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IMPROVING FINANCIAL PERFORMANCE THROUGH PROBABILISTIC INVENTORY MANAGEMENT AND COST EFFICIENCY ANALYSIS: LEARN FROM A DAIRY MILK COOPERATIVE

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Abstract

The study mainly focused on the inventory management of wheat pollard, the most essential material for the production of concentrates required by cooperative members. A probabilistic inventory management model is applied to address the issue of uncertainty in concentrates requirements. The model recommends a potential inventory cost savings. More precisely, the model suggests to order an amount of 60,000 kg of wheat pollard and transport using three trucks with the capacity of 20 tons respectively. As a consequence, the company save IDR32.63 million of inventory cost each year. In addition, the cooperative can meet nearly all requests for wheat pollard with a 98% service level. The study's findings indicate that adopting the probabilistic inventory management model can enhance the financial performance of the cooperative through inventory cost efficiency. The study highlights the importance of inventory management in bridging cooperative long-term productivity and uncertainty, an area still underexplored in operations research.

Keywords: cooperative performance; probabilistic inventory management; financial performance; uncertainty

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INTRODUCTION

A cooperative is unlike any other kind of business as the owner also serves as the consumer. In terms of ownership structure, financial goals, operational effectiveness, and community impact, cooperatives and investor-owned businesses are very different. While investor-owned businesses concentrate on increasing profits for shareholders through market-driven tactics, cooperatives prioritize member needs and local development through democratic governance and cost-based operations. Cooperatives are said to have the most influence when they recognize and capitalize on their distinct organizational ideals and traits (Novkovic et al., 2022). This implies that cooperatives have a significant positive impact on their communities and members, driven by their unique values and organizational structure. This includes economic stability, social benefits, and community wealth creation. Because the cooperative is member-owned and democratically controlled, members should use its products or services. Members want the cooperative to provide them with the best service possible. Meanwhile, as owners, members place their trust in management, who are appointed based on the decision of the members' meeting, to manage the firm, meet member requirements, and create a surplus (ICA2023).

There is a large body of study on cooperative performance. In general, these investigations focus on two types of measurement: financial and non-financial. Measuring financial performance entails assessing how well these member-owned businesses use their resources to attain sustainability, profitability, and financial stability. Meanwhile, non-financial performance measurement relates to the welfare, success, and influence of the organization in general given the distinctive character of member-driven and community-focused cooperatives. Financial performance can be quantified using tools such as profit margin, return on assets, return on equity, and liquidity current ratio (Chungyas & Trinidad, Ph.D., 2022). Traditional financial metrics such as size, specialization, capital base, return on assets, loan to assets, leverage, and cost to income ratio can also be used to assess cooperative performance (Lauermann et al., 2020); (Pokharel et al., 2020). Financial performance can be measured using the profitability ratio, specifically Return on Assets (ROA). This measurement assesses the extent to which business achievements are measured through financial reports, providing an overview of the efficiency of the use of funds and the resulting profit (Cahya et al., 2021).

Cooperative performance is reasonably straightforward to measure in terms of finances and internal business operations, but not from the standpoint of customers. Customer-side performance measurement is concerned with the interests of members as customers, who are interested in price, delivery, service, cooperative governance, coverage, member service quality, and management systems and procedures (Jamaluddin et al., 2023; Benos et al., 2018). Measuring diverse member needs, subjectivity, communication barriers, engagement level, cultural differences, and complexity are the challenges need for tailored and inclusive approaches to accurately measure and address member satisfaction in cooperatives. From a marketing standpoint, brand equity has a good association with cooperative financial performance (Grashuis, 2019). It is revealed that trademark and service mark ownership affect financial performance. A 1% increase in trademarks and service marks results in significant increases in net sales and net income.

While performance measurement in cooperatives has traditionally focused on financial stability, some research has been performed to assess cooperative performance in non-financial areas. Economic, social, and environmental variables can be used to assess cooperative success (Aris et al., 2018; Marcis et al., 2019; Macagnan and Seibert, 2021). Indicators such governance, social, and environmental can be used to ensure that cooperatives not only focus on financial performance but also on their social, environmental, and governance responsibilities (Aris et al., 2018). Social indicators like member welfare and quality of life of both employees and cooperative members, education and qualification of both employees and cooperative members, and member participation help in assessing the cooperative's performance beyond financial metrics, focusing on their social and environmental impact, as well as their adherence to cooperative principles (Marcis et al., 2019).

Other research uses a non-financial element method to determine cooperative performance. Non-financial variables include social capital (Yu & Nilsson, 2021), board of cooperative (Ghosh and Ansari, 2020; Kusmiati et al., 2023), motivation of the board (Chareonwongsak, 2017), membership (Wassie et al., 2019), cooperative governance (Jamaluddin et al., 2023), cooperative size (Pokharel et al., 2020), economic policy uncertainty (Singh et al., 2019), the importance of initial farmer capital in livestock cooperatives (Sembada et al., 2022), active participation of members (Cheng et al., 2022), and adherence to cooperative principles (Golovina et al., 2020). Member involvement in capitalizing and utilizing products/services can also boost cooperative success (Kusmiati et al., 2023). The entrepreneurial competencies play the importance role in achieving business success. Hence, the cultivation and development of entrepreneurial competencies are indispensable to foster business growth and long-term viability (Yuldinawati and Yelliantty, 2023).

Research on cooperative performance in terms of operations is still scarce. The rarity of research on measuring cooperative performance from an operations point of view can be attributed to the multifaceted nature of cooperatives, methodological challenges in capturing their dual objectives, a lack of standardization in measurement practices, and a historical focus on traditional financial metrics. Most of the current research employs both financial and non-financial approaches; nevertheless, it lacks the service component for members who are also users and owners. More study on other measures of efficiency and performance is required (Benavides and Ehrenhard, 2021). Efficiency in business can be realized by minimizing resource usage throughout the entire process (Agustin and Rusliati, 2020).

Cooperatives are truly unique commercial entities. Measuring cooperative performance just in terms of financial and non-financial aspects is insufficient. Aggregated metrics, such as the Balanced Scorecard (BSC), should be examined (Zachow & Bertolini, 2019). The application of BSC allowed cooperatives to measure results, identify areas for improvement, and ensure that their activities align with both economic and social objectives. However, the use of Balance ScoreCard to measure cooperative performance also faces challenges such as lack of clear objectives and strategies, inadequate data collection and analysis, collecting accurate and comprehensive data for all four BSC perspectives, resistance to change, limited understanding of BSC, resource constraints, and focus on short-term results (Surjaatmadja & Kusniawati, 2020)

The BSC framework can help the organization articulate its vision and goals and put them into tactics. The BSC is a very useful tool for communicating how different parts of the organization contribute to the overall success. This allows companies to identify areas that need improvement and ensure that all elements of the organization are moving towards the same goal (Rahardjo, 2020). The BSC allows companies to link strategies with specific KPIs, so that the organization can conduct a comprehensive performance evaluation. With this approach, companies not only focus on finances, but also other factors such as customers, business processes, and employee development (Sukmawan, 2019). Research on cooperative performance in operational management is relatively limited in number, especially in Indonesia. Until this day, the most significant research on cooperative performance, in terms of operation, was undertaken by Nuraina et al. (2021). In this study they assessed the dairy farmer cooperative's supply chain performance in terms of long-term productivity.

Inventory management is a key component of operations management. Inventory management is crucial to corporate performance, both in terms of customer service and efficient operations. Inventory must be managed to meet or exceed consumer expectations (Khan et al., 2020) while also maintaining operational success and organizational performance (Munyaka & Yadavalli, 2022). Inventory must be managed to anticipate demand fluctuation and ensure smooth operations (Nemtajela & Mbohwa, 2017).

Effective inventory management based on demand information is essential for reducing the level of uncertainty and enabling businesses potentiality to make the best decisions about stock levels and replenishment strategies (Ralfs & Kiesmüller, 2022), as well as assists businesses in determining suitable reorder points, safety stock levels, and order timing, all of which are critical under uncertain conditions (Hofstra et al., 2024).

As with any business, planning, personnel expertise, documentation/store records, and other elements have been shown to have a significant impact on inventory management effectiveness. Firms face inventory management difficulties such as ordering costs, holding costs, stock outs, productivity, profitability, and even customer happiness or discontent (Srour, 2022). Among the inventory management problems that businesses face include overproduction, underproduction, stock outs, delays in the delivery of raw materials, and inconsistencies in documentation (Chan et al., 2017). Maintaining an adequate inventory ensures that products are available when customers need them. By implementing effective inventory management strategies like EOQ, companies can ensure product availability, improve delivery speed, and enhance order accuracy—all key drivers of customer satisfaction. Technology helps companies maintain a balance between the availability of goods and inventory costs to minimize the risk of shortages or excess inventory under uncertain conditions.

Meeting client demand and having proper inventory when buyers require them is critical to maintaining customer pleasure and loyalty. Materials (final goods, raw or auxiliary materials, components, or supplies) must be available in adequate quantities to reduce the risk of stockouts, which occur when there is insufficient material to meet consumer demand or operational needs. On the other hand, having too much inventory reduces efficiency since inventory expenses rise, resulting in a decrease in business performance.

Inventory levels become more difficult to determine when there is uncertainty. Uncertainty can emerge on the demand side, the supply side, or the supplier's lead time. An inaccuracy in determining the level of inventory can be deadly because it interferes with the level of service or the smooth operation of manufacturing, lowering efficiency owing to rising inventory expenses.

Both service level and fill rate are critical measures for managing inventory in the face of uncertainty, which a higher service level or fill rate might boost the level of satisfaction within customer side, yet it is essential to weigh this level of benefit against inventory carrying costs and the potential of inventory write-offs. The service level and fill rate have a direct impact on customer satisfaction. Establishing an appropriate service level is critical for businesses to balance customer happiness and expected profit.

Maintaining ideal service levels and fill rates helps manage uncertainty, lowering the risk of stockouts (Barros et al., 2021). The variability of fill rate could potentially have a detrimental effect on performance (Harbi et al., 2018). As suggested by Aulia et al. (2024), one way to begin satisfying and cultivating customer loyalty is by focusing on product availability, which is an important component of fill rate. With its unique character, where customers are members, cooperatives should be able to manage uncertainty because demand patterns more easily by members are more predictable than demand patterns in ordinary companies. Records of transactions between members as a customer base are sufficient for the preparation of demand forecasts so that the optimal quantity ordered can be easily determined.

The XYZ Cooperative, a dairy milk producers cooperative in West Java, Indonesia, hereinafter referred to as the cooperative, serves the needs of concentrate for members' cow feed mixtures. The concentrate is made from coconut cake, molasses, wheat pollard, soybean meal (SBM), corn gluten feed (CGF), and mixed with all rum. Research indicates that wheat pollard and SBM, when protected by condensed tannin, can positively affect feed quality (Chuzaemi et al., 2014). Wheat pollard contains practically all the nutrients needed to make concentrates, except for moisture content (Nuraina et al., 2020). Wheat pollard is the most important raw resource for the cooperative because of its utility and worth. Until now, in meeting the needs of wheat pollard, the cooperative completely relies on instantaneous demand predictions, resulting in severe swings in the amount of concentrate stockpiled, where if it not tackled precisely thus may lead to a potential of running out of stock at times while overstocking at others.

In fulfilling the needs of wheat pollard, the cooperative fully relies on instantaneous demand estimates, resulting in extreme fluctuations in the amount of concentrate stored. This may cause the cooperative to experience stock-out at certain periods, and over stock at other periods. This condition has an impact on the low level of service to members and low efficiency due to increased inventory costs. This may also result in losses for members because the product fails to suit the needs of cows and affects milk output (Nuraina et al., 2021). These factors, rather than benefiting the cooperative, have the potential to diminish member engagement and economic benefits.

The purpose of this study is to look at how employing an inventory management model in the face of uncertainty affects customer service and efficiency. The fill rate measures the cooperative's ability to meet members' wheat pollard needs. Meanwhile, efficiency is assessed by a reduction in inventory costs, which boosts the cooperative's earnings.

Despite its potential to provide important insights into effectiveness, efficiency, and member service, there is still a dearth of research on assessing cooperative performance from an operations management viewpoint. This disparity results from the complexity of cooperatives, which frequently have both social and economic goals in addition to a wide range of member requirements. Current research ignores the complex operational factors that contribute to cooperative success in favor of concentrating primarily on financial measurements or general non-financial variables. Additionally, comparative research and the creation of best practices are hampered by the absence of established operational performance metrics for cooperatives. This research gap offers a chance to create and implement operational performance assessment frameworks that are specific to cooperatives' features, which will ultimately lead to a more thorough understanding of their performance drivers and allow for focused changes.

The study integrates probabilistic inventory models, cost efficiency analysis, Monte Carlo simulation, and sensitivity analysis to create a quantitative method for evaluating operational performance in cooperatives. It connects operational efficiency with financial outcomes and member participation, a perspective largely absents in cooperative research. This research uniquely contributes to understanding how inventory management can serve as a tool for cooperative performance improvement, both operationally and financially. It fills critical gaps by addressing uncertainty and combining advanced quantitative methods within a cooperative-specific framework.

METHOD

The study was carried out on XYZ Cooperative, which is a dairy milk producers cooperative based in Garut, West Java, Indonesia. This study utilized primary data including carrying out field observations, combined with datasets from structured in-depth interviews with the executive officers of the cooperative, and lastly from the administered questionnaires. The data collected through observation includes the flow of receiving and storing the ordered wheat pollard, the storage capacity, and the method of fulfilling members' wheat pollard needs. Structured interviews are used to collect data on demand patterns by members, inventory costs incurred and their values, frequency and quantity of orders, instances of excess or shortage of stock, and other relevant data that will be analyzed for inventory management modeling.

This study employed three continuous stages in its practice, as presented in Figure1 below. It starts from building the forecasting demand model(s) in the first phase, continued with the process of analyzing the level of services and efficiency of wheat pollard procurement in the second phase, and concluded with the sensitivity analysis in the final phase. The first phase is designed to build a forecasting demand model based on Monte-Carlo simulation analysis to estimate the forecasting demand schedule for wheat pollard. The superiority of the Monte Carlo method is in its ability to optimize the inventory level, guaranteeing economic efficiency while maintaining a designated service level (Cui et al., 2021). Practically, the Monte Carlo Method takes historical data of wheat pollard demand, determines the probability distribution of historical demand data, and generates random numbers to simulate future demand. With a more accurate demand forecast, the determination of other parameters in inventory management will be more precise so that the determination of the number of orders, order frequency, and safety stock will result in the right decision for the cooperative.

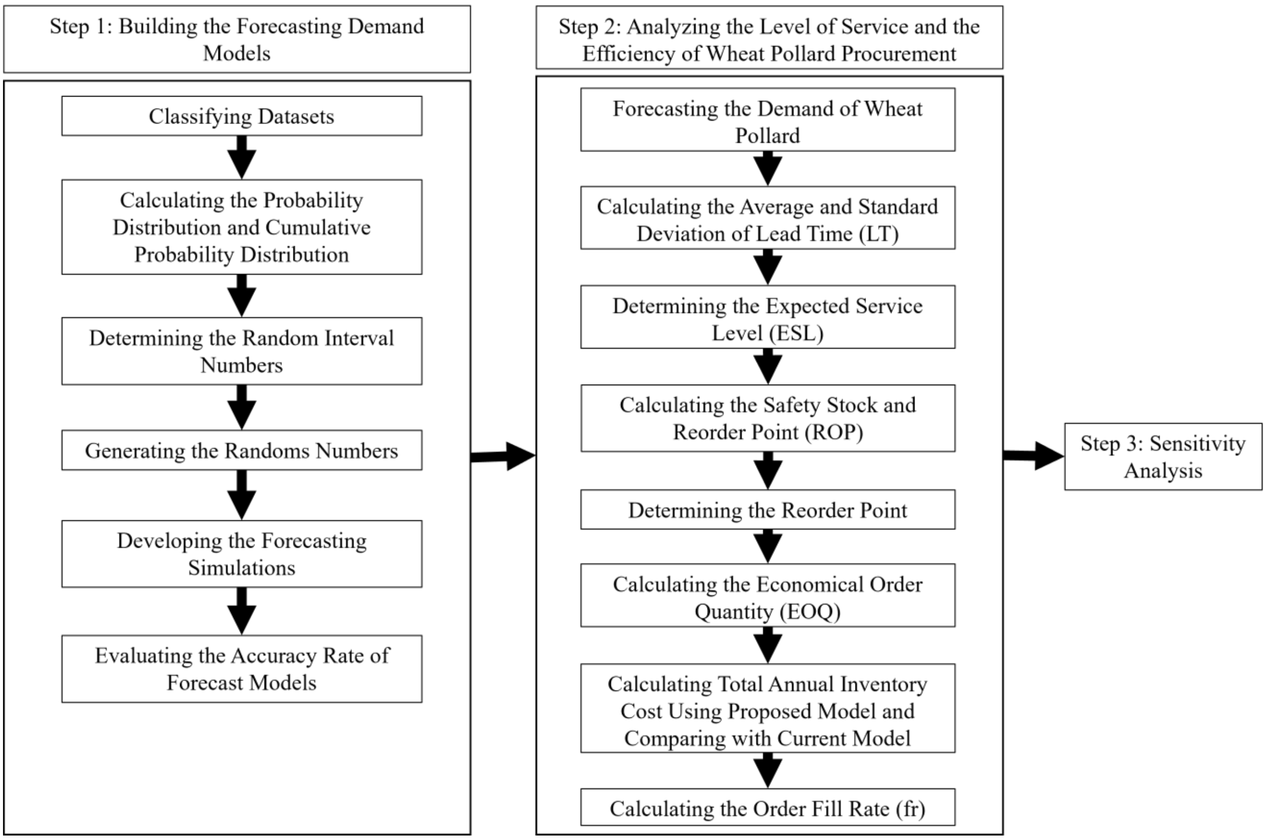

Figure 1. Multi-Stages Research

The main principle of Monte Carlo simulation is to compute the desired probability in a stochastic model by performing a predetermined number of trials, which leads to the development of the intended distribution (Hill and Spall, 2019). Furthermore, if combined with sensitivity analysis, the analysis may provide a superiority in terms of probabilistic forecasting over deterministic methodologies, hence enhancing the accuracy of forecasts (Duque et al., 2023). The utilization of Monte Carlo simulation allows for the prediction of future sales to plan for next periods by analyzing time series data, which aids in the development of production plans (Fabianova et al., 2019).

This study utilizes Monte Carlo simulation to address uncertainty in the demand for wheat pollard within a cooperative. The application steps start from calculating demand distribution, determining random number to forecast the demand. Forecast accuracy is measured using the Mean Absolute Percentage Error (MAPE). After forecasted demand is determined, the next step is integrating with inventory management. The parameters calculated in this integration include safety stock, reorder point, EOQ, and inventory costs arising from these parameters. The study compares a baseline (Monte Carlo results) with favorable and unfavorable scenarios based on growth rate variations.

Next, the second phase is designed to analyze the level of service and efficiency of wheat pollard procurement based on probabilistic inventory management concept. The output of the first stage in the form of demand forecasts is necessary to perform the second stage. In this phase, there are eight stages that have been concluded, firstly forecast the demand of wheat pollard, continued on with calculation on the average and standard deviation of lead time (LT), along with the expected service level (ESL), safety stock (SS) and reorder point (ROP), economic order quantity (EOQ), next calculate total annual inventory costs using proposed model and compare it with current policy, and lastly calculate the order fill rate. The final phase, which is the third one, is designed to build sensitivity analysis to measure the strength of the model and compares the economics on the effects in different cost(s) parameter(s), and the number of order fill rate. The fundamental thing about these stages is that the output of each stage will become the input for the next stage.

RESULTS

The cooperative has 1,401 dairy farmers currently participating, organized into 34 distinct groups. The cooperative produces and provides all the required concentrate for its members to use. There are six separate kinds of raw materials required to produce concentrate, which are: 1) coconut cake; 2) molasses; 3) wheat pollards; 4) soybean meal (SBM); 5) corn gluten feed (CGF); and 6) max all rum. From a practical and economic perspective, wheat pollard stands out as the most critical raw material among the six ingredients required to produce the concentrate. This study focused on identifying which scenarios may bring the best of potentiality to increase the operational performance within cooperative organization, in terms of maximizing economic benefit and minimizing the level of uncertainty within the production process. Operational performance can be measured using inventory cost, service level, demand variability, and operational cost efficiency. In addition, economic benefits can be in the form of financial performance and the remaining results of cooperative operations.

The first step in applying the probabilistic inventory management model is to develop demand forecasting by employed Monte Carlo simulation and combined it with the scenario analysis, with the results from Monte-Carlo simulation serve as the baseline scenario, thus further being compared to two scenarios, favored and unfavored. Based on information from the historical datasets for 24 months and past interviews with the stakeholders, the level of growth rate can be used as the main parameter(s) that determine these scenarios (favored and unfavored), and thus compare them to the baseline scenarios as the mirror image of the existing policy conditions. The growth rate level varied from 13.09% in the lowest until 16.14% in the highest.

Next, this study determines the baseline scenario that is gained from the Monte Carlo simulation was performed using the following steps. The first step is classifying the dataset of wheat pollard demand. Data on the demand for wheat pollard over a span of 12 months are presented in Table 1 below.

Table 1. Demand for Wheat Pollard (kg)

Period	Demand	Period	Demand
1	64,364	7	57,769
2	54,627	8	62,360
3	56,466	9	54,727
4	54,391	10	56,903
5	59,222	11	57,873
6	54,004	12	56,985
Total			690,230

The next step involves calculating the probability distribution and cumulative probability distribution, by dividing the demand in period t by the aggregate demand across all observed times.

$$P_t = \frac{D_t}{\sum_{t=1}^{n} D_t} \quad \text{.....(1)}$$

While the cumulative probability distribution is calculated by adding the cumulative probability distribution of the previous period with the current probability distribution.

$$CP_t = CP_{t-1} + P_t \quad \text{.....(2)}$$

The third step is determining random interval numbers based on the cumulative distribution calculation, with the start limit is the number after the end limit number of the previous frequency's random number interval. Meanwhile, if the frequency is beginning to count at the beginning, the initial limit of the random number interval number is zero (0). The final limit of the random number interval number is the result of the cumulative distribution of the frequency.

The fourth step is generating random numbers. Linear Congruential Generator (LCG) can be applied to generate random numbers. LCG is a pseudorandom generator that produces a sequence of numbers. LCG is obtained by the formula:

$$X_{t+1} = (aX_t + c)\ mod\ m \quad \text{.......................................(3)}$$

Where X is the sequence of pseudo-random values, and m, 0 < m = the modulus. a, 0 < a < m = the multiplier. c, 0 ≤ c ≤ m = the increment. X0, 0 ≤ X0 ≤ m = the "seed" or start value.

Microsoft Excel has a built-in method for generating random numbers called the =RAND() function. In this study, the replication process is approximately 12 times, which corresponds to the number of observation periods (12 periods).

The next step entails the development of a forecasting simulation, where the data inside the range of random numbers is gathered and thus combined with the generated random numbers to develop final data of the simulation. The data within the random number range represents the predicted value obtained through the process of matching. The sixth phase involves evaluating the accuracy of the forecast model with the Mean Absolute Percentage Error (MAPE) formula.

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\left[\frac{AD_t - FD_t}{AD_t}\right] \quad \text{...(4)}$$

Where ADt is the actual demand, FDt is the forecasting demand, and n is the total number of observations. MAPE indicates an average of the absolute percentage errors; the lower the MAPE the better (Chen et al., 2018). MAPE less than 10 percent is highly accurate forecasting (Lewis in Moreno et al., 2013).

The Monte Carlo simulation results and forecasting accuracy calculations are presented in Table 2. The table shows that the total wheat pollard requirement for 12 months is 712,287 kg. The forecasting accuracy is calculated as follows:

$$MAPE = \frac{0.74}{12} = 6.21\% \quad \text{...(5)}$$

The MAPE of 6.21% above shows that forecasting with Monte Carlo simulation has a high level of accuracy. Thus, Monte Carlo simulation can be used to forecast wheat pollard demand of cooperative members. The results of all the steps are presented in Table 2 as follows.

Table 2. Monte Carlo Simulation Results for the Baseline Scenario

Per.	Actual Demand	Prob. Distr.	Cumulative Prob. Distr.	Rand. Int.	Rand. Number	Forecast Demand	Absolute Percent. Error
1	64,364	0.093	0.093	0-0.093	0.06	64,364	-
2	54,627	0.079	0.17	0.094-0.17	0.01	64,364	0.18
3	56,466	0.082	0.25	0.18-0.25	0.47	54,004	0.04
4	54,391	0.080	0.33	0.26-0.33	0.77	56,903	0.04
5	59,222	0.086	0.42	0.34-0.42	0.6	62,360	0.05
6	54,004	0.078	0.50	0.43-0.50	0.69	54,727	0.01
7	57,769	0.084	0.58	0.51-0.57	0.01	64,364	0.11
8	62,360	0.090	0.67	0.58-0.67	0.9	57,873	0.07
9	54,727	0.079	0.75	0.68-0.75	0.18	56,466	0.03
10	56,903	0.082	0.83	0.76-0.83	0.04	64,364	0.13
11	57,873	0.084	0.92	0.84-0.92	0.14	54,627	0.06
12	56,985	0.083	1.00	0.93-1.00	0.85	57,873	0.02
Total	690,230					712,287	0.74

The probabilistic distribution is obtained by dividing the value in period i by the total value in one year. Meanwhile, the cumulative probability for a given period is the sum of probabilities for all previous periods up to the current period. The cumulative probabilistic value at a given period is used to create a random interval.

After the forecast demand is determined, further analysis required to combine the result of Monte Carlo analysis as the baseline scenario with the two other scenarios, favored scenario (based on average growth rate 16.14%) and unfavored scenario (based on average growth rate 13.09%). Results of the scenario analysis are presented in Table 3 below. During the 12-month(s) period, the range of wheat pollard real production varied between 52,423 – 65,177 tons per month, for the three scenarios. Total production amounted to 721,276 tons per year for the favorable scenario, with level of growth/annum reach 16.14% a year. MAPE rates range from 5.71 – 6.8 with accuracy rate 95.7% - 97.93% for the three scenarios, with level of growth ranging from 1.05% - 1.26% per month, for the three scenarios (base line, favored, unfavored). Discrepancies of 1% growth leads to potential changes in the level of production points up to 5,605 – 6,073 tons per year for the three scenarios.

Table 3. Scenario Analysis for the Forecasting Demand Model(s)

Month(s)	Wheat Pollard Real Demand	Probability Distribution	Cumulative Probability Distribution	Favorable Scenario		Baseline Scenario		Unfavorable Scenario	
				Forecast	MAPE	Forecast	MAPE	Forecast	MAPE
1	64.364	9,32%	9,32%	65.176	-	64.364	-	63.691	-
2	54.627	7,91%	17,23%	65.176	0,19	64.364	0,178	63.691	0,166
3	56.466	8,18%	25,41%	54.685	0,03	54.004	0,044	53.439	0,054
4	54.931	7,96%	33,37%	57.621	0,05	56.903	0,036	56.309	0,025
5	59.222	8,58%	41,95%	63.147	0,07	62.360	0,053	61.708	0,042
6	54.004	7,82%	49,77%	55.418	0,03	54.727	0,013	54.155	0,003
7	57.769	8,37%	58,14%	65.176	0,13	64.364	0,114	63.691	0,103
8	62.360	9,03%	67,17%	58.603	0,06	57.873	0,072	57.268	0,082
9	54.727	7,93%	75,10%	57.178	0,05	56.466	0,032	55.876	0,021
10	56.903	8,24%	83,34%	65.176	0,15	64.364	0,131	63.691	0,119
11	57.873	8,38%	91,72%	55.317	0,04	54.627	0,056	54.057	0,066
12	56.985	8,26%	100,00%	58.603	0,03	57.873	0,016	57.268	0,005
Total	690.230			721,277	0.817	712,287	0,032	704.843	0,685
			Growth per annum	16,24%		14,76%		13,29%	
			Growth per month	1,26%		1,15%		1,05%	
			MAPE		6.811		6.206		5.706
			Accuracy Rates		95,70%		96,90%		97,93%

In this phase, the authors employed the forecast model (from the three scenarios) and further analyze the level of service and efficiency of wheat pollard procurement to meet the needs of members with a probabilistic inventory management model. In conditions of uncertainty, management concerns on the product availability, often called as service level, and inventory cost. Service level is the complement of the probability of stockout. In the context of the order cycle, cycle service level (CSL) is the fraction of replenishment cycles that end with all the customer demand being met. CSL equals the probability of not having a stockout in a replenishment cycle. CSL is a key metric in inventory management that measures the probability that inventory is sufficient to meet demand during a replenishment cycle without running out of stock. For wheat pollard inventory used to produce concentrate (e.g., livestock feed), CSL can help ensure smooth production while minimizing costs.

Uncertain conditions, both demand and lead time, raise the possibility of stockouts. Safety stock is needed to reduce these stockouts, or to satisfy the demand that exceeds the amount forecast. Safety stock is the inventory held to avoid shortages caused by uncertainty (Yamazaki et al., 2016). In the context of service level, for normally distributed demand, the safety stock needed to obtain a service level is obtained by multiplying the lead time demand standard deviation with some safety factor (Prak et al., 2017).

In addition to safety stock, to measure management's ability to meet demand, fill rate indicators are often applied. Fill rate represents the fraction of demand that is immediately or directly fulfilled from the on-hand stock (Babiloni and Guijarro, 2020).

Determining the inventory level of wheat pollard in this research is developed through several steps. The first, forecast the demand of wheat pollard including demand standard deviation. The second step, calculate the average and the standard deviation of lead time (LT), and then the third, determine the expected service level, i.e., the probability of not having stock out in a cycle of wheat pollard order. This is obtained based on interviews with the executive officers of the cooperative. This officer is responsible for wheat pollard procurement and the interview results were quantified for further analysis.

The fourth step, calculate the safety stock and reorder point. Safety stock (ss) is calculated using the formula:

$$ss = Z.\sigma_{dL} \qquad (5)$$

Where: Z = z-score of expected service level. σ dL= standard deviation of demand during LT.

In this case, both demand of wheat pollard and LT from supplier are uncertain. Therefore, σdL is calculated using the formula:

$$dL = \sqrt{(average\ LT.\sigma_d^2) + (d^2\sigma_{LT}^2)} \qquad (6)$$

The ss value will be used in the fifth step, determining the reorder point (ROP) using the formula:

$$ROP = ss + d.LT \qquad (7)$$

Where: d = daily average use of wheat pollard. LT = average lead time in day.

The sixth step, calculate the economic order quantity (EOQ), an acceptable number of orders as consequent of ordering cost and holding cost. EOQ is calculated using the formula:

$$EOQ = \sqrt{\frac{2.D.S}{h.C}} \qquad (8)$$

Where: D = annual demand of wheat pollard. S = ordering cost for an order. h = holding cost per year as a fraction of product cost. C = buying price of wheat pollard per kg.

If there is any limitation of resource (K, can be in the form of truck or warehouse capacity) so that an order of EOQ cannot be carried out, then the optimal order quantity is obtained by comparing the order cost of K units with Q/K (Q*) units. The quantity order will be the minimum value of the EOQ or K (Chopra, 2019: 674).

The Q* value will be used in the seventh step, calculate total annual inventory costs using the proposed model and compare them with those using the current policy. Inventory costs consist of order cost and holding cost. Annual inventory costs (IC) are calculated using the formula:

$$Annual\ IC = \left[\left(\frac{D}{Q^*}.S\right) + \left(\left(ss + \frac{Q^*}{2}\right).h.C\right)\right] \qquad (9)$$

The final step, calculate the order fill rate, which is the fraction of orders that are filled from available inventory. Fill rate (fr) is calculated using the formula (Chopra, 2019: 780):

fr = 1-ESC/Q* ……………………………………….(10)

Where: ESC = expected shortage per replenishment cycle, which can be calculated (with the help of Microsoft Excel functions) using the formula (Chopra, 2019: 781):

ESC = -ss [1 – NORMDIST(ss/σ_{dL}, 0, 1, 1)] + σσ_{dL}.NORMDIST(ss/σ_{dL}, 0, 1, 0) ……….(11)

DISSCUSSION

The cooperative is obligated to pay IDR2.25 million for a single procurement or order, which covers transportation, loading, and unloading costs, along with other related ordering costs. The cost of buying one kilogram of wheat pollard is IDR6,750, excluding the quantity discount. To store the wheat pollard, the cooperative must expend administrative costs, obsolescence costs, and lost opportunities for warehouse use, amounting to 12% of the value of the wheat pollard stored. The following table concisely states the comparison between the current policy and the probabilistic model.

Table 4. Comparison of Inventory Costs Between the Current Policy and the Probabilistic Model

Parameters	Current Policy	Probabilistic Model	
		Unfavorable Scenario	Favorable Scenario
Average demand per month (tons)	57.52	59.36	60.11
Average demand per day (tons)	2.30	2.37	2.40
Stdev demand per month (tons)	N/A	4.27	4.23
Stdev demand per day (tons)	N/A	0.171	0.169
Lead time (average)	3.00	3.00	3.00
Lead time (standard deviation)	0.79	0.79	0.79
Stdev of demand during lead time - thousands	N/A	1.90	1.92
Average use during lead time - thousands	6.90	7.12	7.2
Cycle Service Level (CSL)	N/A	0.98	0.98
Z(CSL)	N/A	2.05	2.05
Safety Stock (SS) - thousands	N/A	3.90	3.95
Reorder Point (ROP) – thousands kg	60.00	11.02	11.161
Order cost (S) per order (IDR) - millions	2.25	8.25	7.43
Buying price (IDR/kg) - thousands	6.75	6.75	6.08
Holding cost (h) per unit per year	0.12	0.12	0.11
EOQ (unit) (tons)	N/A	120.46	127.07
W/H capacity (tons)	60.00	60.00	60.00
Q (tons)	15	60	13.500
Order frequency (times)	46	11.87	11.75
Order cost (IDR) - millions	103.53	99.00	89.12
Holding cost (IDR) - millions	6.075	24.30	19.45
Total cost (IDR) - millions	109.61	123.30	108.57
Excess inventory (tons)	6.47	-	-
Material Cost due to excess inventory (IDR) - millions	43.70	-	-
Holding cost for excess inventory (IDR) - millions	2.62	-	-
Total inventory cost – per year - IDR (millions)	155.93	123.30	108.57
Net Benefit in Saving (IDR) – per year (millions)		32.63	47.36
ESC	N/A	13.94	14.11
FR (%)	N/A	0.98.2	0.98.2

Table 4 above presents summarized results for the three scenarios that represent comparison of inventory costs between the current policy and the probabilistic model. To meet the needs of wheat pollard, the cooperative relies on estimates of real needs based on the level of potential demand (as reflected in the growth rate/year and growth rate/month). Potential demand is an estimate of demand that already accommodates fluctuations throughout the period. The cooperative places average demand ranges between 702.48 – 721.12 tons per year with standard deviation of demand varied between 4.23 – 4.27 tons per month.

To meet the demand wheat pollard, with current policy, the cooperative places orders at least 46 times while using probabilistic model, it only needs 12 times. With ordering cost of IDR2.5 million per order in current policy, every year the cooperative is required to spend IDR103.53 million of ordering costs, and IDR6.08 million to hold the inventory (as reflected in the base scenario). Using probabilistic model, the cooperative spends only IDR99 million a year for order costs, and IDR24.30 million a year for holding cost.

Under the current policy, the cooperative's records indicate that procurement has resulted in a surplus inventory of 6.474 thousand kilograms of wheat pollard annually. This leads to additional material costs of IDR43.7 million and holding costs IDR2.62 a year. The current inventory policy incurs a waste of IDR32.63 million a year due to order costs and excess inventory costs. If procurement is adjusted based on a favorable scenario, the holding costs could be reduced by 62.88%, equivalent to a savings of IDR32.95 million. This reduction in holding costs associates with excess inventory.

The total inventory cost per year under the current policy is IDR155.93 million. This may lead to discrepancies net benefit of saving between the current policy and recommended policy, in which the net benefit saving level may rise to 30.37% in the favorable scenario coming from decreasing total inventory costs from IDR155.93 million to IDR108.57 million a year.

In terms of non-economic performance, this inventory cost efficiency will certainly increase the profitability of the cooperative. Satisfying the 98% service level has an impact on the ESC, as refer to formula (11), for all three scenarios, resulted in > 98.2% fill rate level, thus implies that with safety stock ranging from 3,850-3,950 kg per order, the cooperative can satisfy almost all demands for wheat pollards. Satisfying the service level means that in 98% of the replenishment cycles, the cooperative can meet all demand without experiencing a stockout. It reflects the probability that inventory on hand will be sufficient to satisfy customer (or member) demand during the lead time. In addition, fill rate indicates that 98.2% of the total demand can be immediately fulfilled from available inventory, accounting for shortages during some cycles. It measures the fraction of demand that is directly satisfied without delays. Factors must be considered to achieve the two parameters are demand variability, lead time uncertainty, safety stock, replenishment policy, and supply chain reliability.

Efficiency is measured through inventory cost savings using probabilistic inventory management models. The key metrics include ordering costs and holding costs (calculated using Economic Order Quantity and safety stock levels), service levels (Cycle Service Level and Fill Rate, ensuring adequate stock availability without overstocking), and forecasting accuracy (e.g., using Monte Carlo simulations with a MAPE below 10% to optimize demand prediction).

The discussion of inventory management as a measuring tool for cooperative performance has not been found in the literature on cooperative performance. Being a member-owned firm, it is necessary to evaluate the cooperative's success based on two aspects: operational efficiency, which refers to how well inventory is managed, and member services, which refers to the availability of resources. The scarcity of studies exploring inventory management as a performance measurement tool in cooperatives highlights a significant gap in the literature. Previous research on inventory management, such as by Khan and Siddiqui (2019) or Barros et al. (2021), primarily focuses on investor-owned firms (IOFs), whose priorities and structures differ fundamentally from cooperatives. Addressing this gap, studies on cooperative-specific inventory management could offer valuable insights into how efficient resource allocation and uncertainty management directly influence member satisfaction and financial performance. This research presents an opportunity to integrate probabilistic inventory models and cost efficiency analysis to develop a more comprehensive framework for cooperative performance evaluation.

Studies on cooperative performance measurement that have been conducted by researchers generally focus on measurements from the financial side, such as profit margins, ROA, ROE, and liquidity ratios (Chungyas and Trinidad, 2022), capital base, leverage, and cost-to-income ratios, such as research by Lauermann et al. (2020) and Pokharel et al. (2020). The current financial performance measurement lacks the ability to capture the board's efforts in cooperative management given that financial indicators are mainly influenced by operational and other managerial factors.

Research on non-financial performance measurement, such as conducted by Cheng et al. (2022), among others, discussed the impact of active participation of members in shaping the environmental and economic performance of cooperatives. While research by Kusmiati et al. (2023) only examines the effect of observed factors on cooperative performance, not on the formation of performance itself. Research on inventory management, service levels, and fill rates, such as those conducted by Harbi et al. (2018), Khan and Siddiqui (2019), Barros et al. (2021) and Munyaka and Yadavalli (2022) were conducted in investor-owned firms (IOFs), which are very different in characteristics from cooperatives.

The novelty of this study is the quantitative operational performance measurement that is practically required by the management board, using multi-stage analysis combining the principles of probabilistic inventory model, cost efficiency analysis, the Monte-Carlo simulation and sensitivity analysis, which as far as the author knows, has not been done before, specifically within the cooperative performance context. This research also answers the problem of measuring cooperative performance from the operational side, which will have an impact on finance, and member participation, which is expected to increase due to the high service level of the cooperative.

CONCLUSION

The cooperative's financial performance would likely benefit from this inventory cost efficiency. The current procurement techniques result in an excessive quantity of inventory. To fulfil the annual requirement of 690,000 kg of wheat pollard, the cooperative needs to place 46 orders of 15,000 kg per week with a total cost of IDR155.93 million.

The probabilistic inventory management model considers the uncertainty rate at a 98% service level predicts an annual demand of 712,287 tons for wheat pollard, with the expected shortage for every replenishment cycle is amounted to 14 kg out of a total order of 60,000 kg (high fill rate up to 100%). This means that the cooperative can fulfil almost all wheat pollard needs, which in turn is expected to lead to increased member participation.

The application of the probabilistic model also has an impact on increasing efficiency in the form of saving inventory costs. Using this model, a safety stock of 3,900 kg is proposed to meet a 98% service level, and the cooperative can save IDR32.63 million annually in inventory costs, compared to the current policy. This is expected to improve the cooperative's financial performance in the end.

The study has several limitations that should be considered. Firstly, it focuses on a single dairy milk cooperative in West Java, Indonesia, which may limit the generalizability of the findings to other cooperatives with varying operational scales, geographic regions, or member structures. Additionally, the analysis is based on a relatively short dataset of 12 to 24 months, which may not capture long-term demand trends or anomalies comprehensively. The study simplifies certain variables, such as assuming constant lead times and uniform cost structures, without addressing external factors like supply chain disruptions, price fluctuations, or competition. Furthermore, while the probabilistic inventory model demonstrates operational efficiency, its practical application may face challenges due to constraints such as warehouse capacity and logistical limitations. The static scenario analysis does not account for unexpected disruptions or dynamic market variations. Lastly, the study's reliance on theoretical assumptions, such as demand predictability and the applicability of a normal distribution, may affect the accuracy and real-world relevance of the model. Future research should aim to address these limitations by incorporating broader datasets, benchmarking against alternative models, and considering real-world implementation challenges.

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