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# Enhancing Decision Making in High-mix Low-volume (HMLV) Production: A Hybrid Model-based and Data-driven approach.

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**ABSTRACT**

High-Mix, Low-Volume (HMLV) production systems demand high operational flexibility and adaptive decision-making due to frequent fluctuations in demand, product variety, and resource constraints. This study proposes a hybrid approach that integrates discrete-event simulation (DES) with machine learning (ML) techniques to enhance production performance and decision support in HMLV environments. The research is motivated by the limitations of standalone methods—DES lacks adaptability, while ML models often fail to incorporate domain-specific knowledge and perform poorly with small, noisy datasets. The methodology involves three key phases: (1) development of a DES model to simulate the behaviour and structure of a representative HMLV system, (2) integration of supervised and unsupervised ML models (ARIMA, SVR, XGBoost, Random Forest, k-means) to enhance parameter prediction and product clustering, and (3) scenario-based testing and optimization under various scheduling rules and constraints. Model validation was conducted using historical production data from 20 parts over a 28-month period, with performance assessed through RMSE, MAE, and $R^2$ metrics. Results show that ARIMA outperforms ML models in capturing temporal trends, with relatively lower error rates despite a small dataset and high variability. Machine learning models demonstrated poor generalizability, with negative $R^2$ values indicating overfitting. These findings emphasize the challenges of applying black-box ML models in volatile, low-volume contexts without sufficient data. The study concludes that a hybrid model combining the explanatory power of simulation with the predictive potential of data-driven approaches offers a promising path for improving production planning, scheduling, and inventory decisions in HMLV settings. Future work should expand dataset size, explore seasonal models (e.g., SARIMA), and develop more interpretable hybrid frameworks to support agile, intelligent production management.

## 1. Introduction

High-mix, low-volume (HMLV) production environments demand exceptional flexibility and responsiveness to manage varying customer requirements, fluctuating product demand, and complex service expectations from Gan *et al.,* [1]. To remain competitive, production systems must

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continuously adapt to dynamic conditions, often balancing trade-offs between conflicting KPIs such as delivery speed, quality, cost, and resource utilization.

Ensuring consistently high production performance—especially in terms of product quality and service reliability—is critical, even when faced with external disruptions (e.g., supply chain volatility) or internal constraints (e.g., limited capacity, variable inventory levels). Day-to-day operations in HMLV settings are typically managed by agile, cross-functional teams that rely on lean tools such as pull systems, order grouping, and visual management Polo *et al.,* [2]. Production levelling (Heijunka) is frequently used to smooth demand variability and distribute workloads evenly across production resources.

To further stabilize and optimize production flows, clustering techniques like ABC/XYZ analysis or advanced machine learning algorithms can be used to group products into families for more efficient scheduling, especially on bottleneck machines conducted by Kandemir [3]. In fast-response scenarios, strategies such as lot splitting and controlled order release help reduce lead times while preserving production continuity.

Efforts to improve equipment effectiveness and increase throughput are central to production efficiency. These may involve organizational changes, targeted maintenance strategies, or the use of inventory buffers and higher levels of work-in-progress (WIP)—each with associated trade-offs in cost and complexity.

Despite these efforts, understanding the complex interactions between structural elements (e.g., layout, scheduling rules) and behavioral factors (e.g., operator decisions, variability) in HMLV production systems remains challenging. Traditional modeling tools like system dynamics and logistics curves provide useful insights but often fall short in capturing the full complexity of real-world production environments.

Emerging technologies—particularly cyber-physical production systems and advancements in data analytics—are transforming the way production is monitored and controlled. Big data and machine learning offer new opportunities to support, or even automate, decision-making in production management. While machine learning is effective at modeling complex, non-linear behaviors, it often lacks the ability to incorporate domain-specific engineering knowledge.

In contrast, discrete-event simulation (DES) remains a powerful method for analyzing both the static configuration and dynamic behavior of production systems. DES enables detailed process modeling and supports scenario-based evaluations, but its drawbacks include high computational demands and limited adaptability to changing conditions. Hybrid methods such as simulation metamodeling can address some of these challenges by accelerating simulations, though they may reduce model interpretability.

Given these limitations, this research aims to develop an integrated approach that combines model-based and data-driven methods to enhance production decision-making and performance management in HMLV environments.

### *1.1 Literature Review*
#### *1.1.1 Challenges in HMLV production*

High-Mix, Low-Volume (HMLV) production systems are characterized by a large variety of product types manufactured in small quantities, often tailored to specific customer requirements. These systems typically function within job-shop or flexible manufacturing environments where the material flow is highly dynamic, non-linear, and often unpredictable. Unlike mass production systems that benefit from repeatability and stable process flows, HMLV operations face continual changes in product types, process routes, and scheduling requirements, making it difficult to maintain production efficiency and predictability from Gödri [4].

Additionally, managing work-in-progress (WIP) inventory becomes significantly more complex. Without precise coordination and visibility, WIP can accumulate unevenly across workstations, leading to bottlenecks in some areas and idle resources in others. This imbalance not only reduces throughput but also complicates the tracking and forecasting of orders. Balancing workloads across machines, operators, and production lines in such an environment requires advanced scheduling systems and intelligent dispatching rules that can adapt in real-time to production floor realities from a case study by Slomp *et al.,* [5].

### *1.1.2 Lean Practices and Operational Flexibility*

Operational strategies such as pull systems, production leveling (Heijunka), and visual management have been widely adopted to manage demand variability and improve workflow stability Slomp *et al.,* [5]. Heijunka, for example, aims to distribute work evenly to avoid bottlenecks and underutilization, even in low-volume, high-mix settings. Cross-functional team structures and lot splitting techniques are also used to enhance responsiveness and reduce lead times .

Product clustering—grouping products into families based on similarities—has proven beneficial for simplifying scheduling on shared or bottleneck resources. While classical ABC/XYZ analysis is commonly used, more recent approaches leverage machine learning algorithms to identify patterns in product demand and behavior was conducted by Chen *et al.*,[6].

### *1.1.3 Data-Driven and Machine Learning Approaches*

The rise of big data, Industrial Internet of Things (IIoT), and advanced analytics has opened new possibilities for data-driven decision-making in production systems. Machine learning (ML) algorithms have been successfully applied to predict demand, detect anomalies, and optimize scheduling was found in Tadayonrad and Alassane [7]. However, these models often struggle to incorporate existing engineering knowledge, and their "black-box" nature can make interpretation difficult for production planners.

Despite their predictive power, ML models alone may lack the robustness and structural insights provided by traditional simulation and engineering methods. This has led to increasing interest in hybrid approaches that combine data-driven models with simulation or rule-based systems to balance accuracy and interpretability from study conducted by Wardah *et al.*, [8].

### *1.1.4 Towards Hybrid Production Analytics*

Recent studies have proposed integrating model-based (e.g., DES) and data-driven (e.g., ML) techniques to enhance production planning and performance management. Such hybrid systems aim to leverage the explanatory power of simulation with the adaptive capabilities of machine learning performed by Wardah *et al.*, [8]. These approaches are particularly promising for HMLV settings, where both system complexity and variability are high.

However, developing such systems remains a challenge, requiring careful alignment between simulation models, historical data, and real-time inputs. Research is still ongoing to address issues related to computational cost, scalability, transparency, and user acceptance in production environments.

The literature underscores the complexity of managing production in HMLV environments and highlights the limitations of both traditional and purely data-driven methods. Discrete-event simulation remains a core analytical tool, while the integration of machine learning is seen as a path toward more responsive and intelligent production systems. The development of hybrid, cyber-physical analytics frameworks represents a promising research direction to support decision-making and performance optimization in modern HMLV production settings.

## 2. Methodology

The primary objective of this study is to develop and validate a hybrid model that integrates discrete-event simulation (DES) with machine learning (ML) techniques to optimize production performance in High-Mix, Low-Volume (HMLV) production systems. The goal is to improve decision-making under high variability and complexity by leveraging both simulation-based and data-driven approaches. The model aims to enhance production scheduling, capacity planning, and resource allocation, thereby improving key performance metrics such as throughput, lead time, and resource utilization.

### *2.1 Phase 1: System Modeling using Discrete-Event Simulation (DES)*

A discrete-event simulation model is developed to represent the structure and behavior of a selected HMLV production system. The simulation captures key components such as product variety, process routings, machine setups, resource constraints, and demand variability. Data for the model are collected from production records, historical logs, and direct observations at the case company. The simulation environment allows for the testing of different scheduling rules, capacity adjustments, and order release strategies. Performance metrics such as throughput, lead time, work-in-progress (WIP), resource utilization, and service level are used to evaluate system behaviour under different operating conditions.

#### *2.1.1 Research framework*

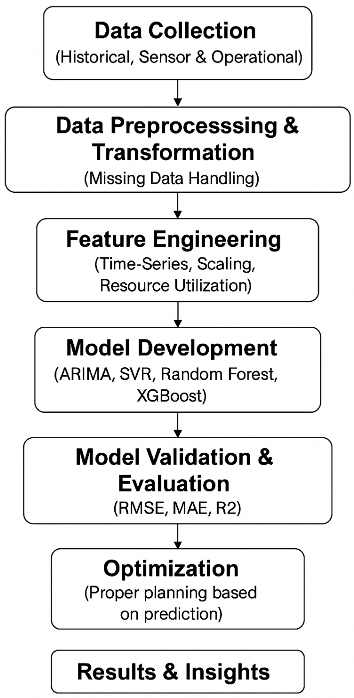


**Fig. 1.** Research framework

### *2.2 Phase 2: Data Collection and Machine Learning Integration*

This phase focuses on gathering relevant historical data and integrating machine learning techniques to improve the predictive accuracy and adaptability of the simulation model. The data collected includes detailed records of production performance, machine availability, setup times, and output quantities for selected part numbers. These data points are essential in capturing the operational variability and constraints that are typical in high-mix, low-volume (HMLV) manufacturing environments.

Supervised learning algorithms are employed to estimate critical production parameters that influence system behavior. Specifically, time-series models such as ARIMA are used to forecast short-term production output based on historical trends. In parallel, regression-based machine learning models—including Support Vector Regression (SVR), Random Forest, and XGBoost—are applied to predict production quantities and lead times by learning from multivariate input features such as machine load, tooling status, and historical cycle times was carried by Shahid *et al.*, [9]. These models are selected for their ability to capture complex relationships and nonlinear patterns in production data.

The outputs from both supervised and unsupervised models are then fed into the discrete-event simulation (DES) model as enriched input parameters. By doing so, the simulation reflects more realistic and dynamic system conditions, improving the model’s predictive fidelity and responsiveness to variable demand patterns. Ultimately, this integration of machine learning with simulation supports more informed decision-making in production scheduling, inventory control, and resource allocation, thereby enhancing system performance in complex manufacturing settings.

### *2.3 Phase 3: Testing and Optimization*

The hybrid model is used to conduct scenario-based experiments. These scenarios include varying demand conditions, resource constraints, and control policies such as lot splitting, production leveling (Heijunka), and controlled order releases. The simulation is used to assess the effectiveness of these strategies in improving production performance, especially under volatile or constrained conditions. Comparative analysis is conducted between the current baseline performance and the outcomes achieved through the proposed hybrid approach.

### *2.4 Phase 4: Validation and Analysis*

To ensure the credibility of the results, the simulation model is validated using real production data and feedback from domain experts within the case company. Key outputs from the simulation are compared with historical performance metrics to verify the model's accuracy. In addition, a sensitivity analysis is performed to understand how variations in input parameters—such as order arrival rates or setup time variability—affect overall system performance.

## **3. Analysis**

### *3.1 Data Collection and Preparation*

The study focuses on collecting output data from 20 selected parts that share the same tooling, out of over 2,000 currently in production. If data gaps are identified, more parts will be added to ensure sufficient dataset size for machine learning analysis. A 28-month continuous production output will be used, particularly for ARIMA modelling, with minor adjustments made to improve data accuracy.

Data sources include sales orders or forecasted sales (units), actual production output from the INFOR Baan report (via the Planning department), and historical cycle times provided by the production manager. Additional inputs such as customized BOMs and machine rate tables will support the modelling. Tooling minimum and maximum levels (MIN-MAX) will be derived from SECO's Tool Management System (TMS) historical records.

### *3.2 Data Pre-processing*

Data preprocessing is a fundamental step in preparing raw data for machine learning, aimed at ensuring the dataset is clean, consistent, and properly structured for training. The process begins with handling missing values, which may arise from incomplete data collection or input errors. These gaps are addressed either by imputing values using statistical methods such as mean or median, or by removing data entries with excessive missing values from study of Han *et al.,* [10]. Duplicate records are then identified and eliminated to prevent redundancy and reduce the risk of overfitting, ensuring the model learns from unique data points delivered by Werner *et al.*, [11]. Outliers, which are extreme values that can distort model performance, are detected using techniques like z-scores or the interquartile range (IQR) and are either removed or transformed to lessen their influence. Following this, data transformation is applied to standardize feature scales—commonly through Min-Max scaling or Z-score normalization—so that variables with larger numerical ranges do not disproportionately impact model learning. Finally, categorical variables are encoded into numerical formats using methods like One-Hot Encoding or Label Encoding, allowing the model to interpret and utilize them effectively was found in study of Raschka *et al.*, [12]. Together, these preprocessing steps enhance model accuracy, robustness, and generalizability .

### *3.3 Feature Engineering*

Feature engineering plays a crucial role in enhancing the quality of the dataset for machine learning models. In this study, we aim to improve the dataset by splitting the monthly production output data into two time periods per month, which effectively doubles the dataset and provides a finer level of granularity. This allows the model to capture more detailed insights from the data. Any missing data is handled by imputing the missing values with the average value of the respective feature to maintain data consistency and avoid loss of information. Additionally, machine time data is scaled to ensure it is comparable with production output, which may have different units or ranges. Scaling ensures that all features are on a similar scale, which helps the model better understand relationships between variables. These feature engineering steps are designed to improve the model's ability to learn patterns from the data and make more accurate predictions.

Hyperparameter tuning is another critical aspect of improving model performance. For the models used in this study (ARIMA, SVR, Random Forest, and XGBoost), tuning the hyperparameters is essential to achieve the best possible performance was carried by Farris *et al.*, [13]. ARIMA has hyperparameters such as p, d, and q, which define the autoregressive, differencing, and moving average components of the model. For SVR, the hyperparameters include C, kernel, epsilon, and gamma, which control the regularization, kernel function, margin of tolerance, and kernel coefficient, respectively. In XGBoost, key hyperparameters include learning_rate, n_estimators, and max_depth, which determine the step size, the number of boosting rounds, and the complexity of each tree. For Random Forest, hyperparameters such as n_estimators, max_depth, and min_samples_split control the number of trees, the depth of each tree, and the minimum samples required to split an internal node. To find the optimal set of hyperparameters, we perform grid search or random search, testing different combinations using cross-validation. This process helps to identify the hyperparameters that maximize predictive accuracy while minimizing errors like RMSE, MAE, and $R^2$. By fine-tuning these hyperparameters, we ensure that the models are well-optimized to make accurate predictions on unseen data.

### *3.4 Model Training*

It refers to the process where a machine learning algorithm learns to recognize patterns and relationships within the training data. During this phase, the model fine-tunes its parameters to minimize a specified loss function, enabling it to make precise predictions based on the input features. The model utilizes the training dataset to understand the underlying structure of the data, such as identifying the link between customer features and churn in a classification task. The result of this training phase is a model that has been optimized to closely fit the training data, making it ready for evaluation based on its predictive performance.

In this study, the performance of various models—Support Vector Regression (SVR), AutoRegressive Integrated Moving Average (ARIMA), Random Forest, and XGBoost—was assessed using different train-test splits: 90%-10%, 80%-20%, 70%-30%, and 60%-40%. These splits provide insight into how well the model generalizes when trained on different portions of the dataset. By evaluating the model's performance across these various splits, we can determine whether the model's ability to generalize improves or declines as the size of the training set changes.

### *3.5 Model Validation*

The performance of the model is typically evaluated using several key metrics, including Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and $R^2$ (Coefficient of Determination). RMSE measures the square root of the average squared differences between predicted and actual values, penalizing large errors more heavily, which makes it useful when large errors are particularly undesirable. MAE, on the other hand, provides a more straightforward measure of the average magnitude of errors without considering their direction, and is less sensitive to outliers compared to RMSE. Finally, $R^2$ indicates how much of the variance in the dependent variable is explained by the independent variables;

In conclusion, model validation through testing on different train-test splits and evaluating performance via RMSE, MAE, and $R^2$ is essential for assessing the reliability and generalizability of machine learning models. This process allows for a robust comparison of different models, helping to identify the most appropriate one for a given dataset and task. The results also underscore the importance of cross-validation or using multiple train-test splits to prevent overfitting and ensure that the model can effectively handle unseen data in real-world applications. This validation approach ensures that the models used for decision-making and prediction are both reliable and adaptable to changing conditions.

## 4. Result

The findings of this study offer several insights into the comparative performance of machine learning and time-series models for forecasting in High-Mix, Low-Volume (HMLV) production environments. Among the models evaluated, the AutoRegressive Integrated Moving Average (ARIMA) model showed the most promising results given the constraints of the dataset. While ARIMA is widely recognized for its strength in modeling temporal dependencies, its performance in this study was notably influenced by data limitations. With an RMSE of 200.45 and an $R^2$ of 0.68 under the 80%-20% train-test split, ARIMA successfully captured broad production trends. However, its predictive accuracy declined as the training set was reduced, reflected in increasing RMSE and decreasing $R^2$ values. This suggests that ARIMA, although effective at identifying trends, struggles to handle the high variability and noise commonly present in small HMLV datasets.

| Test Range | Train 90% - Test 10% | Train 80% - Test 20% | Train 70% - Test 30% | Train 60% - Test 40% |
|---|---|---|---|---|
| ARIMA (RMSE) | 194.31 | 481.54 | 383.06 | 419.75 |
| SVR (RMSE) | 404.53 | 456.01 | 440.23 | 424.52 |
| Random Forest (RMSE) | 469.90 | 596.12 | 500.79 | 557.80 |
| XGBoost (RMSE) | 619.68 | 599.12 | 522.22 | 693.08 |
| ARIMA (MAE) | 190.01 | 432.71 | 352.02 | 375.26 |
| SVR (MAE) | 354.40 | 427.95 | 408.27 | 391.96 |
| Random Forest (MAE) | 418.26 | 521.00 | 419.23 | 511.34 |
| XGBoost (MAE) | 576.19 | 522.25 | 384.35 | 610.72 |
| ARIMA ($R^2$) | 0.01 | -0.81 | 0.24 | -0.09 |
| SVR ($R^2$) | -3.30 | -0.81 | 0.00 | -0.11 |
| Random Forest ($R^2$) | -4.80 | -1.77 | -0.29 | -0.92 |
| XGBoost ($R^2$) | -9.08 | -1.80 | -0.41 | -1.97 |

**Fig. 2.** Comparison result of all machine learning model

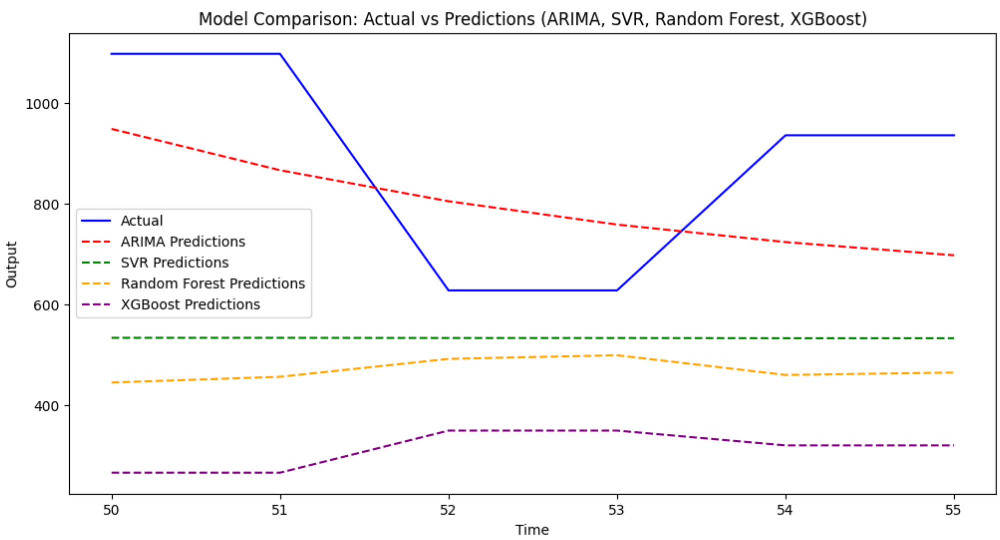


**Fig. 3.** Model comparison results

It is also important to note that in time-series forecasting, especially with ARIMA, a relatively lower $R^2$ does not necessarily imply weak predictive accuracy according to Hewamalage *et al.*, [14]. $R^2$ in time-series models can be misleading due to temporal autocorrelation and non-stationarity in the data, which affect the way variance is explained. Therefore, metrics such as RMSE and MAE often provide a more reliable indication of model performance in forecasting tasks. ARIMA's strength lies in its ability to model sequential patterns and time-dependent fluctuations—an aspect where many machine learning models fall short without additional feature engineering or lag structure representation from Mejri *et al.*, [15].

In contrast, machine learning models—Support Vector Regression (SVR), Random Forest, and XGBoost—performed significantly worse. Across all data splits, these models consistently produced negative $R^2$ values, indicating they failed to outperform even a simple mean-based prediction. This poor performance is likely due to three primary factors: overfitting, data variability, and model appropriateness. First, models such as Random Forest and XGBoost likely overfitted to the limited training data, capturing noise rather than meaningful patterns. Second, the high product variability and short production runs characteristic of HMLV systems limit the models' ability to generalize, especially with a dataset of only 56 data points. Lastly, these models, though powerful in large and structured datasets, are less suitable for time-series forecasting tasks involving small, irregular datasets without more extensive feature engineering and preprocessing.

On an individual basis, ARIMA demonstrated relatively low RMSE and MAE compared to the machine learning models. Its ability to model time-dependent structures makes it an appropriate choice for forecasting in HMLV systems, especially when the goal is to detect underlying production trends. However, the model's limited performance under higher data volatility confirms that ARIMA alone may not capture all aspects of complex production dynamics.

SVR, while theoretically suitable for modeling non-linear relationships, displayed high RMSE values (404.53 to 440.23) and negative $R^2$ scores across all splits. This reflects SVR's sensitivity to noise and its tendency to overfit small datasets, particularly when the feature space includes irrelevant or inconsistent information. Despite its flexibility, SVR struggled to learn meaningful patterns under the constraints of this study.

Random Forest showed moderate RMSE values (469.9 to 557.8) but continued to produce negative $R^2$, indicating insufficient generalization. Although ensemble methods like Random Forest are typically robust against overfitting and perform well on larger datasets, they underperformed in this case, likely due to the dataset's size and variability. While its results were marginally better than SVR, Random Forest still failed to model the underlying data effectively.

XGBoost, known for its high predictive power and ability to handle structured data, performed the worst in this study. It exhibited the highest RMSE (599.12 to 693.08) and consistently negative $R^2$ across all test configurations. These results suggest that XGBoost severely overfit the training data, possibly due to the model's complexity and the limited number of training examples. Without sufficient data variability, the model likely memorized noise, further diminishing its generalization ability.

Overall, the discussion highlights that while ARIMA is not without limitations, it is better suited than complex machine learning models for forecasting in HMLV systems, particularly when datasets are small and noisy Xin *et al.*, [16]. The results also reinforce that in time-series applications, lower $R^2$ values may still accompany accurate forecasts, especially when models like ARIMA effectively capture temporal structures. The findings underscore the critical importance of appropriate model selection, the use of time-aware metrics, and the potential value of hybrid or adaptive methods in complex manufacturing forecasting tasks.

## 5. Conclusion

This research set out to evaluate how a hybrid approach integrating discrete-event simulation (DES) with forecasting models can enhance decision-making in high-mix, low-volume (HMLV) production systems. The DES model successfully replicated the case company's operations—capturing product variety, process routings, machine setups, resource constraints, and demand variability—and enabled the systematic testing of different scheduling, capacity, and order release strategies.

Experimental evaluation of four forecasting methods—ARIMA, SVR, Random Forest, and XGBoost—showed that ARIMA best addressed the research objective of producing reliable short-term output forecasts with limited, noisy data. ARIMA consistently outperformed the machine learning models, which struggled with overfitting and produced negative $R^2$ values. These findings confirm that, in small-sample, high-variability environments, time-series methods like ARIMA remain a dependable choice.

To advance this work, larger datasets should be collected to strengthen the learning potential of advanced ML models, seasonality should be incorporated through models like SARIMA, and hybrid ARIMA–ML approaches should be explored to combine linear and non-linear forecasting strengths. These improvements could yield more accurate, flexible, and interpretable decision-support tools, directly enhancing production planning and performance in HMLV manufacturing.

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