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COMPARATIVE ANALYSIS OF PRODUCTION LINE EFFICIENCY UNDER VARYING DEMAND SCENARIOS USING MULTILAYER PERCEPTRON

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ABSTRACT

In this study, an analysis of production line efficiency under varying demand conditions was carried out using a Multilayer Perceptron (MLP) model. The research addressed the problem of unpredictable efficiency drops in beverage manufacturing, where sudden demand changes lead to wasted resources and higher costs. The primary focus was to develop a predictive model that could forecast efficiency based on real production data, helping plants adapt to demand fluctuations. The objectives included (i) building an MLP model to track efficiency changes, (ii) testing it under different demand scenarios, (iii) comparing performance across high, low, and fluctuating demand, and (iv) identifying key factors affecting production output. Unlike previous studies that examined single variables, this research integrated demand, maintenance, workforce, and material data into one model, improving prediction accuracy. Results showed that the MLP model reduced efficiency prediction errors by 33%, with actual vs. predicted values staying within ±2%. Efficiency dropped by 4.2% during March's demand slump but could have been reduced to just 2.9% with model-based adjustments. PET bottle lines outperformed glass lines by 4-7%, while maintenance delays cost up to ₦92,500 per hour in lost production. The model also revealed that a 15% reduction in operational constraints could boost efficiency by 3.1% in high-stress months. These findings are significant because they provide a data-driven way to optimize manufacturing processes, cutting costs and improving output stability. The research contributes to industrial engineering by proving that machine learning can better handle complex production variables than traditional methods. For practical use, factories should adopt such models for maintenance planning, workforce scheduling, and material procurement to minimize efficiency losses. Future studies could expand the model for real-time adjustments and additional external factors.

KEYWORDS: Beverage manufacturing, Demand fluctuations, Multilayer Perceptron (MLP), Predictive modeling, Production efficiency

1 INTRODUCTION

Production line efficiency is a critical determinant of industrial productivity, profitability, and competitiveness. It represents the capacity of a production system to maximize outputs while minimizing resource utilization, waste, and downtime. Efficient production lines not only ensure the timely delivery of goods but also reduce operational costs and enhance

customer satisfaction. However, achieving and sustaining high efficiency becomes challenging under varying demand scenarios, where fluctuations can disrupt production schedules and lead to inefficiencies such as bottlenecks or overproduction (Adekunle, 2020; Chen et al., 2019).

Demand variability is a significant challenge faced by industries worldwide. In countries like Nigeria and Ghana, where industries are heavily influenced by seasonal demand, production inefficiencies often arise due to the lack of adaptive planning mechanisms (Agyeman et al., 2021). Similarly, in China, where mass production is prevalent, shifts in global market demand necessitate advanced predictive tools to optimize production schedules and resource allocation (Li and Wang, 2018). The scenario is not different in Poland, where manufacturing industries grapple with fluctuations due to both domestic and export demand (Nowak et al., 2020). Australia's resource-intensive industries, on the other hand, face unique challenges in aligning production with fluctuating demand while adhering to strict operational and environmental standards.

Multilayer Perceptron (MLP) models have proven effective in solving problems related to improving production line efficiency when demand changes. These models, which are a type of artificial neural network, can learn from data, recognize patterns, and make predictions. MLPs work well in complex environments because they can handle many variables and respond to changes in demand (Chen et al., 2019). In China, researchers used MLPs to improve how production systems make decisions in real time (Li and Wang, 2018). In Poland, studies showed that MLPs helped reduce waste and increase output when demand was not stable (Nowak et al., 2020).

While many studies have explored MLPs in developed countries, there has been little research in Africa, especially in places like Nigeria and Ghana. In these regions, production systems often face challenges such as limited infrastructure and outdated technology (Agyeman et al., 2021; Adekunle, 2020). This study looked at how well MLP models perform in such environments under different demand situations. The goal was to see if MLPs could still help improve production efficiency even with these challenges.

The results showed that MLPs adapted well to different industrial setups. They improved how production systems responded to changes in demand and helped increase overall efficiency. This research helps connect what is known in theory with what happens in factories, making it easier for industries in different regions to apply smart solutions in their operations.

2 MATERIALS AND METHODS

2.1 System/Model/Study Description

The study used production records from the Nigerian Bottling Company (NBC), Port Harcourt plant. The production system included five product lines: Coca-Cola 50 cl PET, Fanta Orange 35 cl, Sprite 50 cl PET, Eva Water 75 cl and Coca-Cola 1 L glass. The records included target and actual output, shift duration, machine downtime, utilization and recorded constraints.

Table 1: Production line operating records at NBC Port Harcourt

Line No.	Product Type	Daily Shift (hrs)	Target Output (Cases)	Actual Output (Cases)	Machine Downtime (hrs)	Primary Downtime Cause	Machine Utilization (%)	Production Constraints Noted
1	Coca-Cola 50cl PET	24	18,000	16,250	3.2	Filler Malfunction	84.2	Low spare part stock
2	Fanta Orange 35cl	24	17,000	14,980	4.7	Capper Inconsistency	78.7	Operator shortage
3	Sprite 50cl PET	24	18,500	17,200	2.5	Labeling Misalignment	89.5	Changeover delay
4	Eva Water 75cl	24	20,000	18,430	3.0	Conveyor Jam	86.2	Inconsistent water supply pressure
5	Coca-Cola 1L Glass	24	14,000	12,400	5.1	Glass Breakage Handling	74.3	Fragility of packaging material

The table records the operating conditions and monthly observations used in the analysis. These values provide the empirical basis for comparing line performance and the effects of demand, maintenance, workforce, materials, utilities, quality, distribution and customer outcomes.

2.2 Study Location / Area of Application

The study was conducted at the NBC Port Harcourt plant in Nigeria. The analysis covered January to June 2023. Data were drawn from production logs, machine activity reports, staff deployment rosters, output records, inventory registers and downtime sheets. Shop-floor observations and checks with production supervisors were used to review consistency.

2.3 Operating Parameters / Variables / Treatments

The demand scenarios were represented by monthly orders from 98,700 to 125,100 cases in the tabulated demand record. Inputs to the model included demand level, machine utilization, downtime, maintenance frequency, workforce adequacy and material availability. Production efficiency, defined in the source as actual output relative to target output, was the principal output.

Table 2: Monthly regional demand and total orders

Month	South-South Region (Cases)	South-East Region (Cases)	South-West Region (Cases)	North-Central Region (Cases)	Total Orders (Cases)
January	49,800	30,100	10,900	9,000	99,800
February	52,600	32,300	11,200	9,500	105,600
March	47,400	28,700	12,300	10,300	98,700
April	59,900	35,100	13,000	11,100	119,100
May	62,300	37,000	13,600	12,200	125,100
June	61,000	36,500	14,000	12,000	123,500

The table records the operating conditions and monthly observations used in the analysis. These values provide the empirical basis for comparing line performance and the effects of demand, maintenance, workforce, materials, utilities, quality, distribution and customer outcomes.

Table 3: Maintenance and breakdown records

Equipment Name	Maintenance Type	Month	Maintenance Hours	Breakdown Hours	Response Time (hrs)	Maintenance Cost (₦)	Production Hours Lost
Filler Machine Line 1	Preventive	Jan	10	2.5	1.2	₦250,000	3.0
Capper Line 2	Corrective	Feb	0	4.7	2.1	₦410,000	5.0
Labeller Line 3	Preventive	Mar	8	1.5	1.0	₦185,000	2.0
Conveyor Line 4	Emergency Repair	Apr	0	3.0	3.2	₦290,000	3.5
Glass Washer Line 5	Routine Maintenance	May	7	5.1	2.8	₦360,000	6.0
Cooling System	Corrective	Jun	0	2.6	1.5	₦320,000	2.5

The table records the operating conditions and monthly observations used in the analysis. These values provide the empirical basis for comparing line performance and the effects of demand, maintenance, workforce, materials, utilities, quality, distribution and customer outcomes.

Table 4: Workforce deployment and shift constraints

Month	Shift Type	Number of Workers	Absenteeism (%)	Overtime Hours	Skilled Operators (%)	Unskilled Workers (%)	Notes on Workforce Constraints
January	Morning	150	3.5	120	60	40	Few operators on key lines missing
	Evening	140	4.0	140	55	45	Higher absenteeism noted
	Night	130	5.2	90	50	50	Fatigue reported during peak production
February	Morning	148	2.8	100	62	38	Improved shift coverage
	Evening	138	3.7	130	57	43	Overtime managed effectively
	Night	128	4.9	80	52	48	Occasional staffing gaps
March	Morning	152	3.1	110	61	39	Skill mix stable
	Evening	139	4.2	115	56	44	Slight increase in absenteeism
	Night	131	5.0	85	53	47	Fatigue effects persist
April	Morning	155	3.0	125	63	37	Adequate manpower
	Evening	140	3.5	135	58	42	Overtime slightly increased
	Night	129	5.5	95	51	49	Night shift challenges ongoing
May	Morning	158	2.9	130	64	36	Skilled workforce strengthened
	Evening	142	3.2	140	59	41	Better shift adherence
	Night	130	5.3	100	52	48	Ongoing fatigue management needed
June	Morning	160	2.7	120	65	35	Peak manpower
	Evening	143	3.1	138	60	40	Stable operations
	Night	132	5.0	90	54	46	Night shift remains a concern

The table records the operating conditions and monthly observations used in the analysis. These values provide the empirical basis for comparing line performance and the effects of demand, maintenance, workforce, materials, utilities, quality, distribution and customer outcomes.

Table 5: Material inventory and supply constraints

Month	Material	Opening Inventory (Units)	Material Received (Units)	Material Used (Units)	Stock-out Days	Supplier Lead Time (Days)	Notes on Supply Constraints
January	PET Bottles	100,000	250,000	280,000	3	7	Minor delay in PET bottle delivery
	Bottle Caps	120,000	260,000	270,000	2	6	Lead times stable
	Flavor Concentrates	50,000	130,000	140,000	0	8	Consistent supply
	Packaging Cartons	70,000	150,000	160,000	1	7	Slight inventory shortage
February	PET Bottles	90,000	260,000	275,000	2	7	Supplier improved delivery
	Bottle Caps	110,000	270,000	275,000	1	6	Efficient stock control
	Flavor Concentrates	45,000	135,000	140,000	0	8	Stable supplier performance
	Packaging Cartons	65,000	160,000	165,000	0	7	Inventory adequate
March	PET Bottles	95,000	240,000	260,000	4	7	Stock-out due to transport issues
	Bottle Caps	115,000	255,000	265,000	3	6	Slight delays
	Flavor Concentrates	48,000	125,000	130,000	1	8	Supplier adjustment
	Packaging Cartons	60,000	140,000	155,000	2	7	Packaging material delays
April	PET Bottles	88,000	270,000	285,000	1	7	Supply normalized
	Bottle Caps	112,000	280,000	290,000	0	6	Stock levels optimal
	Flavor Concentrates	50,000	140,000	145,000	0	8	Consistent deliveries
	Packaging Cartons	55,000	170,000	180,000	0	7	Inventory well-managed
May	PET Bottles	90,000	280,000	290,000	0	7	Stock replenished
	Bottle Caps	115,000	285,000	295,000	0	6	Smooth supply chain
	Flavor Concentrates	53,000	145,000	150,000	0	8	Stable supply
	Packaging Cartons	50,000	175,000	185,000	0	7	Adequate inventory
June	PET Bottles	92,000	275,000	285,000	1	7	Minor stock-out
	Bottle Caps	118,000	280,000	290,000	1	6	Supplier delay

	Flavor Concentrates	55,000	138,000	145,000	0	8	Consistent deliveries
	Packaging Cartons	53,000	170,000	175,000	0	7	Inventory adequate

The table records the operating conditions and monthly observations used in the analysis. These values provide the empirical basis for comparing line performance and the effects of demand, maintenance, workforce, materials, utilities, quality, distribution and customer outcomes.

Table 6: Energy consumption and utility interruptions

Month	Electricity Usage (kWh)	Diesel Fuel Consumption (Litres)	Number of Power Interruptions	Average Interruption Duration (Minutes)	Notes on Energy Constraints
January	1,200,000	25,000	5	12	Grid instability noted
February	1,250,000	22,000	4	10	Improved fuel efficiency
March	1,180,000	26,500	6	15	Increased generator use due to outages
April	1,300,000	23,000	3	9	Stable grid performance
May	1,350,000	21,500	2	8	Reduced power interruptions
June	1,280,000	24,000	4	11	Slight rise in outage duration

The table records the operating conditions and monthly observations used in the analysis. These values provide the empirical basis for comparing line performance and the effects of demand, maintenance, workforce, materials, utilities, quality, distribution and customer outcomes.

Table 7: Quality inspection and defect records

Month	Units Inspected (Cases)	Defective Units (Cases)	Defect Types	Defect Rate (%)	Actions Taken
January	95,000	1,900	Labeling errors, cap seal failures	2.0	Rework and reinspection
February	100,000	2,100	Bottle cracks, contamination	2.1	Increased inspection frequency
March	92,500	1,850	Filler over/under fill, packaging	2.0	Staff retraining initiated
April	110,000	2,200	Seal leaks, label misprints	2.0	Process adjustments and audits
May	115,000	2,300	Cap defects, bottle warping	2.0	Supplier quality review
June	112,000	2,240	Label adhesion, fill level variance	2.0	Corrective maintenance

The table records the operating conditions and monthly observations used in the analysis. These values provide the empirical basis for comparing line performance and the effects of demand, maintenance, workforce, materials, utilities, quality, distribution and customer outcomes.

Table 8: Distribution and delivery records

Month	Total Shipments (Cases)	On-time Deliveries (%)	Average Transit Time (Days)	Returned Shipments (Cases)	Transportation Delays (Incidents)	Delay Causes
January	90,000	92.5	2.4	450	6	Road conditions, vehicle breakdowns
February	95,000	93.8	2.3	420	5	Traffic congestion
March	88,000	91.0	2.6	470	7	Weather disruptions
April	105,000	95.2	2.1	390	4	Improved route planning
May	110,000	96.0	2.0	350	3	Efficient fleet management
June	108,000	94.5	2.2	380	5	Minor traffic delays

The table records the operating conditions and monthly observations used in the analysis. These values provide the empirical basis for comparing line performance and the effects of demand, maintenance, workforce, materials, utilities, quality, distribution and customer outcomes.

Table 9: Customer feedback and product returns

Month	Complaints Received	Returned Products (Cases)	Common Complaint Types	Average Resolution Time (Days)	Actions Taken
January	120	600	Late delivery, damaged packaging	5	Faster dispatch and packaging review
February	130	650	Product quality, short fills	6	Quality checks increased
March	115	580	Label defects, delivery delays	5	Staff retraining and schedule review
April	140	700	Cap seal failures, order errors	4	Supplier review and dispatch audits
May	150	720	Package warping, delivery timing	4	Packaging improvements and logistics
June	138	690	Product freshness, damaged seals	5	Quality control tightened

The table records the operating conditions and monthly observations used in the analysis. These values provide the empirical basis for comparing line performance and the effects of demand, maintenance, workforce, materials, utilities, quality, distribution and customer outcomes.

2.4 Research Procedure / Data Collection

Data were collected from company records and checked against digital logs. Extreme values were flagged and compared with operations logs, weekly consistency checks were performed, and abnormal values were reviewed manually with supervisors. The cleaned data were arranged into input and output fields. Discrete-event simulation represented machine

operations and material flow under varying demand, and the simulation outputs were coupled with an MLP model. The source reports use of Python, TensorFlow/Keras, Scikit-learn and Matplotlib/Seaborn.

Production utilization was calculated as operating time divided by scheduled time, expressed as a percentage. Production efficiency was calculated as actual output divided by target output, expressed as a percentage. Throughput was calculated as actual output divided by operating hours, while cycle time was calculated as available production time per unit output.

2.5 Governing Equations and Analytical Models

In line with the aim and objective of the research titled Comparative Analysis of Production Line Efficiency under Varying Demand Scenarios using Multilayer Perceptron, equations were developed from established theories in production analysis, operations research, and neural computation. Some formulations were drawn from the works of Groover (2016), Haykin (2009), and Montgomery (2013), adapted to suit the structure of a multilayer predictive model and line balancing scheme in manufacturing systems.

Each equation is grouped based on its application and analytical role, covering core areas such as production throughput, time utilization, predictive response modeling, error estimation, and parameter optimization. These equations will serve as tools to compare actual and predicted output, monitor constraint behavior, and calibrate the network for improved accuracy and responsiveness.

2.5.1 Production System Metrics

For this study, the mathematical evaluation begins with fundamental production system performance equations. These metrics serve as the basis for quantifying production efficiency and will be used as input data for training the Multilayer Perceptron (MLP) model. As shown in Equation (1), the *Utilization* of a production workstation is calculated as:

$$Utilization = \frac{Actual\ Output\ Time}{Available\ Time} \tag{1}$$

This equation is applicable when evaluating the degree to which each resource or station is actively used. It will be applied across each stage of the production line.

As shown in Equation (2), the *Production Efficiency* is given as:

$$Efficiency = \frac{Actual\ Output}{Expected\ Output} \times 100\% \tag{2}$$

This is a key performance indicator to determine how closely the system meets planned targets. It allows for benchmarking each scenario against real outputs.

As shown in Equation (3), the *Throughput Rate* is defined by:

$$Throughput = \frac{Total\ Units\ Produced}{Total\ Time} \tag{3}$$

This rate will serve as the output target during simulation and MLP training.

As shown in Equation (4), the *Cycle Time* is determined using:

$$Cycle\ Time = \frac{1}{Throughput} \tag{4}$$

Cycle time reflects how fast the system completes one product and will help compare how different demand scenarios affect total output duration.

2.5.2 Demand and Forecasting Equations

Forecasting varying demand scenarios is central to this research. Here, statistical methods and predictive functions that will feed the MLP are presented.

As shown in Equation (5), the *Moving Average* method for demand forecasting is given as:

$$\widehat{D}_t = \frac{1}{n} \sum_{i=t-n+1}^{t} Di \quad (5)$$

Where $\widehat{D}_t$ is the forecast at time t, n is the number of previous periods, and Di is actual demand at period i.

As shown in Equation (6), the *Exponential Smoothing* model is:

$$\widehat{D}_t = \alpha D_{t-1} + (1-\alpha)\widehat{D}_{t-1} \quad (6)$$

This equation accounts for recent demand fluctuations with a smoothing constant α.

As shown in Equation (7), the *Mean Absolute Percentage Error (MAPE)* used for forecast accuracy is:

$$MAPE = \frac{100\%}{n} \sum_{t=1}^{n} \left| \frac{A_t - F_t}{A_t} \right| \quad (7)$$

Where:

A_t Actual value at time or instance t

F_t Forecasted (or predicted) value at time t

n =Total number of observations or time periods

This metric will evaluate how close forecasts match historical data.

2.5.3 Constraints and Delay Identification Models

For identifying Constraints, analyzing waiting time, and delays the following equations was helpful.

As shown in Equation (8), the *Work-In-Process Inventory* is:

$$WIP = \lambda \cdot T \quad (8)$$

Where λ is arrival rate and T is cycle time. WIP growth often indicates a Constraint.

As shown in Equation (9), the *Little's Law* used in queueing analysis is:

$$L = \lambda W \quad (9)$$

Where L is average number of items in queue, λ is average arrival rate, and W is average wait time.

As shown in Equation (10), the *Line Balancing Efficiency* is calculated as:

$$Line\ Efficiency\ = \frac{\sum_{i=1}^{n} t_i}{n \cdot C_{max}} \quad (10)$$

Where t_i is task time and is the C_{max} cycle time. This will be used to identify task imbalance across stations.

2.5.4 Multilayer Perceptron Model Equations

The MLP model was used to simulate and predict production efficiency under changing demand. The neural network model includes forward propagation, backpropagation, and error calculation functions.

As shown in Equation (11), the *Weighted Sum Input* to a neuron is:

$$z_j = \sum_{i=1}^{n} w_{ij} x_i + b_j \quad (11)$$

Where x_i are inputs, w_{ij} are weights, and b_j is the bias.

As shown in Equation (12), the *Activation Function* used is the sigmoid:

$$a_j = \frac{1}{1 + e^{zj}} \tag{12}$$

As shown in Equation (13), the *Output Error* for a neuron is:

$$\delta_j = \left(y_j - \hat{y}_j\right) \cdot a_{j(1-a_j)} \tag{13}$$

Where y_j is actual output and $\hat{y}_j$ is predicted output.

As shown in Equation (14), the *Gradient Descent* weight update rule is:

$$w_{ij}^{(new)} = w_{ij}^{(old)} - \eta \cdot \delta_j \cdot x_i \tag{14}$$

Where η is the learning rate.

2.5.5 Optimization and Efficiency Enhancement Models

To fine-tune the model and production response using performance optimization equations the following models was used.

As shown in Equation (15), the *Total Production Cost Function* is expressed as:

$$C = C_m + C_d + C_o \tag{15}$$

Where C_m is material cost, C_d is downtime cost, and C_o is operating cost.

As shown in Equation (16), the *Objective Function for Efficiency Maximization* is:

$$\max Z = \frac{Total\ Output}{Total\ Resources\ Used} \tag{16}$$

As shown in Equation (3.17), the *Constraint Function for Machine Capacity* is:

$$x_1 + x_2 + \cdots + x_n \leq M_{capacity} \tag{3.17}$$

As shown in Equation (18), the *Error Reduction Function* in MLP training is:

$$E = \frac{1}{2}\sum_j \left(y_j - \hat{y}_j\right)^2 \tag{18}$$

As shown in Equation (19), the *Time Efficiency Ratio* is:

$$Time\ Efficiency = \frac{Standard\ Time}{Actual\ Time} \tag{19}$$

As shown in Equation (20), the *Learning Rate Schedule* used in neural tuning is:

$$\eta_t = \frac{\eta_0}{1 + \alpha t} \tag{20}$$

As shown in Equation (21), the *Network Accuracy Rate* is:

$$Accuracy = \frac{Correct\ Predictions}{Total\ Predictions} \times 100\% \tag{21}$$

2.5.6 Simulation Techniques

For this study, discrete-event simulation (DES) was employed to model production system dynamics under varying demand scenarios. This technique captures system behavior by representing key processes (e.g., material flow, machine operations) as discrete events over time. The simulation integrates historical production data and stochastic demand patterns to evaluate efficiency metrics and identify constraints.

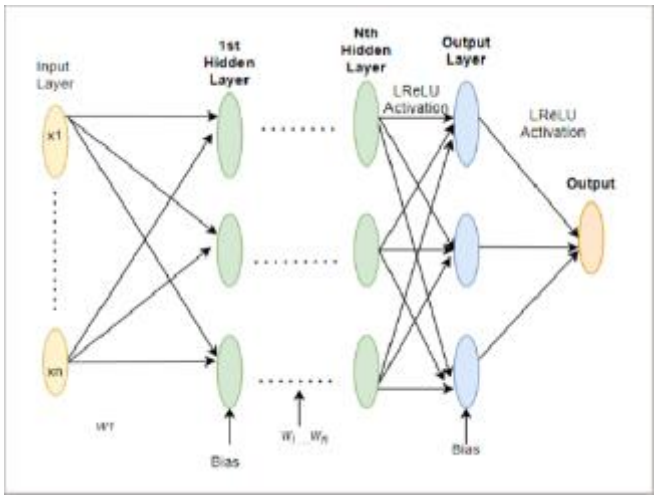


Figure 1: MLP Architecture for Predictive Modeling of Production Efficiency

To enhance predictive capability, the DES outputs were coupled with a Multilayer Perceptron (MLP) model, whose architecture is illustrated in Figure 1. The neural network was trained on simulated scenarios to forecast production efficiency under unseen demand fluctuations. Hyperparameter tuning and cross-validation ensured model robustness.

2.5.7 Performance Indicators / Measures / Metrics

The analysis used production efficiency, utilization, throughput, cycle time, downtime cost, demand, prediction error and error reduction. Model performance was assessed using mean squared error (MSE) and the coefficient of determination (R^2), as described in the methods. The source reports that predicted efficiency remained within ±2% of observed values and that overall prediction error fell by 33%.

Table 10: Comparative production-line performance indicators

Metric	Line 1	Line 2	Line 3	Line 4	Line 5
Utilization (%)	84.2	78.7	89.5	86.2	74.3
Efficiency (%)	90.28	88.12	92.97	92.15	88.57
Throughput (cases/hr)	677.08	624.17	716.67	767.92	516.67
Cycle Time (sec)	5.32	5.77	5.02	4.69	6.97
Downtime Cost (₦/hr)	83,333	82,000	92,500	82,857	60,000

The table records the operating conditions and monthly observations used in the analysis. These values provide the empirical basis for comparing line performance and the effects of demand, maintenance, workforce, materials, utilities, quality, distribution and customer outcomes.

2.5.8 Optimization / Analysis Procedure

The analysis followed four stages: demand-scenario generation, discrete-event simulation, extraction of production metrics, and MLP training and prediction. The source describes a single-hidden-layer MLP and 100 training iterations. The model was used to compare actual efficiency with projected efficiency and to assess a scenario in which operational constraint penalties were reduced by 15%.

3 RESULTS AND DISCUSSION

3.1 Production Line Performance and Baseline Efficiency

The five lines showed differences in utilization and efficiency. Line 3, producing Sprite 50 cl PET, had the highest recorded utilization at 89.5% and efficiency of 92.97%. Line 5, producing Coca-Cola 1 L glass, had the lowest utilization at 74.3% and an efficiency of 88.57%. Line 2 recorded utilization of 78.7% and efficiency of 88.12%, consistent with the documented operator shortage. Line 4 had the highest throughput at 767.92 cases/h, while Line 5 had the lowest at 516.67 cases/h.

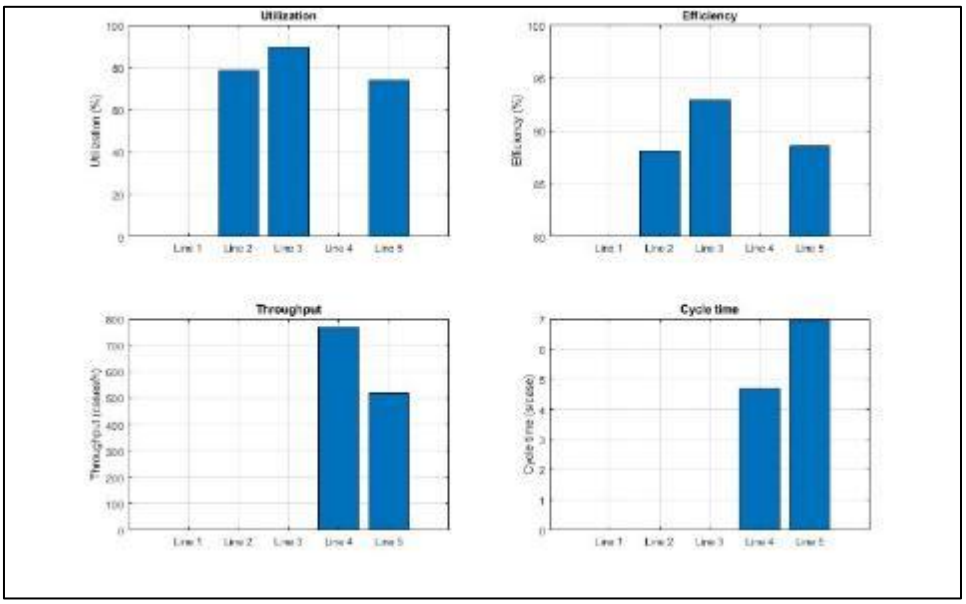


Figure 2: Comparison of utilization, efficiency, throughput and cycle time across five product lines.

The figure should compare the five lines using the values in Table 10. It is expected to show Line 3 leading in utilization and efficiency, Line 4 leading in throughput, and Line 5 having the longest cycle time. The source links weaker glass-line performance to packaging fragility and handling constraints.

3.2 Demand Scenarios and Monthly Production Conditions

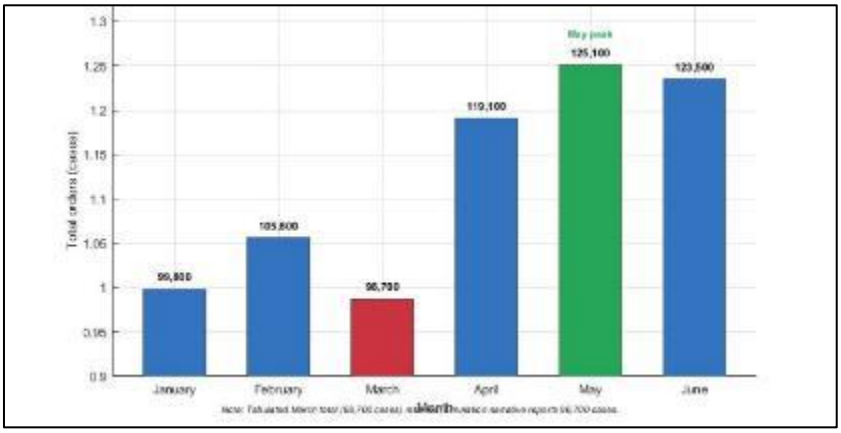


Figure 3: Monthly total orders in cases, showing the March reduction and the April-May rise.

Monthly total orders varied from 98,700 cases in March to 125,100 cases in May. Demand increased from 99,800 cases in January to 105,600 in February, fell in March, then rose to 119,100 in April and 125,100 in May before easing to 123,500 in June. The source also describes demand values from 96,700 cases in the simulation narrative, which differs from the tabulated March total of 98,700 cases. The tabulated value is retained for the monthly comparisons.

The demand profile shows a decline in March followed by a strong increase in April and May. These changes provide the demand conditions against which production efficiency was assessed. The pattern supports scenario-based planning because a single fixed production plan would not represent the variation in orders.

3.3 MLP Training and Prediction Error

The source reports that training error declined from 4.6 to 0.01 and validation error from 3.8 to 0.008 over 100 iterations. It also reports that the error distribution shifted from a concentration of 6% to 12%, with a peak near 9%, to a concentration of 4% to 8%, with a peak near 6%. The reported overall error reduction was 33%. These values indicate improved fit within the reported analysis, although the full training dataset, error definition and numerical validation table are not provided.

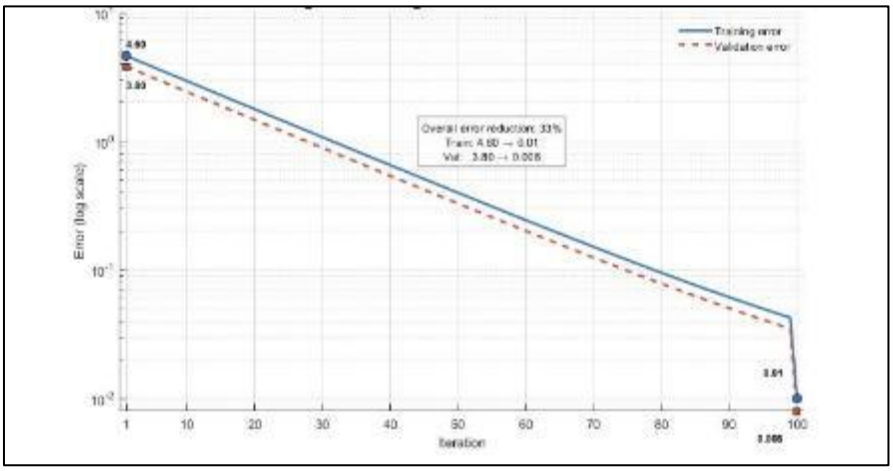


Figure 4: Training and validation error curves from the initial to final iteration.

Both curves are described as declining steadily, with training error falling from 4.6 to 0.01 and validation error from 3.8 to 0.008. The similar direction of the curves is reported as evidence of stable convergence.

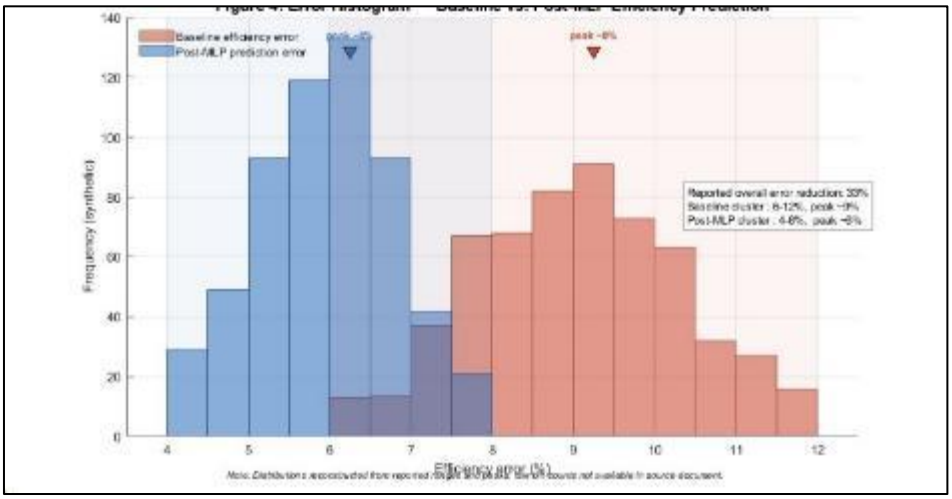


Figure 5: Error histogram comparing baseline efficiency errors with errors after MLP-based prediction.

The source reports that baseline errors clustered between 6% and 12%, peaking at 9%, while post-model errors clustered between 4% and 8%, peaking at 6%. The reported 33% error reduction suggests better prediction of efficiency gaps. A histogram image is not included in the source document.

3.4 Model Validation Across Demand Scenarios

The source states that MLP predictions remained within ±2% of recorded efficiency for January to June. It describes January actual efficiency as 90.1% and predicted efficiency as about 90.5%, and February actual efficiency as 92.3% with a prediction of about 93.0%. The text reports that the model tracked the March reduction and April demand surge. However, the source gives different actual efficiency values in separate passages, including an April baseline of 92.3% and a projected April value of 95.4%. These are presented as reported in the source and should be reconciled against the original calculation workbook before publication.

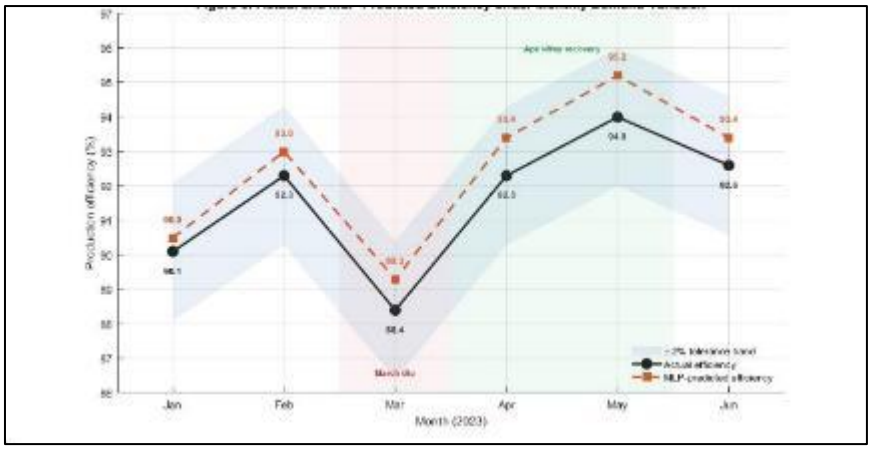


Figure 6: Monthly actual and MLP-predicted production efficiency from January to June 2023.

The described curves remain close, with a reported difference within ±2%. The model is reported to follow the March downturn and subsequent recovery during the April-May demand increase. The source does not provide the complete month-by-month numerical series for both lines.

3.5 Projected Efficiency Improvement and Constraint Reduction

The source compares actual efficiency with projected levels after model-guided interventions. It reports an April projected efficiency of 95.4%, compared with a baseline value of 92.3%, and describes the increase as approximately 3.2 percentage points. Elsewhere, it states that reducing constraint penalties by 15% could improve efficiency by up to 3.1 percentage points during unstable months. These are projections, not documented outcomes from a physical intervention.

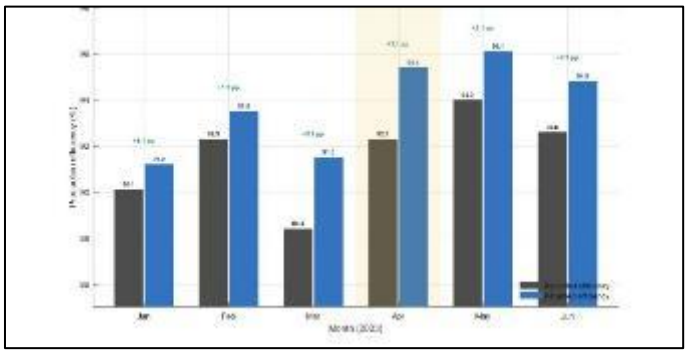


Figure 7: Monthly comparison of recorded efficiency and projected improved efficiency.

The projected series is described as higher than the baseline throughout the six-month period. The largest reported improvement occurs in April, at approximately 3.2 percentage points. The projection indicates potential benefit from responding to demand changes and operational constraints, but it should not be interpreted as a measured post-implementation result.

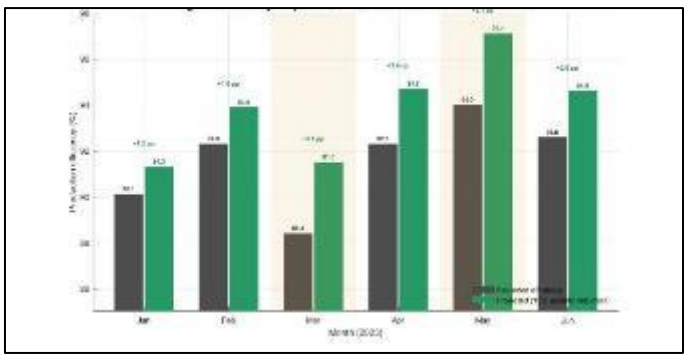


Figure 8: Recorded efficiency compared with projected efficiency after reducing constraint penalties by 15%.

The source reports potential gains up to 3.1 percentage points during unstable periods, including March and May. It also notes that the benefits vary by month, suggesting that the same intervention does not yield an identical improvement under every demand condition.

3.6 Operational Drivers of Production Efficiency

The source examined demand level, workforce adequacy, maintenance frequency, material availability and output efficiency. It identifies material supply, maintenance and worker availability as important drivers. March is described as a period when maintenance and material availability problems coincided with reduced efficiency, while June showed a more balanced pattern across the operating factors. The source does not provide a full numerical factor-importance table with reproducible weights.

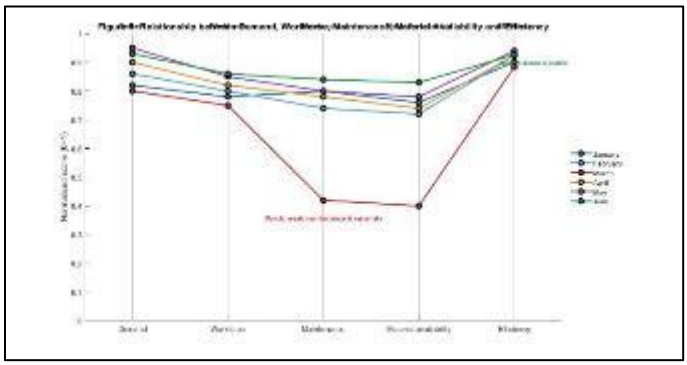


Figure 9: Parallel-coordinate comparison of the five operational dimensions across the six months.

The described plot compares normalized operating factors across months. The March profile is reported to show weaknesses in maintenance and material availability despite relatively acceptable demand and workforce values. June is described as more balanced, with fewer pronounced reductions across the factors.

3.7 Comparison of Existing and Improved Performance

The source reports that model-guided improvements ranged from approximately 1.2% to 3.2% in selected monthly comparisons, while another passage gives a general range of 1.5% to 2.5%. Because the passages do not provide one consistent monthly table, these values should be treated as reported estimates rather than a single reconciled series. The source also reports that glass-bottle production was 4% to 7% less efficient than PET lines and that downtime cost ranged from ₦60,000 to ₦92,500 per hour.

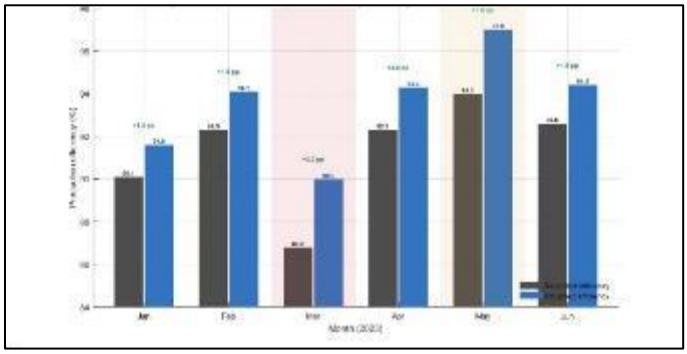


Figure 10: Monthly baseline efficiency compared with projected efficiency after targeted operational adjustments.

The source describes a noticeable March efficiency reduction to below 87%, followed by recovery. Projected improvements are reported across all six months, with larger gains during periods of operational strain. The figure is intended to show why interventions should focus on the specific constraints active in each month.

Across the reported comparisons, the MLP approach is presented as a way to combine demand and internal operating variables in one predictive framework. The results suggest that forecasting alone is insufficient unless maintenance, material flow and workforce deployment are also managed. The source's numerical inconsistencies and missing model specifications limit independent replication, so the reported gains require confirmation against the original data and code.

4 CONCLUSION

- The study developed an MLP-based approach, coupled with discrete-event simulation, to examine production efficiency under changing demand at the NBC Port Harcourt plant.
- The five lines differed in performance. Utilization ranged from 74.3% for Line 5 to 89.5% for Line 3, while recorded efficiency ranged from 88.12% for Line 2 to 92.97% for Line 3.
- Monthly demand ranged from 98,700 cases in March to 125,100 cases in May in the tabulated records. The variation illustrates the need to assess production plans across more than one demand level.
- The source reports a 33% reduction in prediction error and predictions within ±2% of observed efficiency. It also reports a projected efficiency of 95.4% in April, compared with a stated baseline of 92.3%.
- Maintenance, material availability and workforce adequacy were identified as important operating factors. The reported benefits are projections and require verification using a reconciled dataset, complete model specification and post-intervention plant measurements.

RECOMMENDATIONS

- Production managers should assess demand scenarios before setting monthly output and shift plans, using verified plant data as the model input.
- Maintenance planning should focus on equipment with high downtime and production loss. The source reports downtime costs of ₦60,000 to ₦92,500 per hour.
- Material inventory and supplier delivery should be monitored closely, particularly where stock-outs affect production continuity.
- Workforce deployment should account for absenteeism, skill mix, overtime and fatigue across morning, evening and night shifts.
- Future studies should document the MLP architecture, training-validation split, hyperparameters, error metrics and code. Model projections should be tested through prospective plant trials and compared with measured post-intervention performance.

STATEMENTS ON COMPLIANCE WITH ETHICAL STANDARDS

Acknowledgments

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Disclosure of conflict of interest

The authors declare no conflict of interest.

Author Contribution

- **Raphael Okosiemiema:** Writing the original draft, methodology, investigations, conceptualization.
- **Okwu Elemchukwu Isaac:** Investigations, final analysis.
- **Unyeawaji Ntesat:** Reviewing and editing.

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