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OPTIMIZING EGG PRODUCTION IN INDONESIA USING A ROBUST STOCHASTIC APPROACH OF PLANNING

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ABSTRACT

Objective: This study aims to address the challenges of demand variability in Indonesia's poultry industry, which often leads to production inefficiencies, including overproduction and shortages, by proposing a stochastic production plan that minimizes costs associated with these inefficiencies within the context of the Indonesian cooperative funding system. **Research Design & Methods:** A stochastic lot-sizing model was developed, and an experiment was set up with five assessment strategies: basic average demand plan, high reliability demand coverage, cumulative demand, cyclical surplus adjustment, and consecutive surplus adjustment plans. The evaluation phase was conducted at two confidence levels ($\alpha = 0.90$ and $\alpha = 0.95$) to assess each plan's ability to minimize total costs effectively. **Findings:** The results revealed that the cumulative demand strategy consistently outperformed other strategies, minimizing surplus and shortage costs at both $\alpha = 0.90$ and $\alpha = 0.95$. This plan demonstrated the lowest surplus-to-demand ratio, making it the most effective in managing production inefficiencies and reducing costs. **Implications and Recommendations:** Implementing the cumulative demand strategy could significantly enhance the efficiency of production planning in Indonesia's poultry industry by reducing waste and optimizing resources, especially in cooperative funding systems. **Contribution & Value Added:** This study contributes to the literature by providing an empirical analysis of production planning strategies in the context of demand variability, offering valuable insights into cost-effective solutions for handling production inefficiencies in the poultry industry.

Keywords: egg production planning; poultry industry optimization; production cost minimization; stochastic modelling; uncertain demand variability.
JEL codes: Q13, C61, D24, L66
Article type: research paper

INTRODUCTION

The poultry industry is crucial to Indonesia’s economy, providing an accessible and affordable source of animal protein across all socioeconomic levels (Adelia et al., 2024). However, poultry producers in Indonesia face significant challenges in maintaining consistent egg production quality and quantity due to fluctuations in demand, climate conditions, and feed prices. These challenges create inefficiencies, especially among small and medium-sized farms that may lack resources for advanced production planning (Ilham & Saptana, 2019).

To address these issues, this study develops a stochastic production planning model that incorporates a cooperative profit-sharing mechanism tailored to the Indonesian poultry industry. This unique approach aims to not only optimize production efficiency but also support the financial resilience of small and medium enterprises by embedding a profit-sharing model within a cooperative funding system. This

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integration contributes directly to the sustainability of these enterprises, enabling them to better manage demand uncertainty and fluctuating production costs.

However, poultry companies in Indonesia face various challenges in meeting the increasing market needs. One of the most significant challenges throughout the year for Indonesian is how to maintain the uniformity and quality of egg production. In fact, it is understandable that in poultry business it is demanding that high-quality egg production requires careful management of several important factors which not every level of producer scale can follow. For example, proper nutrition, adequate lighting, stable ambient temperature, and strict sanitation (Mallick & Muduli, 2020; Niu et al., 2016). Thus, in order to ensure the productivity optimal nutrition is essential. Moreover, adequate lighting conditions are needed to stimulate the production of hormones that affect ovulation. In addition, stable temperatures help reduce stress in chickens, while good sanitation prevents the spread of diseases that can reduce egg production. Another concern in external factors such as climate change and fluctuations in feed prices also add complexity to production management. So, in this context, poultry companies in Indonesia are required to continue to innovate and adapt in order to maintain the quality and quantity of egg production in the face of fluctuating market dynamics (Utami et al., 2024).

The supply chain in the poultry industry plays a crucial role in ensuring sustainable food availability for the community. This system covers the entire process from raw material procurement, production, to distribution of final products to consumers. As a result, in the poultry industry, the supply chain process starts from the provision of animal feed, chicken breeding, to the maintenance and management of laying hens, and finally the distribution of eggs to the market (Saptana & Yofa, 2016).

One important aspect in this supply chain is maintaining the quality of food products that must always be available on time and are perishable. Eggs, as a perishable product, require fast and efficient handling and distribution to ensure quality is maintained until they reach consumers (Aden et al., 2020). Delays in distribution or errors in handling can cause major losses for both producers and consumers (Timisela et al., 2014). A good supply chain management becomes important aspect. When a good management is taking place, that the poultry products are accessible to the entire community at affordable prices. The other thing is making a sure that efficiency in every stage of the supply chain is being established so that the poultry industry not only contributes to food security, but also to price stability and community welfare (Ali et al., 2023; Henmaidi et al., 2024).

Farmers must have a proper understanding of every stage of production to ensure consistent and quality production. Each stage, starting from seed selection, feed management, cage environment arrangement, to handling livestock health, must be carried out carefully and in accordance with established operational standards (Purnamasari et al., 2020). Based on the research the main challenges that often disrupt the production process in the poultry industry Indonesia, which is located in the equatorial region with a tropical climate, are disease outbreaks such as bird flu, extreme weather conditions, and fluctuations in feed prices. Meanwhile, these diseases can cause a drastic decrease in egg production and even cause mass deaths in laying hens. Other devastating aspect that causes decrease productivity is the extreme weather conditions, such as temperatures that are too hot or too cold, that can trigger an increase of chicken stress levels. In addition, fluctuations in feed prices, which are the largest cost component in egg production, are also a challenge for farmers (Aden et al., 2020).

In order facing the fluctuations of cost components, therefore, the right scientific tools are needed to determine the amount of egg production in various periods to ensure timely fulfilment of demand and ensure that the eggs produced can be sold before they spoil. This approach allows farmers to optimize their production based on accurate demand predictions and reduces the risk of overproduction that can lead to egg spoilage (Purba et al., 2018). The problem faced by egg production is known as multi-period lot-sizing. This problem involves determining the amount of production or product orders in each period so that it can meet total demand and minimize production, storage, and inventory costs so, the larger the problem size, the more difficult it is to find an optimal solution. Based on that, in order to achieve the right solution with a less computing source, game theory was implemented (Dadaneh et al., 2024; Şahin et al., 2009).

In the other side, in Indonesia there are cooperative institutions that often act as funding providers for farmers through a profit-sharing system for small and medium farmers. This system allows farmers to get working capital without having to bear high interest rates. In return, farmers give part of their profits to the cooperative as a form of profit sharing. This system not only helps farmers manage their finances but also strengthens community ties and promotes collective welfare and dealing with uncertainty of business (Susilo, 2013). In order to shape the problem for predicting the uncertainty, stochastic basis programming is used as chance-constraint approach to overcome uncertainty in egg production planning based on Dadaneh et al. (2024) which as the foundation of this research. The novelty of this study lies in the effort to embed the variables of the cooperative's profit-sharing debt-based funding system into mathematical modelling. By embedding cooperative in the system as funding institution, it will reflect the real conditions that occur in Indonesia. It has a role in supporting the sustainability of small and medium enterprises in the poultry industry (Susilowati & Farida, 2024). Thus, this study can be a robust and relevant approach in the Indonesian context, offering more appropriate solutions in facing the challenges of demand uncertainty and market fluctuations.

LITERATURE REVIEW

The poultry industry is a dynamic and intricate sector that necessitates well-thought-out management strategies to maintain efficiency and profitability. One of the primary challenges in this industry is optimizing production planning amidst uncertainties, such as variations in growth rates, financial fluctuations, and the integration of new technologies. As what the Solano-Blanco et al. (2023) do to examine on how uncertainty growth affects production planning in the broiler chicken supply chain. By using a stochastic dynamic programming model, they provide insights into optimizing decisions despite the unpredictable growth rates of broiler chickens. This research gives an important understanding about the need to factor uncertainty into production models in order to avoid the risks of overproduction or underproduction. This will lead severe consequences for efficiency and profitability.

In a similar vein, Najimovich (2023) emphasize the importance of financial management in poultry farming. Their study focuses on how financial results, particularly gross profit, are formed and distributed within poultry businesses. The use factor analysis to show how various financial indicators will impact overall profitability to become more profound. However, their study points out that concentrating solely on gross profit will limit and advocate for financial metrics, such as cash flow and return on investment.

Another aspect is the technology implementation in this contemporary digital era. Smart technologies have opened new frontiers in poultry farming, offering potential improvements in productivity and efficiency. One researcher, Zhang et al. (2022) did explore this by addressing the challenges of traditional feeding practices through the use of autonomous feeding robots in smart poultry farms. This introduces advanced algorithms designed to optimize feeding paths and reduce energy consumption, which in turn lowers production costs and enhances farm efficiency. However, in the other side, this study acknowledges the limitations of these algorithms, particularly in area of computational performance and accuracy. This indicates that further refinement is needed to make these technological solutions more practical and scalable for broader use in the industry.

Recent studies on smart technology in poultry farming explore the use of advanced AI-driven solutions, such as deep learning, genetic algorithms, and artificial neural networks (ANNs), to develop adaptive action plans that improve feed conversion rates and overall efficiency across multiple farms (Klotz et al., 2020; Ribeiro et al., 2019). These technologies, while promising, still require substantial human expertise for initial configuration and extensive computational resources, which limits their full automation and practical implementation. The Internet of Things (IoT) is another key area, with systems like the PEST system monitoring and optimizing environmental factors (temperature, humidity, gas levels) in poultry farms to enhance productivity and health (Rajakumar et al., 2022). Despite benefits like added income from solar-powered energy efficiency, IoT adoption faces challenges, particularly in rural areas, due to inadequate communication infrastructure. Addressing these technological and infrastructural constraints is essential to fully realizing the benefits of these smart solutions in poultry farming. However, based on the review above, we can conclude that the use of this technology is for improving the production planning (Syafar et al., 2021).

Production planning and harvesting in the poultry industry involve balancing numerous factors, such as chicken-henhouse assignment, raising schedules, and harvesting times. You & Hsieh (2018) propose a mathematical programming model to optimize these processes, offering a hybrid heuristic approach that maximizes profits while considering these complex factors. Their model demonstrates effectiveness, particularly in small to medium-sized operations of poultry production, but scalability remains a significant challenge. In response to that finding, when the size of the operation increases will make the complexity of the problem grows. Consequently, this condition often requiring more advanced computational tools that can handle these larger-scale operations.

Managing capacitated lot-sizing and scheduling is another critical area of research in poultry production as Boonmee & Sethanan (2016) research that introduce a variant of Particle Swarm Optimization (PSO) called GLNPSO, which is designed to address these challenges in hen egg production planning. Their model aims to minimize total costs by optimizing the production system, showing particular effectiveness in handling large-scale problems. Unfortunately, the study also leads another issue that once again related to scalability and computational efficiency, especially when dealing with random allocations of chicks and hens, which can significantly increase computation time.

Addressing the complexity of production planning in poultry farming requires the integration of smart technology, financial management, and production planning as complementary elements. Smart technology, including IoT and machine learning, has enabled real-time monitoring and adaptive control, especially in environmental management, thereby improving efficiency and productivity (Mandapuram et al., 2019). However, the high initial costs associated with these technologies make robust financial management essential to support their adoption, especially for small and medium-sized enterprises (Mefid & Ridhaningsih, 2024). Financial management practices, such as managing cash flow and return on investment, can provide a sustainable foundation that allows producers to invest in necessary technology while maintaining financial stability. Meanwhile, stochastic programming plays a critical role in addressing demand uncertainty. Stochastic programming is an optimization approach that incorporates variability by modelling certain parameters as random variables, which is essential in situations where demand and supply fluctuate significantly. Additionally, game theory can be explained as a framework for strategic decision-making among interdependent actors—can be applied to cooperative scenarios within poultry production, where producers may benefit from shared resources and cooperative planning (Dadaneh et al., 2024). By combining these approaches, this study aims to develop a production planning model that is not only robust and efficient but also financially sustainable within Indonesia's unique cooperative system.

One scholar, Dadaneh et al. (2024) began the study for addressing the complexities in production process by implementing mathematical model of heuristic programming based on game theory to address the uncertainty with the change-constraint method. This will make the algorithm efficient. This method become foundation of this research, because it has high degree of precision on its implementation in case of Thailand. However, it is not applicable in Indonesia, because it has different approach of financing activities. In Indonesia financing has begun from the role of institution namely cooperation from giving the farmer chick seeds and returned the loan with profit-sharing basis after harvest period. Therefore, this research will add this phenomenon to previous model for creating robust application model.

Despite these advancements, several limitations persist across the existing research. One major issue is the scalability of computational models. Studies such as those by You & Hsieh (2018) and Boonmee & Sethanan (2016) demonstrate effective solutions for smaller problems but struggle when applied to larger, more complex operations due to the significant computational resources required. This scalability issue limits the practical application of these models in large-scale poultry farming.

One of the big issues that the reliance on extensive data and computational resources, especially in AI-based technology that this poses another challenge that often constrained by the availability of large datasets and the need for high computational power, which may not be feasible for all poultry farms, particularly smaller operations (Ribeiro et al., 2019). Therefore, these issues cannot be well thoroughly implemented in Indonesia. Another aspect inside the algorithm there is also a need for more refined and accurate algorithms to enhance the performance of smart technologies in poultry farming which create a limitation of the current situation. This problem suggests further research in developing more robust and scalable solutions (Klotz et al., 2020; Zhang et al., 2022).

Additionally, in the term of scalability issues the integrating financial management into poultry production planning models remains an area that requires more attention. While Mefid & Ridhaningsih (2024) focus on financial aspects, their study primarily examines gross profit without considering other critical financial metrics or integrating financial constraints into production planning models. This oversight limits the comprehensiveness of the financial planning strategies proposed in the literature.

My research aims to address these limitations by developing a robust, scalable production planning model that integrates previous model from Dadaneh et al. (2024) with a financial management through a stochastic programming and chance-constraint approach. This model will incorporate a cooperative funding system based on profit-sharing, reflecting the real-world financial dynamics of poultry farming in regions like Indonesia. By embedding these financial variables into the mathematical model, the research seeks to offer a more comprehensive solution that not only optimizes production planning under uncertainty but also ensures financial sustainability for poultry farmers. Therefore, this approach will enhance scalability and efficiency of the mathematic algorithm and making the model applicable to the operations. Furthermore, by making it integrated with financial process directly into the production planning will provide a more holistic solution that addresses both operational and financial challenges in the Indonesian poultry industry.

Therefore, in this research this article provides following path: At the beginning, it presents a new mathematic modelling that the aim is to model the production situations that happened in Indonesian poultry business scenario. At the end, this model needs to consider the uncertainty of the egg demand parameter as random variable. Since it happened in Indonesia, there are occasions that there are periods that has a higher demand than it ordinary occasion such as in season of Ied Fitr, New Year, and Christmas. To address the uncertainty, we use stochastic modelling with respect to game theory in order to determine the effective planning. This planning refers to create a strategy for determining a number of hatchings in a certain period for preventing shortage and or surpluses effectively.

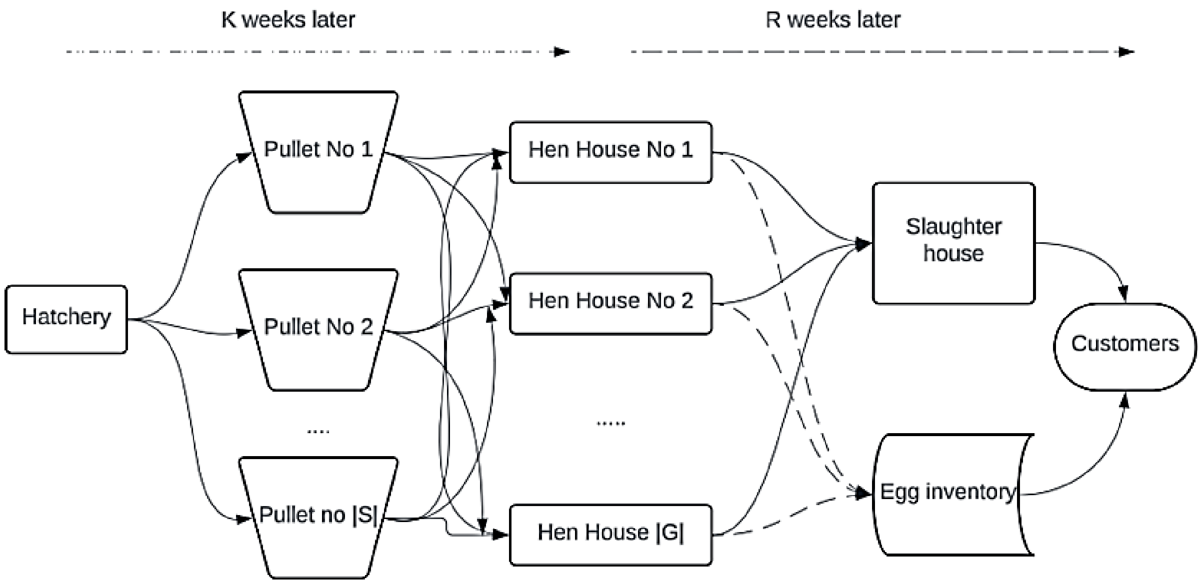


Figure 1. General Indonesian Poultry Farm Supply Chain Production Process
Source: Author's data

METHODS

The problem of optimizing egg production in a poultry farm as shown in Figure 1 involves several interconnected processes that require careful planning and coordination. The system under consideration includes pullet houses, hen houses, and a slaughterhouse, each with specific capacities (Dadaneh et al., 2024). The goal is to optimize the egg production process while accounting for variability in demand, production, and operational constraints. The model we propose is a stochastic mathematical model that aims to do optimization the production and distribution of eggs. The specialty of this model lies in stochastic elements approach in the demand variability and production variability. These are derived from historical dataset. Our model also accounts for periodic demand spikes during holidays and integrates the stochastic approach with a cyclic production process, making it more robust and adaptable to real-world conditions.

The operation (Figure 1) commences with the delivery of ordered chicks to pullet houses, where they are raised until a predetermined age (K weeks), after which they are relocated to laying houses to produce eggs at a defined rate (L_r) over a specified duration (R weeks). Following a decline in egg production, the hens are sent to the slaughterhouse ($R + K$ weeks post-arrival), with egg output from all laying houses dispatched weekly to fulfill customer requirements, while the process cyclically resumes after a designated cleaning period for the housing facilities, influenced by egg demand and infrastructure capacities.

Sets Parameter:

H: sets of the number of hen houses

P: sets of the number of pullets houses

T: sets of the number of time periods in weeks.

C: sets of the number of customer demands.

R: sets of replenishment periods for cleaning and maintenance.

Parameters:

K: Maturity periods for chicken in weeks.

R: Egg-laying periods in weeks.

L_r: Egg-hen egg laying rate.

C_H: Capacity of each hen in the house.

C_P: Capacity of each pullet house.

C_S: Capacity of the slaughterhouse.

D_t: Demand of eggs each period-t.

V_P: Production variability.

I_C: Inventory cost of the eggs.

S_C: Cost of egg's shortage.

F_C: Feed cost for per chicken per week.

α: Confidence level when fulfilling a demand.

Z_α: Z-score corresponding to the confidence level α.

Decision Variables:

x_{pt}: Integer variable representing the number of pullets transferred from pullet house p to hen house h in week t.

y_{ht}: Integer variable representing the number of eggs produced in hen house h in week t.

z_{st}: Integer variable representing the number of chickens sent to the slaughterhouse in week t.

d_{st}: Integer variable representing the egg shortage in week t.

s_t: Integer variable representing the egg surplus in week t.

Where the model equations for the egg production constraint defined as the number of eggs produced in hen house h during week t is determined by the egg-laying rate L_r and the number of mature chickens:

$$y_{ht} = L_r \times x_{pt-K}, \quad \forall h \in \mathcal{H}, t \in \mathrm{T} \tag{1}$$

where x_{pt-K} represents the number of chickens transferred from pullet house p to hen house h in week $t-K$. Next is demand fulfilment and surplus or shortage calculation defined as the number of eggs produced must follows the demand D_t in each week, with any surplus or shortage calculation:

$$s_t = max(0, y_{ht} - D_t), \quad d_t = \max(0, D_t - y_{ht}), \quad \forall t \in \mathrm{T} \tag{2}$$

The capacities of pullet houses, hen houses, and the slaughterhouse must not be exceeded:

$$\sum_{h \in \mathcal{H}} x_{pt} \leq C_p, \sum_{p \in P} x_{pt} \leq C_H, \quad z_{st} \leq Cs, \quad \forall t \in \mathrm{T} \tag{3}$$

As implication, the total cost function incorporates inventory costs, shortage costs, and feed costs:

$$Total\ Cost = \sum_{t \in \mathrm{T}} \left(I_c \times s_t + S_c \times d_t + F_c \times \sum_{h \in \mathcal{H}} y_{ht} \right) \tag{4}$$

The objective is to minimize this total cost while meeting demand and adhering to capacity constraints. To account for variability in demand, we introduce a stochastic element based on a confidence level α. where $\widehat{D_t}$ is the expected demand and σ_{Dt} is the standard deviation of demand.

$$D_t = \widehat{D_t} + Z_\alpha \times \sigma_{Dt}, \quad \forall t \in \mathrm{T} \tag{5}$$

This research has three unique features that different from the other models. Firstly, unlike traditional deterministic models, this model incorporates variability in demand using historical data and confidence intervals, making it more robust against uncertainty. Secondly, this model seamlessly integrates the cyclic nature of poultry farming, including cleaning periods and fixed egg-laying periods, which are often overlooked in simpler models. Thirdly, it optimizes not only production but also accounts for real-world constraints such as cleaning periods and capacity limitations. Consequently, it will provide a more realistic approach to egg production planning in Indonesia.

The optimization of egg production in the poultry industry, in our research can be approached through various mathematical models. In this section, we explain five distinct production plans of stochastic elements to handle better uncertainties in demand and ensuring robust cost-effective operations. Each of the five plans is designed to address specific challenges in managing the variability of egg production and demand, utilizing mathematical logic to optimize outcomes. Plan A, which relies on average demand, is straightforward but risks failing to accommodate fluctuations, making it suitable in stable markets but vulnerable to volatility. Plan B enhances reliability by incorporating a safety buffer through the addition of a Z-score adjustment for demand variability, ensuring higher confidence in meeting peak demands but potentially increasing inventory costs. Plan C advances this by smoothing out variability over time, using cumulative demand to distribute risk, which is mathematically sound in reducing the impact of sudden spikes but requires more sophisticated forecasting. Plan D introduces dynamic adjustments based on observed surplus, employing a feedback loop that corrects production levels in response to previous over production, effectively reducing unnecessary inventory costs while maintaining adaptability. Finally, Plan E further refines this approach by considering the cumulative surplus across multiple periods, providing a comprehensive adjustment mechanism that aligns with the principles of lean production, where minimizing waste and avoiding systematic errors are paramount.

Plan A production based on average demand: The first plan is the most straightforward approach, where the production levels are set to match the expected (average) demand over a given time horizon (Hillier & Lieberman, 2015). Mathematically, this can be expressed as:

$$y_{ht} = \widehat{D_t}, \qquad \forall h \in \mathcal{H}, \quad t \in \mathrm{T} \tag{6}$$

Here, y_{ht} represents the production level in hen house h at time t, and $\widehat{D_t}$ is the expected demand in week t. This plan assumes that meeting the average demand is sufficient to minimize costs, particularly overproduction costs. However, this model does not account for fluctuations in demand, potentially leading to shortages during peak demand periods or excess inventory during low demand periods.

Plan B high reliability demand coverage: This introduces a level of demand coverage that accounts for variability by incorporating a reliability factor. This plan adjusts production to meet demand with a high level of confidence, typically expressed as a confidence level α (e.g., 90%, 95%). The production level is given by:

$$y_{ht} = \widehat{D_t} + Z_\alpha \times \sigma_{Dt}, \tag{7}$$
$$\forall h \in \mathcal{H}, \quad t \in \mathrm{T}$$

In this equation, Z_α is the Z-score corresponding to the confidence level α, and σ_{D_t} are the standard deviation of demand in week t. This plan increases production levels to cover the upper bounds of demand variability, reducing the risk of shortages but potentially increasing holding costs (Silver, 1998).

Plan C cumulative demand with reliability: This extends the reliability concept by considering cumulative demand over the planning horizon. This approach smooths out variability by accumulating demand and adjusting production accordingly:

$$y_{ht} = \frac{1}{t}\left(\sum_{i=1}^{t} \widehat{D_\iota} + Z_\alpha \times \sqrt{t} \times \sigma_{D_t}\right), \tag{8}$$
$$\forall h \in \mathcal{H}, t \in \mathrm{T}$$

Here, the production level is determined by the cumulative demand up to week t, adjusted for variability using the square root of time $\sqrt{t}$, which accounts for the increasing uncertainty over a longer time horizon. This approach mitigates the risk of demand spikes in any single period by distributing the risk over multiple periods (Hopp & Spearman, 2008).

Plan D cyclical surplus adjustment: the model incorporates feedback from previous periods by adjusting production based on observed surpluses or shortages. The production level is modified cyclically:

$$y_{ht} = \widehat{D_t} + Z_\alpha \times \sigma_{D_t} - s_{t-1}, \tag{9}$$
$$\forall h \in H, t \in \mathrm{T}$$

Where s_{t-1} represents the surplus from the previous period. By subtracting the surplus, this plan aims to prevent overproduction in subsequent periods, thereby reducing holding costs. It is a dynamic model that responds to past performance, making it adaptable to changing demand conditions (Xu & Wang, 2017).

Plan E consecutive surplus adjustment: This refines the cyclic approach by considering the cumulative surplus over all previous periods. This model is more sensitive to long-term trends in surplus and adjusts production more conservatively:

$$y_{ht} = \widehat{D_t} + Z_\alpha \times \sigma_{D_t} - \sum_{i=1}^{t-1} s_i, \tag{10}$$

$$\forall h \in \mathcal{H}, t \in \mathrm{T}$$

The cumulative surplus adjustment ensures that production does not only respond to immediate past surpluses but also considers the overall trend. This approach helps in avoiding systematic overproduction and reduces the total cost of surplus inventory.

FINDINGS

The program was executed on Kaggle's platform with standard computing resources, which include a CPU with Intel Xeon processors, 30GB of RAM, and a Tesla P100 GPU. However, for this execution, the program ran without the use of the GPU accelerator, relying solely on the available CPU and RAM resources provided by Kaggle. This setup was sufficient to complete the tasks, although it may have required more processing time compared to runs that leverage the GPU.

In this section, is implemented in deterministic conditions with respect to Dadaneh et al. (2024) setup condition. However, we further incorporated with Indonesian dataset and additional setup variables in Indonesian financial process. The dataset in the Table 1 provides a comprehensive view of the poultry production operations over various time periods and years. The variables include pullet houses, hen houses, time periods (weeks), and a range of financial and operational metrics. In 2021, data shows that during the eight-week periods, total egg production reached 12,3 million eggs, slightly exceeding the demand of 12,2 million eggs. The feed costs were high at approximately 2.44 billion units, while inventory and shortage costs were minimal. The total revenue was around 24.45 billion units, leading to a profit of 2.20 billion units, with an average weekly profit of 879 million units, despite a small 18-week demand spike. For the ten-week periods, egg production increased to 24,703,560 eggs, surpassing the demand of 24,694,482 eggs. Feed costs rose significantly to 4.94 billion units, but the higher production resulted in a revenue of 49.41 million units and a profit of 4.44 trillion units, with a maximum demand spike period of 27 weeks and a loan of 100 million units. In 2022, egg production was 12,471,888 eggs, slightly below the demand of 12,678,996 eggs. Feed costs increased to 2.49 billion units, generating a revenue of 24.94 million units and a total profit of 2.24 billion units, with an average weekly profit of 896 million units. The maximum demand spike remained at 18 weeks, and a loan of 100 million units was taken. In 2023, egg production slightly rose to 12,552,746 eggs, again just below the demand of 12,681,715 eggs. Feed costs further increased to 2.51 billion units, with revenue reaching 25.10 million units and a total profit of 2.26 billion units. The average weekly profit increased marginally to 902 million units, with the maximum demand spike extending to 21 weeks, and the loan amount remaining consistent at 100 million units.

In Table 2 conforms the analysis of Plans A through E based on the data provided reflects the varying strategies in managing demand fluctuations and optimizing profit margins in poultry production. Plan A, which bases production strictly on average demand, often results in surpluses or shortages during periods of unexpected demand spikes, as seen in Week 2, where a shortage occurred despite no surplus in prior weeks. Plan B, by incorporating a Z-score adjustment for demand variability, shows a more balanced approach with fewer shortages but still incurs higher inventory costs, indicating the trade-off between reliability and cost efficiency. Plan C further refines this by smoothing demand over multiple periods, leading to improved cumulative profit but at the expense of higher feed costs, as the model prepares for potential spikes in demand, particularly evident in weeks with significant surpluses. Plan D, which adjusts production based on previous surpluses, demonstrates a dynamic response to past performance, reducing inventory costs in the short term but showing vulnerability in consistently high-demand periods, where overproduction might not be sufficiently curbed. Finally, Plan E, which considers cumulative surplus adjustments over several periods, provides the most comprehensive strategy by effectively mitigating systematic overproduction, leading to more stable profits and minimized surplus-related costs over time, as observed in its smoother profit trajectory compared to other plans.

The chart in Figure 2 displays weekly egg production across five different production plans (Plan 1-5 as Plan A to E) with a confidence level (α) set at 0.90. Each colored line represents a distinct production plan, illustrating how they respond to weekly demand variability while maintaining a 90% confidence level in fulfilling that demand. Plan A (blue line) shows a relatively stable production level across the weeks, indicating a conservative approach that is less responsive to demand fluctuations but minimizes extreme variations in production. Plan B (orange line) exhibits higher peaks and valleys, reflecting a more aggressive response to changes in demand, aiming to cover demand spikes but introducing more volatility. Plan C (green line) maintains a stable production level but at a slightly higher average, designed to meet consistent demands while reducing fluctuations. Plan D (red line) shows significant fluctuations, dynamically responding to demand changes and overproducing in some weeks to cover potential shortages. Plan E (purple line) exhibits the most significant fluctuations, highly responsive to demand spikes, prioritizing avoiding shortages but creating substantial surpluses. Among these plans, Plan C (green line) emerges as the most superior, as it strikes a balance between stability and responsiveness, maintaining a consistent production level that effectively meets demand while minimizing both overproduction and the risk of shortages. This balance makes Plan C the most efficient and reliable under the given conditions.

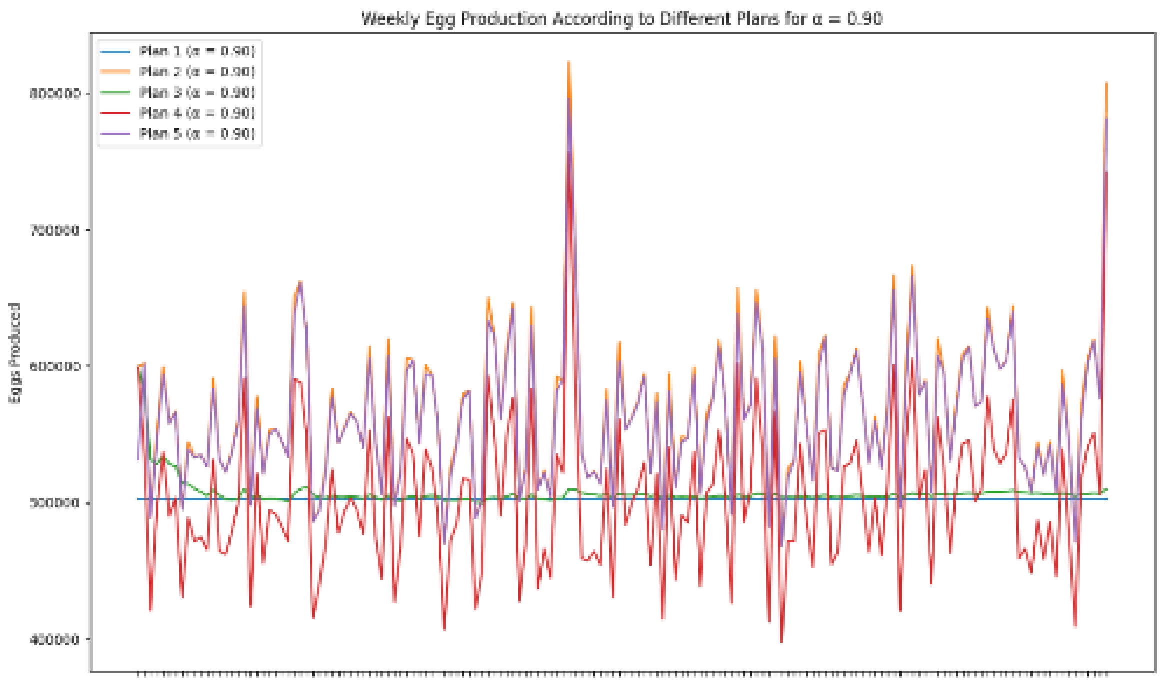
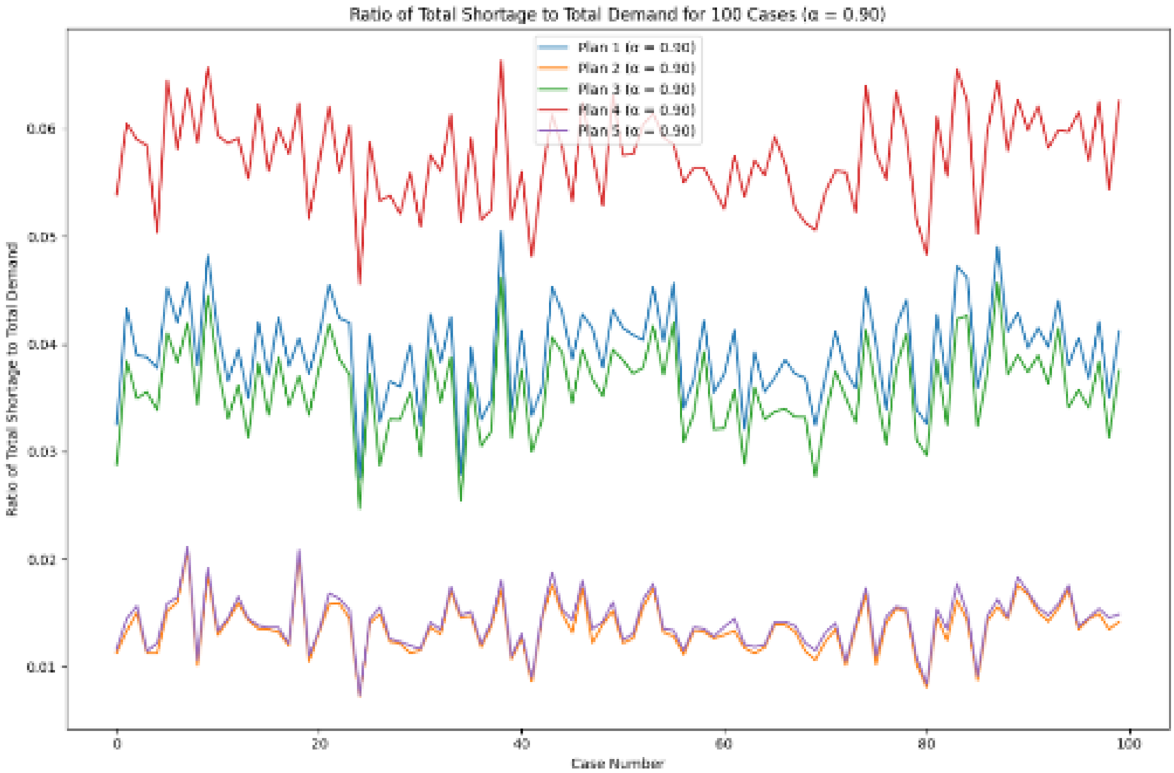
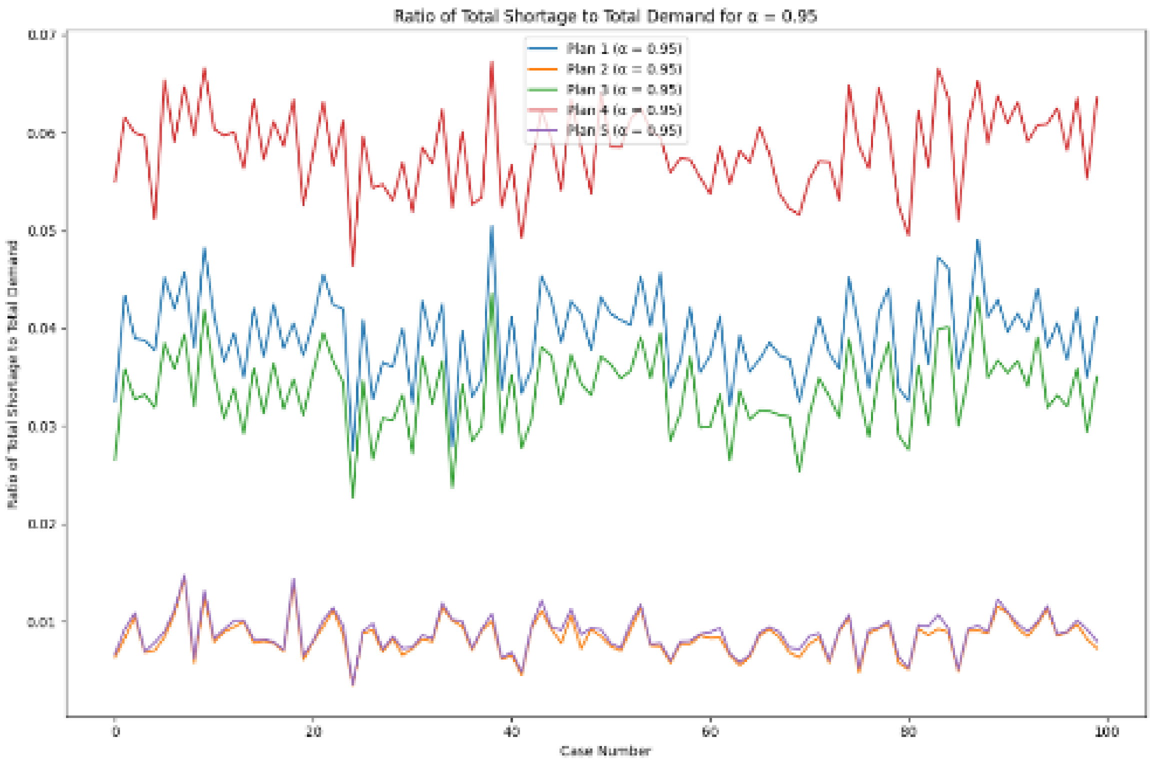


Figure 2. Weekly Egg Production According to Different Plans for $\alpha = 0.9$.
Source: Author’s data

The graphs in Figures 3a and 3b display the ratio of total shortage to total demand across 100 cases for each production plan (Plan A to Plan E) at confidence levels of α = 0.90 and α = 0.95, respectively. Both graphs measure the effectiveness of each plan in meeting demand while minimizing shortages, with a lower ratio indicating better performance. In Figure 3a (α = 0.90), Plan E (purple line) and Plan D (orange line) show the lowest shortage ratios, indicating their superior ability to minimize shortages under these conditions, making Plan E the most reliable. Plan A (blue line) and Plan C (green line) perform moderately well, while Plan B (red line) struggles the most with the highest shortage ratio. In Figure 3b (α = 0.95), the situation shifts slightly as Plan E remains the most effective, consistently maintaining the lowest shortage ratio, now accompanied by Plan B (orange line), which also performs well due to its responsiveness to demand fluctuations. Plan C continues to demonstrate balanced performance with a slightly higher ratio, while Plan A shows moderate effectiveness but with more variability. Plan D now exhibits the highest shortage ratio, indicating it struggles the most at this higher confidence level. These analyses highlight that Plan E remains the most reliable across both confidence levels, consistently minimizing shortages and ensuring demand is met with minimal risk.



(a) with $\alpha = 0.9$.



(b) with $\alpha = 0.95$

Figure 3. Ratio Total Shortage to Total Demand for 100 Cases.
Source: Author's data

Table 1. Performance of the Productions Data

S	G	T	Year	Tot Eggs_ Prod.	Tot Eggs Demanded	Total Feed Cost	Total Inventory Cost	Total Shortage Cost	Total Revenue	Total Loan Taken	Total Loan Repaid	Total Profit	Average Profit Per-Week	Max Demand Spike Period	Max Demand Spike Week	Max Loan Taken	Min Profit Week
0	5	8	5	2021	12224554	12217514	2,44E+15	3195910	15627550	24449108000	1E+08	1E+08	2,20E+16	8,79E+14	03/05/2021	18	100000000
1	5	8	5	2022	12471888	12678996	2,49E+15	3383340	27272100	24943776000	1E+08	2E+08	2,24E+16	8,96E+14	02/05/2022	18	100000000
2	5	8	5	2023	12552746	12681715	2,51E+15	2938740	21142150	25105492000	1E+08	2E+08	2,26E+16	9,02E+14	22/05/2023	21	100000000
3	5	8	10	2021	24703560	24694482	4,94E+15	6204030	30566250	49407120000	1E+08	3E+08	4,44E+16	8,88E+14	05/07/2021	27	100000000
4	5	8	10	2022	24925110	25229193	4,99E+15	6101150	45709900	49850220000	1E+08	4E+08	4,48E+16	8,96E+14	02/05/2022	18	100000000
5	5	8	10	2023	25070339	25325784	5,01E+15	5098710	38265800	50140678000	1E+08	4E+08	4,51E+16	9,01E+14	22/05/2023	21	100000000
6	8	15	10	2021	25638137	25642246	5,13E+15	6204030	31225600	51276274000	1E+08	3E+08	4,61E+16	8,86E+14	05/07/2021	27	100000000
7	8	15	10	2022	25915884	26195517	5,18E+15	6460560	46284450	51831768000	1E+08	4E+08	4,66E+16	8,96E+14	02/05/2022	18	100000000
8	8	15	10	2023	26029717	26552176	5,21E+15	5098710	51616500	52059434000	1E+08	4E+08	4,68E+16	9,00E+14	25/12/2023	52	100000000
9	15	25	20	2021	25638137	25642246	5,13E+15	6204030	31225600	51276274000	1E+08	3E+08	4,61E+16	8,86E+14	05/07/2021	27	100000000
10	15	25	20	2022	25915884	26195517	5,18E+15	6460560	46284450	51831768000	1E+08	4E+08	4,66E+16	8,96E+14	02/05/2022	18	100000000
11	15	25	20	2023	26029717	26552176	5,21E+15	5098710	51616500	52059434000	1E+08	4E+08	4,68E+16	9,00E+14	25/12/2023	52	100000000

Source: Own data processing

Table 2. Glimpse of Five Productions Plans

No	Week	Demand	Feed_Cost	Inv	Surplus	Shortage	Loan	Rep-aid	Reveue	Profit	Cum Profit	Plan A	Plan B	Plan C	Plan D	Plan E
0	04/01/2021	487454	531394	97490800.0	2197000	0	43940	0	0	9,75E+08	875220200.0	8,75E+14	502.499.608.974	599.412.432	599.412.432.000	599.412.432
1	11/01/2021	523199	533522	104639800.0	516150	0	10323	0	0	1,05E+09	941242050.0	1,82E+15	502.499.608.974	601.812.816	580.746.899.086	533.794.384
2	18/01/2021	465601	433567	93120200.0	0	32034	0	0	0	9,31E+08	837761460.0	2,65E+15	502.499.608.974	489.063.576	531.535.296.426	488.791.192
3	25/01/2021	455808	489189	91161600.0	1669050	0	33381	0	0	9,12E+08	818785350.0	3,47E+15	502.499.608.974	551.805.192	528.226.096.000	496.581.000
4	01/02/2021	510111	531339	102022200.0	1061400	0	21228	0	0	1,02E+09	917138400.0	4,39E+15	502.499.608.974	599.350.392	534.217.819.151	591.958.392
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
151	27/11/2023	503135	507223	100627000.0	204400	0	4088	0	0	1,01E+09	905438600.0	1,35E+17	502.499.608.974	572.147.544	505.774.003.529	518.717.784
152	04/12/2023	513742	536972	102748400.0	1161500	0	23230	0	0	1,03E+09	923574100.0	1,36E+17	502.499.608.974	605.704.416	506.302.941.394	594.209.632
153	11/12/2023	547585	549370	109517000.0	89250	0	1785	0	0	1,1E+09	985563750.0	1,37E+17	502.499.608.974	619.689.360	506.728.489.017	562.451.728
154	18/12/2023	482295	510768	96459000.0	1423650	0	28473	0	0	9,65E+08	866707350.0	1,38E+17	502.499.608.974	576.146.304	506.375.924.650	563.064.576
155	25/12/2023	477083	715624	95416600.0	11927050	0	238541	1E+08	0	9,54E+08	846822350.0	1,38E+17	502.499.608.974	807.223.872	509.833.468.170	754.927.296

Source: Own data processing

DISCUSSION

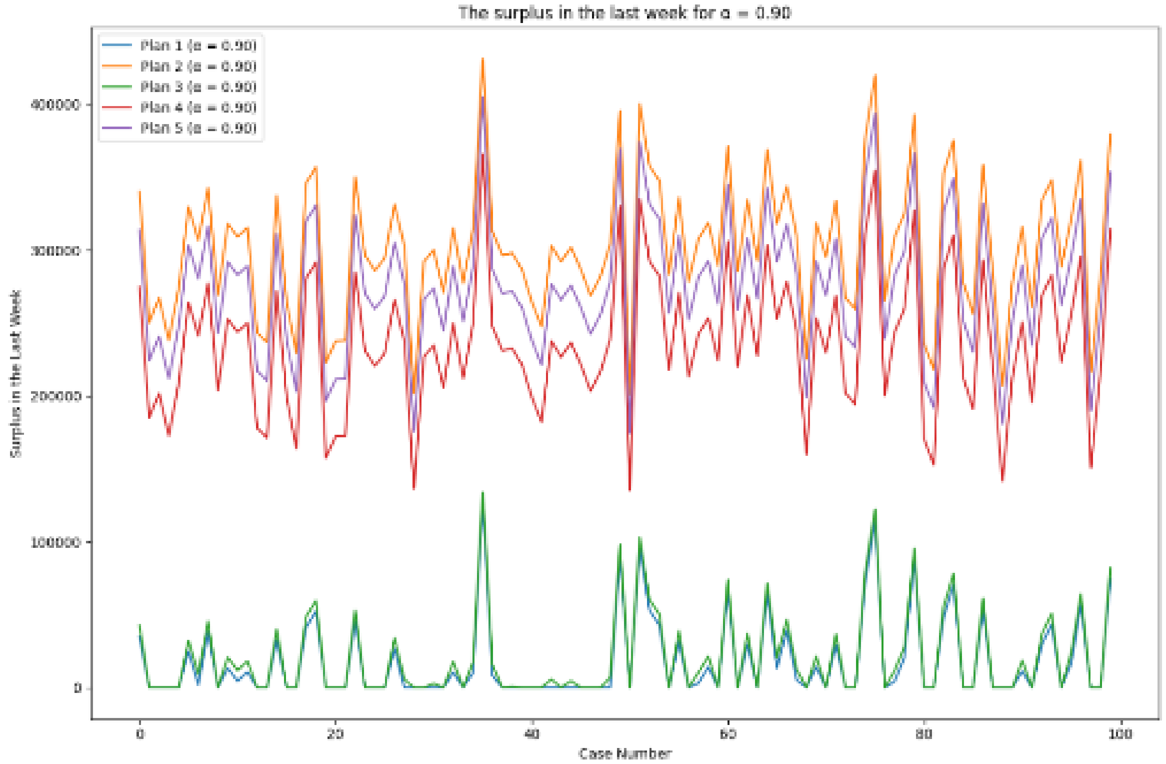
The comprehensive analysis provided by the graphs in Figures 4a through 4d, alongside the cost evaluation in Figure 5, collectively demonstrates the efficiency of different production plans (Plan A to Plan E) in managing) surplus and shortage costs under varying confidence levels ($\alpha = 0.90$ and $\alpha = 0.95$). Across these analyses, Plan C consistently emerges as the most efficient and reliable strategy, maintaining the lowest surplus and surplus-to-demand ratios while also effectively minimizing shortages. This consistent performance is further validated by the economic theory of supply and demand, which emphasizes minimizing the gap between production and demand to reduce inefficiencies, such as waste and excess costs (Mankiw, 2014).

Mathematically, Plan C optimizes the balance between shortage costs (penalties for unmet demand) and surplus costs (storage and waste), leading to an overall optimal solution that aligns with the principles of operations management (Heizer et al., 2020). Which this will $minimize\ C_{total} = \min(C_{shortage} + C_{surplus})$. Where $C_{shortage} = KU \times S$ and $C_{surplus} = h \times Q$. S is being the number of unit in shortage and h and Q are holding cost and quantity of surplus. Based on that optimal solution of plan C as: $\left(\frac{d}{dx}(KU \times S(x) + h \times Q(x)) \approx 0\right)$ will optimize production quantity and minimize the sum of shortage and surplus costs. When applying the Balanced Plan (Plan C), the primary risk lies in its potential vulnerability to extreme demand fluctuations. While Plan C optimizes the balance between shortages and surpluses under typical conditions, it may struggle in scenarios where there are sudden, unpredictable spikes in demand or supply chain disruptions. This could lead to either unexpected shortages or surplus, impacting costs and efficiency. The real implementation, producers should complement the Balanced Plan with real-time monitoring systems and flexible supply chain strategies. This would allow for quick adjustments in production based on actual market conditions. Additionally, maintaining a safety stock or contingency plan for sudden demand surges could help mitigate risks and ensure that the plan remains effective even under unexpected circumstances.

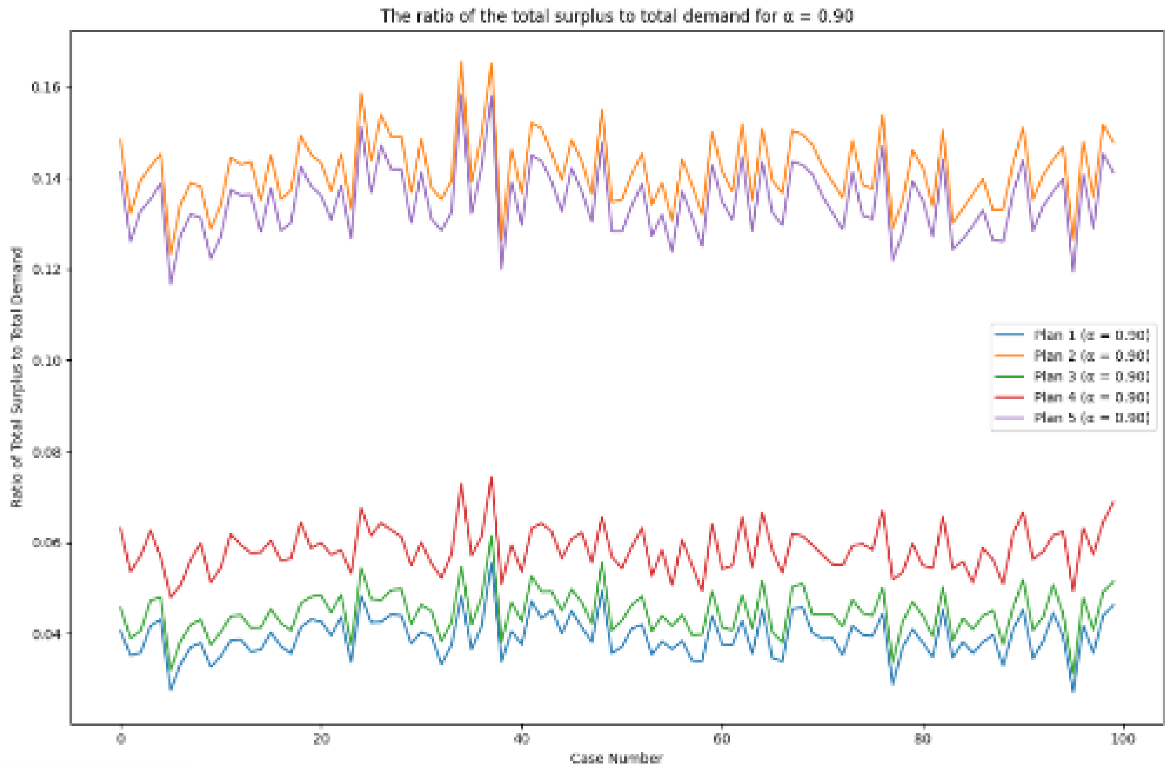
However, in Plan A it has been known that also shows strong performance, particularly in cost-effectiveness, by maintaining the lowest costs at both confidence levels, indicating its ability to balance shortages and surpluses effectively under less stringent conditions. In contrast, Plans B, D, and E exhibit significantly higher costs, with Plan D showing the highest costs overall, particularly under the more stringent condition of $\alpha = 0.95$, reflecting its inefficiency in managing production under strict demand scenarios. The cost increases for Plans D and E further highlight their struggles with effectively managing shortages when penalties for unmet demand are high, reinforcing Plan C as the most reliable choice for minimizing surplus, optimizing production efficiency, and reducing waste, especially under varying levels of demand uncertainty.

The expanded discussion addresses the implications of the findings for production planning and economic resilience, with a particular focus on small farmers in Indonesia. Implementing the cumulative demand strategy enables poultry producers to better anticipate and respond to demand fluctuations, thereby reducing both surplus and shortage costs (Solano-Blanco et al., 2023; You & Hsieh, 2018). This approach enhances production planning efficiency by minimizing waste and optimizing resource utilization. Furthermore, the integration of a cooperative profit-sharing model provides a sustainable financial framework that supports the economic resilience of small and medium-sized poultry farmers (Dadaneh et al., 2024; Susilo, 2013). In the Indonesian context, where farmers experience high variability in production costs and demand cycles, this model offers a stable income structure that allows farmers to sustain their operations even amid challenging market conditions. These insights highlight the practical relevance of the findings, presenting a tailored approach that addresses the unique financial and operational requirements of Indonesia's poultry industry.

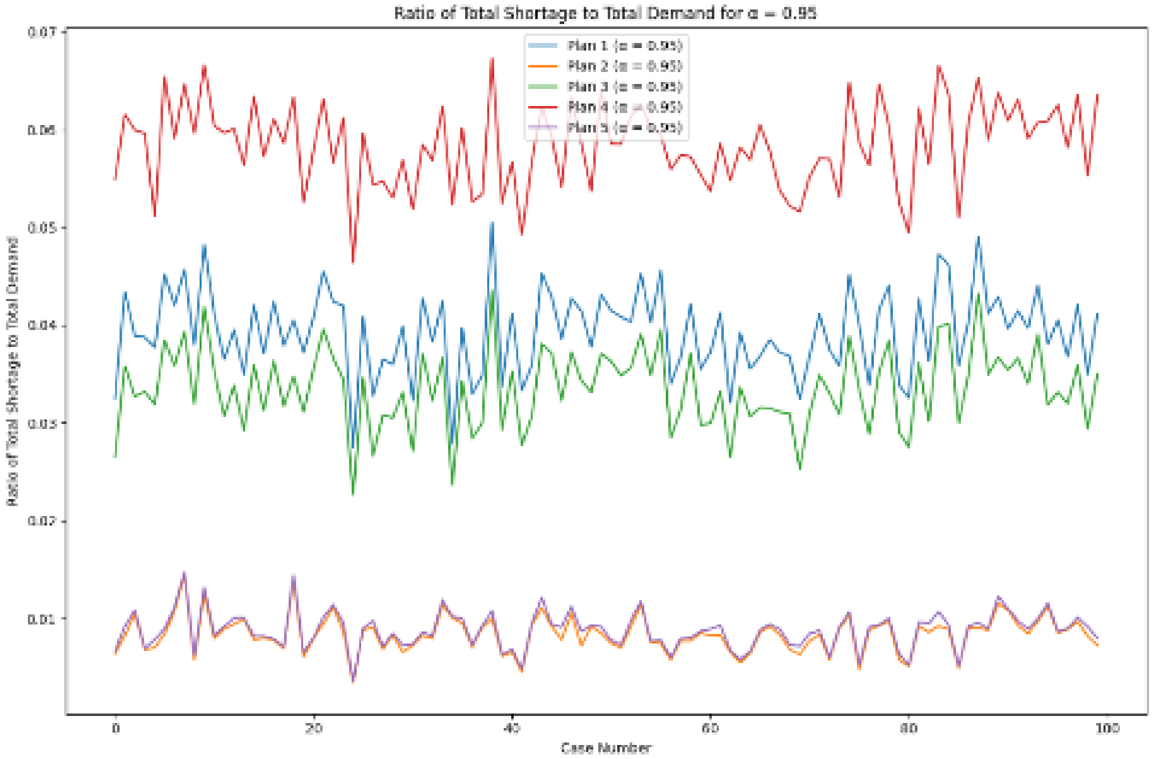
Therefore, based on the finding, finally, it is proper to say that the cumulative demand strategy's success in reducing surplus and shortage costs validates the hypothesis that stochastic programming can effectively manage demand variability in poultry production. Additionally, the cooperative profit-sharing model's alignment with game theory underscores the hypothesis that shared economic incentives within a cooperative structure enhance the financial resilience of small and medium enterprises in Indonesia's poultry sector. Thus, these results provide strong support for the theoretical framework and hypotheses guiding in this study.



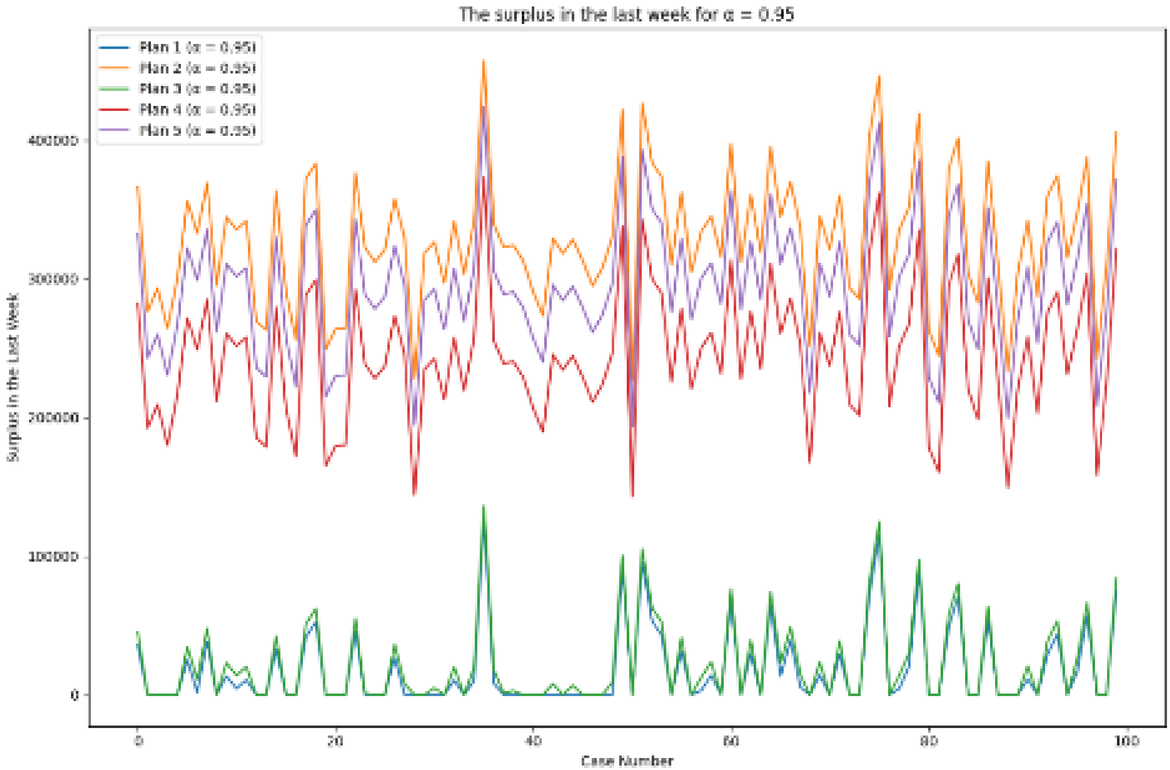
(a) the surplus in last week for $\alpha = 0.9$



(b) ratio of the surplus to demand with $\alpha = 0.9$



(c) the surplus in last week for $\alpha = 0.95$



(d) ratio surplus-demand α=0.95.
Figure 4. Surplus in α=0.9 and α=0.95.
Source: Author’s data

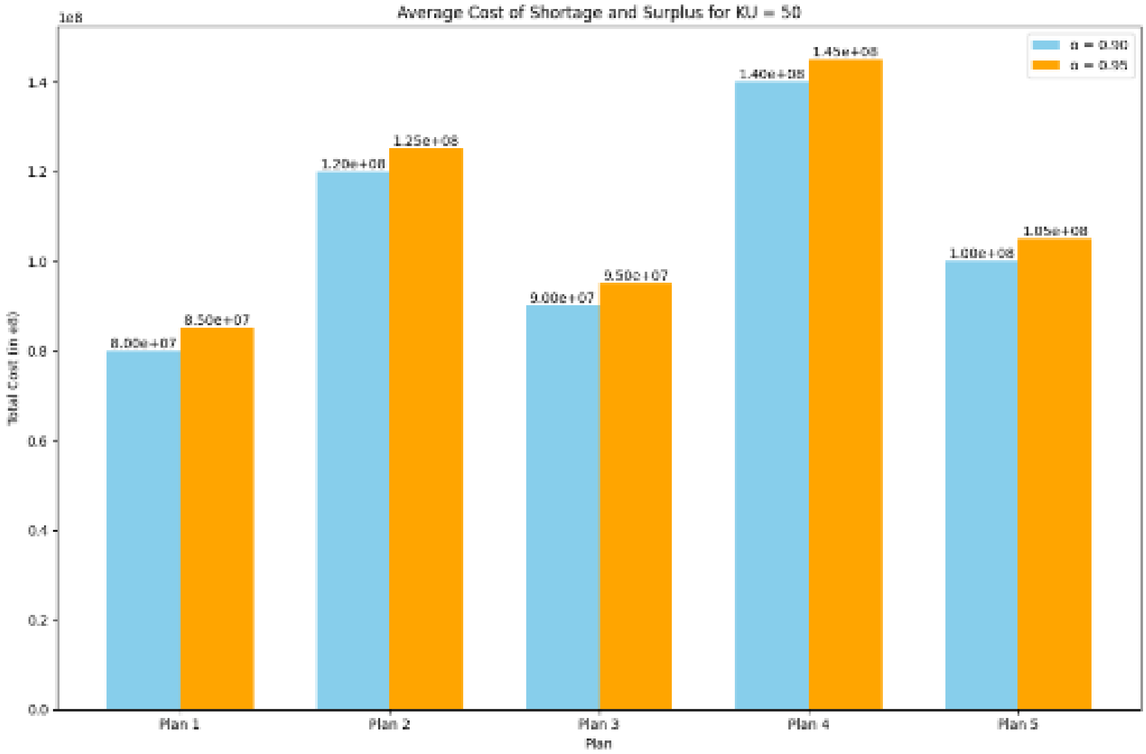


Figure 5. Average Cost of Shortage and Surplus for KU=50.
Source: Author's data

CONCLUSION

After this research present analysis for creating robust model for creating egg production plans based on stochastic method, this research found that these findings demonstrate that Plan C (Cumulative Demand Strategy) consistently outperforms other plans by maintaining the lowest surplus and surplus-to-demand ratios while effectively minimizing shortages. This superior performance is evident at both confidence levels (α = 0.90 and α = 0.95), where Plan C achieves a more optimal balance between shortage costs and surplus costs. Thus, this study presents both theoretical and practical contributions to the field of production planning under uncertainty. Theoretically, it advances the integration of stochastic programming and cooperative game theory, introducing a novel approach to managing demand variability in the poultry industry, particularly within cooperative funding systems. This approach enhances the understanding of optimizing production under fluctuating conditions. Practically, the cumulative demand strategy (Plan C) offers a robust and adaptable model that minimizes surplus and shortage costs, strengthening economic resilience for small and medium poultry farmers in Indonesia. The implications for industry application are significant, as this model supports cost-effective, waste-reducing operations that can dynamically adjust to demand shifts.

However, this research has certain limitations. The model's effectiveness relies on accurate historical data, which may not fully capture sudden shifts in demand due to unforeseen events or market disruptions. Additionally, while Plan C is shown to perform optimally in a controlled environment, its scalability to larger, more diverse poultry operations has yet to be fully tested. In response of that, the future research could address these limitations by exploring the integration of real-time data analytics to enhance responsiveness and accuracy in demand prediction. Additionally, testing the model in diverse production environments could provide insights into its scalability and adaptability across different poultry farming scales and geographic regions.

CONFLICT OF INTEREST STATEMENT

The author declares that there is no conflict of interest regarding the publication of this manuscript.

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