, 18, 23, and 24. This grouping allows the analysis to examine how demand characteristic and defect rate related quality conditions jointly affect REL, DAOH, and stockout events under the standard DDMRP and hybrid DDMRP-OUTL models.

Table 5 presents the comparative average performance evaluation of the standard DDMRP model and the hybrid DDMRP–OUTL model based on demand pattern. The assessment uses three performance indicators: REL, Average On-Hand Inventory, and Stockout Events. The findings present that the hybrid DDMRP–OUTL model consistently decreases REL across all demand type. Under the baseline demand type, REL drops from 2.00 under standard DDMRP to 1.90 under the hybrid model. Demand A also shows a reduction from 11.12 to 10.60, while Demand B decreases from 1.66 to 1.25. Similarly, Demand C shows a reduction from 1.48 to 1.38. These results indicate that the OUTL mechanism contributes to reducing replenishment order amplification and improving replenishment stability across different demand patterns.

However, the effect of REL reduction on Average On-Hand Inventory is not uniform across all demand patterns. Under the baseline demand pattern, the result increases from 2,336 units to 3,727 units after OUTL integration. Demand A also shows an increase from 2,183 units to 3,757 units, while Demand C increases from 7,043 units to 8,162 units. This indicates that the hybrid model tends to maintain a higher inventory level to support more stable replenishment behavior. However, Demand B shows different pattern, where average on-hand inventory decreases from 4,378 units to 907 units. This suggest that the hybrid DDMRP-OUTL model can also reduce inventory accumulation under certain demand characteristics. Thus, the connection between the decrease in REL should be understood alongside the rise in inventory burden.

In the other hand, the stockout results indicate that the impact of the hybrid model differs among demand types. With the baseline demand types, stockout event rate go down from 1% under DDMRP to 0% under the hybrid approach, showing enhanced service performance. Nevertheless, with Demand A, stockout event rate rise from 1% to 2%, while in Demand B they go up from 0% to 0,5%. In Demand C, both models yield an identical stockout value of 12,5%. These findings indicate that while the hybrid DDMRP–OUTL model can decrease replenishment variability, it does not consistently minimize stockout frequency. In certain demand types, the OUTL model can limit reorder quantities, leading to a balance between reorder consistency, inventory levels, and service performance.

Table 6 shows the average performance assessment in comparison, focusing on the conditions of the production process. The conditions of the production process reflect different quality-related operational environments, namely baseline, improved, and deteriorated production conditions. Given that the defect rate is forecasted based on production-related factors, this production circumstances indicate various quality-risk scenarios in the simulation.

The findings show that the hybrid DDMRP–OUTL model decreases REL in every production process scenario. Under the baseline production scenario, REL drops from 4.35 with standard DDMRP to 4.11 with the hybrid model. Meanwhile, the improved production condition affects the REL drops from 4.22 to 3.95, then the deteriorated production condition cause the REL falls from 3.62 to 3.29. These findings confirm that the OUTL approaches plays a role in decreasing the amplification of reorder quantities under various production process conditions.

Nonetheless, the Average On-Hand Inventory outputs indicate that the decrease in REL is associated with an increased average inventory level. The baseline production condition represents that the AOHI rises from 2,978 units under the DDMRP model to 4,000 units under the hybrid model. While, the deteriorated production condition, AOHI rises from 2,907 units to 4,125 units, whereas in worsened production conditions, it grows from 3,116 units to 4,291 units. This pattern suggests that the hybrid model ensures stable replenishment activity by keeping a greater inventory level.

The stockout event rate results indicate comparable service performance between the two models under various production process conditions. In the baseline production scenario, the stockout event rate remains no change, remaining at 2 in both the DDMRP model and the hybrid model. In the improved production condition, both models yield 3 stockout event rate, whereas in the deteriorated production condition, both models yield 6 stockout event rate. This suggests that the deteriorated production situation generates greater service pressure than both the baseline and enhanced conditions. Nonetheless, in this grouped analysis, the hybrid DDMRP–OUTL model does not notably decrease stockout occurrences.

In summary, Tables 4 and 5 indicate that the hybrid DDMRP–OUTL model demonstrates greater effectiveness in minimizing replenishment variability, as evidenced by reduced REL values. Nonetheless, this advantage comes at the cost of increased Average On-Hand Inventory. Consequently, the suggested hybrid model ought to be viewed as a stabilizing mechanism for reorder rather than a universally superior method for every performance metric. Implementing it needs precise adjustments to balance the stability of reorder, the burden of inventory, and the reliability of service.

Following the assessment of the average performance scenario outcome, the examination is broadened to include the overall performance trend influenced by demand types and production condition scenarios. This aggregation is utilized to investigate if the performance variations between the standard DDMRP model and the hybrid DDMRP-OUTL model are uniform across wider operational categories, instead of being influenced solely by specific scenarios. The stratified averages shown in Table 6 offer a diagnostic perspective on mode performance regarding replenishment stability, inventory levels, and stockout frequency.

Table 6 presents the aggregated performance differences. For each demand pattern or defect rate category, the difference is obtained by subtracting the average hybrid DDMRP-OUTL value the average standard DDMRP value. For example, in Demand A category, the average REL value of the standard DDMRP model is 11.12, while the average

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Table 6. Average differences in REL, Average On hand Inventory and Stockout

Average difference per demand pattern			
Demand pattern	**REL Difference**	**Average On hand Inventory Difference**	**Stockout Rate Difference**
Baseline	0.10	-1,391	1
Demand A	0.52	-1,574	-1
Demand B	0.41	-470	-0,5
Demand C	0.10	-1,118	0
Average difference per defect rate			
Production Conditions	**REL Difference**	**Average On hand Inventory Difference**	**Stockout Rate Difference**
Baseline Production Condition	0.24	-1,022	0
Improved Production Condition	0.27	-1,218	0
Deteriorated Production Condition	0.34	-1,174	0

REL value of the hybrid DDMRP-OUTL model is 10.6. The differences is therefore 11.12 minus 10.6, resulting in a REL difference of 0.52. A positive REL difference indicates that the hybrid model reduces the Bullwhip Effect Ratio, while a negative Average On-Hand Inventory difference indicates that the hybrid model maintains a higher inventory level. For Stockout Event Rate, a negative difference indicates that the hybrid model produces more stockout events than the standard DDMRP model.

Based on demand pattern, the hybrid DDMRP–OUTL model reduces REL across all demand categories. The REL difference is 0.10 for the baseline demand pattern, 0.52 for Demand A, 0.41 for Demand B, and 0.10 for Demand C. These results indicate that the OUTL mechanism contributes to reducing replenishment order amplification and improving replenishment stability across different demand patterns. However, the REL reduction is accompanied by an increase in Average On-Hand Inventory. This is shown by the negative average results differences across all demand patterns. For example, the Average On-Hand Inventory difference is -1390.98 units under the baseline demand pattern, -1573.61 units under Demand A, -469.67 units under Demand B, and -1118.43 units under Demand C. These results indicate that the hybrid model tends to stabilize replenishment behavior by maintaining a higher inventory level.

The stockout difference shows mixed results. Under the baseline and Demand C patterns, the stockout difference is 0, indicating that both models produce the same stockout performance. Under Demand A and Demand B, the stockout differences are negative, indicating that the hybrid model produces slightly higher stockout events. This implies that while the hybrid DDMRP–OUTL model minimizes replenishment variability, the OUTL control might limit replenishment volumes in specific demand situations, resulting in a compromise between stability and service performance.

Depending on the state of the production process, the hybrid DDMRP–OUTL model similarly decreases REL under all production circumstances. The most significant REL drop happens in deteriorated production condition, suggesting that the hybrid model offers better reorder stabilization during tougher quality-related operational situations. Nonetheless, the Average On-Hand Inventory variations stay negative under all production scenarios, indicating that the enhancement in replenishment stability occurs with increased average inventory levels. The variations in stockouts are also somewhat negative, indicating that the hybrid model does not consistently enhance service performance when assessed through stockout occurrences.

In general, Table 6 verifies that the proposed model is superior in minimizing replenishment amplification compared to lowering inventory levels or the frequency of stockouts. The model offers improved replenishment stability;

however, this advantage comes with an increased inventory load and, in certain instances, a marginal rise in stockout occurrences. Consequently, the hybrid model must be applied with precise adjustment of OUTL, production capability, and safety stock to achieve a balance between inventory stability, inventory load, and service dependability.

Research Implications

Theoretical Contributions

The theoretical contribution resulting from this research is the integration of three approaches previously used to solve different problems. The reality of uncertainty in the supply chain system, such as demand fluctuations or uncertainty in supply from the production floor caused by defective products, often affects inventory resilience. There is still limited research that examines the integration of inventory problems caused by demand fluctuations and uncertainty in supply influenced by product quality variation. This research provides a solution to these combined problems as evidenced by the numerical test results, particularly in the smaller REL value for the proposed model compared to the DDMRP baseline across scenarios. This integration expands the scope of DDMRP by including defect prediction in the model, so that it does not emphasize only quantity and time aspects, but also quality.

On the other hand, the responsive and stable aspects are also emphasized, where these two aspects are used as a reference for inventory optimization. The responsive target is set in the form of a data-driven DDMRP approach that is sensitive to demand surges but tends to have a high buffer value. The stability target is set through the integration of the OUTL approach to balance inventory levels that tend to be high. The integration of these two models forms a more reliable and efficient system, similar to studies that integrate lean and resilience. This provides a solution to conventional models that have limitations related to flexibility and decreased performance under disruption. In addition to DDMRP and OUTL, defect rate prediction is integrated to make inventory planning estimates closer to the real system, providing insight for procurement planning.

Managerial Implications

The proposed model offers a way to improve more agile inventory planning and cost control. The model also addresses uncertainty in demand or product quality, where these conditions often create situations that are difficult to predict. For example, daily product demand tends to be stable, while spare part demand tends to be rare and limited. The integration of these approaches provides a solution that makes the system more dynamic and flexible. The mechanism of this model uses a stabilization approach from the replenishment signal, controls demand fluctuations, and estimates supply from the production floor adjusted to defect rate prediction. Predictive maintenance and demand prediction are shown to help minimize waste.

In practice, some organizations still use conventional MRP in their inventory systems. Based on this, implementation of the model can be done in stages. It begins with applying defect rate prediction to estimate the likelihood and quantity of defective products, which can be used to determine the number of usable finished goods. Then, the DDMRP approach is applied to determine buffers, calculate NFE by considering defect rates, and determine replenishment decisions.

The trade-off between replenishment stability and inventory load must be considered, as some scenarios indicate an increase in Average On-Hand Inventory after OUTL integration. Therefore, the hybrid model needs to be calibrated according to demand patterns and defect rate conditions rather than applied uniformly. The implementation roadmap is provided as an advisory tool to support managerial interpretation of the simulation findings, outlining practical stages for aligning inventory analytics with supply chain objectives.

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Policy and Sustainability Implications

From a policy standpoint, the proposed hybrid inventory framework supports more quality-aware and data-driven inventory management practices. The framework aligns with sustainability objectives by incorporating predicted defect information into replenishment decisions and applying OUTL-based control to regulate responses under demand variability. However, this study does not directly quantify material waste reduction, carbon emissions, or non-conforming inventory reduction. Therefore, the sustainability implications are interpreted as potential contributions to resource efficiency and quality-risk-aware inventory planning, rather than directly measured outcomes. Public-private collaborations and digitalization incentives could assist companies in adopting predictive analytics and inventory management technologies, promoting sustainable supply chain innovation.

The proposed framework uses predicted defect rates to adjust usable inventory and incoming supplies. However, the results do not directly prove that emissions are reduced or waste is minimized. The hybrid DDMRP–OUTL model can reduce over-replenishment in some situations, although it may require maintaining higher inventory. This shows a balance between supply availability, inventory levels, and service performance. The model supports more stable and efficient inventory control while highlighting trade-offs in decision-making. The findings are useful for companies seeking to improve inventory management.

This can be done by checking indicators such as defective units, material waste, rework, obsolete inventory, transportation-related emissions, and overall carbon footprint. Policymakers can support data-driven inventory management by improving access to supplier quality data, encouraging data sharing, and supporting digital adoption among medium-sized businesses. Partnerships and incentives for digitalization can help companies adopt predictive analytics and inventory control more widely, supporting more sustainable and innovative supply chains.

CONCLUSION

This study developed and evaluated a quality-aware hybrid inventory planning framework that integrates DDMRP, the OUTL method, and defect rate prediction. The evaluation was conducted through simulation-based numerical experiments under predefined demand patterns, production process conditions, and production capacity. The demand inputs used in the simulation were constructed as scenario-based representations. Therefore, the findings should be interpreted within the scope of the simulated inventory planning environment. The simulation results indicate that the proposed hybrid DDMRP–OUTL model can reduce replenishment order amplification across multiple demand conditions. Replenishment stability is interpreted through REL, where lower values reflect more stable behavior. The hybrid configuration shows a consistent tendency to dampen order variability across the examined demand scenarios and production conditions. These findings suggest that integrating demand-driven logic with OUTL contributes to more controlled replenishment adjustments under fluctuating demand patterns. However, the results also show that improved replenishment stability is often accompanied by higher Average On-Hand Inventory. This highlights a trade-off between stability and inventory burden. In addition, Stockout Events are not consistently reduced, indicating that the hybrid model does not uniformly improve service performance. Within the framework, the defect rate prediction component provides quality-related input for inventory planning. The predicted defect rate is used to estimate usable finished products and adjust scheduled receipts so that replenishment evaluation reflects usable inventory rather than total physical stock alone. However, the numerical experiments assess the hybrid configuration as a whole and do not isolate the independent contribution of the defect prediction component. Several limitations should be acknowledged. The evaluation relies on simulation rather than field implementation, and key parameters are treated as static. Additionally, the study does not directly quantify broader operational impacts. Future research can extend this work by incorporating more dynamic parameter adjustments, exploring multi-tier supply chains, and integrating real-time operational data. Careful evaluation remains essential, particularly in balancing replenishment consistency, inventory levels, and service reliability.

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CONFLICT OF INTEREST

The authors declare that there are no conflicts of interest regarding the research, authorship, and publication of this article.

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DATA AVAILABILITY STATEMENT

The data used in this research were obtained from a publicly available dataset on Kaggle, as described in the manuscript. The processed data and simulation results supporting the findings of this study are available from the corresponding author upon reasonable request.

DECLARATION OF AI TOOL USAGE

During the preparation of this manuscript, AI-assisted tools were used to support language refinement, improve academic tone, and enhance the clarity of selected paragraphs. All AI-generated outputs were critically reviewed, verified, and thoroughly edited by the authors to ensure accuracy, clarity of expression, and adherence to academic standards. The authors take full responsibility for the integrity, originality, and content of this manuscript.

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