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Demand Forecasting and Capacity Planning for Eyewear Cleaner Products at PT RAS

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ABSTRACT: This study examines the production capacity challenges faced by PT RAS following the launch of RAS Gleam in November 2023. The significant increase in demand has put pressure on the production, filling, and packing workstations, leading to potential bottlenecks in fulfilling orders. To address this issue, time-series forecasting was applied to project demand for the next year for three products: RAS Self-Cleaning, RAS Instant Antifog, and RAS Gleam. These forecasts guided the development of a Master Production Schedule (MPS) to align production with projected demand and informed Rough-Cut Capacity Planning (RCCP) to identify capacity constraints. The analysis revealed gaps between available and required work hours, particularly during peak periods. To bridge these gaps, the study proposed workforce management solutions, including a controlled overtime system and the strategic use of freelance workers for filling and packing workstations. These measures enabled PT RAS to meet demand while complying with Indonesian labour regulations. The findings demonstrate how accurate forecasting, workforce optimization, and flexible labour management enhance production efficiency and operational flexibility at PT RAS. By forecasting demand, PT RAS can prepare for future conditions, ensuring it has the capacity to meet demand.

Keywords: Demand Forecasting, MPS, RCCP, Workforce Management.

INTRODUCTION

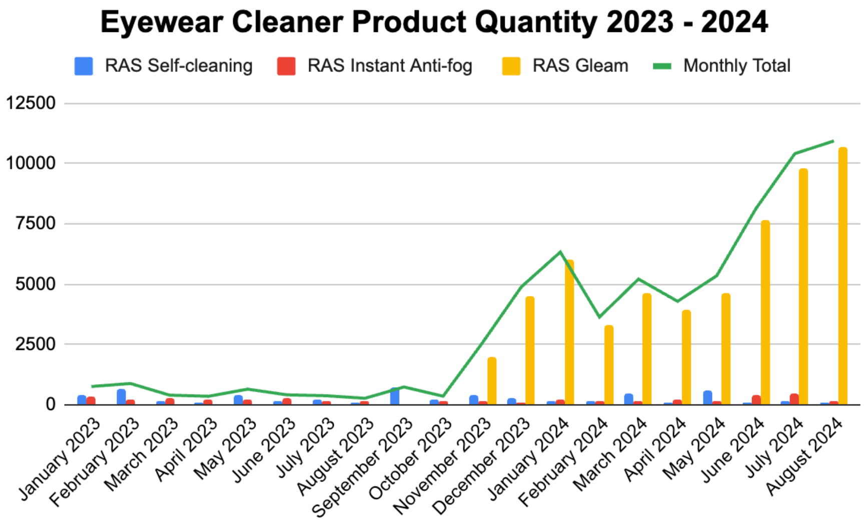
In today's increasingly competitive business landscape, companies face ongoing pressure to enhance product quality, reduce lead times, optimize costs, and improve customer satisfaction.

These challenges are particularly acute for small and medium-sized enterprises (SMEs) in the manufacturing sector, which often contend with resource constraints. SMEs historically struggle to strike a balance between efficient production processes and rising customer expectations, impacting both their market competitiveness and ability to maintain customer satisfaction (Briseño-Oliveros et al., 2019; Debellut et al., 2018; Farida & Setiawan, 2022).

To achieve sustainable and profitable growth, companies need to anticipate and adapt to customer demands through effective forecasting and strategic production planning. By incorporating sustainability into their core business strategies, organizations can balance economic growth with environmental and social responsibilities, ensuring long-term success (Boussalis et al., 2012; Lapping et al., 2014; Zopounidis & Lemonakis, 2024). Demand forecasting is critical for SMEs to achieve economic sustainability and address fluctuating demand. Accurate forecasts enable efficient resource allocation, reduce seasonality impacts, and enhance competitiveness, especially for SMEs with limited resources and data (Fiori & Foroni, 2019). Accurate forecasts also mitigate the risks of supply shortages and excess inventory, ultimately enhancing customer service and reducing obsolescence costs (Allred et al., 2021; Loh, 2015; Van Belle et al., 2021).

For manufacturers like PT RAS, a nanotechnology-based manufacturer, aligning sales and production planning is critical to improving operational efficiency, meeting customer demands, and reducing costs(Dang et al., 2015; Healey, 1998). Demand forecasting supports a variety of short-term planning decisions, such as production scheduling and inventory management(Atherton, 2013; Liu et al., 2018; Wang et al., 2020). Improving forecast accuracy is essential for building a more agile supply chain, helping manufacturers respond effectively to market fluctuations. The eyewear cleaner product category is the backbone of PT RAS and comprises three primary products: RAS Self-Cleaning, RAS Instant Antifog, and Gleam. RAS Self-Cleaning was the first product launched in this category, followed by RAS Instant Antifog. The launch of Gleam in November 2023 triggered a significant increase in both revenue and product demand at PT RAS, putting unprecedented pressure on the company's existing production capabilities.

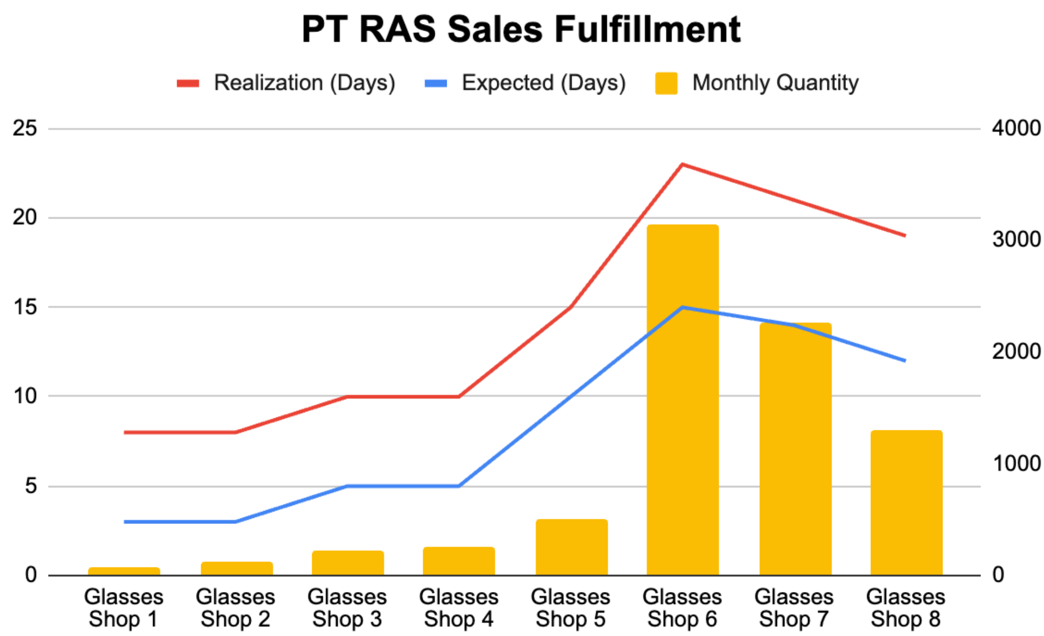
Figure 1. Sales of Eyewear Cleaner Product Category 2023 – 2024 in PT RAS



Source: Primary data of PT RAS

Figure 1 shows the number of sales in the eyewear cleaner product category from January 2023 until August 2024 in PT RAS. The significant increase in demand due to the launch of Gleam in November 2023 introduced new challenges for PT RAS's resources, as the operational department continues to function with its current workforce for production. As a result, over the past six months, the order fulfilment process at PT RAS has experienced delays. Figure 2 shows a comparison between the expected sales fulfilment (in days) and the actual sales fulfilment (in days) at PT RAS.

Figure 2. PT RAS Sales Fulfilment Condition
(Expected Compared to the Realization of Order Fulfilment)



Source: Primary data of PT RAS

According to Figure 2, a gap exists between the expected and actual days of sales fulfilment. This discrepancy arises because PT RAS's monthly available capacity falls short of meeting the monthly order volume, especially during periods of significantly increased demand for Gleam. Table 1 shows the current production capacity at PT RAS in 3 work station : Production, Filling, and Packing. The company's existing resources, 33 hours per month in the production station and 70 hours per month in the filling and packing stations became insufficient to meet this heightened demand. As a result, PT RAS faced production bottlenecks, delayed order fulfillment, and operational inefficiencies.

Table 1. PT RAS Current Production Capacity

PT RAS Current Production Capacity				
Workstation	**Product**	**Regular Capacity (Bottles/Month)**	**Overtime Capacity (Bottles/Month)**	**Outsource Capacity (Bottles/Month)**
Production	RAS Instant Antifog	167	Adjusted by order quantity	850
	RAS Self-cleaning	222	Adjusted by order quantity	0
	RAS Gleam	13333	Adjusted by order quantity	0
Filling	All Products	5600	Adjusted by order quantity	0
Packing	All Products	5600	Adjusted by order quantity	0

Source: Primary data of PT RAS

To maintain consistent daily and monthly production, PT RAS has yet to adopt a proactive approach to production planning that integrates sales forecasting with historical sales data. This reactive approach has led to recurring issues in order fulfilment, including delays that affect customer satisfaction and reduce operational efficiency. For PT RAS, accurate demand forecasting is essential to enhance production scheduling, inventory management, and resource allocation, especially as the company manages multiple product lines within the eyewear cleaner category.

Given the operational challenges posed by the rapid increase in demand, particularly following the launch of Gleam, this study examines the application of time-series forecasting to predict demand and assesses PT RAS's capacity to meet projected needs. A Master Production Schedule (MPS) is developed to align production resources with anticipated sales, while Rough-Cut Capacity Planning (RCCP) evaluates whether PT RAS's current capacity can accommodate future demand. Additionally, the study proposes strategic business solutions, such as implementing structured overtime policies, engaging freelance workers, and considering automation, to address capacity gaps effectively and reduce fulfilment delays.

The research objectives are as follows:
1. Forecast demand for RAS Self-Cleaning, RAS Instant Antifog, and RAS Gleam based on historical sales data.
2. Develop a Master Production Schedule (MPS) that aligns production capacity with forecasted demand, particularly addressing the increased demand after Gleam's launch
3. Identify capacity shortfalls using Rough-Cut Capacity Planning (RCCP).
4. Propose business solutions, including structured overtime policies and hiring freelance workers, to address capacity constraints and improve order fulfilment.

Recent literature has highlighted the critical role of accurate demand forecasting and strategic production planning in enhancing operational efficiency, particularly within SMEs. For instance, Fauzan (2020) explored the application of time-series forecasting models, such as single exponential smoothing, to address inventory management challenges and reduce the risk of overstocking in the healthcare sector. Nirmala et al., (2021)extended this understanding by demonstrating the efficacy of exponential smoothing during the COVID-19 pandemic to stabilize inventory levels and optimize product availability. Additionally Santosa et al., (2023) introduced a novel integration of smart forecasting methods with fuzzy logic to improve production scheduling, emphasizing the need to manage stock levels effectively and adapt to fluctuating demand. Although these studies contribute valuable insights into forecasting and production management, they often do not address the specific challenges faced by SMEs managing product lines with sudden demand increases, such as those encountered by PT RAS.

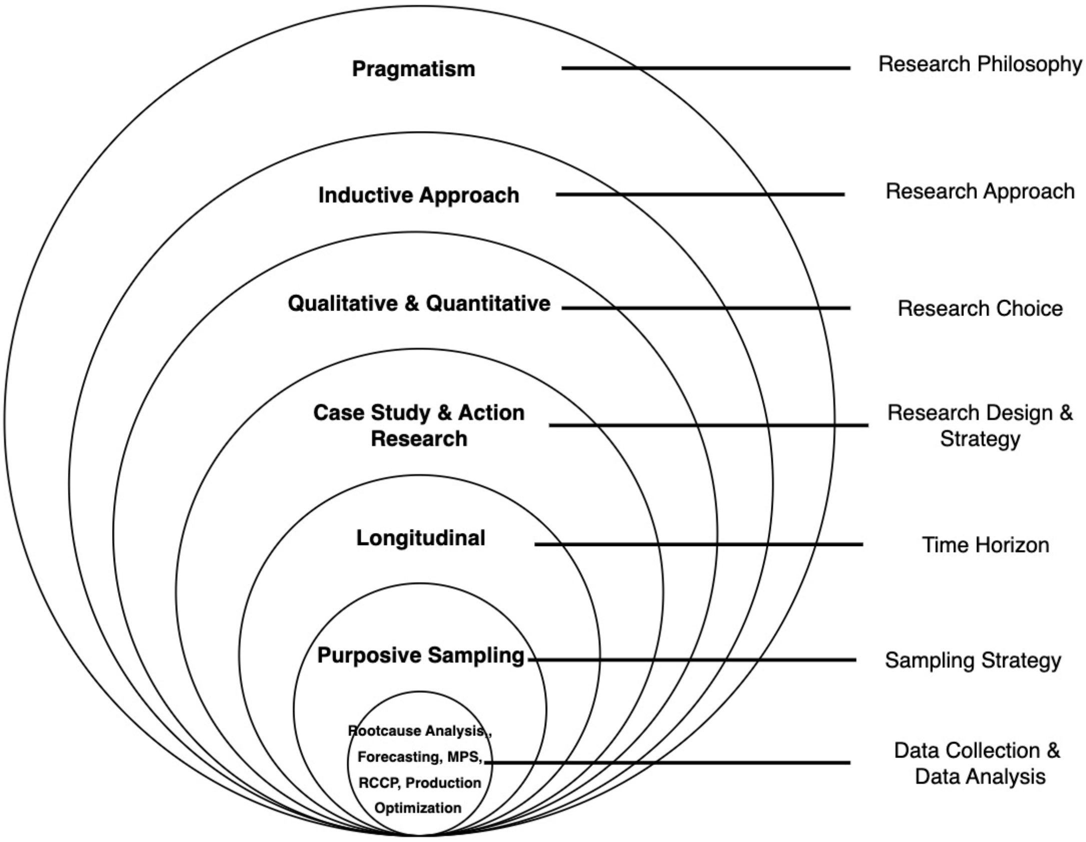
This study advances existing knowledge by applying tailored time-series forecasting models, including the linear trend line and double exponential smoothing, to address the unique operational challenges experienced by PT RAS following the launch of its Gleam product. Unlike prior research, this work integrates Master Production Scheduling (MPS) and Rough-Cut Capacity Planning (RCCP**)** to ensure that production capabilities are effectively aligned with projected demand. Moreover, it introduces the strategic use of structured overtime and freelance labour as flexible workforce management strategies. This approach not only ensures compliance with labour regulations but also enables PT RAS to expand its operational capacity during peak demand periods without overburdening its permanent staff. By bridging the gap between theoretical forecasting models and practical workforce optimization, this research offers an enhanced framework for SMEs aiming to balance efficiency, cost management, and adaptability surpassing traditional methods that do not incorporate such comprehensive solutions.

METHOD

The research onion is a conceptual framework proposed by Saunders et al. (2016) that outlines the various layers involved in developing a research design. It consists of seven layers, including philosophy, methodology, methods, strategies, time horizons, and techniques and procedures. Each layer guides researchers in making informed choices about how to approach their research questions and collect and analyse data (Melnikovas, 2018).

The research onion framework provides a helpful structure for capacity planning in operations management by systematically guiding researchers through the essential stages of research design. This framework aids in aligning philosophical foundations, methodological choices, and specific techniques with the study's objectives, ensuring a coherent and well-structured approach. Through its layered approach, the research onion allows for comprehensive planning that helps address complex issues in capacity management, ultimately contributing to a robust and reliable research outcome(Alturki, 2021).

Figure 3. Research Onion



Source: Author Analysis

Figure 2 depicts research design of this study, which was developed using the Research Onion Framework. The research design follows a quantitative approach to evaluate PT RAS's production capacity and forecasting processes. Historical sales data from January 2023 to June 2024 was used to develop time-series forecasts for RAS Self-Cleaning, RAS Instant Antifog, and Gleam. These forecasts formed the basis for a Master Production Schedule (MPS), which was used to align monthly production levels with projected demand. The Rough-Cut Capacity Planning (RCCP) method was then applied to determine whether the company's existing resources such as labor, machinery, and working hours were sufficient to meet the production requirements outlined in the MPS. The combined use of MPS and RCCP facilitates a comparison between available and required capacity, helping PT RAS plan effectively to fulfil forecasted demand.

This research employs a mixed-methods approach, combining both qualitative and quantitative data collection and analysis to address the operational challenges at PT RAS. The quantitative component focuses on analysing historical sales data to create a demand forecast for PT RAS's key products. This forecast forms the basis for quantitative assessments like the Master Production Schedule (MPS) and Rough-Cut Capacity Planning (RCCP), which align production capacity with forecasted demand.
The qualitative aspect involves focus group discussions key stakeholders within the company. These discussions provide insights into operational bottlenecks, production constraints, and order

fulfilment challenges. By integrating qualitative insights with quantitative data, this research provides a comprehensive understanding of PT RAS's production and capacity issues, enabling tailored, actionable solutions to enhance demand management, capacity planning, and fulfilment processes

Data Collection

1. Sales Data Collection
   The sample data used in this study includes sales records for PT RAS's eyewear cleaner products. Sales records for RAS Self-Cleaning, RAS Instant Antifog, and Gleam were collected for the period from January 2023 to June 2024. This data was critical for generating demand forecasts using time-series models. The data was collected from PT RAS's internal sales systems, which track monthly sales volumes for each product.
2. Production Capacity Data
   Data on production capacity was sourced from PT RAS's internal records. The company operates its production station for 33 hours per month, while both the filling and packing stations operate for 70 hours each per. This data was used to assess whether the current capacity was sufficient to meet forecasted demand.
3. Focus Group Discussion
   Focus Group Discussion (FGD) conducted with key stakeholders, including production and operations managers at PT RAS, to gather insights into the company's operational challenges and potential solutions for capacity constraints. These FGD provided qualitative data that supplemented the quantitative analysis of sales and production data.

Data Analysis

Demand Forecasting

Demand forecasting involves predicting future sales using historical data. In this study, we applied multiple time-series models, including linear trend analysis and exponential smoothing, to estimate demand for each product line. Accurate demand forecasting is fundamental to the production and operational success of manufacturing companies, emerging as a key factor that propels supply chain efficiency. Reliable forecasts are vital for sustaining effective and seamless operations within a company (Li et al., 2021).

One forecasting method is Time Series Forecasting. Time series forecasting specifically uses historical data to predict future demand patterns by analysing trends, seasonality, and volatility within the data. By understanding and leveraging these patterns, companies can make informed decisions to manage fluctuations in demand, which is essential for maintaining operational efficiency and reducing costs (Więcek & Kubek, 2024).

Time-series forecasting models were applied to predict future demand for each product category. Multiple models were considered, including linear trend analysis and exponential smoothing. The accuracy of the forecasts was evaluated using several metrics, including Mean Absolute Percentage Error (MAPE), Mean Absolute Deviation (MAD), and Mean Squared Deviation (MSD). These metrics are essential for determining the reliability of each forecasting model and selecting the most accurate model for each product category (Jacobs & Chase, 2021).

Time-series forecasting will be used to analyze historical sales data from January 2023 to August 2024. The projection predicts future demand for RAS Instant Antifog, RAS Self-Cleaning, and RAS Gleam over the next year. Time series forecasting was utilized to provide an accurate demand forecast for RAS Instant Antifog, RAS Self-Cleaning, and RAS Gleam, which will help with production and capacity planning.

Master Production Schedule (MPS)

The Master Production Schedule (MPS) is a production planning tool that defines optimal production quantities and schedules to meet customer demand efficiently. It helps balance production factors by setting release dates and quantities for finished goods, minimizing costs related to production, inventory, and overtime. Acting as a blueprint for production, the MPS optimizes resource use and helps avoid shortages or excessive inventory, making it essential for managing complex manufacturing systems facing demand fluctuations and production uncertainties (Martín et al., 2020).

The MPS is used to align production with forecasted demand. By stabilizing production levels across the months, the MPS ensures that the company can consistently meet customer demand without overproducing or underproducing. The MPS also helps in planning for resource allocation, especially during high-demand periods (Jacobs & Chase, 2021). In this study, the Master Production Schedule (MPS) was developed to align PT RAS's production capacity with the forecasted demand for RAS Self-Cleaning, RAS Instant Antifog, and RAS Gleam.

The MPS is constructed based on the demand forecasts generated from the time-series models and the monthly production capacity available at PT RAS, as outlined in PT RAS Current Production Capacity. The goal of the MPS is to ensure that PT RAS can consistently meet customer demand by balancing production capacity across different product lines.

The MPS uses forecasted demand to determine how much of each product should be produced each month. By comparing the demand forecast with the company's available production resources, the MPS helps PT RAS plan its production schedules in such a way that it maximizes the utilization of available capacity. This process minimizes overproduction, which can result in excessive inventory, and underproduction, which can lead to stockouts and customer dissatisfaction. With the MPS, PT RAS able to allocate resources efficiently, ensuring that production remains in line with the forecasted demand and that any potential shortfalls in capacity are identified early. This allows PT RAS to adjust production output as necessary, ensuring optimal production levels without overwhelming existing capacity or creating unnecessary delays.

Rough-Cut Capacity Planning

Capacity refers to the maximum output that a production facility can generate within a specific time frame. It represents the level of output during a given period and indicates the highest possible production quantity achievable within that time. Capacity can be adjusted to accommodate fluctuating sales levels, as reflected in the master production schedule (Setiabudi et al., 2018). Capacity planning plays a crucial role in operations management, focusing on adjusting resource levels to effectively meet demand. By optimizing resource allocation, capacity planning helps avoid the negative impacts of underutilization or overutilization, such as increased costs and reduced service quality. (Alalmai et al., 2020).

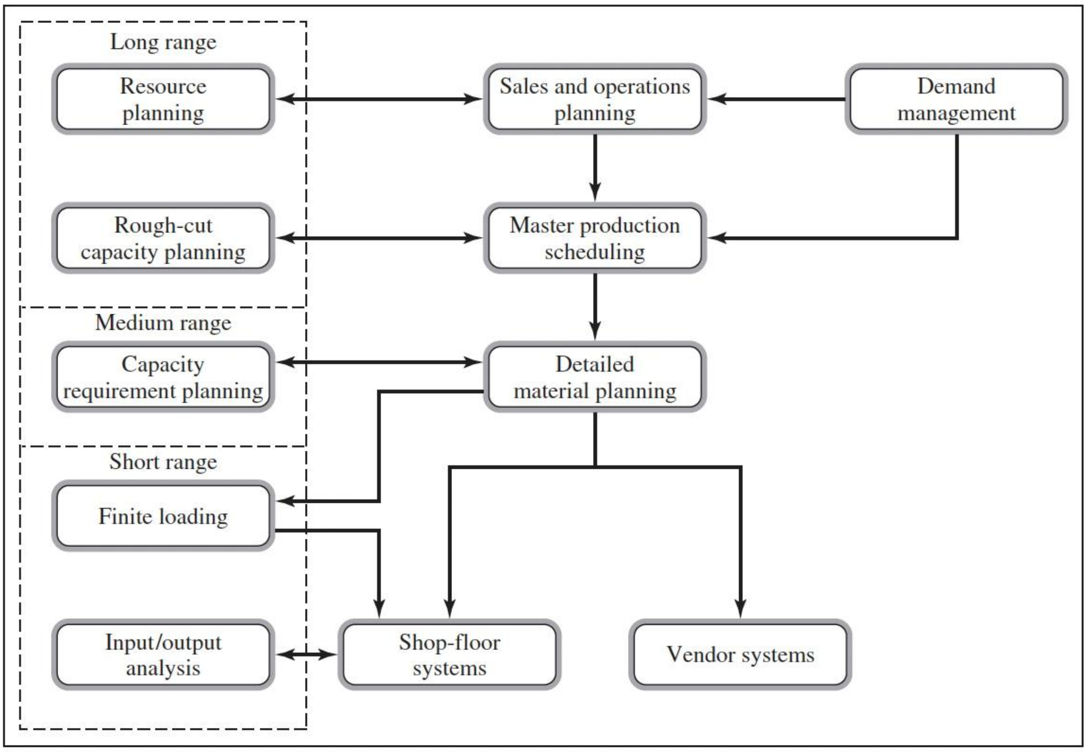


Figure 4. Capacity Planning in the MPC System
(Jacobs et al., 2024)

Figure 3 highlights the crucial role of capacity planning within the Manufacturing Planning and Control (MPC) system. In the long-term, capacity planning encompasses both Resource Planning and Rough-Cut Capacity Planning (RCCP). Resource Planning ensures that enough workforce, equipment, and materials are available to achieve the strategic production goals set by the Sales and Operations Plan (Jacobs et al., 2024).In conjunction with this, RCCP focuses on verifying whether the proposed Master Production Schedule (MPS) can be realistically achieved with the available resources. These two tools are essential for ensuring that long-term production plans are feasible.

RCCP was applied to assess whether PT RAS's available resources were sufficient to meet the production requirements laid out in the MPS. By evaluating the forecasted demand against the company's available production capacity, RCCP provided a high-level view of potential capacity constraints. This analysis was particularly focused on three critical areas: production, filling, and packing stations.

For each product : RAS Self-Cleaning, RAS Instant Antifog, and RAS Gleam, the RCCP analysis calculated the total number of production hours needed to meet the forecasted demand. These production hours were then compared to the monthly capacity available at PT RAS. For example, the filling station, with a capacity of 70 hours per month, was analysed to determine if it could handle the required output based on the MPS.

The RCCP highlighted where additional capacity would be necessary to meet demand, enabling PT RAS to make informed decisions about resource allocation. By identifying capacity gaps, RCCP helped PT RAS take proactive steps to ensure smooth production operations, such as scheduling overtime for employees or bringing in temporary freelance workers to supplement the existing workforce.

RESULT AND DISCUSSION

Time – Series Forecasting

For the time-series forecasting of RAS Self-Cleaning, RAS Instant Antifog, and Gleam will be using sales data from January 2023 until August 2024, and four models were employed: Moving Average, Exponential Smoothing, Linear Trend Line, and Double Exponential Smoothing. The accuracy of each model was evaluated using the following error measurement metrics: Mean Absolute Deviation (MAD), Mean Absolute Percentage Error (MAPE), and Mean Squared Deviation (MSD). The model with the lowest error values for each product was selected as the most accurate forecast for that specific product. Here are the results:

RAS Self-Cleaning

After evaluating the performance of all four models, the Linear Trend Line model produced the lowest error values, indicating that this model provided the most accurate forecast for RAS Self-Cleaning. The nature of the demand for this product, which shows a fluctuating but overall decreasing trend, aligns well with the capacity of the Linear Trend Line model to account for changes in trend and seasonality over time for this product.

Table 2. Demand Forecast Error Measurement for RAS Self-Cleaning

Forecast Error Measurement	Moving Average	Exponential Smoothing	Linear Trend Line	Double Exponential Smoothing
MAPE	92.5	88.1	**80.2**	102.8
MAD	177.4	176.9	**161.8**	196.1
MSD	44499.1	40997	**35890.9**	54063.4

Source: Author Analysis

RAS Instant Antifog

Due to the volatile and steadily increasing demand for RAS Instant Antifog, the Double Exponential Smoothing model was selected as the most accurate forecast method based on its ability to smooth out fluctuations in demand while adapting to a rising trend. This model showed the lowest error values across all error metrics (MAD, MAPE, MSD), making it the most reliable for predicting future demand for RAS Instant Antifog.

Table 3. Demand Forecast Error Measurement for RAS Instant Antifog

Forecast Error Measurement	Moving Average	Exponential Smoothing	Linear Trend Line	Double Exponential Smoothing
MAPE	62.9	57.79	58.29	**48.33**
MAD	78.6	71.55	72.92	**70.45**
MSD	10889	9326.5	8942.29	**8928.58**

Source: Author Analysis

Gleam
Since Gleam is a relatively new product, the Linear Trend Line was determined to be the most accurate model. This product showed a steady growth trajectory since its launch in November 2023, and the Linear Trend Line model was best suited for capturing this upward pattern in sales. Error measurement metrics confirmed that the Linear Trend Line had the lowest MAD, MAPE, and MSD values for Gleam, making it the most appropriate choice for forecasting future demand.

Table 4. Demand Forecast Error Measurement for RAS Gleam

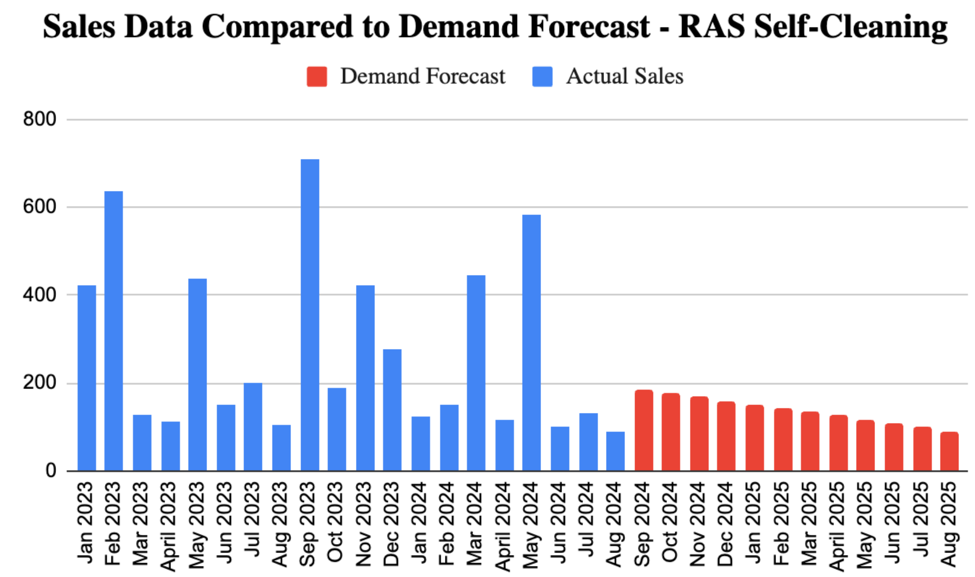
Forecast Error Measurement	Moving Average	Exponential Smoothing	Linear Trend Line	Double Exponential Smoothing
MAPE	28	33	**27**	55
MAD	2304	1561	**1324**	1904
MSD	8679528	3192882	**2318925**	6688182

Source: Author Analysis

By using these selected models, PT RAS can more accurately anticipate the future demand for each of its core products and plan production schedules accordingly. The application of time-series forecasting models, such as Linear Trend Line for RAS Self-Cleaning, Double Exponential Smoothing for RAS Instant Antifog, and Linear Trend Line for RAS Gleam, has allowed the company to fine-tune its production planning processes. Each model has been carefully selected based on the lowest error measurements (MAD, MAPE, and MSD), ensuring the highest level of forecast accuracy for each product.

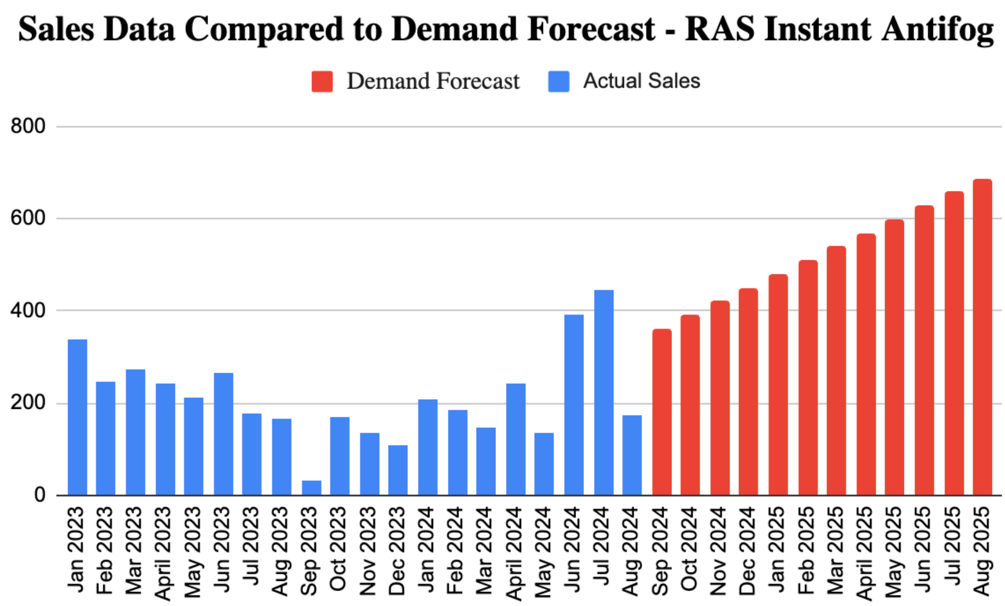
These forecasts were instrumental in developing the Master Production Schedule (MPS) to align production capacity with forecasted demand. The use of these accurate models positions PT RAS to respond more swiftly to market fluctuations and customer needs, creating a more agile production system capable of scaling up or down depending on demand projections.

Figure 5. RAS Self-Cleaning Sales Data and Demand Forecast Result



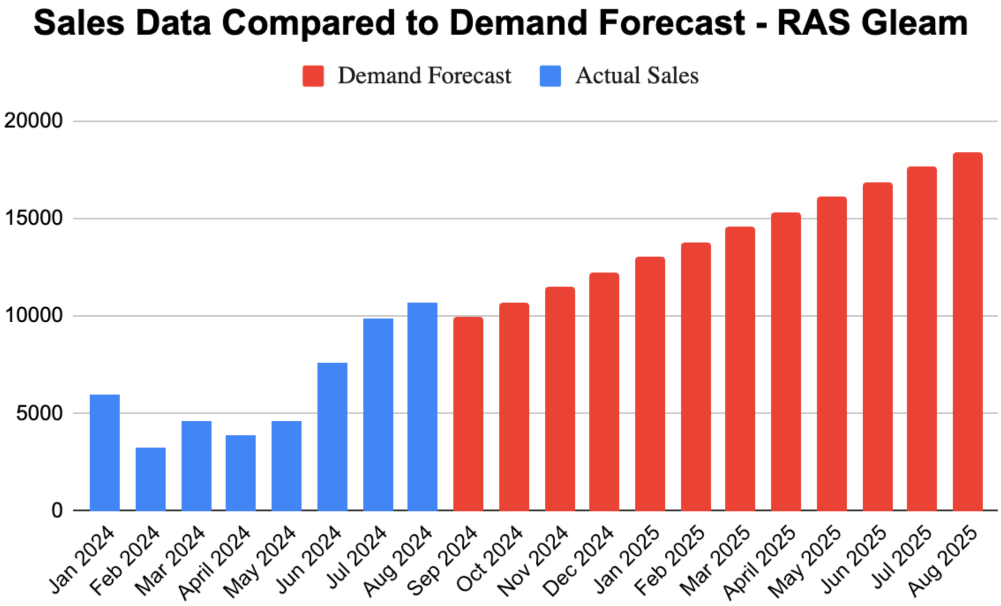
Source: Author Analysis

Figure 6. RAS Instant Antifog Sales Data and Demand Forecast Result



Source: Author Analysis

Figure 7. RAS Gleam Sales Data and Demand Forecast Result



Source: Author Analysis

Figure 4 until Figure 6 shows the result of demand forecasts compared to the sales data that has been generated by PT RAS, illustrating how close the selected forecasting models are to real-world sales trends. Table 2 will be shows the details of demand forecast for PT RAS for the next 1 year:

Table 5. PT RAS Demand Forecast Result

Demand Forecast Result				
Month	RAS Self-Cleaning	RAS Instant Antifog	RAS Gleam	Total Demand (Monthly)
September 2024	186	362	9946	10494
October 2024	178	391	10715	11285
November 2024	169	421	11485	12075
December 2024	160	451	12254	12865
January 2025	152	480	13024	13656
February 2025	143	510	13793	14446
March 2025	134	539	14563	15236
April 2025	126	569	15332	16027
May 2025	117	598	16102	16817
June 2025	109	628	16871	17608
July 2025	100	658	17640	18398
August 2025	91	687	18410	19188

Source: Author Analysis

This forecast demand that shows in the Table 2 will be used to generate the Master Production Schedule (MPS), ensuring that production levels match forecasted demand throughout the year.

The data will also be used to support Rough-Cut Capacity Planning (RCCP), which will focus on determining the labour hours necessary at key production stations such as production, filling, and stickering-packing.

RCCP will ensure that the necessary manpower is available at each station to satisfy the MPS's production targets, allowing PT RAS to effectively manage capacity and avoid labour shortages.

Master Production Schedule

The MPS was created based on the expected demand for RAS Self-Cleaning, RAS Instant Antifog, and Ras Gleam from September 2024 to August 2025. The MPS's purpose is to match production output with predicted demand by employing the Level Production technique, which involves setting production at the maximum regular capacity for each product per month.

RAS Self Cleaning

Table 6. MPS of RAS Self-Cleaning

MPS RAS Self-Cleaning			
Period	**Forecast**	**Balance**	**MPS Regular**
Period 0		0	
Period 1	186	36	222
Period 2	178	80	222
Period 3	169	133	222
Period 4	160	195	222
Period 5	152	43	
Period 6	143	122	222
Period 7	134	210	222
Period 8	126	84	
Period 9	117	189	222
Period 10	109	80	
Period 11	100	202	222
Period 12	91	111	

Source: Author Analysis

Forecast demand for RAS Self-Cleaning declines significantly during the year, beginning with 186 units in Period 1 and falling to 91 units by Period 12. The MPS maintains regular monthly production capacity at 222 units per month, resulting in excess production during periods of low demand. By maintaining steady output, the MPS builds inventory during low-demand months, guaranteeing that there is enough stock to meet future demand variations.

RAS Instant Antifog

Table 7. MPS of RAS Instant-Antifog

MPS RAS Instant-Antifog				
Period	**Forecast**	**Balance**	**MPS Regular**	**Subcontract**
Period 0		0		
Period 1	362	655	167	850
Period 2	391	264		
Period 3	421	10	167	
Period 4	451	577	167	850
Period 5	480	96		
Period 6	510	604	167	850
Period 7	539	64		
Period 8	569	513	167	850
Period 9	598	81	167	
Period 10	628	470	167	850
Period 11	658	829	167	850
Period 12	687	142		

Source: Author Analysis

Demand for RAS Instant Antifog is expected to rise from 362 to 687 units between Periods 1 and 12. The MPS sets regular production at 167 units per month, with 850 units subcontracted monthly to accommodate demand. While subcontracting provides adequate supply, the expenses are greater than in-house production. Given the cost gap, PT RAS may benefit from assessing the long-term viability of growing internal manufacturing capacity. Reducing reliance on subcontracting by investing in additional resources such as machinery and labour may result in lower production costs and improved control over quality and efficiency.

RAS Gleam

The forecasted demand for RAS Gleam increases from 9,946 units in Period 1 to 18,410 units in Period 12. The MPS expects consistent production of 13,333 units each month. During peak seasons, overtime is used to accommodate increased demand. This combination of regular output and overtime contributes to operational stability while allowing for flexibility during peak demand.

Table 8. MPS of RAS Gleam

MPS RAS Gleam				
Period	**Forecast**	**Balance**	**MPS Regular**	**MPS Overtime**
Period 0		0		
Period 1	9946	3387	13333	

Period 2	10715	6005	13333	
Period 3	11485	7853	13333	
Period 4	12254	8931	13333	
Period 5	13024	9241	13333	
Period 6	13793	8781	13333	
Period 7	14563	7551	13333	
Period 8	15332	5552	13333	
Period 9	16102	2783	13333	
Period 10	16871	356	13333	1111
Period 11	17640	493	13333	4444
Period 12	18410	416	13333	5000

Source: Author Analysis

Rough Cut Capacity Planning using Capacity Bill

The Rough-Cut Capacity Planning (RCCP) analysis is designed to determine whether PT RAS has the resources to satisfy its forecasted production needs for RAS Self-Cleaning, RAS Instant Antifog, and RAS Gleam. The analysis employs Capacity Bills to convert the Master Production Schedule (MPS) into exact labour hour requirements for the three primary work station : production, filling, and packing.

Routing and Standard Time Data

The Routing and Standard Time Data table outlines key details such as lot sizes, setup times, and run times for each product at each work station This information is essential for calculating the total labour hours needed for each product category, helping to ensure that capacity planning matches the forecasted demand (Jacobs et al., 2024).

The table reveals the following:

1. The Production Work Station has a monthly production capacity of 33 hours, which is split between RAS Self-Cleaning (4.5 hours), RAS Instant Antifog (4.5 hours), and RAS Gleam (24 hours).
2. Each Filling and Packing Work Station has a regular capacity of 70 hours per month and an output rate of 80 bottles per hour, for a total monthly capacity of 5,600 bottles for filling and packing.

Table 9. Routing & Standard Time Data

Product	Work Station	Lot Size	Setup Time (hours)	Run Time per Unit (hours)	Total Time (hours)
RAS Self Cleaning	Production	222	0,5	0,02025	5,00
	Filling		0,25	0,0125	3,03

Product	Work Station	Lot Size	Setup Time (hours)	Run Time per Unit (hours)	Total Time (hours)
	Packing		0,25	0,0125	3,03
RAS Instant Antifog	Production	167	0,5	0,027	5,01
	Filling		0,25	0,0125	2,34
	Packing		0,25	0,0125	2,34
RAS Gleam	Production	13333	0,5	0,0018	24,50
	Filling		0,25	0,0125	166,91
	Packing		0,25	0,0125	166,91

Source: Author Analysis

Table 6 provides a crucial framework for evaluating the labour requirements at each work station, detailing the setup durations and run rates required to meet the production needs for PT RAS. The routing table data was used to calculate the capacity requirements for each work station over the planned horizon (September 2024 - August 2025). The table below shows the total hours necessary per work station based on projected demand.

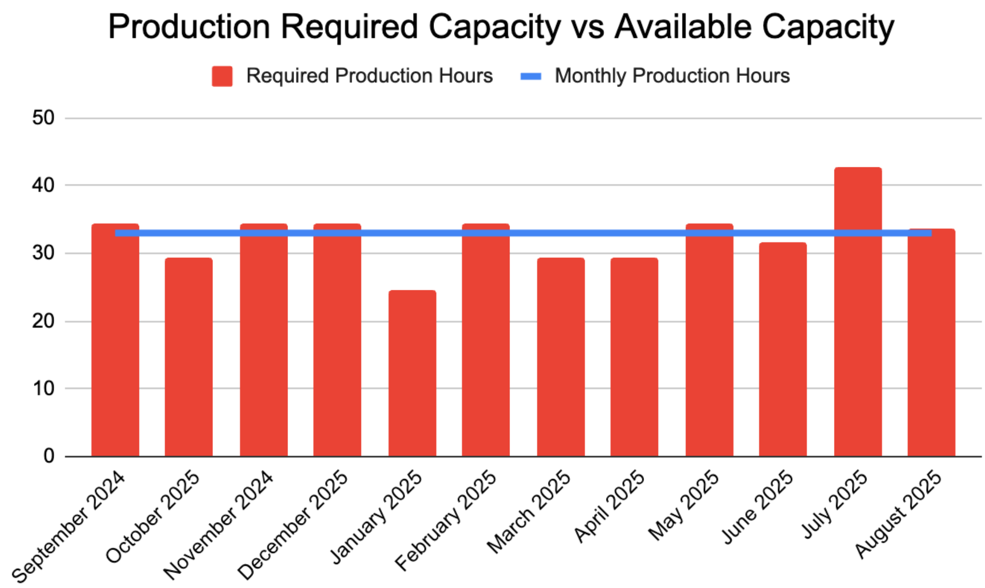
Table 10. Capacity Requirement using Capacity Bills

Capacity Requirement (In Hour)				
Period	**Production**	**Filling**	**Packing**	**Total**
Period 1	34,50	171,78	172,53	378,80
Period 2	29,49	169,68	170,18	369,36
Period 3	34,50	171,78	172,53	378,80
Period 4	34,50	171,78	172,53	378,80
Period 5	24,50	166,91	167,16	358,56
Period 6	34,50	171,78	172,53	378,80
Period 7	29,49	169,68	170,18	369,36
Period 8	29,51	169,00	169,50	368,00
Period 9	34,50	171,78	172,53	378,80
Period 10	31,55	182,90	183,42	397,88
Period 11	42,67	227,41	228,24	498,32
Period 12	33,69	229,50	229,84	493,02

Source: Author Analysis

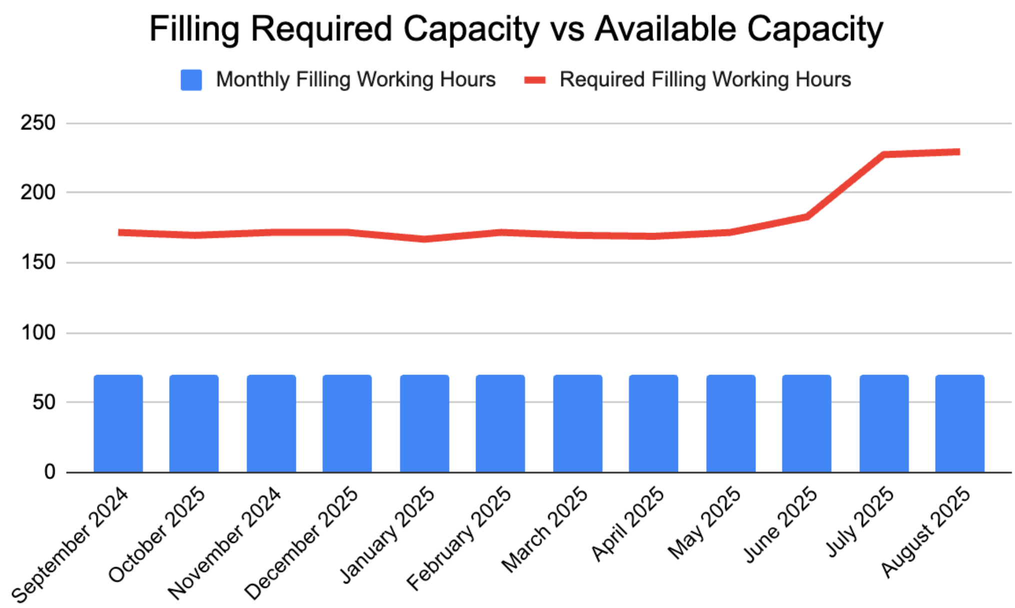
Comparation Available and Required Capacity

Figure 8. Monthly forecasted production required capacity compared to monthly available capacity.



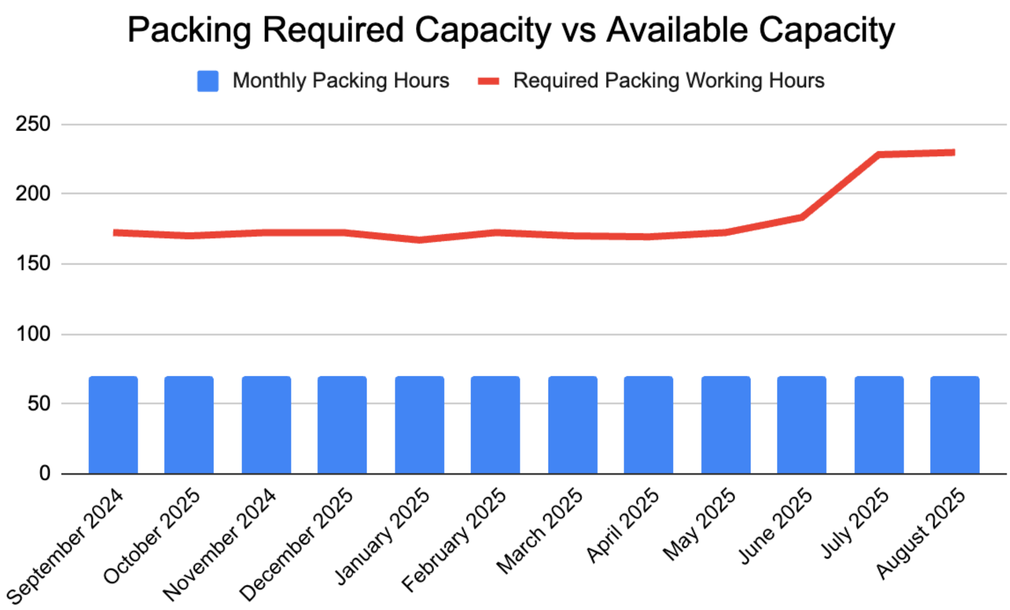
Source: Author Analysis

Figure 9. Monthly forecasted filling required capacity compared to monthly available capacity.



Source: Author Analysis

Figure 10. Monthly forecasted packing required capacity compared to monthly available capacity.



Source: Author Analysis

Figures 7 through 9 illustrate the gap between the required monthly working hour capacity and the current available capacity at PT RAS. The production workstation has a regular monthly capacity of 33 hours, while both the filling and packing stations have 70 hours of regular monthly capacity available. To address these periodic capacity gaps, PT RAS presently leverages overtime by hiring six freelancers, each capable of contributing up to 5 hours each day.

While this strategy provides a temporary buffer to handle workload changes, it is not always enough to fulfil strong demand, potentially resulting to delays in the filling and packing process.

Workforce Optimization and Overtime Management

To effectively meet forecasted demand, PT RAS will adopt a structured system that maximizes resource use by combining regular employees, controlled overtime across all workstations, and freelance workers specifically for the filling and packing stations. This approach ensures compliance with labour laws that applied in Indonesia while maintaining flexibility to manage peak demand.

Overtime Utilization Across All Stations

PT RAS will implement controlled overtime in production, filling, and packing stations, adhering to the Manpower Law No.13 of 2023, the law of labour that applied in Indonesia.

- Production Workers: Regular employees will work 33 hours/month with up to 15 hours of overtime, staying within legal limits. Total capacity 48 hours/month.
- Filling and Packing Workers: Regular employees will work 70 hours/month, with up to 16 hours of overtime, for a total capacity of 86 hours/month.

By implementing structured overtime, PT RAS ensures that it can meet rising demand without overwhelming its regular workforce, while also maintaining adherence to labour regulations. The controlled use of overtime helps the company efficiently scale its operations during peak periods without resorting to permanent staff increases.

Freelance Worker for Filling and Packing Work Station

To supplement regular employees, PT RAS will employ freelance workers specifically for the filling and packing stations during high-demand periods. This provides the company with the necessary flexibility to meet short-term spikes in demand while managing labour costs.

- Freelance Workers: These workers will contribute up to 150 hours/month, working 30 hours/day for a maximum of 5 days/month.

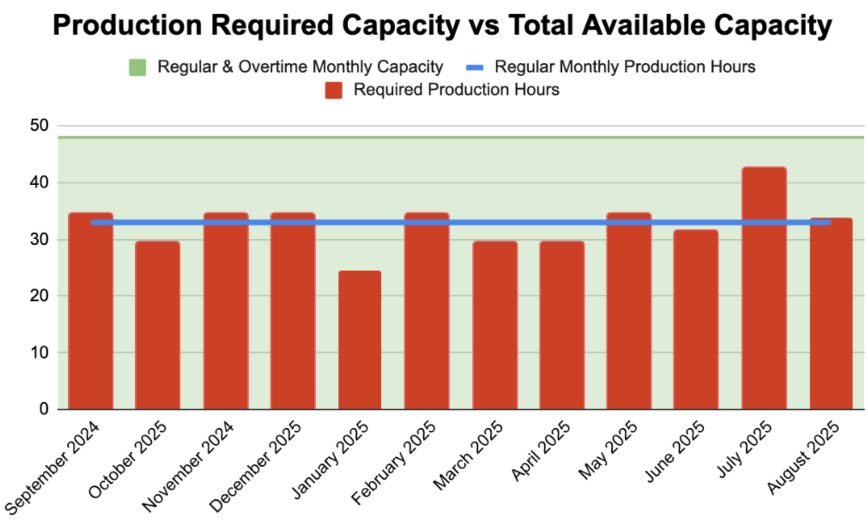
The freelance worker policy helps PT RAS scale its workforce without committing to long-term contracts, which is cost-effective for managing demand fluctuations. This approach ensures the company has the necessary capacity to handle increased production needs without placing excessive pressure on regular staff.

Utilization of Overtime and Freelance Worker Policy

The combination of controlled overtime and the employment of freelance workers enables PT RAS to expand capacity efficiently across key production, filling, and packing stations. This strategy not only helps the company meet fluctuating demand but also maintains workforce well-being by preventing employee burnout. By ensuring flexibility and scalability, the policy contributes to operational stability, especially during demand peaks.

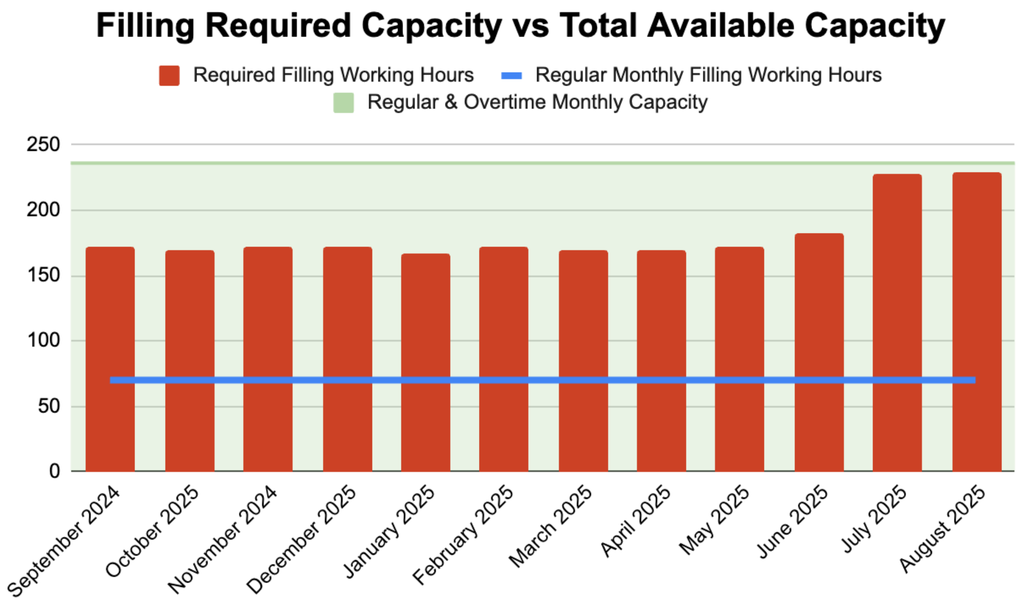
The results of these measures are evident in Figures 10 to 12, where the additional working hours from overtime and freelance labour significantly improve PT RAS's capacity. The company's ability to meet fluctuating demand more effectively, while adhering to labour regulations, is clearly demonstrated, showcasing a more responsive and adaptable operational model.

Figure 11. Monthly required production working hours compared to total available capacity.



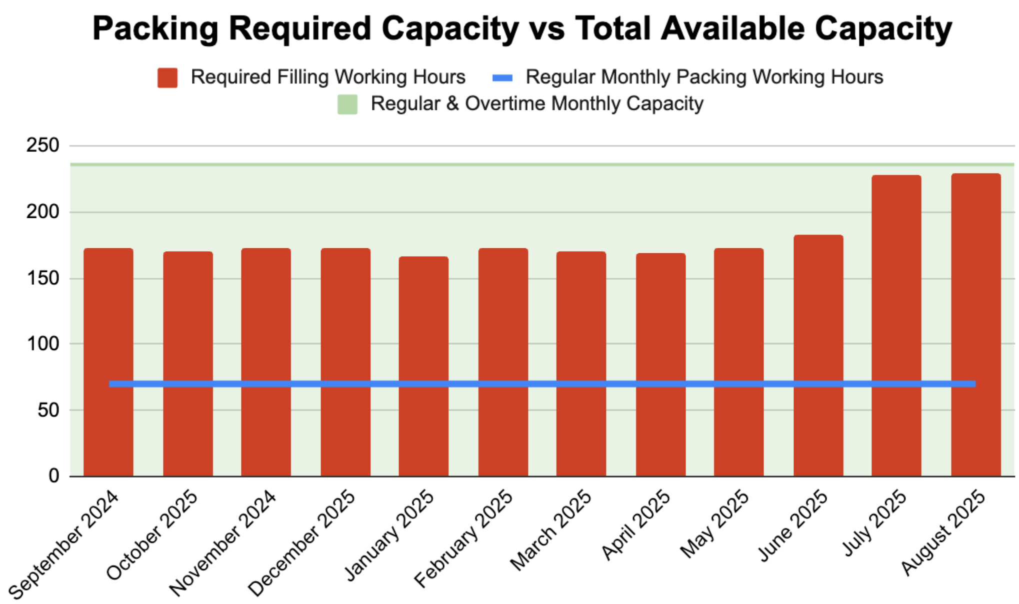
Source: Author Analysis

Figure 12. Monthly required filling working hours compared to total available capacity.



Source: Author Analysis

Figure 13. Monthly required packing working hours compared to total available capacity.



Source: Author Analysis

CONCLUSION

This study explored the production capacity challenges faced by PT RAS due to the significant increase in demand following the launch of Gleam in November 2023. The application of time-series forecasting models, such as Double Exponential Smoothing and Linear Trend Line, allowed PT RAS to predict future demand for RAS Self-Cleaning, RAS Instant Antifog, and Gleam. Based on these forecasts, the Master Production Schedule (MPS) and Rough-Cut Capacity Planning (RCCP) were developed to align production capacity with forecasted demand.

Key findings from this research include:
1. Accurate Demand Forecasting
   The use of time-series forecasting models, such as Linear Trend Line and Double Exponential Smoothing enabled PT RAS to predict future demand with a high degree of accuracy. This ensured that production planning could be closely aligned with customer demand, reducing the risks of overproduction and stockouts.
2. Master Production Scheduling (MPS)
   The MPS, developed based on demand forecasts and existing production capacity, provided a clear roadmap for allocating resources and maintaining balanced production across product lines. This schedule allowed PT RAS to efficiently utilize its resources while minimizing the impact of fluctuating demand.
3. Rough-Cut Capacity Planning (RCCP)
   RCCP helped identify capacity constraints within the production, filling, and packing stations. These insights were crucial in guiding PT RAS's decision to implement overtime and employ freelance workers, ensuring that the company could meet demand peaks without overburdening its regular staff.
4. Effective Utilization of Overtime and Freelance Workers
   The implementation of a controlled overtime system and the strategic use of freelance workers in the filling and packing stations allowed PT RAS to expand capacity flexibly. This approach enabled the company to manage demand fluctuations efficiently while maintaining compliance with labour laws and preventing employee fatigue.

A significant finding of this study is the validation of using a combination of controlled overtime and freelance labour as an adaptable strategy to manage demand fluctuations. This flexible labour arrangement provided PT RAS with the ability to scale up operations during peak periods without incurring the higher costs associated with permanent staffing expansions. The solution also showcased how operational flexibility can be enhanced through better workforce management, ensuring timely order fulfilments during high demand periods.

Empirically, the study underscores the importance of combining accurate demand forecasting with flexible labour management to enhance operational efficiency. Economically, the strategic use of freelance workers and overtime allowed PT RAS to avoid stockouts and excessive production costs, optimizing labour utilization while ensuring timely fulfilments of customer orders.

This study is limited by its reliance on historical sales data, which may not fully account for future market volatility or external factors such as supply chain disruptions. Additionally, the effectiveness of freelance labour may vary, particularly if demand surges become more frequent and sustained over time, raising potential concerns regarding workforce availability.

Future studies could explore the long term sustainability of freelance labour during continuous high demand periods, as well as the integration of external variables into demand forecasting models to account for market shifts. Additionally, investigating capacity improvements through more refined labour strategies or enhanced resource allocation could further optimize production and fulfilments processes.

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