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An Integrated Machine Learning and Mixed-Integer Linear Programming Framework for Intelligent Production Scheduling and Resource Allocation in the Beverage Manufacturing Industry

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ABSTRACT: Efficient production scheduling and resource allocation remain central challenges in manufacturing systems, particularly in fast-moving consumer goods industries, where demand fluctuations can disrupt production operations and resource utilization. To address these challenges, this study developed an integrated machine learning (ML) and mixed-integer linear programming (MILP) framework for improving demand forecasting, production scheduling, and resource allocation at AMA Brewery, Enugu State, Nigeria. First, weekly production schedules and sales data for ten products covering the period 2022–2024 were analyzed using four machine learning algorithms: Extreme Gradient Boosting (XGBoost), Decision Tree Regressor (DTR), Random Forest Regressor (RFR), and Gradient Boosting Regressor (GBR). The predictive performance of these models was evaluated using appropriate forecasting accuracy metrics. XGBoost emerged as the best-performing model, reducing Mean Absolute Error (MAE) by 58% and Symmetric Mean Absolute Percentage Error (SMAPE) by more than 57% compared with the benchmark methods. Its SMAPE values, approximately 2% across product categories, demonstrated strong predictive accuracy. Secondly, the selected XGBoost model was integrated into a MILP optimization framework to generate production schedules while satisfying operational and capacity constraints. The resulting optimization model comprised 1914 decision variables and 1884 constraints and generated a baseline production output of approximately 1,352,250 bottles per week. Furthermore, scenario analysis demonstrated the framework's potential to improve production throughput, with output approaching 1.5 million bottles under improved operating conditions. Sensitivity analysis also revealed the system's response to variations in key production parameters, providing insights into capacity limitations, operational vulnerabilities, and opportunities for improved resource allocation. Finally, the findings demonstrate that integrating machine learning-based demand forecasting with mathematical optimization provides a practical decision-support approach for enhancing production planning, demand fulfillment, and operational resilience in beverage manufacturing. The framework offers both tactical and strategic insights

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for production managers and planners. Future research should incorporate production costs, profitability measures, and real-time operational data to extend the framework towards more comprehensive and adaptive manufacturing decision-making.

Keywords: Machine learning forecasting; Mixed integer linear programming; Production scheduling; Capacity optimization; Smart manufacturing

1. Introduction

The beverage production industry is one of the major dynamic sectors within the Fast-Moving Consumer Goods (FMCG) industry, where manufacturing efficiency depends on maximized resource allocation, effective production scheduling and accurate demand forecasting [1]. Growing supply chain uncertainties, increasing market volatility, changing consumer preferences, and shorter product life cycles have made production planning substantially more tasking than conventional production environments [2]. In this context, manufacturers must consistently align production capacity with fluctuating customer demand while controlling operational costs and minimizing inventory, idle resources, and production delays [3].

Globally, the beverage industry continues to expand rapidly, with the United States remaining the highest market through integrated supply chain management systems, intelligent production scheduling, and advanced digital manufacturing practices [4]. In Africa, South Africa tops the African beverage market through operational optimization technologies, automation, and increased adoption of data-driven scheduling [5]. Inversely, many beverage manufacturers in developing economies consistently experience persistent operational challenges, including increasing production costs, poor resource utilization, supply chain disruptions, unstable energy supply, equipment constraints, inefficient production scheduling, and quality inconsistencies, thereby reducing competitiveness and industrial productivity [6].

To address these issues, researchers have increasingly adopted ML frameworks for demand forecasting because of their ability to enhance prediction accuracy and capture complex nonlinear relationships [7]. Likewise, mathematical optimization techniques, particularly MILP, have been widely utilized to allocate production resources efficiently under operational constraints [8]. However, existing studies largely treat production optimization and forecasting as separate decision-making problems [9]. ML models often establish accurate demand predictions without translating them into applicable production schedules [10]. On the other hand, mathematical optimization techniques continuously depend on deterministic demand assumptions that fail to relate to real market uncertainties [11]. This separation reduces the practical importance of existing decision-support systems for intelligent manufacturing [12]. To position the proposed study within the recent state of knowledge, the following section reveals current studies on ML, mathematical optimization, and production scheduling in manufacturing systems.

Martins et al. [13] highlighted the effectiveness of combining Operations Research (OR) and ML for sustainable production planning in craft breweries. Their ML forecasting model achieved competitive predictive accuracy, with an MAE of 11.76 and MAPE of 5.83%. Furthermore, the optimization model balanced resource utilization, service levels, and production costs under uncertainty through conditional value-at-risk. Similarly, Denizhan et al. [14] applied an intelligent workforce scheduling framework incorporating the Taguchi method, Genetic Algorithm (GA), and Monte Carlo Simulation (MCS). Their integrated model reduced task completion time by 13–15% across manufacturing SMEs, demonstrating the operational value of hybrid optimization strategies under uncertain manufacturing conditions. In a related study, Jafaripour et al. [15] combined discrete event simulation with robust multi-objective optimization to improve sustainability and resilience in automotive supply chains. Their findings demonstrated the potential of integrated simulation and optimization to reduce production disruptions while improving operational and

supply chain resilience. Likewise, Samouilidou et al. [16] developed an integrated MILP and ML scheduling framework to generate computationally efficient production schedules, minimize changeover times, and reduce downtime in multi-product manufacturing systems.

Recent developments further demonstrate the expanding application of hybrid ML-MILP frameworks in manufacturing decision-making. Georgiadis et al. [17] proposed a hybrid ML-MILP framework for integrating photovoltaic (PV) and battery energy storage systems (BESS) into manufacturing facilities. Their framework employed ML-based predictive models to forecast electricity prices, PV generation, and industrial energy demand, while the MILP model determined optimal energy utilization, storage operation, and market participation. Using a real-world Greek manufacturing facility, the study demonstrated potential daily cost savings of up to 352 monetary units through battery supported energy arbitrage. Sensitivity analysis under varying electricity price scenarios further demonstrated the framework's adaptability to changing operating conditions. Although their primary focus was industrial energy management rather than product sequencing, the study provides a relevant methodological precedent for linking predictive ML outputs with MILP-based resource allocation and operational decisions.

At a broader level, Ordu et al. [18] reviewed developments in hybrid ML and mathematical-based optimization approaches for production scheduling and resource allocation between 2020 and 2026. Their review emphasized the complementary roles of the two techniques: mathematical optimization provides structured decision-making and constraint enforcement, whereas ML improves adaptability through forecasting and learning from operational data. The review also identified improvements in scheduling performance and robustness as important benefits of hybrid approaches, while highlighting computational complexity, data quality, interpretability, and real-time scalability as persistent implementation challenges. Importantly, the authors identified sensitivity and scenario analyses as useful approaches for evaluating the stability of intelligent manufacturing systems under operational uncertainty. These observations reinforce the need to combine predictive capability with optimization and systematic robustness evaluation when developing practical manufacturing decision support frameworks. Table 1 summarizes the comparison of the reviewed literature and the proposed study.

Table 1. Comparison of relevant literature and the proposed ML-MILP framework.

Author(s)	Application Area	Methodology	Main Contribution	Distinction of the Present Study
[13]	Brewery production planning	ML + OR + CvaR	Demand forecasting and risk aware production planning	Integrates multiple ML models with MILP-based production scheduling and resource allocation.
[14]	Workforce scheduling	Taguchi + GA + MCS	Improved workforce scheduling under uncertainty	Focuses on product allocation and production scheduling rather than workforce scheduling.
[15]	Automotive supply chains	Simulation + robust optimization	Enhanced supply chain resilience	Addresses production line scheduling and capacity utilization using ML-MILP integration.
[16]	Multi-product manufacturing	ML + MILP	Changeover prediction and production scheduling	Extends the scheduling perspective through demand forecasting and scenario-based robustness evaluation.
[17]	Industrial energy management	ML + MILP	Optimized energy resource allocation and cost management	Applies the ML-MILP approach to product demand driven production planning.
[18]	Smart manufacturing	Review of hybrid ML-optimization	Synthesized advances and challenges in intelligent scheduling	Provides an integrated industrial application combining forecasting, MILP, sensitivity, and scenario analyses.

Present study	Beverage manufacturing	Four ML algorithms + MILP + sensitivity and scenario analyses	Demand-driven production scheduling and resource allocation under varying operating conditions	Integrated predictive and optimization framework evaluated using real industrial brewery data.

Overall, these studies highlight the growing transition from traditional scheduling techniques toward intelligent decision support systems that combine mathematical optimization and predictive analytics to improve manufacturing efficiency under uncertainty [19]. However, their methodological orientations and application domains differ considerably. Jafaripour et al. [15] addressed resilient supply chain planning through simulation and robust optimization; Martins et al. [13] focused on production planning and demand forecasting under risk; Denizhan et al. [14] emphasized workforce scheduling; Samouilidou et al. [16] investigated changeover optimization and production scheduling; while Georgiadis et al. [17] concentrated on predictive energy management and optimal energy resource integration. Ordu et al. [18] provided a broader synthesis of hybrid ML-optimization approaches, identifying both their operational benefits and implementation limitations. Collectively, these studies establish the relevance of integrating predictive intelligence with mathematical optimization, but they also show that applying hybrid frameworks depends on the specific operational decisions, resource constraints, and uncertainty characteristics of each manufacturing environment.

Despite these advances, an important research opportunity remains in developing an integrated framework that combines ML-based demand forecasting, MILP-driven product allocation and production scheduling, and systematic sensitivity and scenario analyses within a unified decision-support structure. In particular, the simultaneous application of these components to real-world beverage production operations in developing economies remains insufficiently addressed in the literature reviewed. Although existing studies have investigated forecasting, resource allocation, production scheduling, and robustness analysis, their combined application to production line allocation, demand fulfillment, capacity utilization, and changeover-related scheduling decisions within a brewery manufacturing environment warrants further investigation [20]. Future research should therefore emphasize hybrid intelligent decision-support systems that integrate predictive ML, mathematical optimization, and uncertainty evaluation to improve manufacturing responsiveness, operational resilience, and resource efficiency [21,22].

This study addresses this research opportunity by integrating four ML algorithms with a MILP model to optimize resource allocation and production scheduling for a Nigerian-based brewery company. Unlike approaches that primarily apply ML to forecasting or mathematical optimization to isolated resource-management decisions, the proposed framework establishes a predictive to optimization workflow in which ML-generated demand forecasts inform MILP-based production and resource allocation decisions. Furthermore, sensitivity and scenario analyses are incorporated to examine the effects of changes in demand and production capacity on objective-function performance, demand fulfillment, capacity utilization, and scheduling feasibility. This integrated predictive and optimization framework provides a practical decision-support approach for improving production planning, operational efficiency, and intelligent manufacturing in the beverage industry.

2. Materials and Methods

2.1. Materials

To ensure efficient implementation of the optimization model and subsequent analyses, a set of well-established computational tools and libraries were employed. These tools support model formulation, data handling, visualization, and performance evaluation, with their latest versions outlined in Table 2.

Table 2. Computational Tools, Software Specifications, and Operational Limits Used in the Study.

S/N	Software Tool and Version	Measuring/Operational Limits	Technical Specifications	Functional Usage in Study
1	Microsoft Excel 365	Row Limit: 1,048,576 rows × 16,384 columns. Numerical Precision: 15 significant digits	Dynamic array spreadsheet platform with 64-bit engine computation	Initial raw data collection, preliminary filtering, and tabular validation from AMA Brewery
2	Jupyter Notebook 7.2	Max Output Cell Limit: 10,000 text lines/100 MB per cell render. Execution Time Out: Unconstrained (interactive session)	Web-based interactive computing environment (Python kernel 8.x)	Interactive development environment for code execution, visualization, and documentation
3	Python 3.12	Max Memory: Limited by host RAM (16 GB), Floating-Point Precision: IEEE 754 double precision (1.7×10^{-308} to 1.7×10^{308})	64-bit interpreter with dynamic typing and enhanced memory management	Core programming language for modelling, data analysis, and system integration
4	Pandas 2.2	Dataset Dimension Limit: 10^6 rows × 10^3 columns (In-memory execution). Study Record Array: 156 weekly intervals across 10 SKU product lines	High-performance columnar data structure processing engine (DataFrame)	Data manipulation, preprocessing, and 2022–2024 weekly sales dataset handling
5	Google OR-Tools 9.10	Variable/Constraint Capacity: 10^7+ variables. Study Implementation Limit: 1914 decision variables, 1884 constraints. Optimality Relative 6Gap Tolerance (*MIPGap*): 1.0×10^{-4} (0.01%)	MILP/CP-SAT solver engine supporting multi-threaded execution	Formulating and solving the MILP model
6	NumPy 1.26	Array Dimensionality Limit: Up to 32 dimensions. Numerical Precision: float64 (15–17 decimal significant digits accuracy)	Multi-dimensional array handling with C-contiguous memory layout	Vectorized numerical computation, array operations, and statistical calculations
7	Seaborn 0.13	Data Point Handling Limit: 10^6 observations per plot canvas. Statistical Confidence Interval: 95% default threshold	High level statistical visualization layer built on Matplotlib structures	Advanced statistical data visualization, heatmap generation, and scenario distributions
8	Matplotlib 3.9	Export Rendering Limit: 300 DPI to 1200 DPI (Vector PDF/SVG and PNG rasterization)	Object-oriented 2D plotting library with vector graphics export engine	Generation of high-resolution diagnostic plots, throughput curves, and sensitivity charts
9	Scikit-learn 1.5	Metric Calculation Precision: 10^{-6} error resolution. Performance Target: Target MAE reduction >50%; SMAPE accuracy threshold ~2.0%	Scientific Python machine learning library with parallel processing engine	ML modelling (XGBoost, DTR, RFR and GBR), cross-validation, and metrics (MAE, SMAPE)

2.2. Methods

The research plan as presented in Figure 1 outlined the road map of the study starting from the research work through data analysis to model development and to the finishing point.

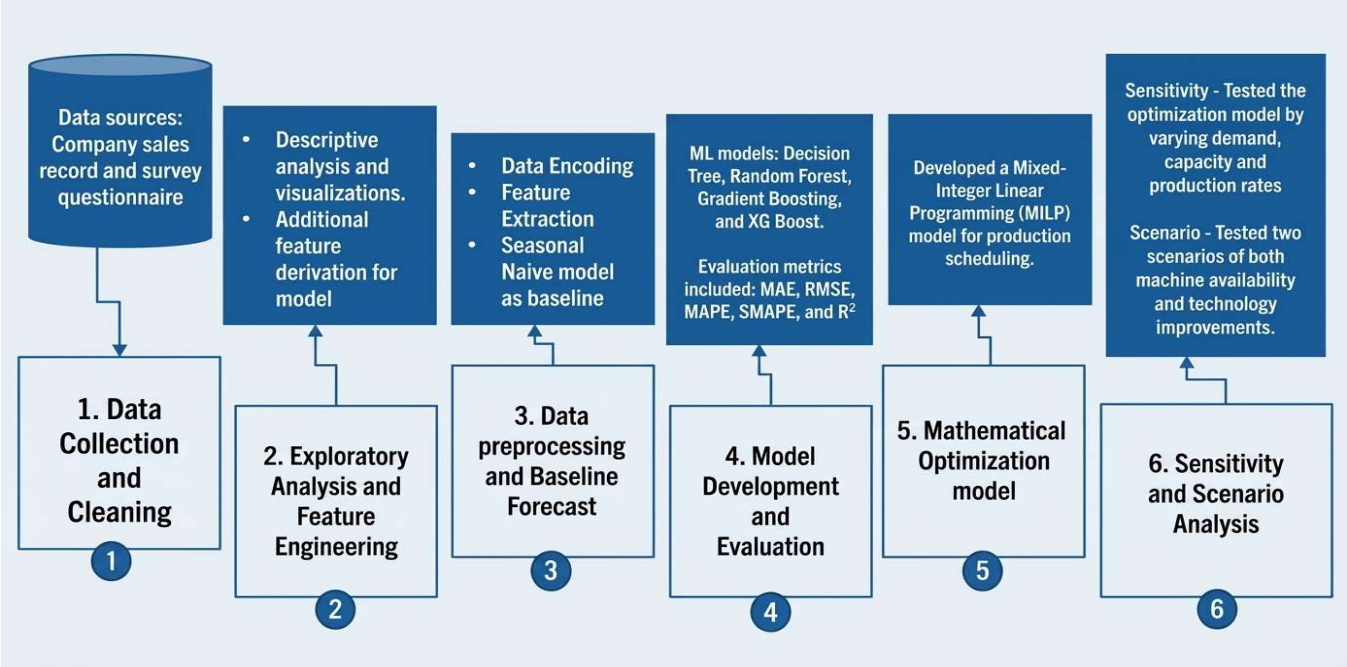


Figure 1. Research Plan.

2.2.1. Study Area

As presented in Figure 2, the study was conducted at AMA Brewery, Enugu State, Nigeria, one of the major production facilities of Nigerian Breweries Plc. and a leading beverage production in Nigeria with operations across several states [23]. The company was established in 2003, producing and distributing both non-alcoholic and alcoholic beverages such as Star Lager, Turbo King, Heineken, Desperados, Amstel Malta, Fayrouz, Maltina, and Goldberg. Operating within the highly competitive FMCG sector, the company is also affected in correspondence with other production industries with high production efficiency, fluctuating market demand, rapid response, and product quality [24]. The company functions consistently on a 24-h production schedule using multiple automated packaging lines supported by involving production management systems [25]. Other production activities in the brewery industry, like those of the case study company, include quality assurance, raw material preparation, warehousing, packaging, product distribution, and demand planning [26]. Performance is also routinely monitored using operational indicators such as Overall Equipment Effectiveness (OEE), production output, machine utilization, downtime, and changeover duration [27].

Despite the case study company's level of automation, the system continues to experience production planning issues from resource allocation constraints, machine capacity limitations, frequent product changeovers, and fluctuating market demand. These operational complexities often result in scheduling conflicts, increased downtime, underutilized capacity, and production inefficiencies that affect the plant's overall performance. This case study company was chosen because it represents a typical large-scale brewery operating under dynamic production conditions commonly observed in developing manufacturing economies [26]. The availability of diverse product and sales records, multiple packaging lines, and detailed production data makes the facility a suitable industrial area for evaluating intelligent production scheduling and capacity optimization using combined ML and mathematical optimization techniques [28].

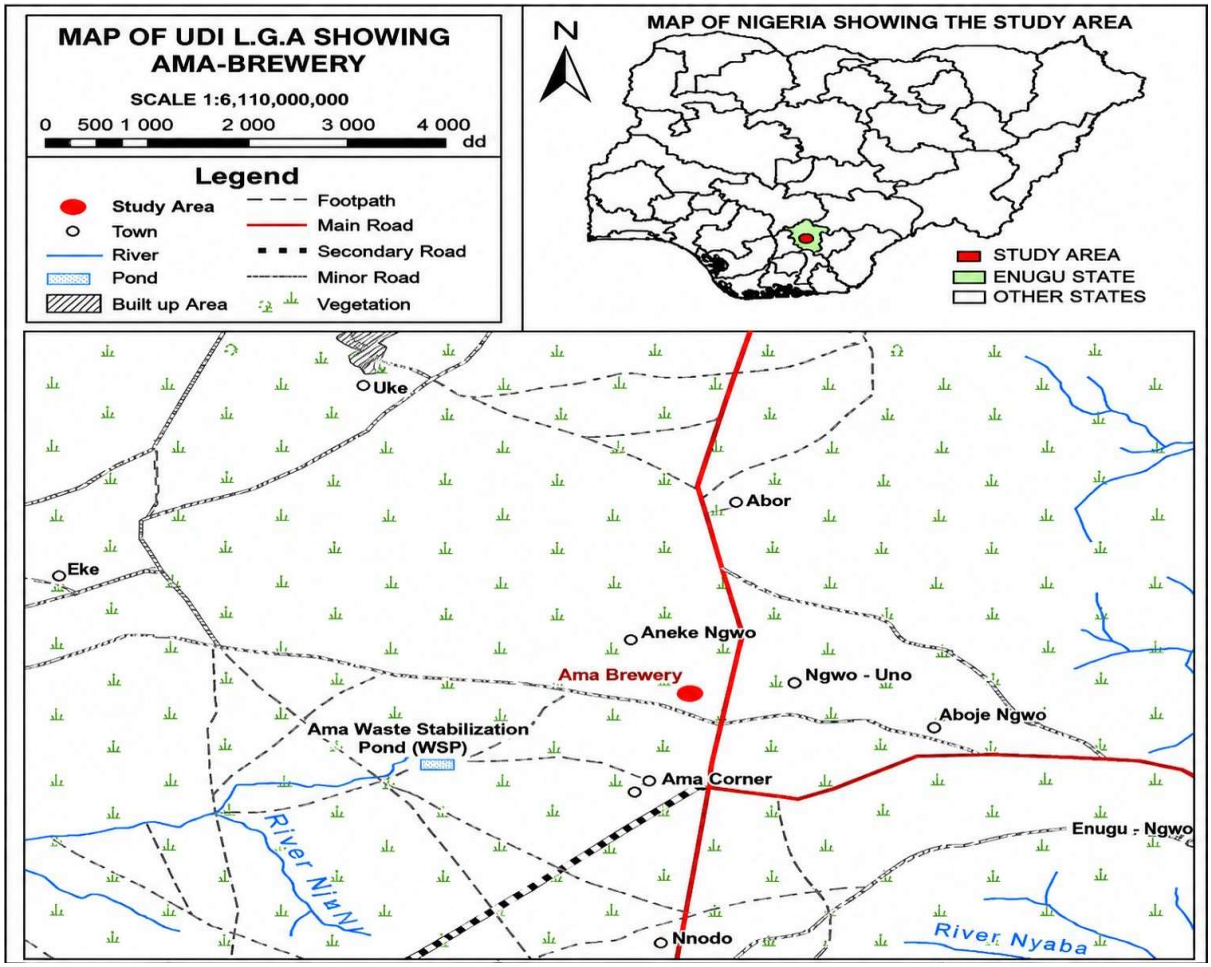


Figure 2. Map location of the case study area. Source: [23].

2.2.2. Data Acquisition and Preprocessing

The production data were obtained from AMA Brewery, Enugu State, Nigeria, covering weekly operations from January 2022 to October 2024 using questionary. The dataset comprised ~143 weeks of observations (>1400 records) for ten beverage products, including Heineken (60 cl and 45 cl), Desperados (45 cl), Star (60 cl), Life (60 cl), Legend (60 cl), Gulder (60 cl), Amstel Malta (33 cl), Maltina (33 cl), and Hi-Malt (33 cl). Weekly production volumes ranged from approximately 5000 to 18,000 units, capturing seasonal demand fluctuations and operational variability. The weekly resolution provides sufficient temporal granularity for both demand forecasting and production optimization.

Following the data activities, Exploratory Data Analysis (EDA) was performed to examine data quality, identify trends, detect outliers, and characterize seasonal demand patterns prior to model development [29]. Also, time-series plots, comparative and boxplots visualizations were used to evaluate product-level variability and temporal behaviour [30]. Extreme observations associated with promotions or supply disruptions were retained because they represent real operational conditions rather than measurement errors [31].

To improve forecasting performance, historical production records were transformed into predictive variables describing temporal demand behaviour and product characteristics [32]. The response variable was weekly demand, while explanatory variables included lagged demand, calendar indicators, seasonality, and product identity. Table 3 presents the input variables used for machine learning model development.

Table 3. Input variables used for ML forecasting.

Variable	Description	Type
Product ID	Ten beverage products	Categorical
Previous-week demand	Demand at $t-1$	Numerical
Previous 2-week demand	Demand at $t-2$	Numerical
Previous 4-week demand	Demand at $t-4$	Numerical
Week number	Week (1–52)	Numerical
Month	January–December	Categorical
Quarter	Q1–Q4	Categorical
Season	Dry/Rainy	Binary
Holiday	Christmas, New Year, Easter	Binary
Year	2022–2024	Numerical

Sequel to the data processing, the calendar features enabled the models to capture recurring seasonal patterns, while lag variables represented short- and medium-term demand dependence. Also, a global forecasting framework was adopted to learn shared demand patterns across all products, improving model generalization while reducing computational complexity compared with training separate models for individual products [33]. Before model training, categorical variables were encoded using one-hot encoding, and date information was decomposed into calendar features including week number, month, quarter, season, and year. Afterward, data manipulation and visualization were implemented employing NumPy, Matplotlib, and Pandas attributes of Python software [12].

2.2.3. ML Model Development

Baseline Forecast Model

Following the data collection and processing, to provide a benchmark for evaluating the proposed ML models, a Seasonal Naïve Forecasting (SNF) model was first implemented [34]. This function was used as a baseline in time-series forecasting because of its ability to preserve recurring seasonal patterns, interpretability, and simplicity without parameter estimation. Remarkably, comparing the ML models against the benchmark of the SNF enables more objective assessment of their predictive value. Also, the SNF model assumes that demand in the current period equals the demand observed in the corresponding period of the previous seasonal cycle, calculated as:

$$\widehat{y_t} = y_{t-s} \tag{1}$$

where $\widehat{y_t}$ is the forecast demand at time t, y_{t-s} is the observed demand in the previous seasonal cycle, and s is the seasonal period. For the weekly production dataset, $s = 52$ weeks was adopted to represent annual seasonality. The baseline model was utilized independently for each of the ten beverage products after chronologically sorting the weekly production records. Its forecasting performance was subsequently compared with the four ML models using statistical evaluation models.

Decision Tree Regressor (DTR)

Following the SNF benchmark evaluation, DTR was employed to model the nonlinear relationship between the engineered predictor variables and historical production demand [35]. The input features comprised holiday indicator, product identity, month, season, and 1 to 4-week lagged demand values, while weekly production demand served as the response variable. Owing to its non-parametric structure, DTR can effectively highlight complex interactions without assuming linear relationships between output and predictors [36]. To determine the training dataset:

$$D = \{(x_i, y_i)\}_{i=1}^{n} \tag{2}$$

where $x_i = [P_i, W_i, S_i, H_i, M_i, Y_i, D_{t-1}, D_{t-2}, D_{t-4}]$. P_i = Product category, W_i = Week number, S_i= Season, H_i = Holiday indicator, M_i = Month, Y_i = Year, D_{t-1} = Previous week demand, D_{t-2} = Two-week lag demand, D_{t-4} = Four-week lag demand, D is the original dataset, x_i is the feature vector for the *i*-th sample, y_i is the target variable and n is the number of training sample. The algorithm recursively partitions the feature space by selecting splits that minimize the Mean Squared Error (MSE). The prediction assigned to each terminal node is the mean response of the training samples contained within that node, given as:

$$\gamma = \frac{1}{N_m} \sum_{x_i \epsilon R_m} y_i \tag{3}$$

where R_m denotes the terminal region and N_m is the number of observations within that region. The split quality was evaluated using:

$$MSE(R_m) = \frac{1}{N_m} \sum_{x_i \epsilon R_m} (y_i - \gamma)^2 \tag{4}$$

and the optimal partition was selected by minimizing the weighted MSE after each split,

$$MSE_{split} = \frac{N_L}{N} MSE(R_L) + \frac{N_R}{N} MSE(R_R) \tag{5}$$

where R_L and R_R denote the number of observations in the left and right child nodes, respectively.

Random Forest Regressor (RFR)

This ML model was employed due to its ability to improve forecasting accuracy predictions using multiple decision trees [37]. The model was trained on the weekly production dataset and engineered predictor variables, including product identity, week number, month, season, holiday indicator, and one-, two-, and four-week lagged demand. Owing to its ensemble learning strategy, RFR effectively captures nonlinear relationships while reducing overfitting and improving model generalization [38]. For a training dataset, bootstrap sampling generates multiple training subsets:

$$D_i = \{(x_i, y_i)\}_{i=1}^{m},\ D_i \subset D, i = 1,2,\ldots,N \tag{6}$$

where D_i represents the *i*-th bootstrap sample utilized to train an individual decision tree. Each decision tree produces a $T_i(x)$ prediction for an input feature vector x. The final RFR prediction is obtained by averaging the predictions from all trees, given as:

$$\hat{y} = \frac{1}{N} \sum_{i=1}^{N} T_i(x) \tag{7}$$

where *N* is the number of trees in the ensemble. The predictive performance of RFR results from variance reduction achieved through bootstrap aggregation (bagging), while random feature selection during tree construction reduces correlation between individual trees and enhances generalization [39].

Gradient Boosting Regressor (GBR)

This ML model was employed due to its capability to capture the nonlinear relationship between the engineered predictor variables and historical production demand [40]. Unlike RFR, which constructs decision trees independently, GBR sequentially builds an ensemble of weak learners, where each successive tree limits the preceding ensemble's prediction errors, thereby improving forecasting accuracy [41]. GBR seeks to estimate a prediction function that reduces the regression loss function. The general form of the model is given as:

$$L(y, F(x)) = \frac{1}{2}(y - F(x))^2 \tag{8}$$

The model is initialized using the mean response of:

$$F_0(x) = \frac{1}{n}\sum_{i=1}^{n} y_i \tag{9}$$

At each boosting iteration, the pseudo-residuals are computed as:

$$r_i^{(m)} = y_i - F_{m-1}(x_i) \tag{10}$$

and a regression tree $h_m(x)$ is fitted to these residuals. The ensemble is then updated according to:

$$F_m(x) = F_{m-1}(x) + \eta y_m h_m(x) \tag{11}$$

where η is the learning rate controlling the contribution of each successive tree. After boosting iterations, the final prediction model becomes:

$$F(x) = F_0(x) + \sum_{m=1}^{M} \eta\, h_m(x) \tag{12}$$

Extreme Gradient Boosting (XGBoost)

This ML model was also applied due to its ability to extend conventional gradient boosting by combining parallel learning, regularization, tree pruning and second-order optimization, thereby enhancing prediction accuracy while minimizing overfitting [42,43]. XGBoost reduces a regularized objective function comprising a prediction loss and a model complexity penalty:

$$L = \sum_{i=1}^{n} l(y_i, \hat{y_i}) + \sum_{m=1}^{M} \Omega(f_m) \tag{13}$$

where $l(y_i, \hat{y_i})$ denotes the Mean Squared Error (MSE) loss:

$$l(y_i, \hat{y_i}) = \frac{1}{2}(y_i - \hat{y_i})^2 \tag{14}$$

and

$$\Omega(f) = \gamma \mathrm{T} + \frac{1}{2}\lambda \sum_{j=1}^{T} w_j^2 \tag{15}$$

penalizes model complexity through the number of Terminal Nodes (T) and Leaf Weights (w_j).

At each boosting iteration, a new regression tree is added to improve the current prediction:

$$\hat{y_i}^{(t)} = \hat{y_i}^{(t-1)} + f_t(x_i) \tag{16}$$

where $f_t(x_i)$ represents the newly fitted tree. The final prediction after *M* boosting rounds is:

$$\hat{y} = \sum_{m=1}^{M} f_m(x) \tag{17}$$

Model parameters were optimized applying grid-search hyperparameter tuning, while forecasting performance was evaluated using SMAPE and MAE. The resulting demand forecasts were subsequently integrated into the MILP optimization model for intelligent resource allocation and production scheduling.

2.2.4. ML Model Evaluation

To ensure good generalization on unseen data and robust forecasting performance, all ML models were assessed using multiple performance metrics, time-series cross validation, and hyperparameter optimization. Since the dataset is temporal, validation preserves the chronological order of observations to simulate real-world forecasting and prevent information leakage conditions [44].

Time-Series Cross-Validation

Adopted from Hall & Rasheed [45] study, this model validation was performed using the TimeSeriesSplit framework available in Scikit-learn. Unlike random train-test splitting, TimeSeriesSplit

preserves the temporal sequence of observations by progressively expanding the training set while testing on the subsequent time window. Also, this concept provides a realistic assessment of forecasting performance under operational conditions and reduces look-ahead bias [46].

Hyperparameter Optimization

As presented in Table 4, to increase prediction accuracy while avoiding overfitting, model hyperparameters were optimized employing a two-stage search strategy adopted from O'Brien et al. [47]. The optimization procedure consisted of two concepts:

i. RandomizedSearchCV, which first explored a broad hyperparameter space to identify promising parameter regions with relatively low computational cost.
ii. GridSearchCV, which subsequently performed an exhaustive search within the narrowed parameter ranges to determine the optimal hyperparameter combination.

For all models, optimization was implemented in the Scikit-learn framework using Mean Absolute Error (MAE) as the primary optimization criterion.

Table 4. Hyperparameters optimized for each ML model.

Model	Hyperparameters Optimized
DTR	max_depth, min_samples_split, min_samples_leaf
RFR	n_estimators, max_depth, max_features, min_samples_split
GBR	n_estimators, learning_rate, max_depth, subsample
XGBoost	n_estimators, learning_rate, max_depth, subsample, colsample_bytree

Performance Evaluation Metrics

Forecast accuracy of the applied ML models was also assessed using five complementary statistical metrics: Symmetric Mean Absolute Percentage Error (SMAPE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), Root Mean Square Error (RMSE), and the Coefficient of Determination (R^2). Collectively, these metrics evaluate goodness-of-fit of the models [48]. The MAE was employed due to its ability to accuracy, relative error, robustness and prediction the average magnitude of the errors irrespective of direction, also, lower MAE values indicate better forecasting performance [49]. RMSE was also selected because it measures the square root of the average squared prediction errors and places greater emphasis on larger deviations; lower RMSE values indicate higher prediction accuracy [50]. On the other hand, MAPE was employed because it expresses prediction error as a percentage of actual observations, facilitating comparison across products with different demand scales and the smaller MAPE values represent better forecasting accuracy [51]. Adopted from Pilarski et al. [52], SMAPE was employed because it provides a balanced percentage error measure and remains stable when actual demand approaches zero. The coefficient of determination (R^2) measures the proportion of variance in the observed data explained by the forecasting model and R^2 value closer to 1 indicates superior model fit [53]. Equations (2)–(4) present the models used for performance evaluation. While Table 5 presents a concise comparison summary of the applied evaluation models.

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \tag{18}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{19}$$

$$MAPE = \frac{100\%}{n}\sum_{i=1}^{n}\left|\frac{y_i - \hat{y}_i}{y_i}\right| \tag{20}$$

$$SMAPE = \frac{100\%}{n}\sum_{i=1}^{n}\frac{|y_i - \hat{y}_i|}{(|y_i|+|\hat{y}_i|)/2} \quad (21)$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y}_i)^2} \quad (22)$$

where: y_i is the actual demand, $\hat{y}$ is the predicted demand, $\bar{y}$ is the mean of the observed values. and n is the number of observations.

Table 5. Comparison summary of the applied evaluation model.

Metric	Ideal Value	Purpose
MAPE	Minimum	Relative percentage error
RMSE	Minimum	Penalizes large errors
MAE	Minimum	Average prediction error
SMAPE	Minimum	Scale-independent accuracy
R^2	Maximum	Goodness-of-fit

2.2.5. Development of MILP Model and Integration of the ML with the Model

Theoretical Background

Following the confirming the best ML model using the evaluation matrices, Mixed-Integer Linear Programming (MILP) was formulated to model the production scheduling problem using the ten allocate ten beverage products across six packaging lines over a weekly planning horizon. During the model development, the process integrated the demand forecasts generated by the selected ML model with changeover requirements, line capacity, production rates, and product-line eligibility. The MILP model formulation was developed following the general production planning framework study by Sifakis et al. [54]. Notably, the operational information required for the MILP formulation was obtained from the production management personnel and the brewery's production records. The system comprises six packaging lines, with Lines 1, 2, 4, 5, and 6 available for 22 h/day and Line 3 available for 12 h/day. Ten beverage products are considered, comprising 60-, 45-, and 33-cl packaging formats. Tables 6–8 outline the daily available operating hours of the packaging lines, the products, and the packaging formats considered in the MILP model, and the product production rates used in the scheduling model, respectively.

Table 6. The Capacity of each Line.

S/N	Lines	Available Hours per Day
1	LINE-1	22
2	LINE-2	22
3	LINE-3	12
4	LINE-4	22
5	LINE-5	22
6	LINE-6	22

The corresponding production capacities are 1375 units/h for 33-cl products, 1500 units/h for 45-cl products, and 2500 units/h for 60-cl products.

Table 7. Type, Size and Total Product Number Produced by the Company.

S/N	Product	Bottle Size
1	Maltina	33 cl
2	Heineken Lager	45 cl
3	Heineken Lager	60 cl
3	Legend Stout	60 cl
5	Star Lager	60 cl
6	Life Lager	60 cl
7	Amstel Malta	33 cl
8	Hi-malt	33 cl
9	Gulder Lager	60 cl
10	Desperado Lager	45 cl

The model also incorporates changeover requirements and product line eligibility. LINE-6 is dedicated to PET-based malt beverages, whereas Lines 1–5 provide flexible production capability for the remaining products. A changeover between products of the same packaging size requires ~2 h, while a changeover involving different packaging sizes requires 3 h.

Table 8. The Daily and Hourly Production Rates.

SSS/N	Bottle Size	Daily Bottle Capacity	Rate (Units/h)
1	33 cl	33,000	1375
2	45 cl	36,000	1500
3	60 cl	60,000	2500

Model Assumptions and Notation

To maintain computational tractability while representing the major operational characteristics of the brewery, the following assumptions were adopted:

i. The forecast weekly demand from the selected ML model is used as the demand input to the MILP.
ii. Production rates are constant for each product-line combination.
iii. At most one product is scheduled on each line per day.
iv. Changeover times are deterministic and depend on the product transition.
v. Initial inventory is assumed to be zero.
vi. Lines are available throughout their specified operating hours, with no unplanned breakdowns or maintenance interruptions.
vii. Intra-day product changes are excluded; changeovers occur only between consecutive production days.
viii. The objective focuses on production and operational performance rather than monetary cost.
ix. All production, capacity, and changeover relationships are linear.

Notation used in the Model Formulation

Let *P, L,* and *D* denote the sets of products, production lines, and planning days, respectively. The principal parameters and decision variables are defined as follows:

Indices:

i. $p \in P$: Set of products, indexed by p.
ii. $l \in L$: Set of production lines, indexed by l.
iii. $d \in D$: Set of days in the planning horizon, indexed by d.
iv. $L_p \subseteq L$: Set of production lines where product p can be manufactured.
v. $P_l \subseteq P$: Subset of products that can be manufactured on production line l.

Parameters:

i. D_p: Weekly demand for product p
ii. H_l: Available hours on line l per day
iii. U_{pl}: Production rate of product p on line l (units/hour)
iv. $S_{pp'l}$: Setup time (in hours) when switching from p to p' on line l
v. M: A large positive constant (Big-M) for logical constraints
vi. K: maximum number of changeovers allowed on a line in a day.
vii. B: The maximum cumulative setup time allowed on a single line within a day.

Decision Variables:

i. $x_{pld} \in \mathbb{R}_{\geq 0}$: Number of units of product p produced on line l on day d
ii. $y_{pld} \in \{0,1\}$: 1 if product p is produced on line l on day d, 0 otherwise
iii. $z_{plp'd} \in \{0,1\}$: 1 if a changeover occurs from p to p' on line l on day d, 0 otherwise

MILP Model Formulation

Objective Function: The primary objective is to maximize total production while satisfying forecast demand and operational constraints:

$$\text{Max Z } = \sum_{p,l,d} x_{pld} - \lambda \sum_{p \neq p',l,d} z_{pp'ld} \tag{23}$$

where α = weight assigned to production output, λ represents the penalty associated with changeovers. This formulation seeks to maximize productive output while the subsequent constraints control demand fulfillment, capacity utilization, product eligibility, and changeovers.

Demand Fulfillment Constraints: To prevent substantial underproduction while limiting excessive production, the scheduled quantity for each product is bounded between 90% and 140% of forecast demand:

$$0.90D_p \leq \sum_{l \in L} \sum_{d \epsilon D} x_{pld} \leq 1.40D_p, \forall p \in p \tag{24}$$

Production Capacity Constraint: For each line and day, production time plus applicable changeover time cannot exceed available operating time:

$$\sum_{p \in P} \frac{x_{pld}}{U_{pl}} + \sum_{p \neq p'} S_{pp'l} * z_{plp'd} \leq H_l, \forall l, d \tag{25}$$

For the first planning day, the changeover component is omitted because no preceding production assignment exists.

Production–Assignment Linking:

$$x_{pld} \leq M * y_{pld}, \forall p, l, d \tag{26}$$

where M is a sufficiently large upper bound on production quantity.

Single-Product Assignment:

$$\sum_{p \in P} y_{pld} \leq 1, \forall l, d \tag{27}$$

This constraint enforces the adopted one-product-per-line-per-day scheduling policy.

Changeover Detection:

$$z_{plp'd} \geq y_{pl(d-1)} + y_{p'ld} - 1 \; \forall p \neq p', \forall l \in L, \forall d \in D, d > 1 \tag{28}$$

Thus, a changeover is activated when a line switches from $d-1$ to product p'on day to product on day d.

Changeover Constraints:

The maximum number of daily changeovers is controlled by:

$$\sum_{p \neq p'} z_{plp'd} \leq K, \; \forall l, d > 1 \tag{29}$$

and the associated changeover time is constrained by:

$$\sum_{p,p'} \sum_{p \neq p'} S_{pp'l} * z_{plp'd} \leq B \ \forall l, d > 1 \tag{30}$$

Finally,

$$x_{pld} \geq 0, \ y_{pld}, z_{plp'd} \in \{0, 1\} \tag{31}$$

Product line eligibility was enforced by defining x_{pld} and y_{pld} only for feasible product line combinations. The demand forecasts generated by the ML models constitute the principal predictive input to the MILP scheduling model. Following time-series validation, the best-performing forecasting model was selected based on the evaluation metrics and used to generate weekly demand forecasts for the ten beverage products. These forecasts, denoted by D_p, were subsequently supplied to the MILP as product specific demand targets. The MILP then translated the predicted demand into feasible production decisions by simultaneously considering production line availability, rates, eligibility, and changeover requirements. Thus, the framework establishes a sequential predictive prescriptive architecture, in which ML provides the expected demand while the MILP determines how available production capacity should be allocated to satisfy that demand. The formulated MILP was implemented in Google OR-Tools and solved to obtain feasible production schedules for the planning horizon. The resulting schedules were evaluated using capacity utilization, production output, changeover frequency, and demand fulfillment indicators. These concepts were subsequently employed to quantify the operational benefits of the optimized schedule and to provide a baseline for the scenario and sensitivity analyses.

Key Performance Indicators (KPIs)

To assess the efficiency and effectiveness of the mathematical optimization model developed for production changeover and scheduling minimization, some KPIs were evaluated following Kalak, [55]. These metrics provide insights into operational drivers such as setup changes, production efficiency, and demand fulfillment [56]. The applied KPIs for the study include:

(i) Total Quality Production (TQP) was incorporated to determine the overall production quantity across all days, lines, and products [57]. This is to confirm how the production schedule plan meets the required scale given as:

$$TQP = \sum_{p,l,d} x_{pld} \tag{32}$$

(ii) Demand Fulfillment Rate (DFR) was applied to measure how well the production plan fulfills the demand for each detects and product the effectiveness of the model in achieving customer demand targets [58]. This was measured using:

$$DFR = \frac{\sum_{p,l,d} x_{pld}}{\Sigma_p D_p} \times 100 \tag{33}$$

(iii) Production Deviation (PD) was employed to access the relative mismatch between the forecasted DFR and TQP [59]. This KPIs offers insight into the degree of underproduction and overproduction, inventory control, and supporting planning accuracy, which is calculated using:

$$PD = \frac{TQP - \Sigma_p D_p}{\Sigma_p D_p} \times 100 \tag{34}$$

(iv) Capacity Utilization (CU) was integrated to measures to how effective the production lines were used relative to its available capacity (time) over a specific period [60]. The matric was done using:

$$CU = \frac{\sum_{p,l,d} x_{pld} / U_{pl}}{\sum_{l,d} H_l} \times 100 \tag{35}$$

(v) Total Changeovers (TC) captured the total number of changeovers that determine the production mechanism switch from producing one product to another across all production lines and days [23]. Given as:

$$TC = \sum_{p \neq p'} z_{pld} \tag{36}$$

(vi) Time Utilization (TU) measured the entire production time including changeover time [34]. Calculated using:

$$TU = \frac{Production\ Time + Setup\ Time}{Available\ Time} \times 100 \tag{37}$$

These KPIs collectively provide a holistic framework for evaluating the performance of the optimization model, ensuring that demand satisfaction, production efficiency, and resource utilization are adequately measured [61]. Building on these performance measures, the next stage involves conducting a scenario and sensitivity analysis to study how variations in key parameters influence model outcomes, thereby validating its robustness and adaptability under dynamic production conditions [62].

2.2.6. Sensitivity and Scenario Analysis

Following the baseline MILP optimization, sensitivity and scenario analyses were conducted to assess the robustness and operational resilience of the proposed ML–MILP production scheduling framework under changes in demand and production conditions. For each sensitivity level and operational scenario, the MILP model was re-solved using the modified parameter values, while all other baseline parameters remained unchanged.

Sensitivity Analysis

Adopted from Grznár et al. [63] this optimization analysis was performed on three critical parameters; forecast demand, production rate, and available production capacity. Each parameter was varied independently by −20%, −10%, 0%, +10%, and +20% relative to its baseline value.

i. Demand sensitivity: Forecast demand for each product was varied within the specified range to evaluate the effect of demand uncertainty on the optimized production schedule.
ii. Capacity sensitivity: Available operating hours for each production line were varied within the specified range to represent potential capacity losses or gains arising from maintenance, downtime, or improved line availability.
iii. Production-rate sensitivity: Production rates were varied within the specified range to represent changes in equipment operating efficiency and production speed.

For each sensitivity case, the re-optimized solution was evaluated using percentages of the scheduling factors (TQP, DF, TC, CU, and ACU). The percentage change from the baseline solution was used to identify the parameters most influential on production performance and to establish operational conditions that could result in schedule infeasibility or capacity constraints [12].

Scenario Analysis

Following Saraçoğlu [64], this optimization framework was subsequently conducted to assess the response of the production system to realistic operational improvement and disruption conditions. The baseline MILP solution was used as the reference case, and each scenario was independently implemented and re-optimized.

Scenario 1: Changeover Reduction and Line Unavailability

The first scenario incorporated lean changeover improvement with temporary production-line unavailability. Same-size product changeover time was minimized from 2.0 to 0.5 h. Different-size product changeover time was reduced from 3.0 to 1.5 h. In addition, LINE-3 was assigned zero available operating

hours to represent equipment failure or planned maintenance. This scenario assessed whether enhanced changeover efficiency can compensate for the temporary loss of one production line [65].

Scenario 2: Increased Production Rate with Line Unavailability and Changeover Reduction

Notably, this Scenario retained the conditions of Scenario 1 while increasing the applicable production rates by 25%. This scenario assesses whether improved reduced changeover losses can support increased production requirements and compensate for reduced line availability. For both scenarios, the resulting solutions were compared with the baseline using production deviation, idle time, TQP, TC, DF%, ACU%, CU%, and schedule feasibility. The percentage differences between the scenario outcome and the baseline were calculated to quantify the operational effects of each intervention [28].

Together, the applied scenario and sensitivity analyses provide quantitative evidence of the adaptability, stability, capacity limitations, and resilience of the proposed production scheduling framework under changeover improvement, equipment unavailability, capacity variation, production-rate enhancement, and demand uncertainty [42].

2.2.7. Model Testing Procedure and Method of Solution

The developed framework combined ML demand forecasting with MILP-based production scheduling, followed by scenario and sensitivity analysis for operational robustness assessment. Remarkably, the procedure comprised four sequential stages, which include; demand forecasting, optimization, robustness analysis, and performance evaluation. In this study, historical weekly sales data for the ten brewery products (Gulder 60 cl, Heineken 60 cl, Desperado 45 cl, Heineken 45 cl, Hi-Malt 33 cl, Star 60 cl, Life 60 cl, Amstel 33 cl, Maltina 33 cl, and Legend 60 cl) were pre-processed and transformed into explanatory variables comprising product identity, week number, month, season, lagged demand values, and holiday indicator. Afterward, four supervised ML models, namely Extreme Gradient Boosting (XGBoost), Decision Tree Regressor (DTR), Gradient Boosting Regressor (GBR), and Random Forest Regressor (RFR), were trained for weekly demand forecasting. Time-series split cross-validation was then used to preserve the chronological structure of the sales data. Also, hyperparameters were optimized by applying randomized search followed by grid search. To assess the goodness of fit of the applied ML models, MAPE, RMSE, SMAPE, MAE, and R^2 were used, and the best-performing model was selected as the demand forecasting model.

Following the performance evaluation, the resulting weekly demand forecasts were then transferred directly to the MILP model as the product demand parameter D_p. The MILP simultaneously determined changeover decisions, product-to-line assignments, and production quantities subject to demand, line eligibility, production capacity, setup time, and production rate. The model was implemented and solved using Google OR-Tools to obtain the baseline production schedule. For each analysis, the relevant parameters were modified, and the MILP model was re-solved under the modified conditions. The resulting production schedules were compared with the baseline, applying ACU%, TQP, TC, DF%, CU%, idle time, schedule feasibility, and production deviation.

2.3 Computational Requirements and Model Solution Time

The proposed hybrid ML–MILP framework was implemented in Python and executed on a workstation equipped with an Intel Core i7-12700H (14 cores, up to 4.7 GHz) processor, 16 GB DDR4 RAM, running Windows 11 Pro (64-bit). The implementation utilized NumPy 1.26, Pandas 2.2, Scikit-learn 1.5, Statsmodels 0.14.4, Matplotlib 3.9.2, and PuLP 2.9.0 for data preprocessing, machine learning, visualization, statistical analysis, and MILP optimization. The optimization model was solved using the CBC (Coin-or Branch and Cut) solver through the PuLP interface.

To evaluate computational efficiency, execution times were recorded for model training, demand prediction, and optimization under the final experimental configuration. As shown in Table 9, all ML

models completed training within approximately 6 s, while the complete hybrid framework required less than 11 s, indicating that the proposed approach is computationally efficient for production scheduling and resource allocation in manufacturing environments.

Table 9. Computational performance of the proposed ML–MILP framework.

Computational Component	Algorithm/Tool	Execution Time (s)	Remarks
Model training	Random Forest	5.8	Training time
Model training	XGBoost	4.9	Training time
Model training	Decision Tree	1.6	Training time
Model training	Linear Regression	0.4	Training time
Demand prediction	Selected ML model (Random Forest)	0.3	Forecast generation
MILP optimization	CBC Solver	3.9	Time to optimal solution
Complete framework	Hybrid ML–MILP	10.0	End-to-end execution

These execution times demonstrate that the proposed framework can generate accurate demand forecasts and optimized production schedules within a few seconds, supporting its practical applicability for near-real-time decision support in smart beverage manufacturing systems.

3. Results and Discussion

3.1. Exploratory Data Analysis (EDA)

Figures 3–8 present the initial analysis of weekly sales data spanning three to ten years. These different products highlight valuable insights into demand variability, product performance, and seasonal patterns.

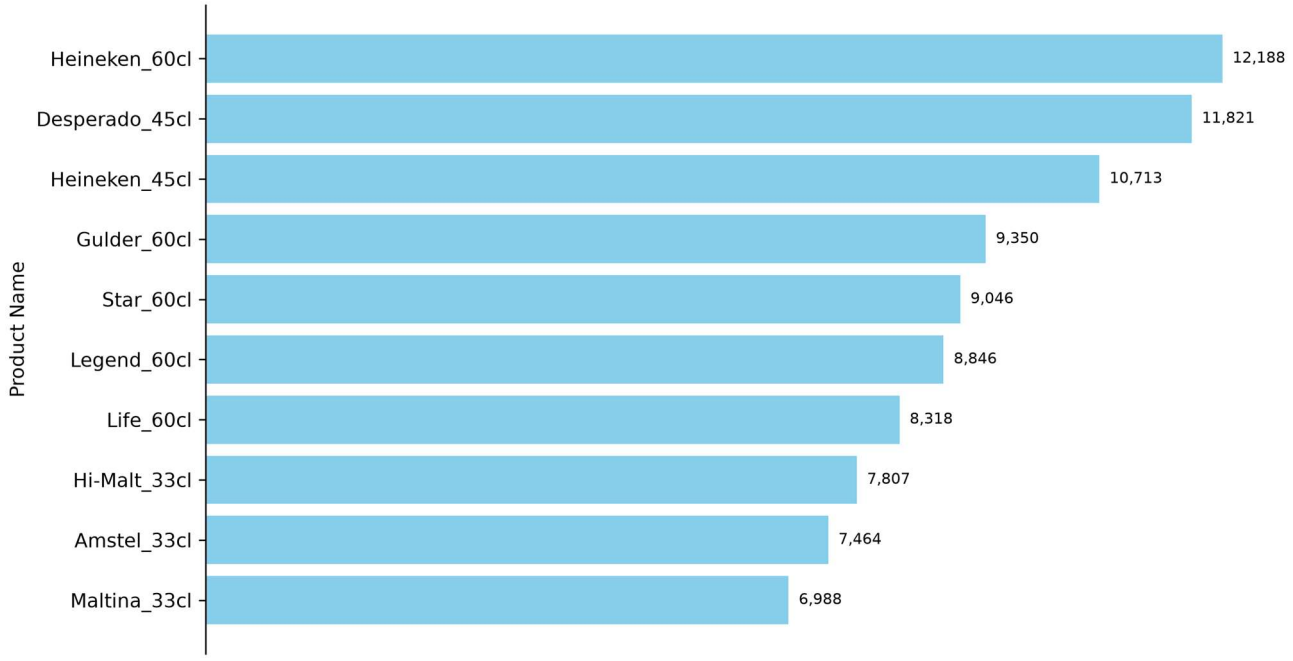


Figure 3. Average Demand per Product.

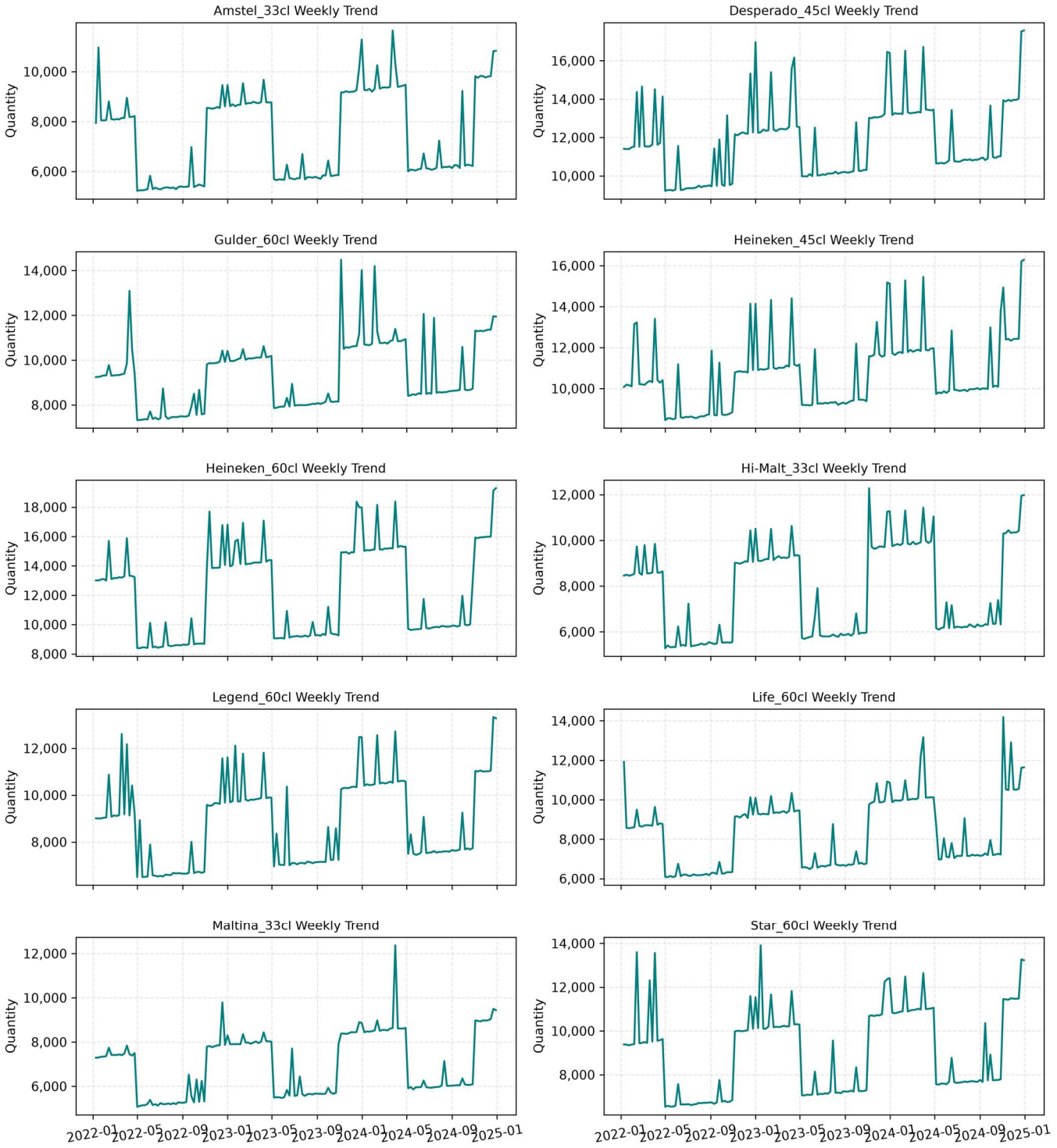


Figure 4. Weekly Demand Trend Per Product.

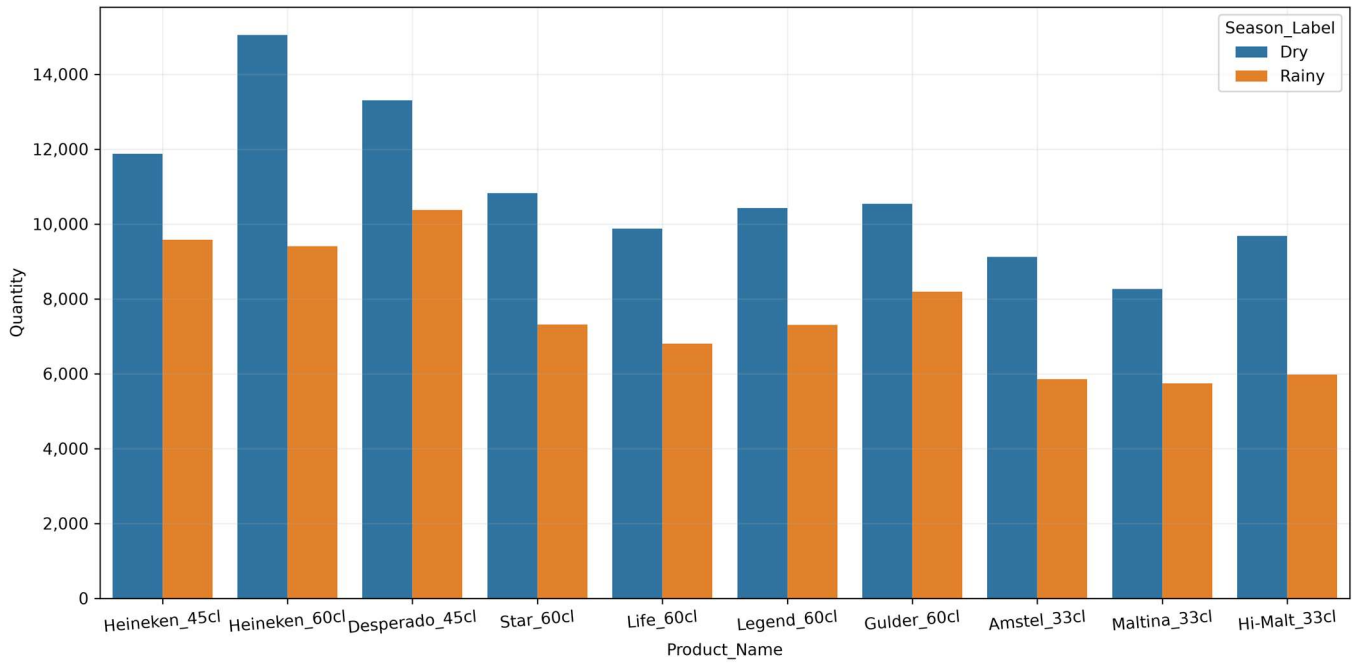


Figure 5. Average Product Demand by Season.

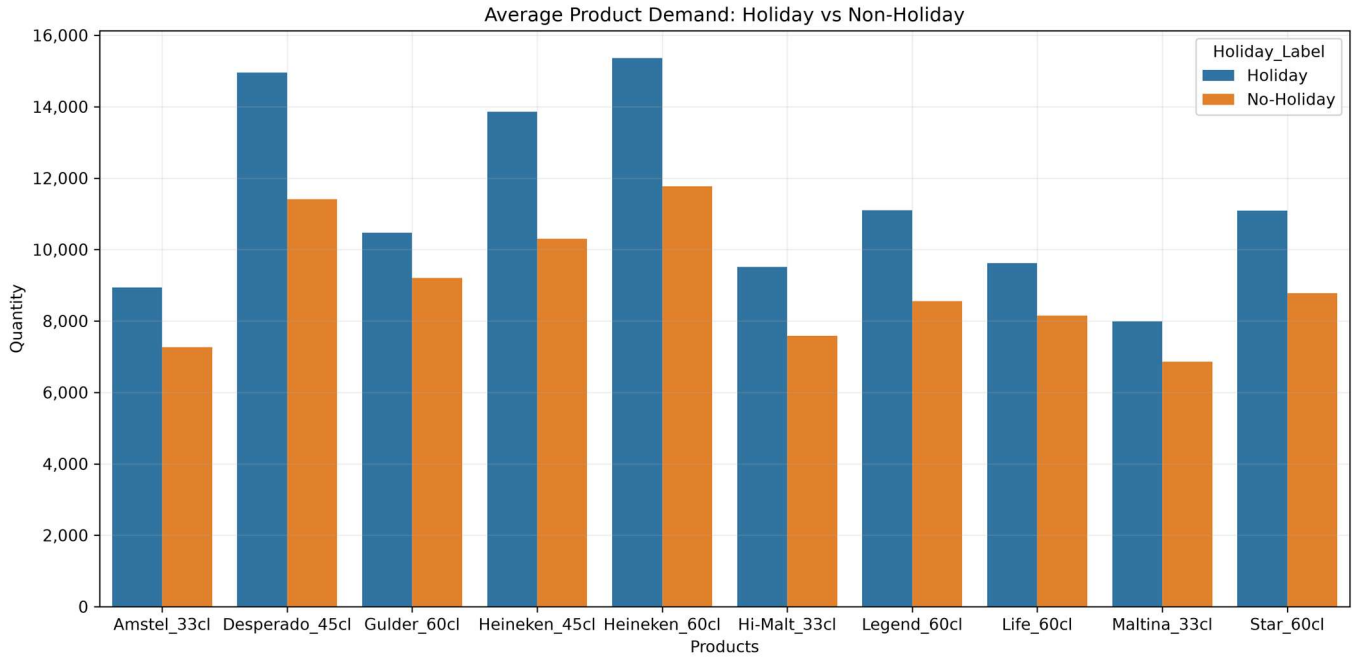


Figure 6. Average Product Demands Analysis Based on Holiday *vs.* Non-Holiday.

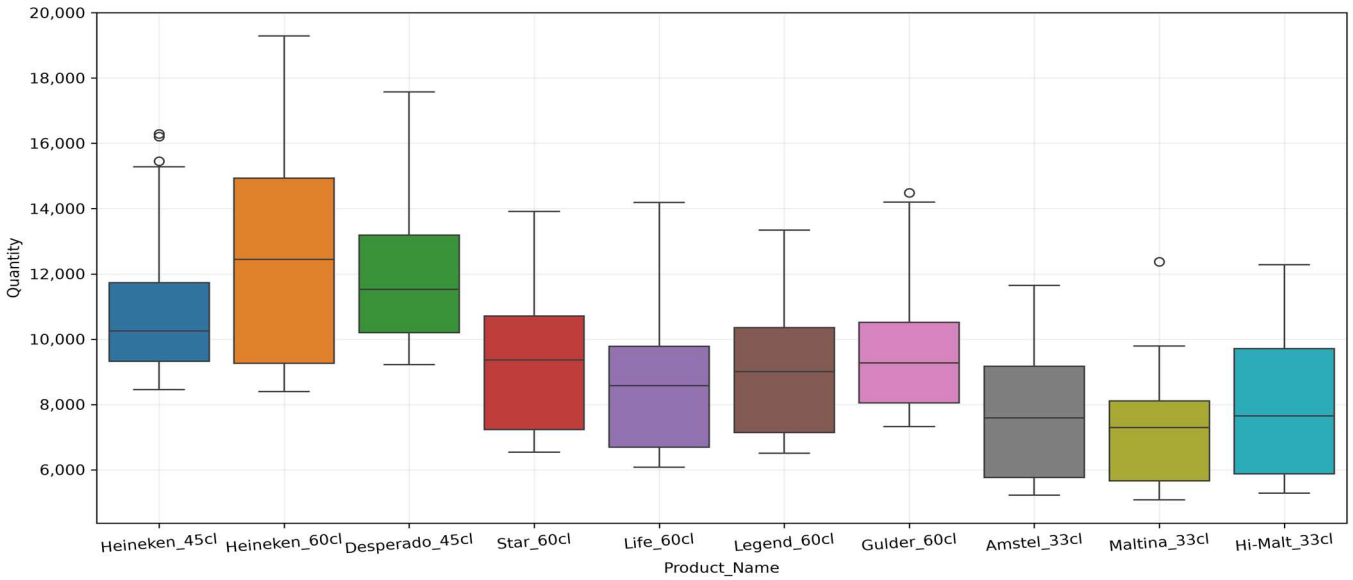


Figure 7. Outlier Analysis of the Products Distribution.

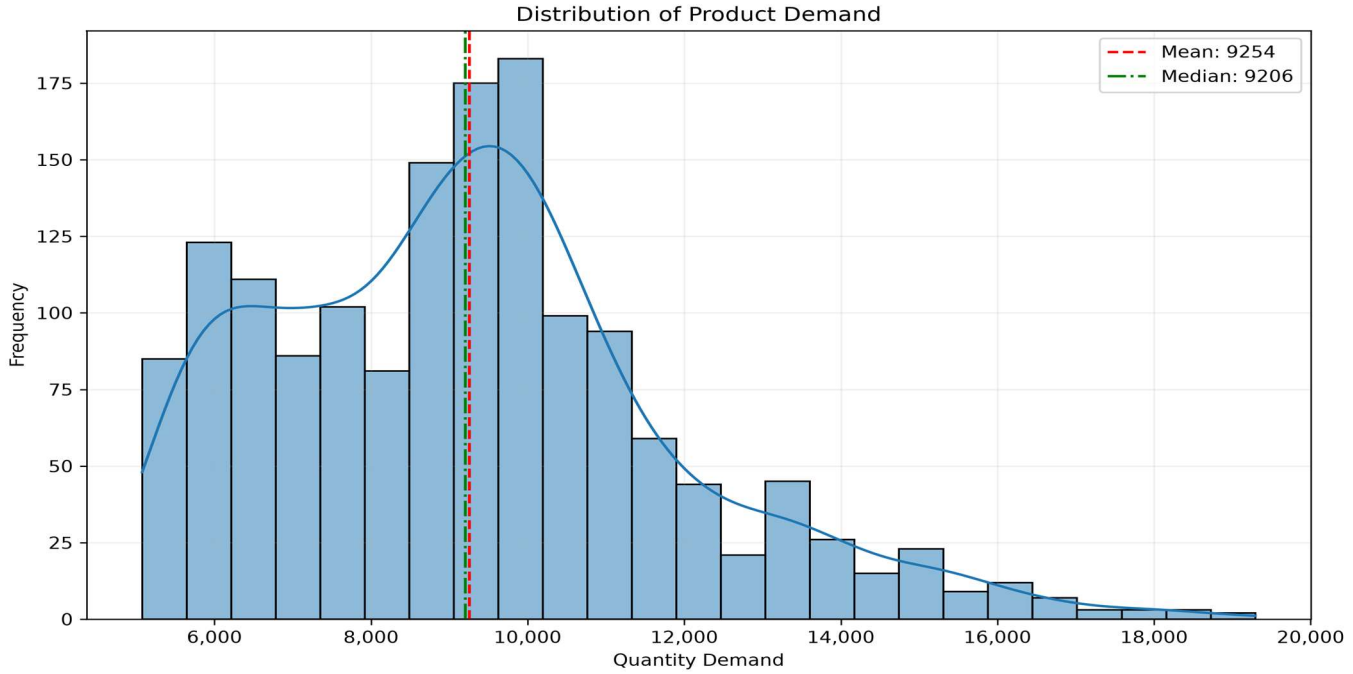


Figure 8. Quantity Demand Distribution Analysis.

Figures 3–7 outlined substantial differences in demand across the ten product categories, highlighting clear product level segmentation within the brewery portfolio. The findings show that Heineken 45 cl, Heineken 60 cl and Desperado 45 cl recorded the highest demand volumes, whereas Maltina 33 cl, Amstel 33 cl and Hi-Malt 33 cl showed comparatively lower demand. Furthermore, from a production planning perspective, the demand differences outcomes provide an important basis for demand responsive capacity allocation. This establishes that low-demand products should be scheduled according to actual consumption patterns to avoid unnecessary inventory accumulation and capacity occupation, while high-demand products require sufficient production capacity to minimize potential shortages [66]. In this context, incorporating product-level demand behaviour into the proposed ML forecasting and MILP optimization framework provides a quantitative basis for aligning production quantities with observed market requirements.

Interestingly, Figure 8 presented a positively skewed demand distribution, with most observed concentration is ~6000 and 11,000 units and occasional peaks approaching 20,000 units. Also, the average demand of 9254 units being slightly above than the median of 9206 units supports the presence of positive skewness. These maximum demand observations indicate periods of elevated production demands that could be underestimated by forecasting approaches based solely on central tendency. This differentiation aligns with the view that consumer heterogeneity can create distinct product preferences and market segments, requiring operational strategies and differentiated products [67]. Likewise, the use of customer segmentation concept demonstrates the value of identifying groups with distinct demand and behavioural characteristics for enhanced decision making [68]. Consequently, the distribution outcome emphasizes the importance for forecasting models capable of capturing extreme observations and demand variability, which subsequently helps in more capacity optimization and responsive production scheduling [41]. Overall, this varied demand pattern suggests that products should not be assigned inventory priorities and uniform production.

3.2. ML Model Evaluation and Deployment Outcomes

Following the EDA, different ML models were developed to predict product demand based on the identified features and patterns. The goal was to establish a reliable model that captures and generalizes well the underlying trends in the data. Table 10 and Figure 9 present the performance evaluation of the applied ML models to establish the best. Figure 10 outlines the actual *vs.* predicted outcome of the applied ML model (XGBoost), while Figure 11 shows the error margin of the applied ML model. Also, the relationship between the best applied ML model and the case study company products is represented in Figure 12, while the weekly relationship based on product demand was further interpreted in Figure 13.

Table 10. The Seasonal Naïve Model Performance Matrices of each ML.

Models	MAE	RMSE	MAPE	SMAPE
XGBoost	+58.9%	+48.4%	+56.3%	+57.2%
Gradient Boosting	+57.7%	+45.1%	+59.0%	+59.3%
Random Forest	+56.3%	+43.1%	+57.0%	+56.9%
Decision Tree	+30.2%	+22.7%	+32.3%	+31.6%

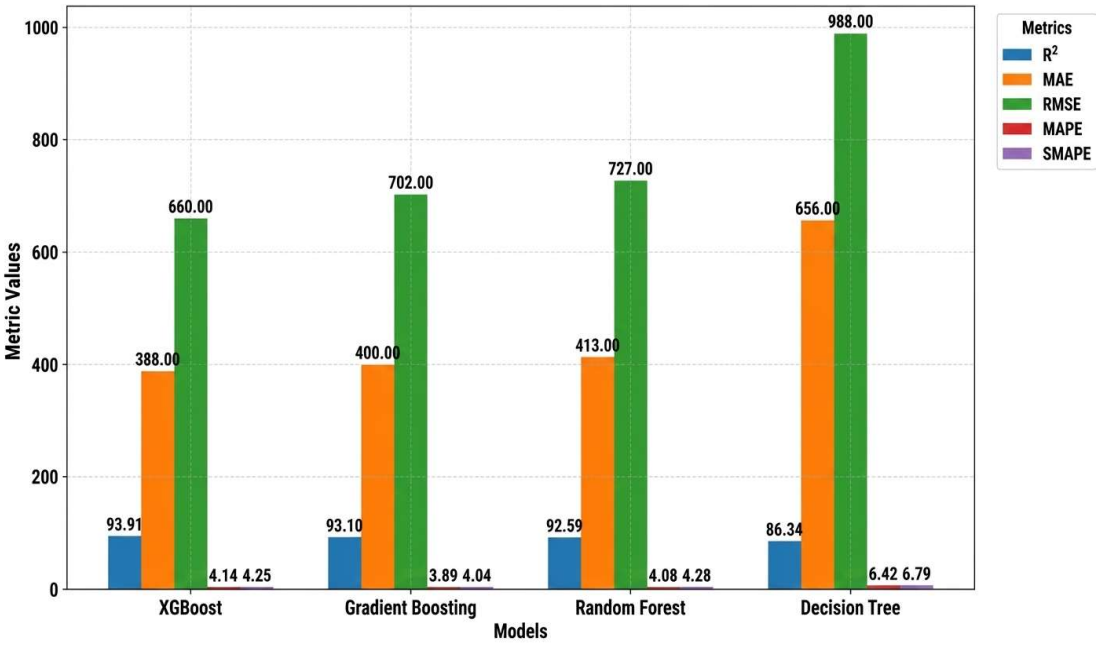


Figure 9. Evaluation Performance Matrices of the Applied ML Models.

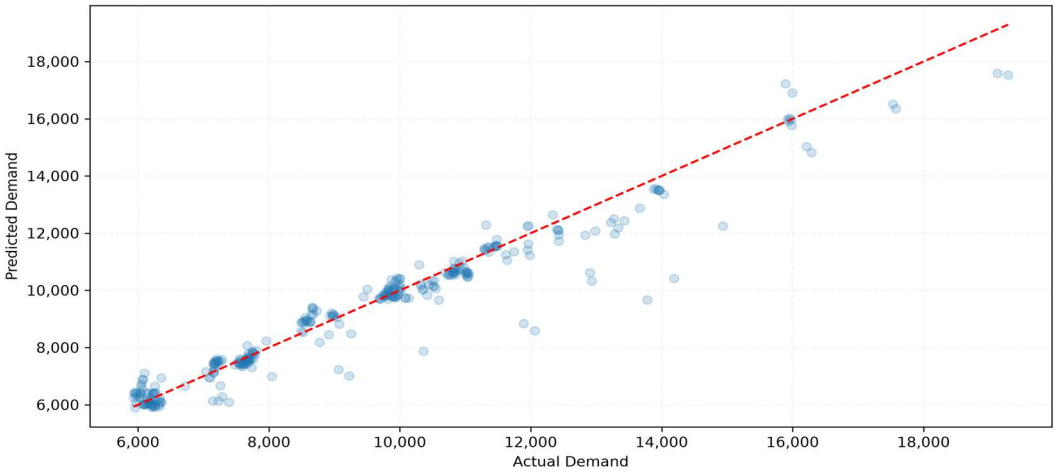


Figure 10. Actual *vs.* Predicted XGBoost Model Trends.

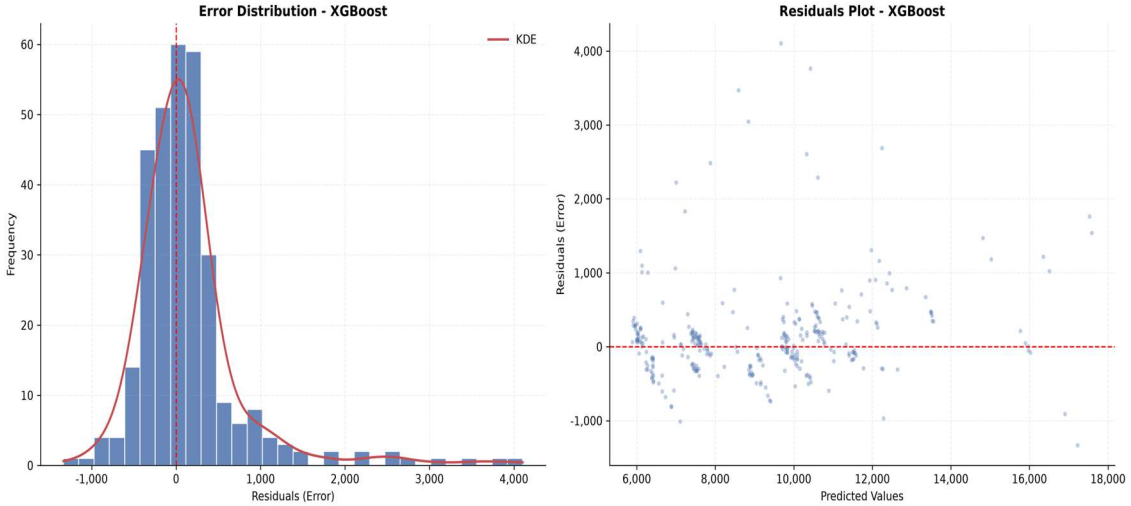


Figure 11. Residual and Error Distribution Analysis of XGBoost Model.

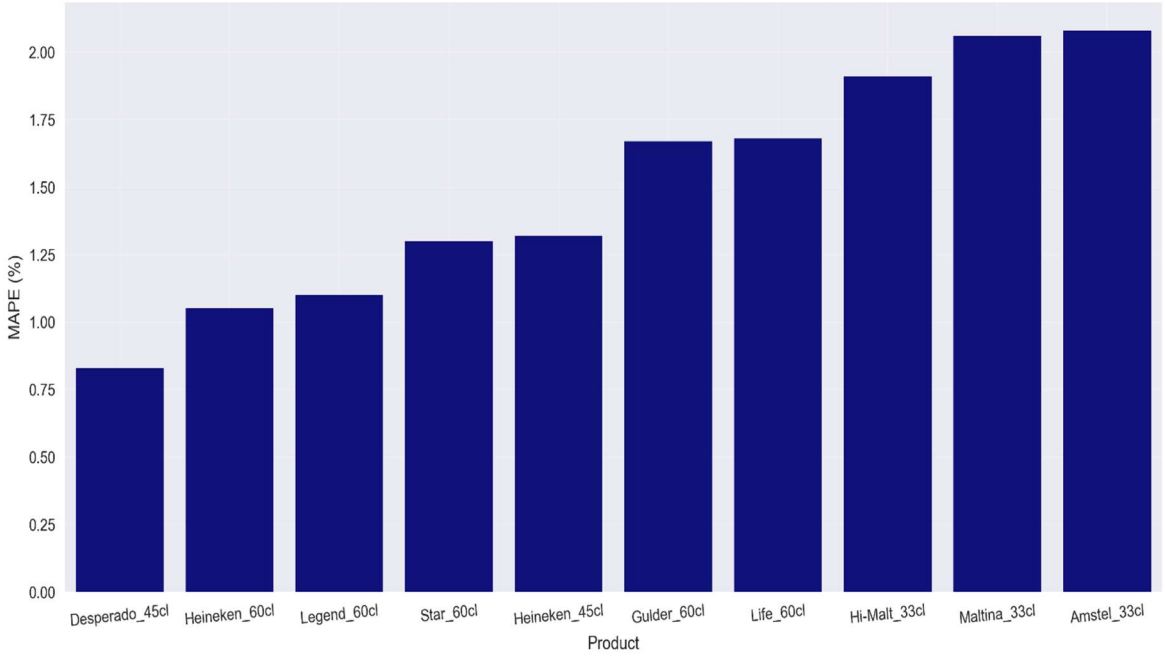


Figure 12. SMAP Performance Analysis of each Product using XGBoost Model.

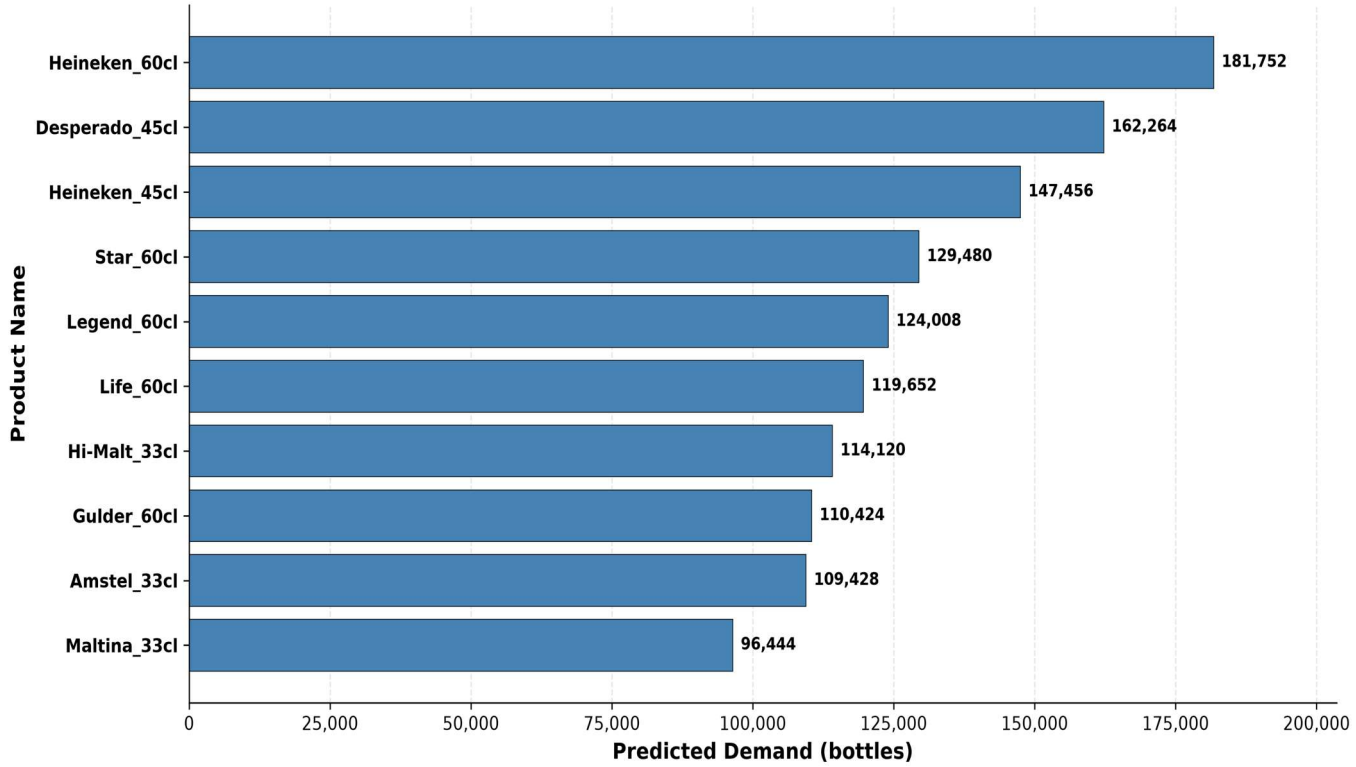


Figure 13. XGBoost Forecasted Product Demand for Week 1 in 2025.

The comparative evaluation in Figure 9 shows that the ensemble boosting model (XGBoost) indicated the best forecasting performance, achieving an overall predictive accuracy of RMSE = 660, MAE = 388, and R^2 = 93.91%. Although GBR showcased comparable performance on some percentage error metrics, however, XGBoost gave the most balanced performance across the principal evaluation measures. On the other hand, RFR showed moderate predictive capability while DTR performed comparatively poorly. This superior performance is consistent with studies by Kim et al. [36], who reported the effectiveness of boosting-based algorithms for nonlinear, complex forecasting problems.

The strong agreement within the predicted and actual demand presented in Figure 10 further supports the predictive reliability of XGBoost, with observations closely distributed around the ideal prediction line. Furthermore, the residual diagnostics in Figure 11 also outlined the errors concentrated around zero without an evident systematic pattern, which established satisfactory model stability and limited prediction bias [40]. At the product level, Figure 12 demonstrated consistently minimum forecasting errors, with SMAPE values generally below 2%, including ≤1% for Desperado 45 cl. More importantly, relative to the seasonal naïve benchmark of SMAPE and MEA value of 9.92% and 945, respectively, the XGBoost reduced SMAPE by more than 57% and MAE by ~59%, demonstrating a substantial forecasting improvement.

Figure 13 further highlights the practical value of the model by identifying substantial differences in expected product demand in Week 1, 2025, with Heineken 45 cl, Desperado 45 cl, and Heineken 60 cl requiring the highest production attention. These results show that XGBoost can translate historical demand patterns into supporting demand responsive capacity allocation, actionable production information, production scheduling, and inventory control. This finding agrees with Ordu et al. [18] and Ogbu et al. [10], who highlighted the applicability of ML approaches to enhancing production decision making around brewery manufacturing systems. Overall, the findings provide empirical justification for incorporating XGBoost forecasts with the subsequent capacity optimization and MILP scheduling models developed in this study.

3.3. Applied Optimization Model Outcome

With the weekly product demand now forecasted employing different ML models, with the XGBoost ML model indicated as the best performed model, this phase established the outcomes involved in integrating these predictions into the developed MILP model. Figures 14 and 15 illustrate the production schedule chart, comprising time, day, product unit, and line. Table 11 presents the KPIs from the schedule developed by the mathematical model (MILP). Figures 16 and 17 outline the effect of changeover frequency and demand fulfilment on each production line, respectively. Figures 18–20 present the production deviation per product and line utilization rate after the application of the optimization model respectively. Furthermore, to analyze the effectiveness of the model, Figures 21 and 22 present the setup and product line heatmap, respectively. Finally, Figures 23 and 24 highlighted line flexible index and daily production output respectively on the application of the developed model.

Table 11. The KPIs from the Schedule Developed by the Mathematical Model.

S/N	Metric	Value	Interpretation
1	Available Line Hours	732.0 h	Total time available for production in the planning week.
2	Scheduled (or Actual) Production Hours	707.0 h	Time allocated specifically for production activities.
3	Setup or Changeover Hours	25.0 h	Time spent switching between different products (setup time).
4	Production Hours	732.0 h	Full utilization of available time (Scheduled Production + Changeover).
5	Total Idle Hours	0.0 h	No unused time—indicating full scheduling efficiency.
6	Capacity Utilization	96.6%	Percentage of time spent directly producing products.
7	Adjusted Capacity Utilization	100.0%	Includes both production and changeover time, showing total time usage.
8	Total Quantity Demanded	1,295,028	Forecasted demand for the upcoming week.
9	Total Quantity Produced	1,352,250	Total number of units planned for production in the schedule
10	Demand Fulfillment	108.4%	Production exceeds demand by 8.4% (*i.e.* Production Deviation%), ensuring buffer stock and preventing shortages.

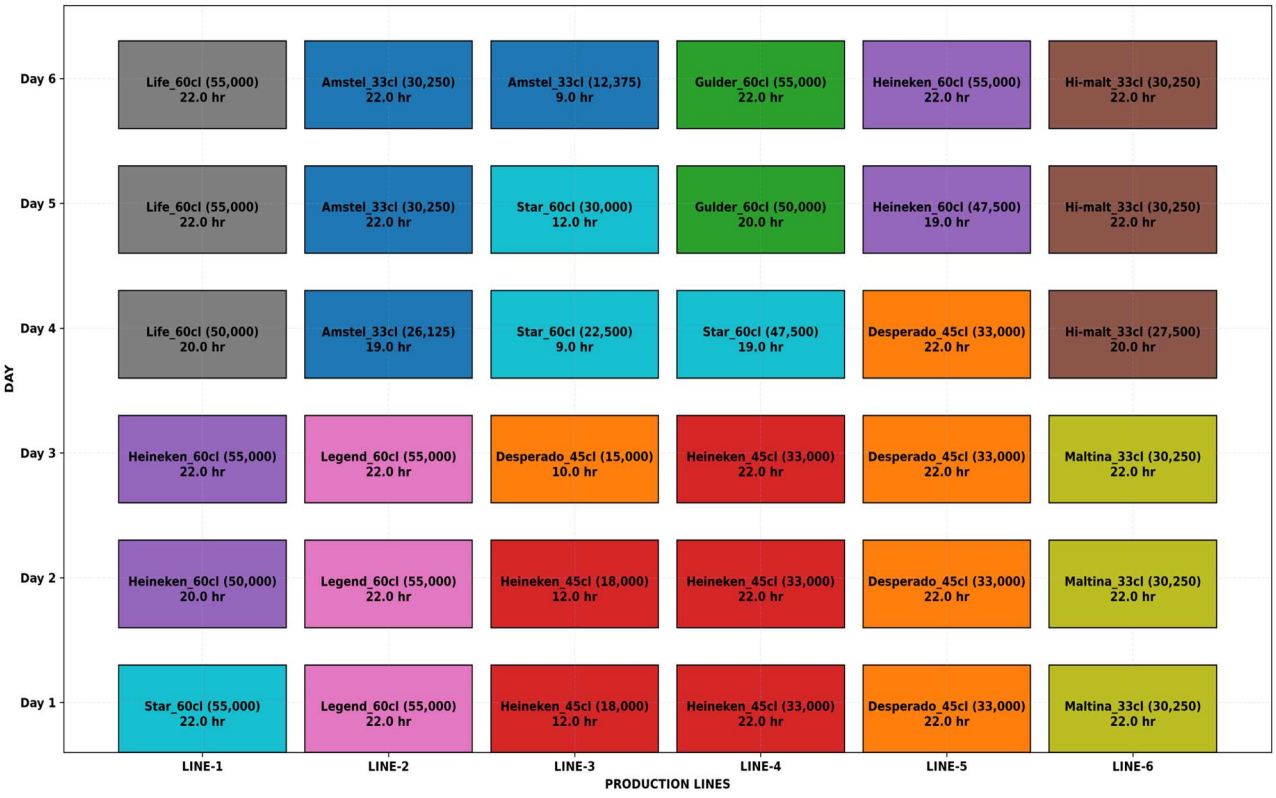


Figure 14. Production Scheduled Chart Comprising Day, Line, Product Unit and Time.

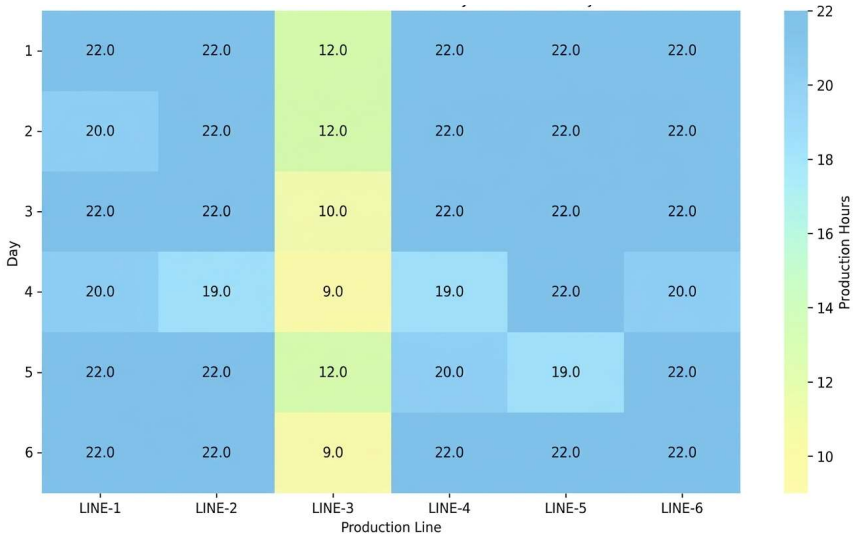


Figure 15. Chart on the Schedule/Production Hours by Line and Day.

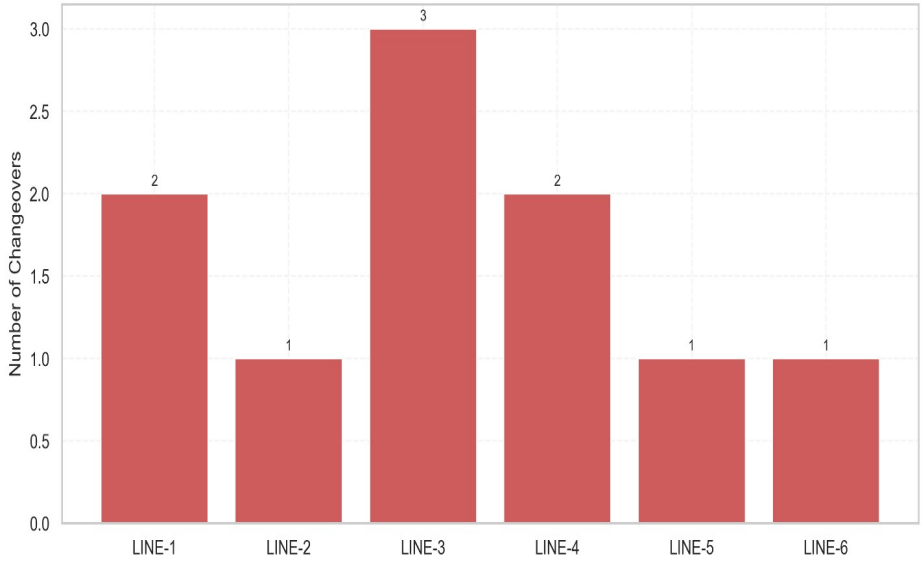


Figure 16. Changeover Frequency Per Line.

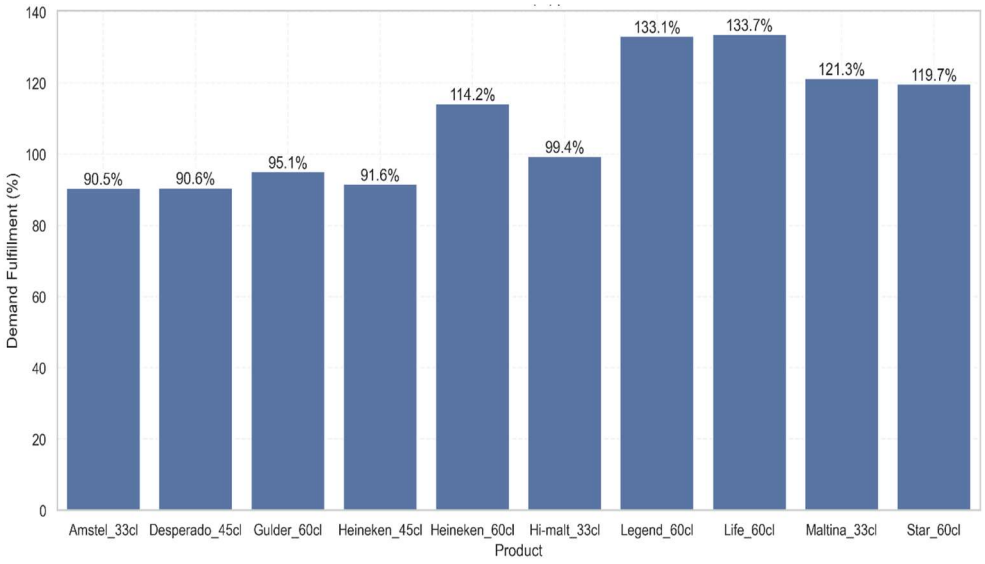


Figure 17. Demand Fulfilment Per Product.

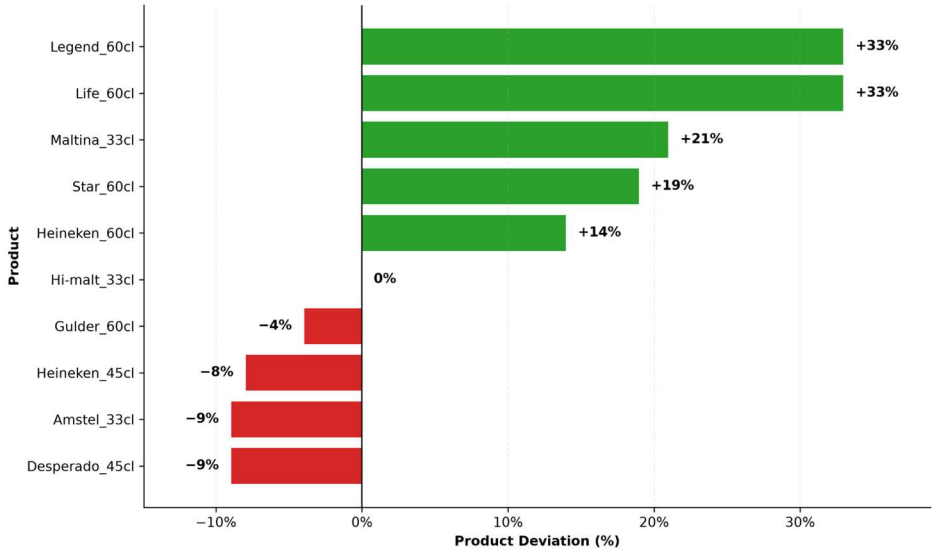


Figure 18. Production Deviation Per Product.

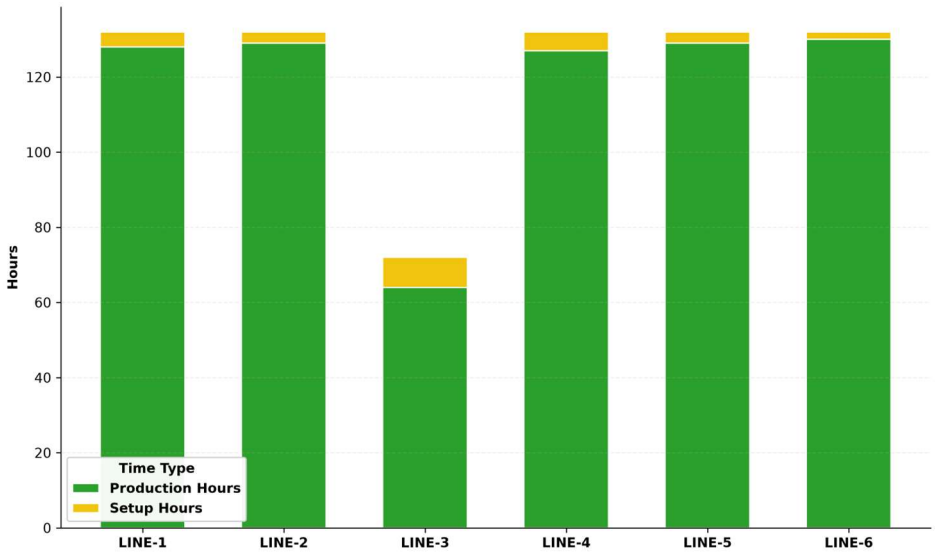


Figure 19. Line Utilization based on Production *vs.* Setup *vs.* Idle Hours Per Line.

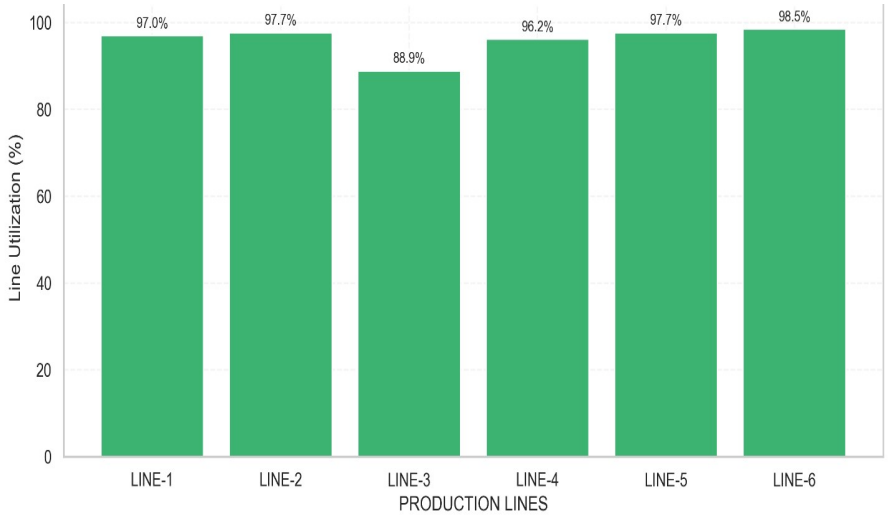


Figure 20. Line Utilization Rate.

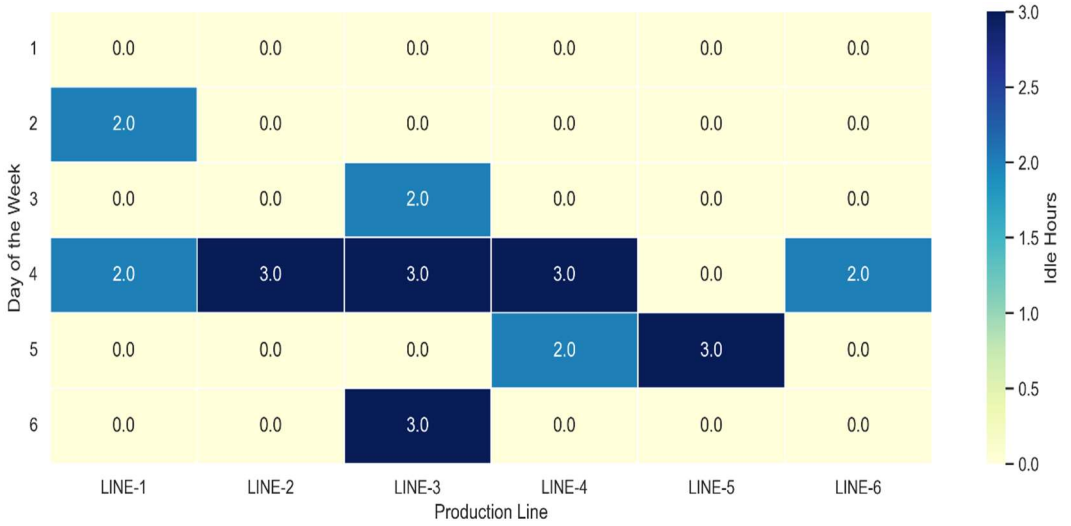


Figure 21. Heatmap Outcome of Setup Time at Every Line and Day.

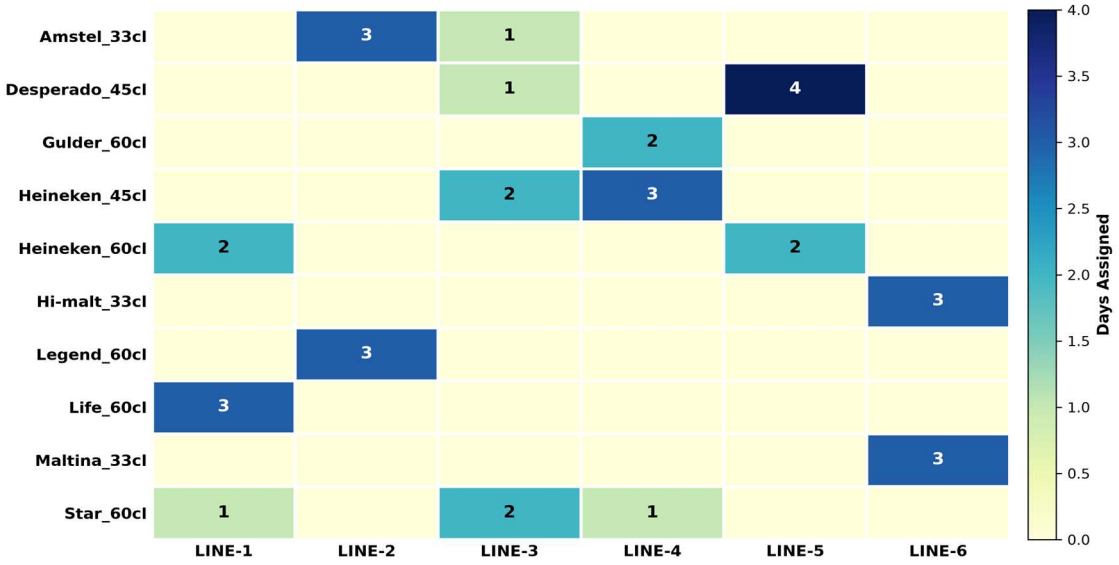


Figure 22. Product Line Assignment Frequency.

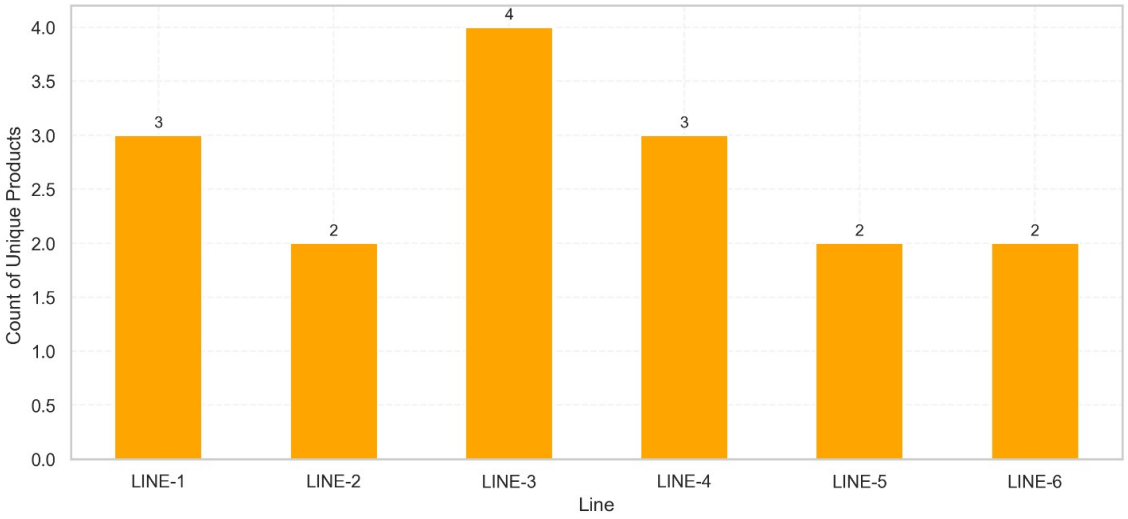


Figure 23. Line Flexible Index.

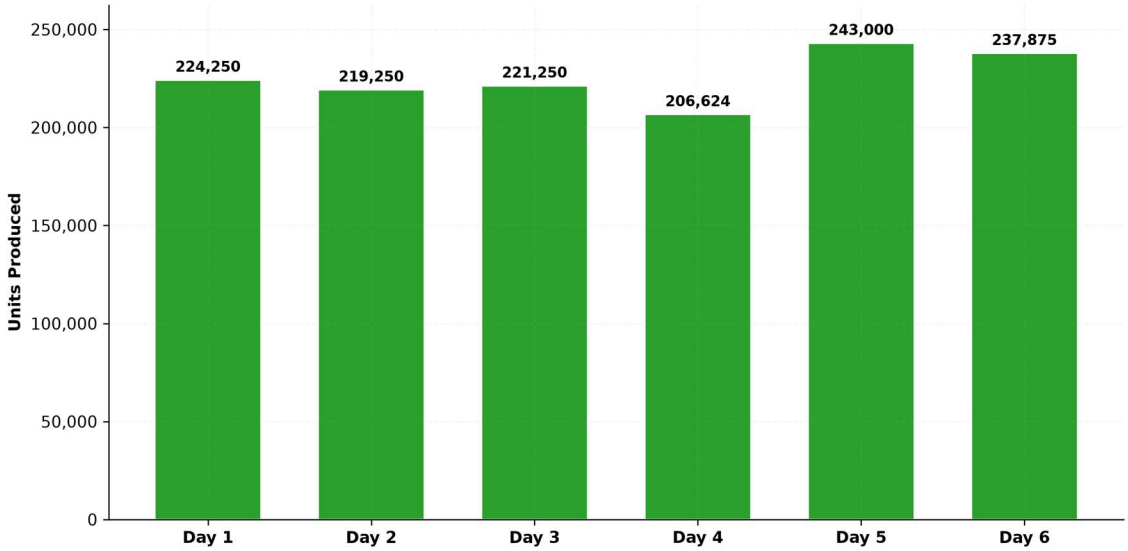


Figure 24. Daily Production Output.

As presented in Figures 14–24, the developed and applied MILP model translated the XGBoost demand forecasts into a feasible six-day production schedule, which recommends applicable, showing good, controlled changeovers and production deviations. From the findings, high-demand products, particularly Legend 60 cl and Heineken 60 cl, received greater production allocation, whereas lower volume products were concentrated on selected lines. This indicates that the applied model effectively matched production capacity with forecasted demand while maintaining product line specialization.

The applied model incorporated into the schedule also limited changeover related losses, where most lines required only one changeover, however, Line 3 recorded three changeovers because of its broader product mix. Interestingly, despite this flexibility requirement, all lines maintained high applicability, ranging from 88.9% to 98.5%, with negligible idle time. Furthermore, the production deviation results remained within the prescribed −10% to +40% range, indicating a controlled trade-off between capacity limitations and demand fulfilment [67]. Interestingly, the moderate overproduction of some of the products indicates a potential buffer against demand uncertainty, whereas minimized underproduction of other products reflects capacity prioritization rather than scheduling infeasibility.

The line-level product allocation results highlight the potential benefits of coordinating specialized and flexible production resources. Line 3 accommodated the widest product variety, whereas Lines 2, 5, and 6 were assigned fewer products, suggesting that the optimized schedule distributed products across available lines while limiting unnecessary changeovers. Daily production exceeded 200,000 units, although output declined temporarily on Day 4 before recovering on Day 5. This reduction coincided with increased changeover activity, suggesting that product transitions may have temporarily constrained production throughput. These findings are consistent with the broader scheduling literature. Parmar & Raman [50] demonstrated the value of rolling-horizon MILP scheduling for adapting production plans to changing capacity information while managing schedule instability. Similarly, Marzia et al. [3] integrated process planning and scheduling through an optimized rule mining approach, highlighting the importance of coordinating interrelated manufacturing decisions. Building on these studies, the present research integrates ML-based demand forecasts with MILP optimization to support product allocation and daily production scheduling in beverage manufacturing. The results illustrate how this integration can align production decisions with demand and resource availability while accounting for changeover-related constraints.

3.4. Applied Sensitivity Analysis Model Outcome

This approach enables a clearer understanding of the trade-offs between meeting customer demand and managing production capacity, with the results focusing on two critical performance indicators, which are demand fulfillment (%) and capacity utilization (%). Figure 25 outlines the feasibility region map of demand fulfillment *vs.* capacity utilization under parameter variations. Figures 26–31 showcased the various sensitivity analysis trends on demand, demand on the objective value, machine capacity, general capacity impact, production rate, and its impact on the varied objective value, respectively.

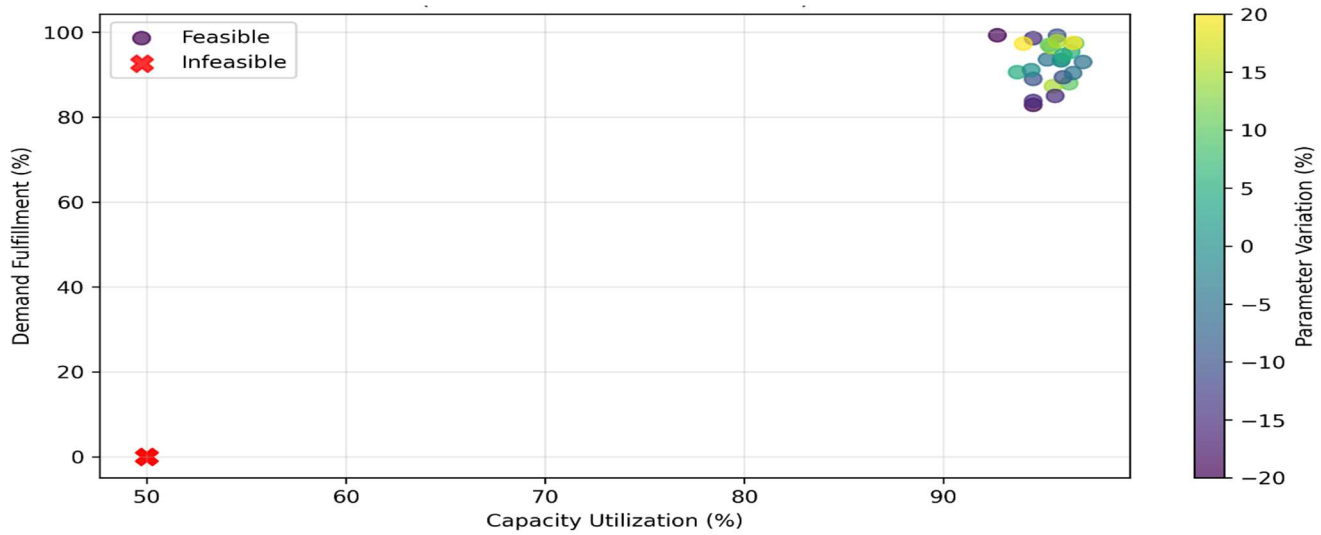


Figure 25. Feasibility Region Map of Demand Fulfillment *vs.* Capacity Utilization under Parameter Variations.

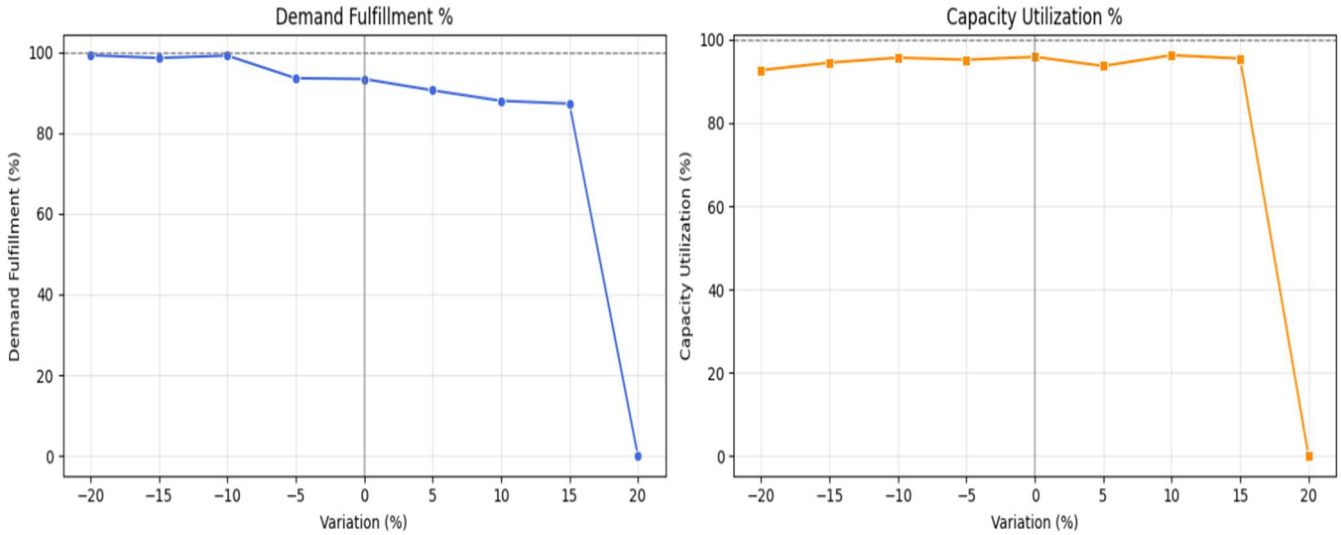


Figure 26. Sensitivity Analysis Outcome of the Demand.

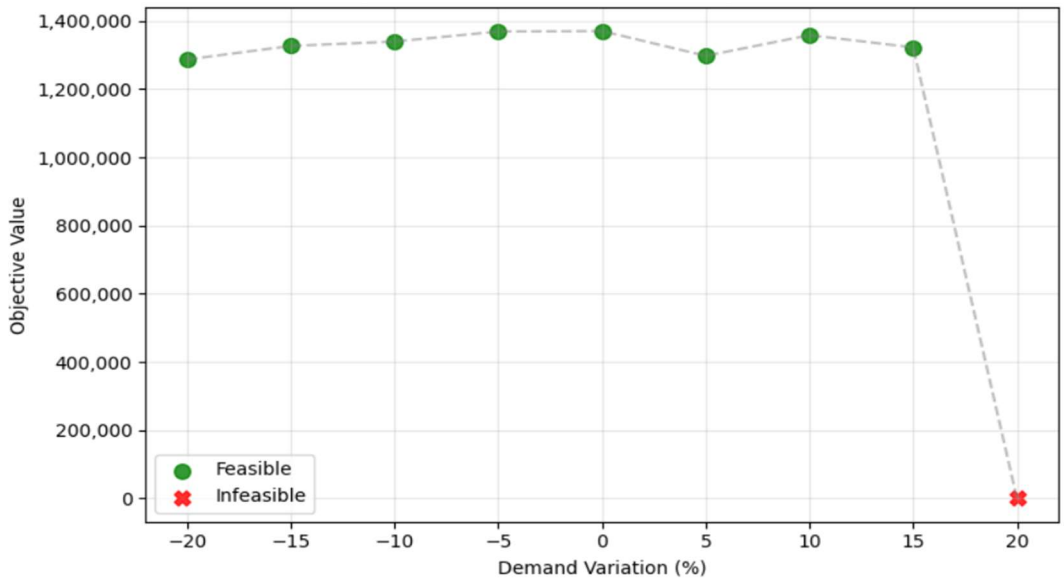


Figure 27. Impact of Demand Variation on Objective Value.

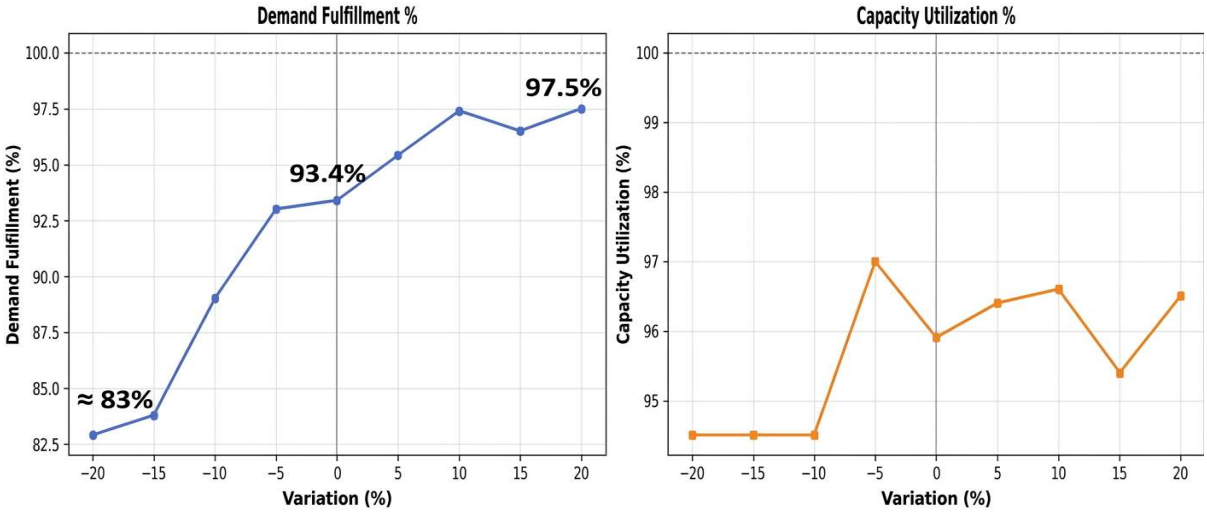


Figure 28. Sensitivity Analysis on the Machine Capacity Variation Test.

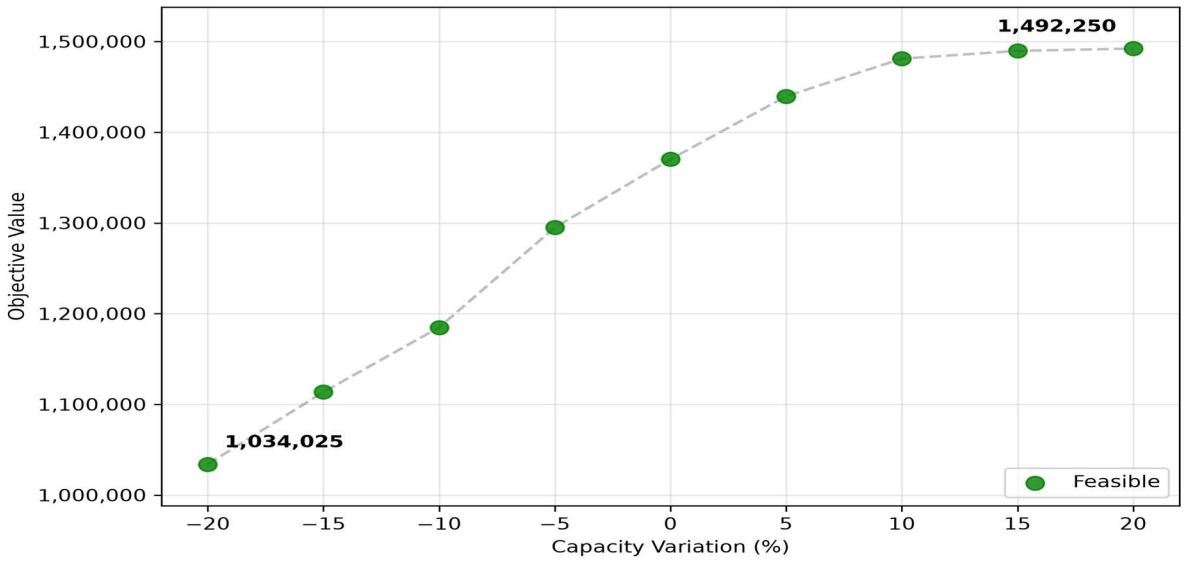


Figure 29. Impact of Capacity Variation on Objective Value.

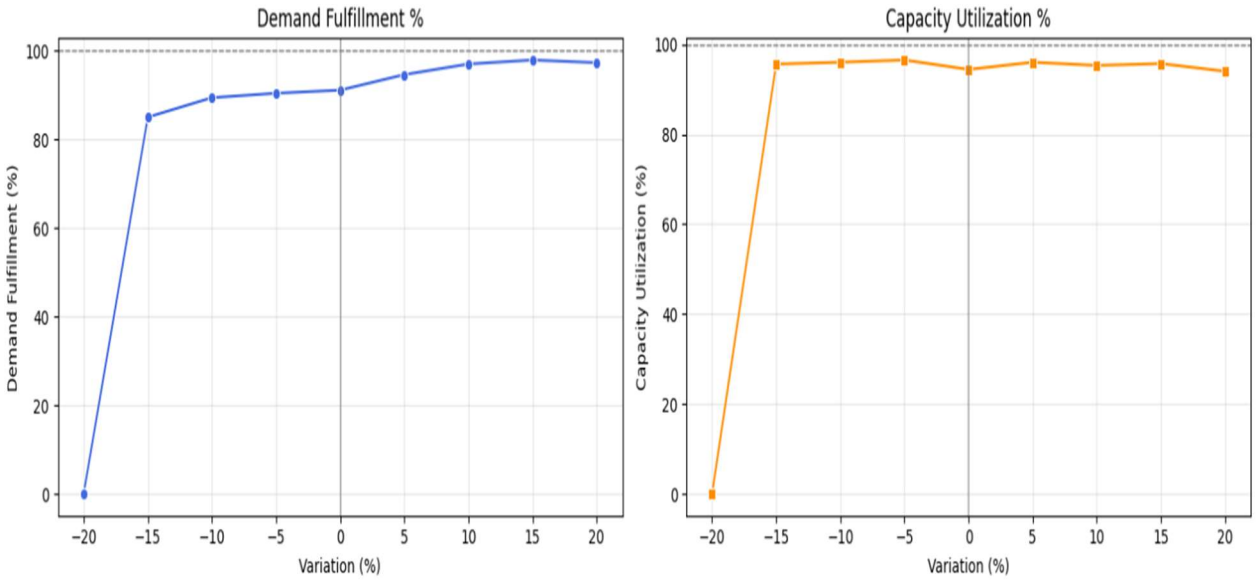


Figure 30. Sensitivity Analysis Outcome of the Production Rate Variation Test.

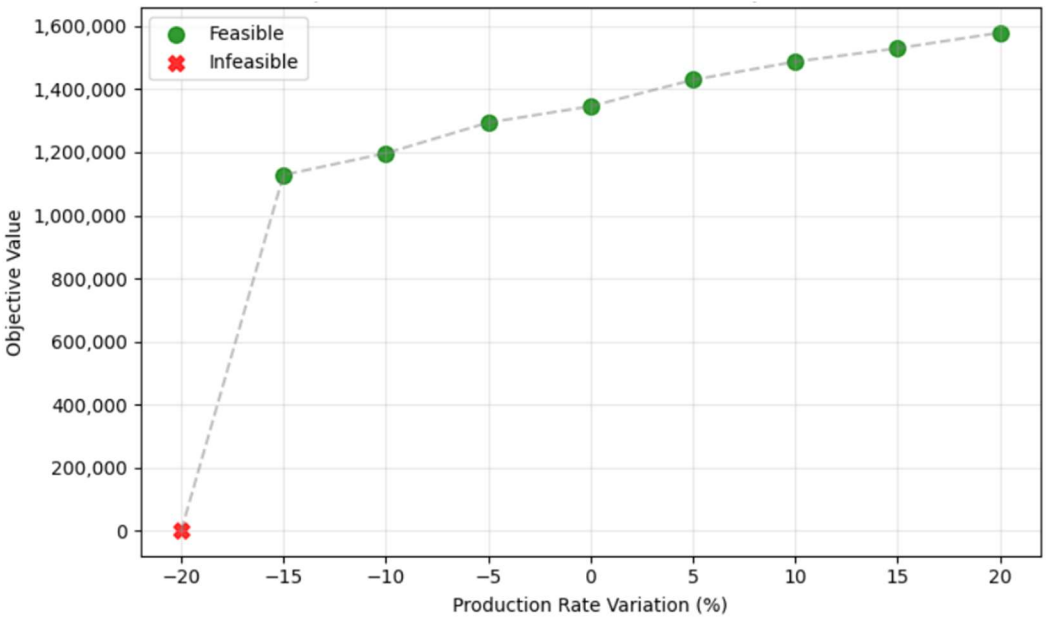


Figure 31. Impact of Production Rate Variation on Objective Value.

As shown in Figure 25, the optimization model generally maintained feasible solutions under moderate parameter variations of up to ±20%, achieving capacity utilization above 90% and demand fulfillment of approximately 80%. However, larger demand perturbations and severe capacity constraints resulted in infeasible solutions, indicating the presence of critical operational thresholds beyond which the production schedule could not satisfy the model's constraints. These findings suggest that the integrated optimization framework can accommodate moderate uncertainty while identifying conditions that threaten production feasibility. This observation is consistent with the broader importance of integrated optimization and robustness analysis in manufacturing decision making, as discussed by Denizhan et al. [14]. Nevertheless, the results indicate that high-capacity utilization does not necessarily translate into equally high demand fulfillment, highlighting the importance of evaluating both performance indicators when assessing production scheduling robustness.

Demand sensitivity presented in Figure 26 showed that the system remained stable under variations of ~±15%, whereas a 20% demand increase exceeded available production capacity and resulted in infeasibility. Furthermore, the corresponding objective value response presented in Figure 27 shows that baseline demand produced the strongest solution, while excessive demand growth progressively increased capacity pressure before eventual collapse. Capacity variation, presented in Figure 28, demonstrates the effect of available production capacity on system performance. Demand fulfillment increased from approximately 82.9% at −20% capacity variation to 93.4% under baseline conditions, reaching approximately 97.4% and 97.5% at +10% and +20% variation, respectively. Capacity utilization remained above 94% across all tested scenarios, indicating consistently high utilization of available production resources. The corresponding objective function results in Figure 29 increased from 1,034,025 to 1,492,250 across the relevant capacity scenarios, further illustrating the effect of capacity variation on the optimization outcome. However, the interpretation of this increase depends on the objective function's definition and optimization direction. Overall, the results highlight the importance of evaluating demand fulfillment, capacity utilization, and the objective function together when assessing the performance of the proposed production scheduling framework [49].

Also, as presented in Figures 30 and 31 on the production rate sensitivity, the findings revealed the strongest operational effects, that 20% reduction caused infeasibility, whereas increasing the production rate will restore feasibility and increase the objective value from 1,128,222 to 1,578,944. However, demand fulfillment approached a plateau of ~98%, showing that additional production capacity alone cannot eliminate all system constraints [69]. Generally, the outcomes identified production rate stability as the major significant operational factor, followed by demand variation and capacity availability, while the proposed framework can schedule decisions, support proactive capacity, and quantify operational thresholds under uncertain manufacturing conditions, which is consistent with Lyu et al. [70] and Palominos et al. [60] studies.

3.5. Scenario Analysis Results on the Impact of Reduced Setup Times and Line Downtime

Following the sensitivity analysis, scenario analysis was conducted to evaluate how combined operational changes affect system performance. This approach tested the resilience of the optimization model under practical improvement strategies. Scenario 1 specifically examined the effects of reducing setup times (30 min for same-size changeovers and 1.5 h for different-size changeovers), the complete unavailability of Line 3 due to maintenance, and an adjusted lower production bound of 80%. The goal was to assess whether efficiency gains from reduced setup times could compensate for the lost capacity and to determine the extent to which demand could still be satisfied. Table 12 presents the KPIs for Scenario 1, while Figures 32–34 illustrate line utilization, demand fulfillment, and production deviation per product, respectively, all in Scenario 1.

On the other hand, Scenario 2 extends Scenario 1 by introducing a 25% increase in production rate while retaining the shorter setup times and complete downtime of Line 3. To reflect higher operational expectations, the production lower bound was raised to 95%, ensuring stricter demand fulfillment requirements. This scenario evaluates whether higher throughput can offset the resource constraints introduced by Line 3's unavailability and the increased frequency of product switches. The results focus on key performance indicators such as utilization, production efficiency, and demand fulfillment to capture the system's adaptability under enhanced rate conditions. Table 13 presents the KPIs for the second scenario, while Figure 35 illustrates line utilization for production, setup, and idle time in Scenario 1. Figures 36–38 present the applied second scenario model on line utilization rate, demand fulfilment per product, production deviation per product, and the objective value comparison, respectively. Finally, Figure 39 outlines the comparative evaluation between the baseline and the 2 scenarios.

Table 12. The KPIs under Scenario 1—Reduced Setup Times and Line 3 Downtime.

S/N	Metric	Value	Interpretation
1	Available Line Hours	660 h	Total time available for production in the planning week.
2	Scheduled Production Hours	654.5 h	Time allocated specifically for production activities.
3	Changeover (Switching) Hours	5.5 h	Time spent switching between different products (setup time).
4	Production Hours	660 h	Full utilization of available time (Scheduled Production + Changeover).
5	Total Idle Hours	0.0 h	No unused time—indicating full scheduling efficiency.
6	Capacity Utilization	99.2%	Percentage of time spent directly producing products.
7	Adjusted Capacity Utilization	100.0%	Includes both production and changeover time, showing total time usage.
8	Total Quantity Demanded	1,295,028	Total demand for the upcoming week.
9	Total Quantity Produced	1,241,749	Total number of units planned for production in the schedule.
10	Demand Fulfillment	99.5%	Production is below demand by −0.5% deviation.

Table 13. KPIs for Scenario 2 (Increased Production Rate, Reduced Setup, and Line 3 Downtime).

S/N	Metric	Value	Interpretation
1	Available Line Hours	660 h	Total time available for production in the planning week.
2	Scheduled Production Hours	639.9 h	Time allocated specifically for production activities.
3	Changeover (Switching) Hours	11.5 h	Time spent switching between different products (setup time).
4	Production Hours	651.4 h	Full utilization of available time (Scheduled Production + Changeover).
5	Total Idle Hours	8.6 h	No unused time—indicating full scheduling efficiency.
6	Capacity Utilization	97%	Percentage of time spent directly producing products.
7	Adjusted Capacity Utilization	98.7%	Includes both production and changeover time, showing total time usage.
8	Total Quantity Demanded	1,295,028	Total demand for the upcoming week.
9	Total Quantity Produced	1,506,655	Total number of units planned for production in the schedule
10	Demand Fulfillment	116.3	Production exceeds demand by 16.3% deviation

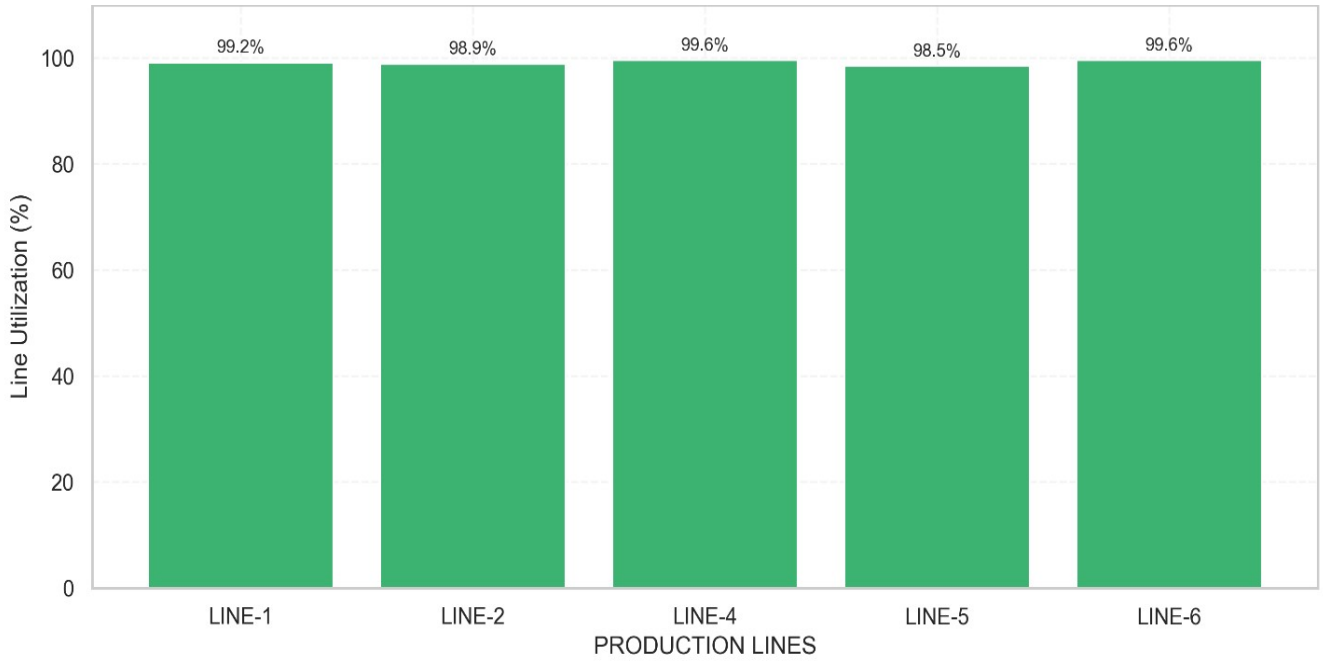


Figure 32. Scenario 1—Line Utilization.

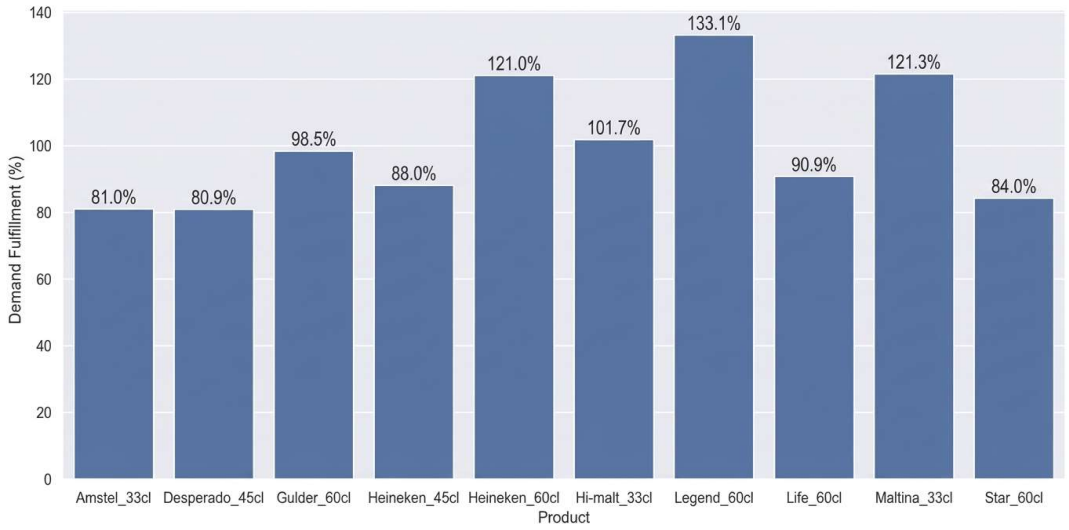


Figure 33. Scenario 1—Demand Fulfilment.

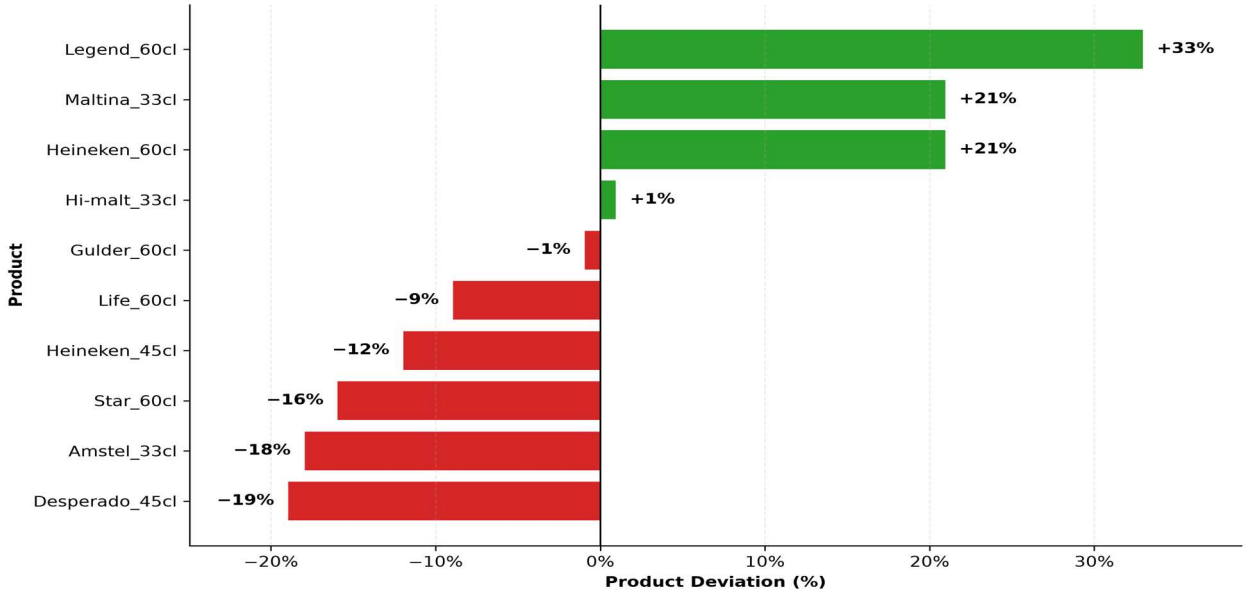


Figure 34. Scenario 1—Production Deviation Per Product.

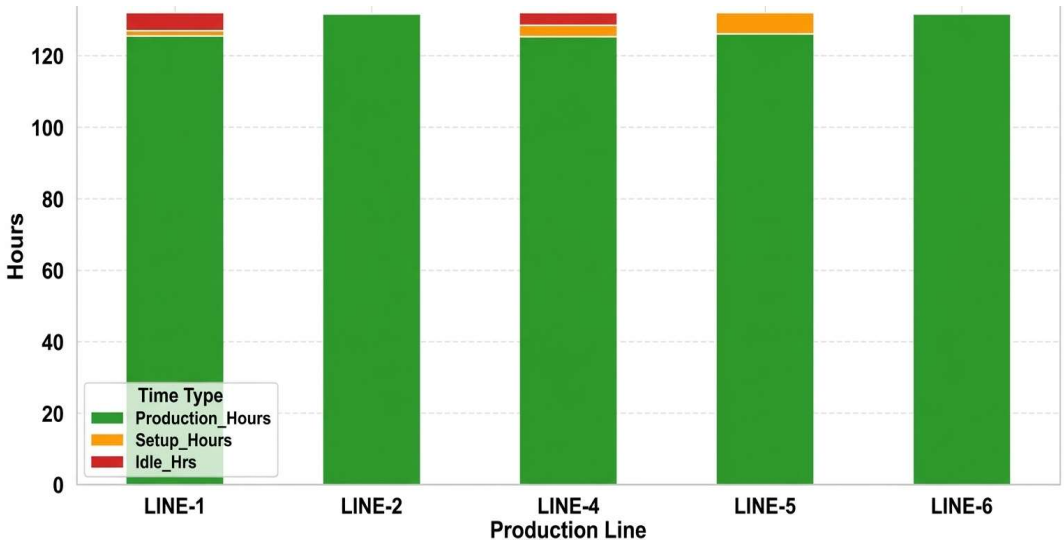


Figure 35. Scenario 2 Line Utilization Summary (Production *vs.* Setup *vs.* Idle Time).

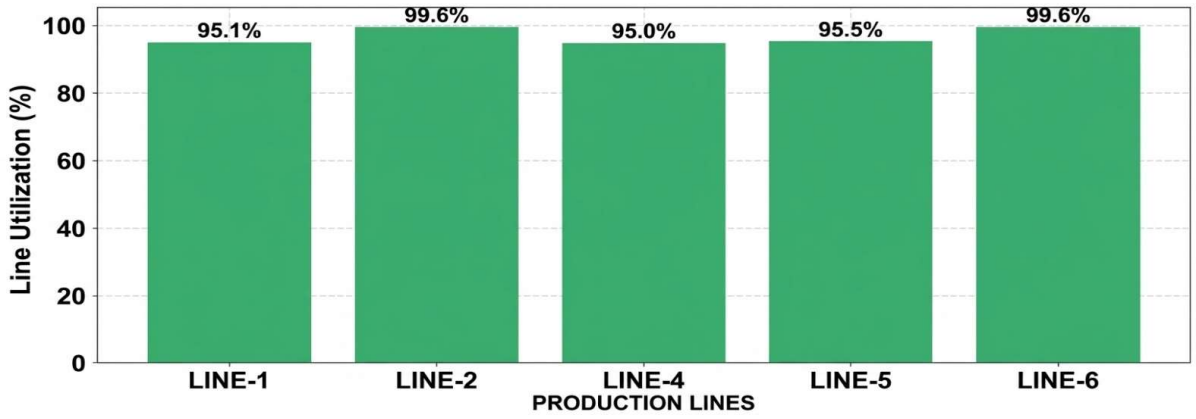


Figure 36. Scenario 2 Analysis Outcome on the Line Utilization Rate.

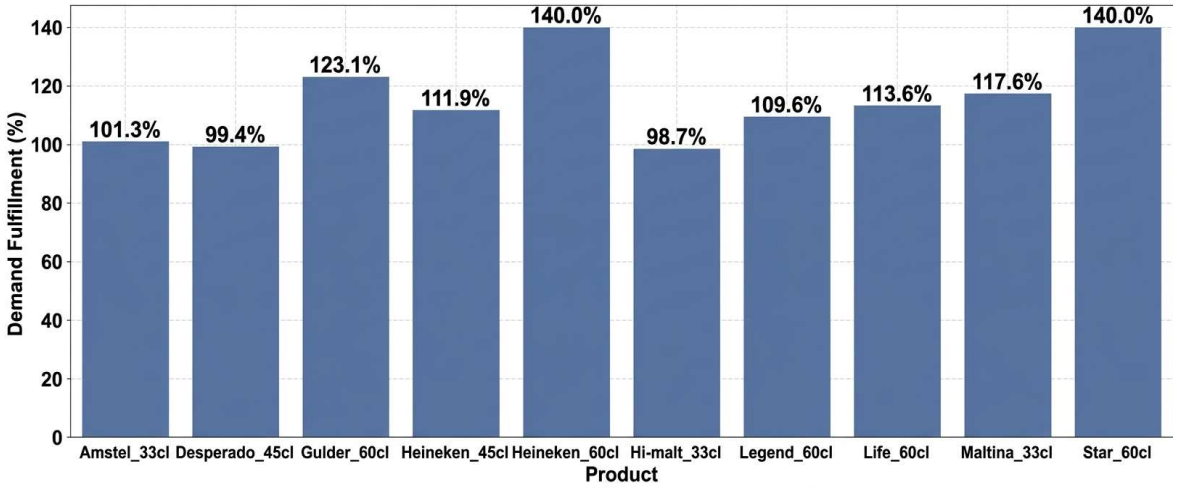


Figure 37. Scenario 2 Analysis Outcome on Demand Fulfilment Per Product.

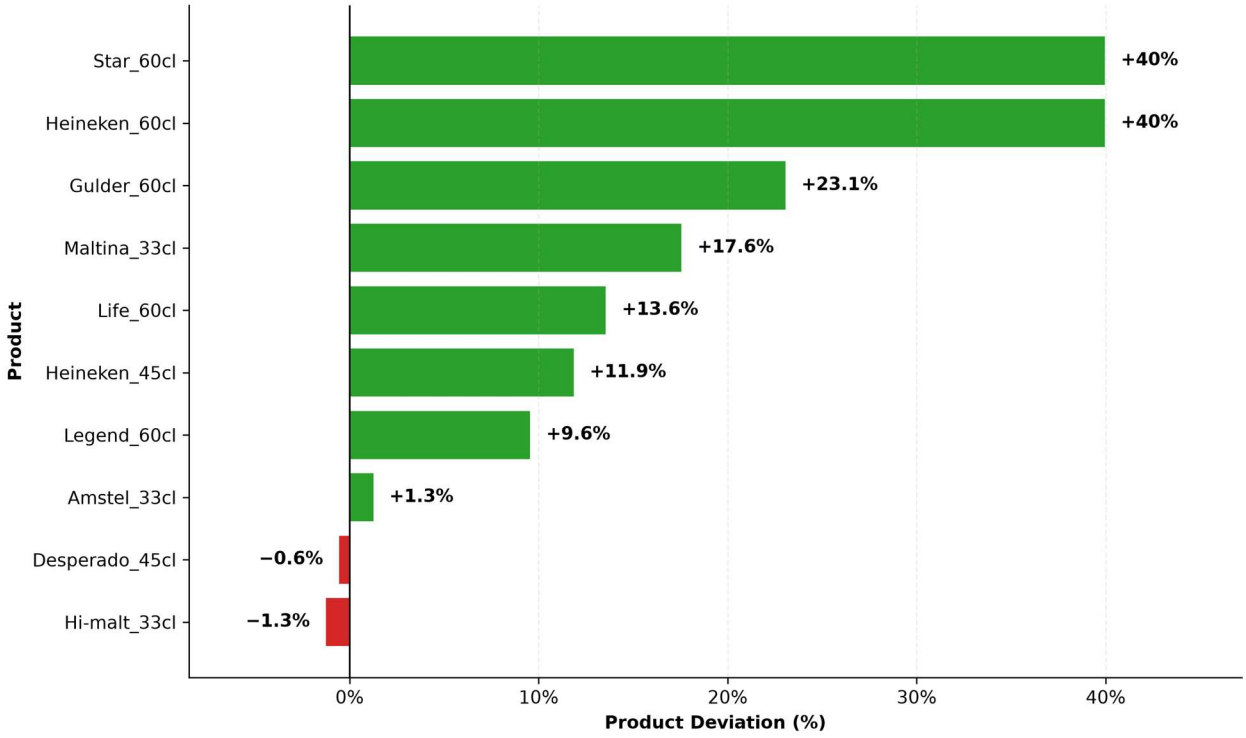


Figure 38. Scenario 2 Analysis Outcome on Production Deviation Per Product.

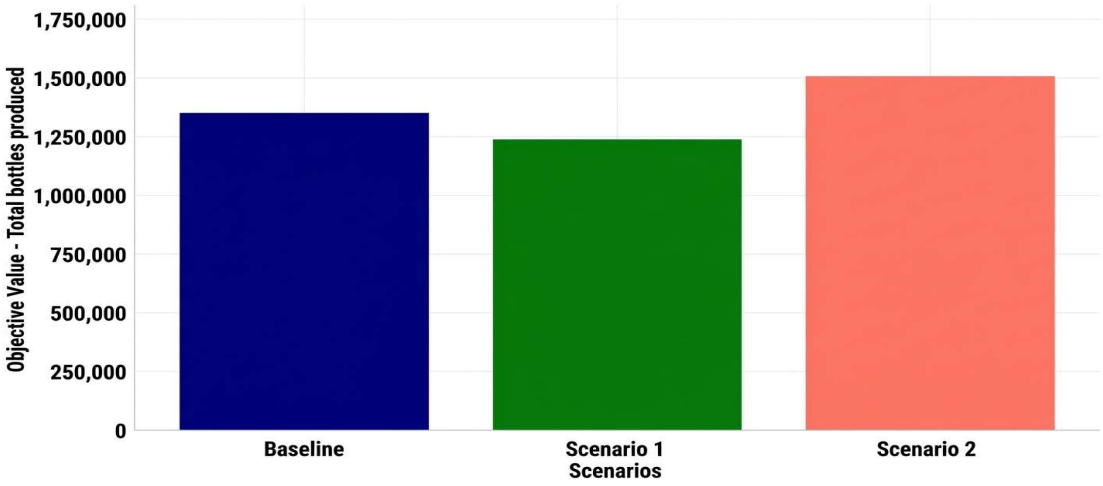


Figure 39. Total Bottles Produced Across Scenarios.

As presented in Tables 13 and illustrated across Figures 32–34, the first scenario, which combined reduced setup times with the complete unavailability of Line 3, enhanced setup efficiency but could not fully compensate for lost production capacity. The resulting output of 1,241,749 units and a high average line utilization of ~99.5% (as depicted in Figure 32) indicate that setup time reduction can partially salvage capacity losses, although line downtime remains a significant constraint. This demonstrates the need to evaluate improvement measures jointly with equipment availability rather than considering setup reduction in isolation [71]. On the other hand, the second scenario outlined in Table 12 and illustrated across Figures 35–38 produced a substantially stronger response by integrating reduced setup times with a 25% increase in production rate and a stricter 95% production lower bound. In the comparative evaluation shown in Figure 38, total output increased to 1,506,655 units, representing output increases of ~21.3% over Scenario 1 (1,241,749 units) and 11.4% over the baseline (1,352,250 units). Furthermore, line utilization remained robust at an average of ~97% (as presented in Figure 36), while several products achieved demand fulfillment above 100% (Figure 37), creating additional production buffers. However, the relatively small shortfalls for Hi-Malt 33 cl (98.7%) and Desperado 45 cl (99.4%) indicate that the increased production rate largely compensated for the loss of Line 3.

The results reveal an important capacity efficiency trade-off: Scenario 1 prioritizes setup efficiency and utilization, whereas Scenario 2 sacrifices a negligible degree of utilization to obtain substantially higher demand coverage and throughput. Consequently, this establishes that integrating production rate improvement with setup time reduction provides greater resilience to line downtime than either intervention as a single objective [72]. This scenario-based evaluation aligns with recent manufacturing studies by Antonacci et al. [42] and Bubeník et al. [38], which demonstrate the value of scenario analysis for assessing improvement strategies, disruptions, and operational alternatives. Overall, Scenario 2 represents the most effective operational strategy, particularly where maintaining demand coverage during equipment downtime is prioritized.

4. Conclusions

This study developed and evaluated an integrated ML–MILP framework for adaptive production planning, scheduling, and resource allocation in brewery manufacturing. The findings demonstrate that ML can provide reliable demand forecasts to support proactive production decisions, while MILP translates these forecasts into feasible production schedules that coordinate demand fulfillment, production capacity, line allocation, and setup requirements. The integration of predictive analytics and mathematical optimization therefore provides a structured approach to improving production planning in complex beverage manufacturing environments.

The sensitivity and scenario analyses further demonstrated the framework's ability to assess operational flexibility, identify production bottlenecks, and evaluate the effects of changing manufacturing conditions. The findings indicate that improving production rates can provide greater throughput benefits than reducing setup times alone, while flexible demand constraints and structured downtime strategies can strengthen production resilience. The analysis also highlights the importance of maintaining adequate production capacity and throughput margins to prevent scheduling infeasibility under adverse operating conditions. These insights can help manufacturing managers identify improvement opportunities and develop contingency plans before implementing operational changes.

The proposed framework offers practical decision support capabilities for brewery managers, supply chain practitioners, FMCG manufacturers, and production planners seeking more adaptive and data-driven approaches to production scheduling and capacity planning. Its integration into routine planning processes can support demand allocation, production-rate improvement, setup time management, and proactive responses to operational disruptions.

Future research should extend the framework to incorporate predictive maintenance, production cost and profitability optimization, multi-product and multi-site scheduling, and real-time production data integration. Further integration of reinforcement learning, stochastic optimization and digital twin technologies could also enhance the framework's robustness, scalability and adaptability under dynamic manufacturing conditions.

Statement of the Use of Generative AI and AI-Assisted Technologies in the Writing Process

During the preparation of this manuscript, the author(s) used ChatGPT in order to technically improve sentences and images. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the published article.

Author Contributions

R.M.O.: Conceptualization, methodology, data curation, investigation, formal analysis, visualization, and original drafting. O.O.O.: Methodology, investigation, data curation, formal analysis, and manuscript drafting. O.C.N.: Methodology, software, validation, formal analysis, and manuscript review. B.E.O.: Data curation, investigation, validation, visualization, and manuscript review. V.U.O.: Methodology, data analysis, validation, visualization, and manuscript review. D.A.E.: Conceptualization, methodology, supervision, project administration, validation, and manuscript review and editing. All authors contributed to the interpretation of results, critically reviewed the manuscript, and approved the final version.

Ethics Statement

This study did not involve human participants, animals, or clinical samples. Therefore, ethical approval and informed consent were not required.

Informed Consent Statement

Not applicable.

Data Availability Statement

Data will be made available upon request using arinze.ekpechi@futo.edu.ng.

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Declaration of Competing Interest

The author declares no conflict of interest.

Nomenclature

Parameters and Variables	Description
$\hat{y}$	Forecast demand
T	Time
s	Seasonal
y	Observed demand
x_i	feature vector for the i^{th} sample
n	Number of training sample
D	Demand
P	Product category
W	Week number
S	Season
H	Holiday indicator
M	Month
Y_i	Year
A	Weight assigned to production output
Λ	Penalty associated with changeovers
R_m	Terminal region
N_m	Number of observations within that region
R_L	Number of observations in the left child nodes
R_R	number of observations in the right child nodes
D_i	$i-th$ bootstrap sample
T_i	Prediction for an input feature
x	Vector
η	Learning rate
F_0	Initial Base Model
$L\big(y, F(x)\big)$	Loss function
$r_i^{(m)}$	Pseudo-Residual
h_m	Base Learner/Regression Tree
R_{jm}	Terminal Regions (Leaves)
γ_{jm}	Leaf Output Value
$f_m(x)$	Updated Ensemble Model
T	Terminal Nodes
w_j	Leaf Weights
$f_t(x_i)$	Newly fitted tree
P	Sets of products
L	Production lines
D	Planning days
D_p	Weekly demand for product
H_l	Available hours on the line
U_{pl}	Production rate of product p on the line l
$S_{pp'l}$	Setup time (in hours) when switching from p to p' on the line l
K	Maximum number of changeovers allowed on a line in a day.
B	The maximum cumulative setup time allowed on a single line within a day
$x_{pld} \in \mathbb{R}_{\geq 0}$	Number of units of product p produced on line l on day d
$y_{pld} \in \{0,1\}$	1 if product p is produced on line l on day d, 0 otherwise
$z_{plp'd} \in \{0,1\}$	1 if changeover occurs from p to p' on line l on day d, 0 otherwise

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