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An Integrated ANN-Aggregate Planning-RCCP Framework for Make-to-Stock Bag Production: A Case Study of Keyna Products

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Abstract. *Company XYZ applies a make-to-stock (MTS) system for bag production, where inaccurate demand estimation can cause overstock, stockouts, and infeasible shop floor plans. This study proposes an integrated planning framework for the Keyna product family by combining demand forecasting using an Artificial Neural Network (ANN), aggregate production planning, master production scheduling, and Rough-Cut Capacity Planning (RCCP) using the Bill of Labour Approach (BOLA). Historical weekly demand data from 7 January 2023 to 24 February 2024 were used to develop the ANN model and generate six-week forecasts of 2601, 4635, 1542, 5773, 2394, and 5097 units. Forecasts were allocated into Keyna Mini Satchel (80%) and Keyna Round Satchel (20%), followed by aggregate planning and disaggregation using the Britan and Hax method to produce the Master Production Schedule (MPS). Capacity feasibility was evaluated across ten work centers using RCCP-BOLA. The level strategy produced a lower total cost (IDR 1,109,575,000) than the mixed strategy (IDR 1,975,350,000). RCCP results indicate recurring capacity shortages at work center 5 (painting), work center 6 (drying), and work center 7 (eyelets), for which targeted improvement actions were proposed.*

Keywords: *Aggregate Planning, Artificial Neural Networks, Bottleneck, Demand Forecasting, RCCP*

I. INTRODUCTION

In make-to-stock (MTS) environments, firms respond to customer demand through available stocks, making demand forecasting critical to avoid excess inventory and related holding costs (Upadhyay et al., 2023). Inaccurate forecasts may lead to excess inventory and higher holding costs when demand is overestimated, while underestimation increases the risk of stockouts that can trigger lost sales and reduce customer satisfaction or service level (Liu et al., 2025; Debnath et al., 2023). Therefore, an effective forecasting approach is essential to support production planning and capacity-related decisions in MTS systems (Tang et al., 2022).

Company XYZ is a bag manufacturer producing multiple brands and models, including the Keyna Product family, which contributes the largest share of total output. Although historical sales data are available, the company has not yet transformed these data into an analytical forecasting model, and production is still largely decided from simple historical judgment. As a consequence, the company frequently experiences mismatches between demand and output for Keyna product, indicating a recurring gap between what the market requires and what the factory delivers. As shown in Figure 1, demand and production for Keyna bags fluctuate across 17 weekly periods and repeatedly diverge, indicating weeks of potential overproduction (production exceeding demand) as well as weeks of potential underproduction (demand exceeding production). This mismatch increases the risk of overproduction or underproduction and complicates downstream planning decisions such as workforce allocation, scheduling, and inventory control (Kourentzes et al., 2020).

Although ANN has been widely applied for demand forecasting, many studies primarily emphasize prediction accuracy and stop short of validating whether the forecast-driven production plan is feasible at the shop-floor resource level. Conversely, capacity planning studies such as RCCP often assume deterministic demand or use simplified demand inputs without explicitly

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integrating a data-driven forecasting model into the MPS and capacity-checking stages. As a result, decision makers may obtain forecasts that are statistically sound but operationally infeasible, or capacity plans that are not tightly linked to validated demand projections. This gap motivates an end-to-end approach that connects forecasting, production planning, and work-center feasibility verification within a single framework (Gansterer, 2015; Babaveisi et al., 2023; Jamalnia et al., 2019; Babazadeh et al., 2025).

The selection of ANN in this study is motivated by both the characteristics of the demand data and the production planning context. Historical demand for the Keyna product family exhibits substantial week-to-week fluctuations, indicating nonlinear demand behavior that is difficult to represent using conventional linear time-series models. Unlike stastistical forecasting approaches that generally require assumptions regarding data distribution or linear relationships, ANN is capable of learning complex nonlinear patterns directly from historical observations. This capability makes ANN particulary suitable for make-to-stock production systems, where forecasting errors directly influence inventory levels, aggregate production planning, and capacity utilization. Therefore, ANN was selected as the forecasting method because it provides a flexible data-driven approach for capturing demand variability and producing forecasts that can support subsequent production planning and RCCP analysis.

Therefore, this study contributes by developing an ANN-based weekly demand forecasting model for the Keyna product family and using the forecasts as planning inputs; second translating the forecasts into an aggregate plan and an item-level MPS using the Britan and Hax disaggregation method; and third validating plan feasibility through RCCP using the Bill of Labour Approach (BOLA) to identify bottleneck work centers and formulate targeted capacity improvement actions. The proposed framework provides practical managerial value because it links demand uncertainty to executable schedules and prioritizes interventions on the true capacity constraints.

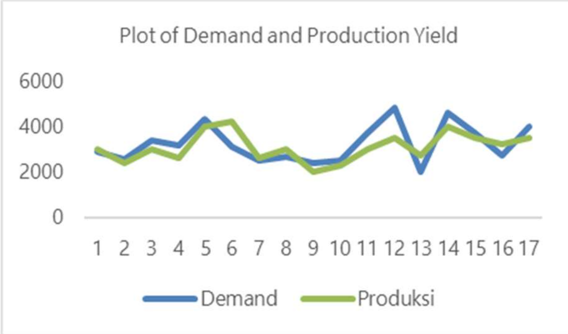

Figure 1. Demand and Output Chart of Keyna Bags

To address this practical need, this study proposes an integrated approach that connects demand forecasting using ANN with production planning and capacity validation. First, an ANN (backpropagation) model is developed using historical Keyna demand data to generate forecasts for the weekly planning horizon. Second, the forecast is converted into an aggregate plan and disaggregated into a Master Production Schedule (MPS) for Keyna variants. Third, Rough-Cut Capacity Planning (RCCP) using the Bill of Labour (BOLA) approach is conducted to evaluate whether each work center has sufficient capacity to meet the planned output and to identify bottleneck resources. The novelty of this work lies in integrating forecast-driven aggregate planning and MPS with RCCP-based feasibility validation (BOLA) to generate bottleneck-oriented capacity improvement decisions in an MTS bag manufacturing case. In this study, BOLA was selected as the RCCP method because it estimates capacity requirements based on standard processing times and routing information for each work center, allowing production plans to be evaluated at the operational level. Compared with Capacity Planning Using Overall Factors (CPOF), which estimated capacity using aggregte historical ratios, BOLA provides more detailed and work-center-specific capacity calculations, making it more suitable for identifying bottleneck resources. Although methods such as Resource Profile can capture time-phased capacity requirements with greter detail, they require more comprehensive routing and lead-time information than was available in the present case. Therefore, BOLA represents an appropriate balance between analytical detail, data availability, and practical implementation for Company XYZ. Accordingly, the objective of this research is to forecast Keyna product demand using an ANN model and determine feasible production strategies by evaluating capacity adequacy through RCCP at the work center level.

II. RESEARCH METHOD

This study employed an applied case study approach in a make-to-stock (MTS) manufacturing setting to integrate demand forecasting, production planning, and capacity feasibility analysis for Keyna bag products at Company XYZ. The analysis was conducted on a weekly basis. Data were obtained from two sources. Secondary data comprised historical weekly Keyna demand/ sales records from 7 January 2023 to 24 February 2024, which were used to build the forecasting model and generate forecasts for the subsequent six-week planning horizon (26 February to 6 April 2024). Primary data were collected through direct observation and interviews, including routing and work center structure, type and number of machines at each work center, standard processing times per operation, and production calendar parameters, along with inventory related parameters required for aggregate planning. The historical demand data represent the most recent operational records available when this research was conducted. The company confirmed that no major changes occurred in the Keyna product family, make-to-stock production policy, manufacturing process, or production resources during the study period. Therefore, these historical data remain representative for developing and evaluating the proposed integrated planning framework.

The methodological workflow followed the framework shown in Figure 2. First, demand forecasting was performed using an Artificial Neural Network (ANN) with backpropagation learning. The historical demand series was prepared for modelling (including normalization/denormalization procedures as required) and divided into training and testing subsets to evaluate forecasting performance using an appropriate error metric. Forecasting performance was evaluated using the mean squared error (MSE). The ANN architecture was selected through a trial-and-error procedure by choosing the configuration that produced the smallest MSE among the tested combinations of activation functions, training algorithms, and learning rates. The best performing ANN configuration was then used to produce demand forecasts for the next six weekly periods. Second, the forecasted demand was allocated into Keyna product family, which consists of two bag variants, namely Keyna Mini Satchel (80%) and Keyna Round Satchel (20%). Since both products share similar manufacturing processes, routing sequences, work centers, and production resources, they were treated as a single product family for aggregate production planning. To account for differences in processing requirements between the two variants, a conversion factor was applied to express demand in equivalent product units at the aggregate (family) level. Using these aggregate demand data, alternative production planning strategies

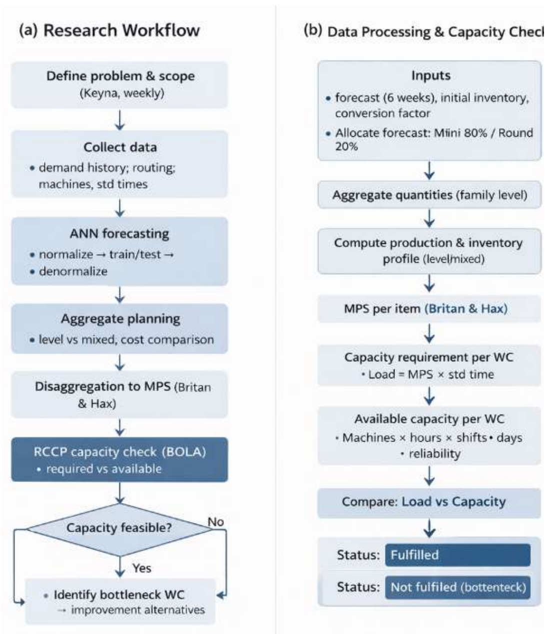

Figure 2. Research Flow and Data Processing & Capacity Check

(level and mixed) were evaluated, and the strategy with the lowest total production cost, including regular production, overtime, and inventory holding costs, was selected.

Third, the selected aggregate plan was disaggregated into an item-level Master Production Schedule (MPS) using the Britan and Hax method, producing weekly schedules for Keyna Mini Satchel and Keyna Round Satchel. Fourth, capacity feasibility was assessed using Rough Cut Capacity Planning (RCCP) with the Bill of Labour Approach (BOLA). In this stage, capacity requirements (load) for each work center and week were calculated based on the MPS and standard processing times, while available capacity was computed from the number of machines, working hours, number of shifts, number of working days, and machine availability/reliability assumptions. Required capacity was then compared with available capacity to classify each work center as fulfilled (load ≤ capacity) or not fulfilled (load > capacity), where the latter indicates a bottleneck resource. Finally, for any bottleneck work centers, improvement alternatives were formulated such as overtime, additional shifts, machine additions, or process support enhancements and the RCCP evaluation was conceptually iterated by updating capacity assumptions to verify whether the proposed alternatives could achieve a feasible production plan.

III. Result and Discussion

Company XYZ and Production System

Company XYZ is a manufacturing company that produces various types of bags and accessories. The company's business process uses a make-to-stock policy, where bag production is based on historical demand data. The company has 270 employees and uses machines in bag production. This research focuses on the Keyna bag product, which accounts for 65% of the company's total bag production. To produce Keyna bags, ten types of machines are used: cutting machine, strap machine, suture machine, embossing machine, painting machine, drying machine, eyelets machine, flat sewing machine, computer sewing machine, and cangklong machine. Each machine is 100% reliable and has a setup time of 15 minutes (900 seconds). The production time for the Keyna Mini Satchel is 1,125 hours, while the Keyna Round Satchel is 1,181 hours.

Historical Demand Preparation for ANN Modelling: The normality test at this stage is carried out to know whether the data obtained is normally distributed (Tyastirin & Hidayati, 2017). The Kolmogorov–Smirnov test was performed using SPSS. The result indicates that the Keyna demand data (60 weekly observations from 7 January 2023 to 24 February 2024) are normally distributed because the significance value is greater than 0.05 (0.83 ≥ 0.05). Figure 3 presents the normality test result.

Although ANN does not strictly require normally distributed input, this test provides descriptive assurance about the demand dataset characteristics and supports the use of standard preprocessing procedures. In practice, the more important point for ANN performance is consistent preprocessing and an appropriate train–test evaluation to avoid overfitting.

N		60
Normal Parameters[a,b]	Mean	3250.00
	Std. Deviation	752.272
Most Extreme Differences	Absolute	.107
	Positive	.107
	Negative	-.058
Test Statistic		.107
Asymp. Sig. (2-tailed)		.083[c]

a. Test distribution is Normal.

b. Calculated from data.

c. Lilliefors Significance Correction.

Figure 3. Normality Test Results of Keyna Historical Data

The 60 historical demand data were normalized using a sigmoid function with a target range of [0.1], as shown in Eq.(1) (Hambali & Safii, 2024). The normalized values were then used to form training and testing input patterns in MATLAB. Table 1 presents the normalization result.

Table 1. Normalisation Result 60 Historical Demand Data of Keyna Bags.

No	Week	Demand	Normalization Result
1	07-Jan-23	3270	0.4629
2	14-Jan-23	2530	0.2514
3	21-Jan-23	4670	0.8629
↓	↓	↓	↓
58	10-Feb-24	3700	0.5857
59	17-Feb-24	2700	0.3
60	24-Feb-24	4000	0.6714

Table 2. Keyna Bag Product Forecasting Results with ANN Method

Period	Date (2024)	Prediction Results	Denormalization	Unit
1	26 Feb – 02 Mar	0.2716	2600.2	2601
2	4 - 9 Mar	0.853	4635.5	4635
3	11 - 16 Mar	-0.0309	1541.85	1542
4	18 - 23 Mar	1.1781	5773.35	5773
5	25 - 30 Mar	0.2125	2393.75	2394
6	1 - 6 Apr	0.985	5097.5	5097

$$x' = \frac{0.8(x - a)}{(b - a)} + 0.1 \tag{1}$$

Normalization is important in ANN training because it stabilizes gradient updates and improves numerical efficiency, especially when raw demand values are relatively large. This step helps ensure that the learning process is not dominated by scale effects.

ANN Configuration, Pattern Formation, and Forecasting Results

Input patterns were formed based on the normalized demand series. The study used 20 training patterns and 20 testing patterns obtained by clustering 60 historical observations. Forecasting performance was evaluated using the mean squared error (MSE), and the best network configuration was selected through trial-and-error by choosing the architecture and training parameters that produced the smallest MSE among the tested combinations. The best ANN architecture is 20-10-1 (Input-Hidden-Output), using tansig activation for the input to hidden layer and purelin for the hidden to output layer. Training was carried out in MATLAB using trainlm with a learning rate of 0.001, producing a training MSE of 3.74E-19 and converging at epoch 3. The resulting network structure is shown in Figure 4 (Kushwaha, et al., 2024).

The ANN prediction outputs were denormalized to obtain demand forecasts in unit quantities using Eq. (2) and Table 2 presents the

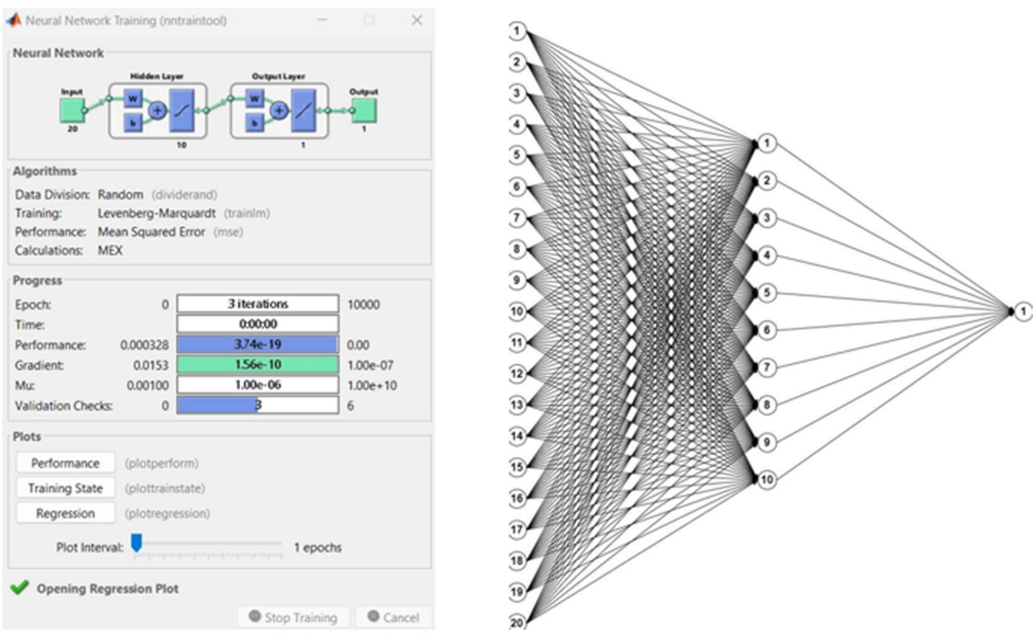

Figure 4. 20-10-1 Pattern Training

six-weeks Keyna demand forecast generated by the selected ANN model.

$$X = \frac{(x' - 0.1)(b - a)}{0.8} + a \quad (2)$$

The forecast results show substantial week-to-week variation, indicating that Keyna demand is not stable across the horizon. For an MTS system, this volatility is operationally meaningful because it influences inventory and workload. Therefore, forecast output must be converted into feasible production plans and verified using capacity checks; otherwise, planning decisions may become unrealistic at the work-center level.

Aggregate Planning Result

Aggregate planning was conducted to determine the production level operated on the shop floor to support scheduling decisions (Nizami, 2019). The forecasting was allocated into two variants; Keyna Mini Satchel (80%) and Keyna Round Satchel (20%). The conversion factor for Keyna Round Satchel is 1, while Keyna Mini Satchel is 0.9689. After obtaining the conversion factor, initial inventory conversion was computed. The total initial inventory of Keyna Mini Satchel and Keyna Round Satchel is 1181 units. In period 1, the aggregate unit was obtained by subtracting the initial inventory from the production quantity of both products, resulting in 1420 units. The same procedure was applied for periods 2-6, resulting in aggregate quantities of 4635, 1542, 5773, 2394, and 5097 units.

This stage is crucial because it bridges forecasting outputs with medium-term production decisions. The conversion factor approach enables the two variants to be represented at the family level so that aggregate planning can be performed more consistently. However, an aggregate plan may still hide capacity constraints in specific work centers—hence the need for item-level MPS and RCCP verification.

Strategy Selection and MPS Generation (Britan and Hax Method)

The cost parameters used were IDR 10,000 inventory/unit/period, IDR 40,000/unit for regular production, and IDR 45,000/unit for overtime. The selected strategy was the level strategy because it produced a lower total cost (IDR 1,109,575,000) compared to the mixed strategy (IDR 1,975, 350,000). The disaggregation process used the Britan and Hax method to determine the Master Production Schedule (MPS/JIP) for Keyna Mini Satchel and Keyna Round Satchel (Wibowo & Oktiarso, 2019). The resulting MPS for periods 1–6 is 904, 2995, 978, 3736, 1534, and 3298 units for

Table 3. Comparison of Capacity Requirement with Available Capacity

Family Keyna										
Period	Work Center 1		Work Center 2		Work Center 3		Work Center 4		Work Center 5	
	Needs	Available	Need	Available	Need	Available	Needs	Available	Need	Available
1	62.4	280.8	14.1	93.6	3.1	312	7.7	31.2	243.0	592.8
2	178.8	280.8	40.4	93.6	8.9	312	22.1	31.2	696.1	592.8
3	59.2	234	13.3	78	2.9	260	7.3	26	230.4	494
4	222.8	280.8	50.4	93.6	11.2	312	27.6	31.2	867.2	592.8
5	92.2	234	20.8	78	4.6	260	11.4	26	359.0	494
6	196.7	234	44.5	78	9.8	260	24.3	26	765.9	494
Period	Work Center 6		Work Center 7		Work Center 8		Work Center 9		Work Center 10	
	Needs	Available	Need	Available	Need	Available	Need	Available	Need	Available
1	364	31.2	87.2	187.2	211.3	1029.	56.05	436.8	224.3	998.4
2	1043	31.2	249.8	187.2	582.9	1029.	160.5	436.8	642.5	998.4
3	345.4	26	82.7	156	193.7	858	53.1	364	212.7	832
4	1300	31.2	311.2	187.2	725.8	1029	200	436.8	800.4	998.4
5	538	26	128.8	156	301.2	858	82.8	364	331.3	832
6	1148	26	274.8	156	641.2	858	176.6	364	706.9	832

Mini Satchel, while Round Satchel is 217, 216, 85, 264, 122, and 235 units.

The choice of a level strategy suggests that under the current cost structure, stabilizing production is economically preferred. In practice, level production can also reduce operational turbulence (frequent switching and rescheduling). However, once disaggregated into MPS, the actual workload distribution across work centers may become uneven because each variant imposes different processing requirements. Therefore, feasibility must be validated through RCCP.

RCCP Process Using BOLA Method and Bottleneck Identification: RCCP was applied to determine whether each work center has sufficient capacity to meet the MPS requirements for Keyna Mini Satchel and Keyna Round Satchel. The Bill of Labour Approach (BOLA) method was used to compute capacity requirements and compare them with available capacity (Irawan et al., 2020). Table 3 presents the comparison between required capacity and available capacity across ten work centers over six periods, while Table 4 summarizes fulfilled and not fulfilled status. The results indicate recurring capacity infeasibility in Work Center 5, 6, and 7, while other work centers are generally fulfilled.

Proposed Improvements and Managerial Implications

Based on Table 3, bottlenecks are concentrated in WC6, WC5, and WC7 with different severity patterns. WC6 (drying) is the most critical, with required capacity around 364–1300 hours/week versus only 26–31.2 hours/week available, indicating a structural constraint. WC5 (painting) is mainly infeasible during peak periods (2, 4, and 6) when requirements exceed capacity (e.g., 696.1>592.8; 867.2>592.8; 765.9>494 hours/week), making overtime a suitable short-term response. WC7 (eyelets) shows recurring overload (e.g., 249.82>187.2; 311.2>187.2; 274.87>156 hours/week), supporting an equipment-based capacity upgrade to prevent repeated weekly infeasibility.

Based on Table 4, WC 5, WC 6, and WC 7 cannot meet required capacity, motivating improvement proposals. For WC5, two alternatives were evaluated: adding nine painting

Table 4. Description Capacity Requirement With Available Capacity

Period	Family Keyna									
	WC1	WC2	WC3	WC4	WC5	WC6	WC7	WC8	WC9	WC 10
1	√	√	√	√	√	-	√	√	√	√
2	√	√	√	√	-	-	-	√	√	√
3	√	√	√	√	√	-	√	√	√	√
4	√	√	√	√	-	-	-	√	√	√
5	√	√	√	√	√	-	√	√	√	√
6	√	√	√	√	-	-	-	√	√	√

Note: √ = Fulfilled ; - = Not Fulfilled

Table 5. Alternative Strategy Work Center 5

Alternative Strategy Work Center 5 (Painting Machine)				
	Solution	Action	Capacity (hours/week)	Note
1	Adding Machine	Add 9 Painting Machines	867 → 874	Fulfilled
2	Overtime	Add 4 Hours	867 → 889	Fulfilled

Table 6. Alternative Strategy Work Center 6

Alternative Strategy Work Center 6 (Drying Machine)				
No	Solution	Action	Capacity (hours/week)	Note
1	Adding Machine	Add 41 drying machines	1300 → 1310	Fulfilled
2	Provide a special hot room for the drying process	Create a special room for the drying process	1300 → 10140	Fulfilled

machines or adding four overtime hours (Table 5). Overtime was selected because it can satisfy demand while optimizing the use of existing resources, though it requires overtime compensation and careful management of fatigue and quality. For WC6, alternatives included adding 41 drying machines or providing a special heated room for the drying process (Table 6). The heated room option was selected because it substantially increases effective capacity and uses an available unused room; however, it introduces operational risks related to temperature and humidity control and potential additional energy costs. For WC7, alternatives included adding four eyelet machines or replacing the strap hole machine with a rope machine (Table 7). The replacement option was selected due to its large capacity improvement, although it requires investment cost (IDR 107,500,000) and implementation readiness (installation time and operator training). Table 8 summarizes the effectiveness and risk considerations for each selected alternative.

Overall, these actions demonstrate that capacity feasibility in an MTS environment is best improved through targeted bottleneck interventions rather than uniform capacity expansion, because the RCCP results clearly localize constraints at specific work centers and periods.

Beyond identifying bottleneck work centers, the proposed improvement alternatives were also evaluated in terms of their technical, financial, and operational feasibility. From a technical perspective, the recommended actions are compatible with the company's existing manufacturing system because they do not require substantial changes to product design, routing sequences, or production workflows. The overtime strategy for the painting process utilizes the existing equipment and workforce, while the provision of a special heated room for the drying process improves production continuity without altering the production sequence. Likewise, replacing the strap hole machine with a rope machine increases production capacity while remaining compatible with the existing production system. From a financial perspective, overtime was selected for WC5 because it satisfies the required capacity with minimal capital investment, whereas the heated room for WC6 requires relatively moderate investment compared with purchasing additional drying machines. Although replacing the strap hole

Table 7. Alternative Strategy Work Center 7

Alternative Strategy Work Center 7 (Eyelet Machine)				
No	Solution	Action	Capacity (hours/week)	Note
1	Adding Machine	Adding 4 Eyelet Machines	311 → 313	Fulfilled
2	Rope Machine	Replacing the Rope Machine	311 → 2247	Fulfilled

Table 8. Evaluation of Selected Alternative Strategies

Consequences of Selected Alternative Strategies			
WC	Selected Alternative Strategies	Effectiveness	Action (Risk)
WC 5	Overtime	Can meet product demand, operational efficiency, and optimal use of existing capacity.	The company must prepare overtime pay for employees.
WC 6	Providing a Special Heated Room for the Drying Process	Can meet product demand and has large capacity.	The company must continuously control the temperature and humidity
WC 7	Replacing the Strap Hole Machine	Can meet product demand and the new strap hole machine has large capacity.	Requires a cost of IDR 107,500,000 for purchasing the new strap hole machine

Table 9. Comparison of Current Company Strategy and Proposed Strategy

Strategy	Demand Forecasting	Production Planning
Current Strategy	The company uses a simple forecasting method based on historical sales data.	Capacity planning is based on forecasted demand and available production capacity.
Proposed Strategy	Using the ANN method that utilizes historical sales data, minimizing overstock or understock.	Using RCCP to evaluate whether the available production capacity can meet the projected demand.

machine requires an investment of IDR 107,500,000, it provides sufficient capacity to eliminate the bottleneck identified through RCCP and is expected to improve long-term production efficiency. Operationally, these recommendations can be implemented within the company's existing make-to-stock production system with limited disruption to daily production activities. Therefore, the proposed alternatives are considered practical and feasible for supporting future production planning while improving overall capacity utilization.

The results provide several practical implications for Company XYZ. First, adopting ANN-based forecasting creates a structured basis for weekly production decisions, reducing reliance on judgement-only forecasting and lowering the risk of overstock or stockout. Second, the integration of aggregate planning and MPS links demand expectations to a detailed weekly schedule, improving coordination between planning and execution. Third, RCCP (BOLA) acts as an early feasibility screen that prevents the company from committing to plans that are cost-efficient but infeasible in execution. Most importantly, the bottleneck results focus managerial attention on targeted interventions at WC5–WC7, where capacity expansion or process-support changes will have the largest impact on overall throughput. In short, the proposed approach shifts the planning practice from "forecast → produce" to "forecast → plan → verify capacity → improve bottlenecks," which is more consistent with effective MTS production management.

As summarized in Table 9, the company's current strategy relies on simple historical-based forecasting and informal capacity planning. The proposed strategy introduces ANN forecasting and RCCP-based capacity evaluation to ensure that forecast-driven schedules remain feasible at the work-center level. This comparison highlights that the main contribution of the proposed approach is not only improved forecasting but also improved execution feasibility through bottleneck-oriented capacity management.

Discussion in Relation to Previous Studies: This study reinforces the view in prior research that demand forecasting and production planning should be integrated, particularly under demand uncertainty in make-to-stock settings (Jamalnia et al., 2019; Babaveisi et al., 2023; Qasim et al., 2024). As summarized in Table 9, Company XYZ's current practice relies on simple historical judgement and informal capacity considerations, which may produce plans that appear reasonable but are not validated for execution feasibility. In contrast to many forecasting-focused studies that primarily report prediction performance, this study extends ANN forecasts into aggregate planning and an item-level MPS, and then verifies feasibility using RCCP-BOLA, providing a complete forecast-to-execution planning pipeline (Babaveisi et al., 2023). Recent research also combines ANN with optimization models for production planning under demand volatility; however, the linkage to aggregate planning–MPS translation and RCCP-based bottleneck validation is often not the central focus (Babazadeh et al., 2024). The RCCP results further show that infeasibility is concentrated in a limited number of work centers (WC5–WC7) rather than across the entire system, implying that bottleneck-oriented interventions are more effective than broad capacity expansion. Therefore, the proposed approach contributes not only by generating demand forecasts, but by translating them into feasible schedules and directing managerial action to the true capacity constraints.

IV. CONCLUSION

This study proposed an integrated planning framework for Company XYZ's Keyna bag production in a make-to-stock (MTS) environment by linking ANN-based demand forecasting, aggregate production planning, MPS generation (Britan and Hax), and RCCP capacity verification using Bill of Labour Approach (BOLA). Using 60 weeks of historical demand data (7 January 2023-24 February 2024), the selected ANN model generated six weeks demand forecast of 2601, 4635, 1542, 5773, 2394, and 5097 units. These forecasts were then translated into an aggregate plan and disaggregated into an item level MPS for Keyna Mini Satchel and Round Satchel. The cost-based comparison between planning strategies showed that the level strategy was preferable, yielding a lower total cost (IDR 1,109,575,000) than the mixed strategy (IDR 1,975,350,000), indicating that stable production is economically favorable under the company's current cost structure.

Capacity feasibility analysis using RCCP revealed that the production plan is not constrained uniformly across the system; instead, bottlenecks are concentrated in specific work centers. The comparison of capacity requirements and available capacity identified recurring infeasibility in WC 5 (painting), WC 6 (drying), and WC 7 (eyelets). Accordingly, targeted improvement alternatives were proposed and evaluated. For WC5, overtime was selected to satisfy demand while utilizing existing resources efficiently, with the trade-off of additional labor cost. For WC6, the company selected the provision of a special heated room for drying, a process-support intervention that substantially increases effective capacity but requires continuous control of temperature and humidity. For WC7, replacing the strap hole/eyelet-related machine with a rope machine was selected to achieve a large capacity increase, albeit with investment cost implications. Overall, the results indicate that combining forecasting with RCCP provides a more reliable decision-support basis than relying on simple historical judgement alone, because it not only estimates demand but also verifies whether the resulting schedule is executable at the work-center level and directs managerial attention to the true bottlenecks.

Several limitations of this study should be noted. First, the forecasting model uses only historical data, so external factors (e.g., promotions or market conditions) are not considered. Second, the capacity analysis assumes 100% machine reliability and standard processing times, whereas real-world conditions can be affected by downtime, rework, and operator variation. Third, the cost evaluation only includes the main components (regular, overtime, and inventory), while other costs such as energy/monitoring for the heated room and implementation costs have not been modeled. Future research could include downtime/availability data.

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