JOURNAL LA MULTIAPP

VOL. 06, ISSUE 05 (1280-1291), 2025
DOI: 10.37899/journallamultiapp.v6i5.2213

Optimization of Phoska Fertilizer Production Planning Using Dynamic Programming Method

Muhammad Hadziqul Afkar Ciko[1], Sumiati[1]

[1]*The National Development University "Veteran" of East Java, Industrial Engineering, Surabaya, Indonesia*

**Corresponding Author: Muhammad Hadziqul Afkar Ciko*
EMail: cikoafkar8@gmail.com

Article Info

Article history:
Received 14 May 2025
Received in revised form 05 June 2025
Accepted 3 October 2025

Keywords:
Dynamic Programming
Production Optimization
Phonska Fertilizer

Abstract

Indonesia's agricultural sector plays a crucial role in ensuring food security and bolstering the national economy. A major challenge, however, is the declining quality of land due to the unregulated use of chemical fertilizers. PT Gresik Nusantara Fertilizer addresses this issue by producing soil-enhancing fertilizers. Their main offerings include GNF Mutiara, GNF SP-36, and GNF Phoska, which aim to enhance soil health and increase agricultural yields. The company operates with a continuous production system, where raw materials represent the most significant expense due to their variety and volume. Labor costs arise from worker wages involved in tasks like mixing, granulating, and packaging. Energy costs, especially electricity, are critical for operating production machinery, particularly during the drying phase using a rotary dryer. Packaging costs entail the use of sacks for distributing the fertilizer to markets. To effectively manage these components and minimize resource waste, a strategy is needed to optimize production and maintain cost-efficiency. This study employs Dynamic Programming (DP) to enhance the use of raw materials in producing Phoska fertilizer. This method helps determine the optimal mix of raw materials by considering potential price variations, thereby promoting more efficient production. Additionally, forecasting techniques are utilized in the study to predict fertilizer demand based on historical data.

Introduction

Optimization is about crafting systems to reach the best possible outcomes or conditions by adjusting key variables. The term "optimization" stems from "optimal," highlighting the aim to achieve the highest or most excellent state conceivable. This methodology spans across various sectors, including computing, web development, startup processes, CPU optimization, enhancing laptop battery life, and improving audio-visual quality, among others (Sunandar, 2020). According to Sholehah et al. (2021), forecasting is a method for anticipating future needs by analyzing previous data and historical situations. This process can manage diverse necessities like quantity, quality, timing, and location to effectively meet demands for goods or services. Lubis et al. (2022) typifies forecasting as predicting or estimating future events, a practice inherently fraught with uncertainty. Adam (2022) describes forecasting as a strategy for foreseeing future occurrences. Forecasting is vital due to its ability to provide meaningful insights for better decision-making. Putra et al. (2025) characterize forecasting as an approach to predicting future behaviors or values based on past data. Standard forecasting metrics include MAD, MSE, MFE, and MAPE, with patterns often presenting as seasonal, horizontal, trend, or cyclical (Hamirsa, 2022; Biva, 2024; Costa, 2024).

ISSN: 2716-3865 (Print), 2721-1290 (Online)

The Moving Average technique for forecasting involves calculating the average of a sequence of data points, then using this average for future predictions. "Moving average" refers to the continuous updating of this mean with each new dataset for subsequent forecasts (Riki and Stefanus, 2020). Single Exponential Smoothing is a straightforward and popular method for forecasting time series data, focusing on a weighted average of past data where newer information is given more importance, ideally suited for data without evident seasonal or trend components (Mico et al., 2022; De Livera et al., 2011; Montgomery et al., 2015). The Weighted Moving Average (WMA) is a statistical method that gives more importance to recent data over older information, and it is a variant of the moving average used to discern trends in time series (Darwati & Yulia, 2023; Perry, 2010; Lotysh et al., 2023; Mabude et al., 2021). The Moving Range Chart (MRC) is instrumental in observing and managing data variability in production processes where forecasting is necessary. In quality control, it helps pinpoint data changes signaling potential issues or deviations from the norm (Afandi & Ismiyah, 2024; Campbell et al., 2013).

The goal of production processes is to augment utility or add value by transforming inputs into outputs according to the company's quality standards. This involves setting targets and benchmarks to compare with actual outcomes (Herlina et al., 2021; Staiger et al., 2019). Proper scheduling is crucial for efficient production, making certain that machinery and labor are used effectively and each production phase is timed correctly. This boosts productivity, cuts down resource waste, maximizes facility usage, and helps meet production targets, enhancing a company's competitive edge (Dwimahendrawan, 2021; Chaturvedi et al., 2023; Beheshti & Beheshti, 2010). Additionally, production planning is vital for ensuring smooth operations and on-time deliveries without compromising quality. It goes beyond production volumes to consider crucial factors like quality and delivery schedules, helping ensure customer satisfaction with the right product delivered on time (Soeltanong & Sasongko, 2021). The term 'production' refers to creating or providing goods sourced from suppliers rather than manufactured (Marselina & Rokamah, 2022; Hawkins, 2012; Moser, 2013).

As highlighted by Thenu et al. (2021), production costs include all expenses incurred in converting raw materials into marketable products. Examples are depreciation on machinery and equipment, raw material costs, costs of auxiliary materials, and employee wages directly or indirectly linked to production. These costs are crucial for calculating, enabling companies to accurately determine expenses at each production stage. Maulidyanti Rosdiana and Wahyuningsih (2020) point out that the components closely tied to manufacturing activities in companies involve direct raw materials, direct labor, and factory overhead. A production system is a sequence of interconnected and organized activities requiring efficient integration of various components (Nuraeni & Santoso, 2024; Hitomi, 2017). Production systems fall into categories like Engineering to Order (ETO), Assembly to Order (ATO), Make to Order (MTO), and Make To Stock (MTS) (Hayati & Firdaus, 2024; Peeters & van Ooijen, 2020).

Standardizing fertilizer content ensures that every fertilizer product meets quality benchmarks set by authorities. This standardization maximizes the effectiveness of fertilizers in boosting agricultural productivity and avoids inconsistencies in nutrient content that may negatively impact plant growth (Nakachew et al., 2024; Xing & Wang, 2024). In Indonesia, the National Standardization Agency (BSN) enacted the Indonesian National Standard (SNI) for various fertilizers, both organic and inorganic. Among the standards in the fertilizer industry is RSNI3 7763:2024, which stipulates the quality requirements for solid organic fertilizers, including parameters such as macronutrient levels (N, P_2O_5, K_2O), water content, organic carbon levels, pH, heavy metals, grain size, and other physical and chemical properties. Dynamic programming is a method for tackling problems by dividing the solution into a sequence of stages, with the final solution emerging from a series of interrelated decisions (Wahyono et al., 2024; Bao et al., 2022; Bao et al., 2022). Oktavianty & Sukmono (2020) illustrate how

ISSN: 2716-3865 (Print), 2721-1290 (Online)

dynamic programming (DP) is a mathematical technique crafted to enhance efficiency during calculations, especially in complex mathematical programming challenges.

Saputra et al. (2020) explain that dynamic programming (DP) tackles problems by breaking down the solution into a series of smaller, systematic steps or stages. Each step is linked, forming a chain of decisions that collectively address the broader issue. This method breaks down daunting challenges into manageable parts, each handled step-by-step. Consequently, the main problem-solving occurs through a series of connected decisions, where each choice affects subsequent decisions. This method optimizes problem-solving by reducing redundant calculations. In dynamic programming, issues are approached recursively, which means each decision considers consequences from previous choices. This recursive approach involves two procedures: forward recursive equations and backward recursive equations. Herawati et al. (2021) outline necessary steps for constructing a goal programming model in dynamic programming, including breaking down problems, setting input variables (state), identifying decision variables, defining objective functions, establishing constraints, and formulating recursive equations.

Linear programming, alternatively, is a mathematical technique focused on systematically identifying and solving problems (Alotaibi & Nadeem, 2021; Azevedo et al., 2024; Gharibi et al., 2024). Its aim is to optimally deploy scarce resources to obtain the best results possible. Linear programming is comprised of three main elements essential for problem modeling: the objective function, constraints or limitations, and decision variables. By integrating these components, linear programming provides a structured and systematic approach to finding optimal solutions for problems involving resource constraints. The success of linear programming modeling depends significantly on accurately formulating the objective functions and constraints to reflect the present scenario. Linear programming is utilized for effectively assigning limited resources among competing activities (Dorfman, 2022). The essence of employing linear programming resides in the clear problem formulation, based on the data available. QSB (Quantity System for Business) software, known as WinQSB, operates on Windows systems and supports operations research and management science applications. WinQSB deploys a variety of problem-solving algorithms to tackle a wide range of operations research and business management challenges.

Methods

The current research was carried out in PT Gresik Nusantara Fertilizer (GNF), which is a manufacturing plant of fertilizer located within the area of Jalan Raya Daendles B 115, Wadeng Village, Sidadu District, Gresik Regency, East Java. The study was started in January 2025 and went until the data needed to analyze it were collected. The research will center on Phoska fertilizer, which is among the flagship products of the company, and the main aim of the study is to find ways of lowering the cost of production. To this end, a mathematical optimization tool, the Dynamic Programming (DP) method, was implemented and the generated results were contrasted with the existing production planning process at the company. Because of it, the study can assess the efficiency of DP in a practical industrial situation and will show how the cost optimisation can increase the competitiveness of the company in the fertilizer market.

The study area included a series of variables that have a great impact on the cost architecture of the Phoska fertilizer manufacturing. The information about the production demand, cost of goods sold (HPP), composition of raw materials, raw material prices, and the cost of operations in terms of labour, electricity, and packaging was gathered and compared. These variables were chosen since they are some of the variables that can be controlled and those that cannot be controlled in the production process. Although demand and price of raw materials are highly influenced by the external market forces, other factors like labour

ISSN: 2716-3865 (Print), 2721-1290 (Online)

deployment, packaging and use of electricity indicate internal cost parameters that the company can observe and control. Combining these variables, the study will bring a comprehensive picture of how the decisions about the production planning affect the total costs.

The company records were used to collect data and provided the historical data on the demand of fertilizers, price of raw materials, and the cost of running the company every month. The study was centered on a 6 months observation period, between September 2024 and February 2025. This period was specifically selected since it reflects the volatility of a demand and the price of raw materials thus providing a practical depiction of the production scene. To illustrate the input volatility, the changes in dolomite and molasses prices over this period; the cyclical nature of fertilizer requirements in agricultural markets is demonstrated by the changes in demand on a month in month out basis. The methodology anchored in this temporal context provides the optimisation model to be well-established on the practical production issues of the company instead of assumptions.

This analysis started with demand forecasting phase. Every production planning process has to be done with accurate demand forecasting because it guarantees efficient allocation of raw materials and operational resources. In this regard, the paper has conducted a test of three forecast methods: Moving Average, Weighted Moving Average, and Single Exponential Smoothing. Each technique has its own advantages - the Moving Average filters noise, the Weighted Moving Average lays more emphasis on recent trends, the Exponential Smoothing technique easier adapts to a change in the short run. Mean Absolute Deviation (MAD) was used to determine which technique gave the best forecast. It was then projected into the demand using the chosen model covering the next 6 months, i.e. March to August 2025. These estimates were used as a basis to simulate future production planning, and test the cost optimisation model with the expected conditions.

After the stage of forecasting the research shifted to the calculations of the cost of production. There were two types of costs, which included variable and fixed costs. The variable costs included raw materials, the cost of which varies according to the conditions in the market, and the packaging material, which is directly proportional to the volume of output. Such fixed costs as labour wages and electricity consumption were also involved and do not alter much in terms of volume of production. This difference enabled the study to more effectively describe the dynamics of cost formation, owing to the strong effect of the changes in the prices of raw materials on the total expenses. The methodology identified the sources of inefficiencies more clearly by separating out these elements and leaving the focus of optimisation efforts on the sources that have the greatest contribution to inefficiency.

The main part of the methodology is the use of the Dynamic Programming method. The reason behind the choice of DP is the fact that it is highly applicable to intricate decision-making processes that demand the necessity to balance a number of constraints across a series of steps. The use of DP in the Phoska fertilizer production saw the utilisation of the tool to find the best mixture of raw materials, which would result in a minimum cost of production without compromising quality standards. The process works by breaking down the decision process into small and consecutive steps that are used to represent the production process stages. Recursive equations were used to connect these steps and so that every choice regarding the allocation of resources has taken into account the current expenses and the future ramifications. The DP approach found the cost-minimising strategy mathematically by step-by-step considering alternative decisions in a systematic way.

The last stage of the methodology process was the comparative analysis of the production costs produced by the company under the available planning strategy with those produced under the Dynamic Programming model. This was compared throughout the six-month period

ISSN: 2716-3865 (Print), 2721-1290 (Online)

of observation to evaluate the level of cost-saving of the optimised model. In addition, future results of the forecasts of March to August 2025 have been incorporated into the DP framework to predict future production planning. This integration did not only help in testing the strength of the optimisation model but also offered practical information to be deployed in the production cycles of the company in the future. The methodology provided a balanced shift between empirical validation and predictive use by integrating both a historical study and forward-looking projections, then providing a holistic approach to cost optimisation.

Results and Discussion

The table below will explain the amount of production and HPP of phoska fertilizer for September 2024-February 2025. The 6-month calculation is adjusted to the research time conducted by the company. The hope is to minimize production costs and optimize production planning at PT. Gresik Nusantara Fertilizer.

Table 1. Phoska Fertilizer Demand Data September 2024 – February 2025

Month	Production Quantity (tons)	HPP
September	124	Rp46.500
October	184	RP46.500
November	164	Rp47.000
December	133	Rp47.000
January	105	Rp47.500
February	117	Rp47.500

Source: Company Data

In September, the recorded production volume reached 124 tons, with an HPP of 46,500. By October, production had risen to 184 tons, maintaining an HPP of 46,500. Moving into November, a slight decrease in production volume occurred, dropping to 164 tons while the HPP edged up to 47,000. In December, there was another reduction in output to 133 tons, with the HPP holding steady at 47,000. January saw a further decline in production to 105 tons, accompanied by an HPP increase to 47,500. Finally, February experienced a modest uptick in production to 117 tons, with the HPP continuing at 47,500.

Table 2. Phoska Fertilizer Composition Data

Type of Raw Material	Quantity (Kg)
Dolomite	11,25
Clay	7,5
Calcium	2,5
Urea	1,25
Sugar Molasses	1,25 L
Red Sinox Dye	0,625

Source: Company Data

The information provided outlines the percentage of each ingredient necessary to produce Phoska fertilizer in compliance with the designated quality parameters. The list of raw materials consists of 11.25 kg of Dolomite, 7.5 kg of Clay, 2.5 kg of Calcium, 1.25 kg of Urea, 1.25 liters of Molasses, and 0.625 kg of Red Sinox Dye.

Table 3. Phoska Fertilizer Raw Material Price Data

Type of Raw Material	Price per Kg (Rp)					
	September	October	November	December	January	February
Dolomite	Rp170	Rp170	Rp170	Rp170	Rp200	Rp200

ISSN: 2716-3865 (Print), 2721-1290 (Online)

Clay	Rp180	Rp180	Rp180	Rp180	Rp200	Rp200
Calcium	Rp200	Rp200	Rp200	Rp200	Rp200	Rp200
Urea	Rp6.700	Rp6.800	Rp6.800	Rp6.800	Rp7.000	Rp7.000
Sugar Molasses	Rp350/L	Rp350/L	Rp350/L	Rp350/L	Rp450/ L	Rp450/ L
Red Sinox Dye	Rp25.000	Rp25.000	Rp25.000	Rp25.000	Rp26.000	Rp26.000

Source: Company Data

The table above shows the prices of the raw materials used in the production of Phoska fertilizer over a six-month period, from September to February. The prices of each raw material are shown per kilogram (kg), with the exception of molasses, which is priced per liter (L). Changes in the prices of these raw materials reflect market dynamics and other factors that affect the cost of production of Phoska fertilizer, including increases in the price of certain raw materials, such as molasses. The calculation of production costs and selling prices for Phoska fertilizer can be affected by increases in the price of some raw materials, such as dolomite, clay, and molasses. Internal procurement policies, external market forces (like inflation, currency fluctuations, or global commodity prices), and seasonal availability of materials are all factors that can cause price increases. Jika tidak ada konteks seperti itu, data menjadi statis daripada berubah, yang mencegah mereka untuk memberikan kontribusi yang signifikan untuk pemahaman tentang volatilitas biaya dan risiko keuangan dalam produksi planning. Furthermore, the effect of these price changes on COGS or overall profitability is not measured or discussed, which limits the practical value of the information presented.

Table 4. Average Percentage Increase in Raw Material Prices from September - February

Type of raw material	Average Percentage Increase/Month (%)
Dolomite	14.52 %
Clay	8.89 %
Calcium	0 %
Urea	0 %
Sugar Molasses	5.71 %
Red Sinox Dye	0.8 %
Dolomite	29,92 %
Clay	4.99 %

Source: Company Data

The table above shows that the price fluctuation between September and February is 29.92%. To determine the average monthly percentage increase in total prices, one would sum the average monthly price increases for each raw material, then divide the result by the number of raw materials, arriving at an average of 4.99% per month.

Table 5. Data on Operational Costs of Phoska Fertilizer Production in February

Type of Operational Cost	Cost (Rp)
Labor Cost per Ton	100.000
Sack Price	10.000
Electricity Cost	1.996.833

Source: Company Data

The table above showcases information on the operational expenses involved in the Phoska fertilizer production process throughout February. The documented expenses include three elements: Labor Cost per Ton, Sack Price, and Electricity Cost.

ISSN: 2716-3865 (Print), 2721-1290 (Online)

Table 6. Comparison of Total Production Costs Before and After Implementing Raw Material Standards

Month	Total Real Cost of the Company (Rp)	Total Cost After Implementing Raw Material Standards (Rp)
September	Rp222.600.000	Rp200.368.833
October	Rp342.240.000	Rp268.968.833
November	Rp308.320.000	Rp246.308.833
December	Rp250.040.000	Rp211.185.833
January	Rp199.500.000	Rp185.709.333
February	Rp222.300.000	Rp200.019.333
Total	**Rp1.544.000.000**	**Rp1.312.561.998**

Source: Data Processing

Based on the table above, it shows the total production costs of the company before and after implementing raw material standards. Secara keseluruhan, the company's real production costs for six months were Rp1,544,000,000, tetapi after implementing the raw material standards, the total costs rose to Rp1,425,694,800. This shows that, although there were several months after implementing the raw material standards, there were cost savings.

Table 7. Comparison of MAD Values in Each Forecasting Method

Forecast	Moving Average Method	Weight Moving Average Method	Sinle Exponential Smoothing Method
Phoska Fertilizer Production	24,125	19,975	27,256

Source: Data Processing

The table above illustrates the company's overall production expenses both prior to and following the implementation of raw material standards. Initially, over six months, the company's actual production costs amounted to Rp1,544,000,000. However, after the raw material standards were put into place, these costs dropped to Rp1,312,561,998. This demonstrates a reduction in costs after the introduction of raw material standards, even though some months saw higher expenses post-implementation. The documented savings were Rp231,438,002, representing a decrease of approximately 15% in the company's total actual production costs.

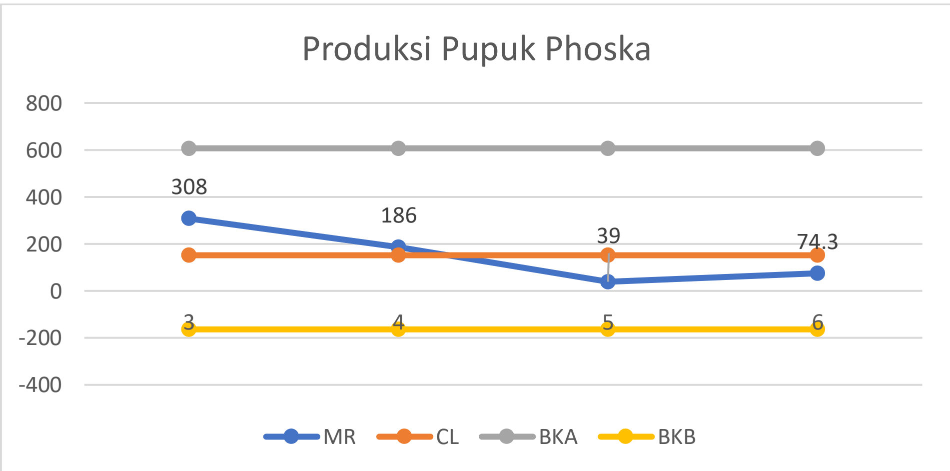

Figure 1. Moving Chart of Phoska Fertilizer Production

Source: Data Processing

ISSN: 2716-3865 (Print), 2721-1290 (Online)

The image above illustrates that the production data for Phoska fertilizer does not include any figures surpassing the upper control limit (BKA) or falling below the lower control limit (BKB).

Table 8. Phoska Fertilizer Production Forecast March 2025 to August 2025

Phonska Fertilizer Production		
Number	**Month**	**Request (tons)**
1	March 2025	113,5
2	April 2025	113,5
3	May 2025	113,5
4	June 2025	113,5
5	July 2025	113,5
6	August 2025	113,5
Total		**681**

Source: Data Processing

According to the table above, the projected output of phoska fertilizer from March 2025 to August 2025 is estimated at 113.5 tons, bringing the cumulative production to 681 tons.

Table 9. Summary of Total Production Costs from March 2025 to August 2025

Month	**Total Production Cost (Rp)**
March	Rp199.595.561
April	Rp206.694.307
May	Rp213.600.027
June	Rp221.721.757
July	Rp231.907.631
August	Rp240.606.932
Total	Rp1.354.127.212

Source: Data Processing

The table provided details the total production expenses from March through August, determined by both the cost of raw materials and fixed operating expenses. Each month, the cost of raw materials per bag rose by 4.99%, while the fixed operating expenses remained constant at Rp60,496,833 per month. The total monthly production expenses were the sum of raw materials costs and operating expenses, leading to a continuous increase in total production costs over the months, culminating in a total of Rp1,354,127,212.37 for the March to August period.

Table 10. Recapitulation of Total Real Production Costs of the Company and After Using Raw Materials According to Standards with the Dynamic Programming Method

Real Cost of the Company	**After Compliance with the Procedure**	**Total Difference in Production Costs**
Rp1.544.000.000	Rp1.312.561.998	Rp231.438.002

Source: Data Processing

Based on the table above, it shows the total production costs of the company before and after implementing raw material standards. Secara keseluruhan, selama enam bulan, total production costs of the company were IDR 1,544,000,000, tetapi after implementing raw material standards according to procedures, the total cost became IDR 1,425,694,800. Ini menunjukkan bahwa, meskipun ada beberapa bulan ketika biaya setelah penerapan raw material standards menjadi lebih rendah daripada sebelumnya, costs menjadi lebih rendah.

ISSN: 2716-3865 (Print), 2721-1290 (Online)

Dengan menggunakan dynamic programming method, Phoska fertilizer production planning showed total production costs based on raw material costs and fixed operating costs. Following forecasting production demand from March 2025 to August 2025, this method was used. Per bulan Maret 2025, production cost was Rp231,230,688, rising to Rp238,394,947 in April, then it went up to Rp246,193,674 in May, then it went up to Rp253,929,415 in June, and then it went up to Rp279,900,000 in July. The total production cost per month is calculated by adding the cost of raw materials and operating costs, which results in an increase in the total production cost per month.

Conclusion

From the calculations conducted, it's clear that adhering to the standard procedures for raw materials can cut production costs by IDR231,438,002, equating to a reduction of about 15% in the overall costs. This demonstrates the effectiveness of the dynamic programming method in minimizing waste and boosting the efficiency of production costs. Additionally, considering the production demand forecast for March to August 2025, the cost of raw materials per sack climbed by 4.99% each month, whereas operational costs held steady at IDR60,496,833 monthly. The monthly production costs rose from IDR199,596,561.65 in March to IDR240,606,932.69 by August, summing up to a total production cost of IDR1,354,127,212 for the period. Despite the rise in production costs, employing the Dynamic Programming method has proved to be effective in the optimal planning of raw material and operational costs, enabling the company to manage its resources in a more efficient and controlled way. Suggestions for further research include considering the warehouse capacity and the stock of raw materials during production planning to optimize storage and minimize the risk of shortages or wastage. Additionally, further investigation is advised to focus on all types of fertilizers being produced, factoring in raw material needs, production time, and the necessary production capacity for each fertilizer type. Companies are also urged to strengthen the implementation of SOPs at each stage of production, particularly during the mixing of raw materials. Adhering to established procedures can help reduce errors, optimize raw material usage, and decrease waste during production.

Acknowledgment

The author wishes to express gratitude to their supervisor for offering valuable feedback to enhance this thesis and refine the research. The author also extends thanks to classmates who have stood by their side throughout both the lectures and the thesis writing process.

References

Adam. (2022). New student registration application using forecasting method. *Journal of Informatics Engineering, 2*(1).

Afandi, R. R. (2024). Analisis Peramalan Penjualan Semen Menggunakan Metode Single Moving Average Dan Single Eksponential Smoothing. *JUSTI (Jurnal Sistem dan Teknik Industri)*, *5*(2), 188-196. https://doi.org/10.30587/justicb.v5i2.9314

Alotaibi, A., & Nadeem, F. (2021). A review of applications of linear programming to optimize agricultural solutions. *International Journal of Information Engineering and Electronic Business*, *10*(2), 11. https://doi.org/10.5815/ijieeb.2021.02.02

Azevedo, B. F., Rocha, A. M. A., & Pereira, A. I. (2024). Hybrid approaches to optimization and machine learning methods: a systematic literature review. *Machine Learning*, *113*(7), 4055-4097. https://doi.org/10.1007/s10994-023-06467-x

Bao, S., Sun, P., Zhu, J., Ji, Q., & Liu, J. (2022). Improved multi-dimensional dynamic programming energy management strategy for a vehicle power-split hybrid powertrain. *Energy*, *256*, 124682. https://doi.org/10.1016/j.energy.2022.124682

ISSN: 2716-3865 (Print), 2721-1290 (Online)

Bao, S., Sun, P., Zhu, J., Ji, Q., & Liu, J. (2022). Improved multi-dimensional dynamic programming energy management strategy for a vehicle power-split hybrid powertrain. *Energy*, *256*, 124682. https://doi.org/10.1016/j.energy.2022.124682

Beheshti, H. M., & Beheshti, C. M. (2010). Improving productivity and firm performance with enterprise resource planning. *Enterprise Information Systems*, *4*(4), 445-472. https://doi.org/10.1080/17517575.2010.511276

Biva, A. T. (2024). *A Comprehensive Study of Machine Learning Approaches for Financial Time Series Forecasting* (Doctoral dissertation, University of Dhaka).

Campbell, J. L., Rustad, L. E., Porter, J. H., Taylor, J. R., Dereszynski, E. W., Shanley, J. B., ... & Boose, E. R. (2013). Quantity is nothing without quality: Automated QA/QC for streaming environmental sensor data. *BioScience*, *63*(7), 574-585. https://doi.org/10.1525/bio.2013.63.7.10

Chaturvedi, R., Darokar, H., Patil, P. P., Kumar, M., Sangeeta, K., Aravinda, K., & Kadhim, A. A. (2023). Maximizing towards the sustainability: Integrating materials, energy, and resource efficiency in revolutionizing manufacturing industry. In *E3S Web of Conferences* (Vol. 453, p. 01036). EDP Sciences. https://doi.org/10.1051/e3sconf/202345301036

Costa, L. (2024). *In-depth study and development of a planning and forecasting application to generate forecasting scenarios in support to annual and monthly planning activities* (Doctoral dissertation, Politecnico di Torino).

Darwati, I., & Hayuningtyas, R. Y. (2023). Simple moving average and weighted moving average methods in predicting rice production. *Journal of Science and Management, 11*(2). https://doi.org/10.31294/evolusi.v11i2.17267

De Livera, A. M., Hyndman, R. J., & Snyder, R. D. (2011). Forecasting time series with complex seasonal patterns using exponential smoothing. *Journal of the American statistical association*, *106*(496), 1513-1527. https://doi.org/10.1198/jasa.2011.tm09771

Dorfman, R. (2022). *Application of linear programming to the theory of the firm: including an analysis of monopolistic firms by non-linear programming*. Univ of California Press.

Dwimahendrawan, A. (2021). Sosialisasi Perencanaan Dan Penjadwalan Produksi Pada Industri Rumah Tangga Keripik Kedelai Di Desa Kertonegoro, Kecamatan Jenggawah, Kabupaten Jember. *Majalah Ilmiah Pelita Ilmu*, *4*(2), 58-75. https://doi.org/10.37849/mipi.v4i2.255

Gharibi, A., Doniavi, E., & Hasanzadeh, R. (2024). A metaheuristic particle swarm optimization for enhancing energetic and exergetic performances of hydrogen energy production from plastic waste gasification. *Energy Conversion and Management*, *308*, 118392. https://doi.org/10.1016/j.enconman.2024.118392

Hamirsa, M. H. (2022). Usulan Perencanaan Peramalan (Forecasting) dan Safety Stock Persediaan Spare Part Busi Champion Type RA7YC-2 (EV01/EW-01/2) Menggunakan Metode Time Series pada PT Triangle Motorindo Semarang. *Industrial Engineering Online Journal*, *11*(1).

Hawkins, C. (2012). Manufacturing. *The Cambridge companion to the Roman economy*, 175-94.

ISSN: 2716-3865 (Print), 2721-1290 (Online)

Hayati, T., & Firdaus, H. (2024). Peningkatan Kualitas Sistem Produksi Di Perusahaan Sandal Sandria Tasikmalaya Dengan Menggunakan Assembly To Order. *Jurnal Media Teknologi*, *11*(01).

Herlina, E., Prabowo, F. H. E., & Nuraida, D. (2021). Analysis of quality control in improving the production process. *Journal of Business Management Focus, 11*(2), 173. https://doi.org/10.12928/fokus.v11i2.4263

Hitomi, K. (2017). *Manufacturing systems engineering: a unified approach to manufacturing technology, production management and industrial economics*. Routledge.

Lotysh, V., Gumeniuk, L., & Humeniuk, P. (2023). Comparison of the effectiveness of time series analysis methods: SMA, WMA, EMA, EWMA, and Kalman filter for data analysis. *Informatyka, automatyka, pomiary w gospodarce i ochronie środowiska*, *13*(3), 71-74. https://doi.org/10.35784/iapgos.3652

Lubis, M. H., Tanjung, A. A., & Martina, D. (2022). Forecasting for batik production with single moving average. *Journal of Computer Technology and Information Systems, 2*(2).

Mabude, K., Malela-Majika, J. C., Castagliola, P., & Shongwe, S. C. (2021). Generally weighted moving average monitoring schemes: Overview and perspectives. *Quality and Reliability Engineering International*, *37*(2), 409-432.

Marselina, E., & Rokamah, R. (2022). Production management of Galih Kurnia chips home industry, Bubakan Village, Tulakan District, Pacitan Regency. *Niqosiya: Journal of Economics and Business Research,* *2*(1), 105–120. https://doi.org/10.21154/niqosiya.v2i1.706

Mico, A. D., Arifianto, D., & Zakiyyah, A. M. (2022). Peramalan Penjualan Batu Gamping Pada UD eko jaya menggunakan single exponential smoothing dan double exponential smoothing. *Jurnal cafetaria*, *3*(2), 151-160.

Montgomery, D. C., Jennings, C. L., & Kulahci, M. (2015). *Introduction to time series analysis and forecasting*. John Wiley & Sons.

Moser, H. (2013). manufacturing. *Economic Development Journal*, *12*(1), 5.

Nakachew, K., Yigermal, H., Assefa, F., Gelaye, Y., & Ali, S. (2024). Review on enhancing the efficiency of fertilizer utilization: Strategies for optimal nutrient management. *Open Agriculture*, *9*(1), 20220356. https://doi.org/10.1515/opag-2022-0356

Nuraeni, N., & Santoso, B. (2024). The role of raw material inventory management in production scheduling of PT XYZ. *Journal of Business Management, 2*(2), 379–394.

Oktavianty, V. N., & Sukmono, T. (2020). Optimization of minimum cost determination in raw material inventory control using dynamic programming method (Case study at PT. XYZ). *Spektrum Industri, 18*(1), 15. https://doi.org/10.12928/si.v18i1.10972

Peeters, K., & van Ooijen, H. (2020). Hybrid make-to-stock and make-to-order systems: a taxonomic review. *International Journal of Production Research*, *58*(15), 4659-4688. https://doi.org/10.1080/00207543.2020.1778204

Perry, M. B. (2010). The weighted moving average technique. *Wiley Encyclopedia of Operations Research and Management Science*. https://doi.org/10.1002/9780470400531.eorms0964

ISSN: 2716-3865 (Print), 2721-1290 (Online)

Riki, & Stefanus. (2020). Inventory control with forecasting method: Moving average and exponential smoothing. *Algor Journal, 2*(1). https://jurnal.buddhidharma.ac.id/index.php/algor/index

Sholehah, R., Marsudi, M., & Budianto, A. G. (2021). Analysis of soybean raw material inventory using EOQ, ROP and safety stock of tofu production based on forecasting method at PT. Langgeng. *Jieom Journal*.

Soeltanong, M. B., & Sasongko, C. (2021). Production planning and inventory control in manufacturing companies. *Journal of Accounting and Taxation Research, 8*(1), 14–27.

Staiger, R. D., Schwandt, H., Puhan, M. A., & Clavien, P. A. (2019). Improving surgical outcomes through benchmarking. *Journal of British Surgery*, *106*(1), 59-64. https://doi.org/10.1002/bjs.10976

Sunandar, H. (2020). Optimization of greedy algorithm implementation in Rupiah currency exchange function. *[Nama Jurnal tidak tercantum]*.

Wahyono, A. T., Novianto, D. J., Nugroho, T. A., Agusti, F., Industry, J. T., Science, F., Technology, D., Duta, U., & Surakarta, B. (2024). Optimization of travel routes to Duta Bangsa University Surakarta Campus using dynamic programming method. *Journal of Science Innovation and Technology (SINTECH), 4*, 14–19. https://doi.org/10.47701

Xing, Y., & Wang, X. (2024). Precise application of water and fertilizer to crops: challenges and opportunities. *Frontiers in Plant Science*, *15*, 1444560. https://doi.org/10.3389/fpls.2024.1444560

ISSN: 2716-3865 (Print), 2721-1290 (Online)