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Monte Carlo Algorithm Applications in Shrimp Farming: Monitoring Systems and Feed Optimization

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***Abstract*— Indonesia is one of the world's leading maritime nations, ranking second in fishery export value in 2020. Shrimp stands out as the most lucrative commodity, with an export value of USD 1,997.49 million. Feeding shrimp plays a vital role in their growth and cultivation; however, overfeeding can result in feed residue that negatively impacts the quality of pond water and represents the biggest operational after capital expenditure. The profitability of shrimp farming heavily depends on the feeding cost. This study uses the Monte Carlo algorithm to track feed in shrimp and provides an optimal feeding plan. The algorithm can be used to provide feed recommendations for shrimp start from 33 days of cultivation (DoC), with a best range around 85kg to 92kg. The findings show the potential of the Monte Carlo algorithm in enhancing feeding plans in shrimp farming industries.**

***Index Terms*— Cultivation; Feeding; Feed Recommendations; Margin; Monte Carlo; Operational Cost; Pond Water; Shrimp Farming**.

I. INTRODUCTION

Shrimp farming plays a crucial role in the aquaculture's global industry. It has made a big contribution to the seafood market. As one of the fastest growing industries, shrimp farming drives large economic value around the world, with exports reaching into billions of dollars annually [1]. Indonesia, as a maritime country, holds an important position in the global shrimp market. With the longest coastline and favorable climatic conditions, Indonesia able to capitalize on shrimp aquaculture to become one of the top exporters of shrimp. In 2023, the industry contributed USD 2.2 billion in export value, showing its importance to Indonesia's economy [2]. This growth is driven by increasing global demand, particularly for high-value shrimp species, and Indonesia's commitment to improving shrimp farming practices. However, shrimp farmers are still facing the continuous challenge of increasing productivity and cost-effectiveness.

Litopenaeus vannamei is also known as whiteleg shrimp. It is one of the most popular shrimp species in Indonesia, due to the relatively lower growth period and disease resistance compared to other species [3]. Shrimp uses its sensory organs and appendages to detect food particles dispersed in the water. They scrape or grasp feed particles, more largely by the pereiopods (walking legs). Overfeeding, however, can be both a source of water contamination and an increase in operational cost because feeding that is not utilized is simply wasted. Therefore, controlled feeding is very vital to create an economic-ecological balance with respect to maximized efficiency of feed utilization and water quality maintenance in shrimp culture [4].

Shrimp feed plan and estimation is usually done based on mathematical approaches. Two commonly used techniques to estimate the amount of feed are index feeding and feed rate methods, both with their disadvantages and advantages. In practical situations, factors like water quality, temperature, pH, salinity, and alkalinity certain from environmental causes must be considered by the shrimp farmer, since these play a significant role in influencing shrimp appetite [5]. Whenever environmental parameters are kept to their optimum level, the shrimp shows healthy appetite, growth and development [6].

Although index feeding and feed rate methods are commonly used, most systems still overlook daily environmental changes as well as biological variations in shrimp behavior. Furthermore, even though automatic feeding systems and biofloc-based approaches have potential [7], their combination with probabilistic forecasting models is still underexplored. There is limited research on short-term feed prediction models that following to changes in shrimp biomass and survival rate that can be extracted based on the combination of index and feeding rate calculation.

Monte Carlo algorithm can be used to detemine an optimal shrimp feed calculations. The Monte Carlo algorithm provides a method for forecast of shrimp feed quantities. While other approach like genetic algorithms are better for long-term optimization of feed projection over an extended period of time, Monte Carlo is more suitable for short-range forecast due to its transparency and flexibility [8]. The other approach like regression models are straightforward, but they lack the ability to adjust in real-time for complex, adaptive dynamic systems [6]. Monte Carlo enables processing random data and an ideal approach since it decreases uncertainty via simulation [9]. In shrimp farming, statistical data for feed calculation changes daily. These factors include such as average shrimp weight, biomass, survival rate, density, water conditions, pH levels, and salinity.

Based on those aforementioned factors, a monitoring and feed calculation system was developed using the Monte Carlo algorithm. The aim of this research is to develop and validate a Monte Carlo simulation system for estimating feed quantities of L. vannamei, intended to help farmers to make informed decisions based on changing conditions, enhance feed efficiency, and reduce operational costs.

II. Literature Review

A. *Shrimp Farming and Feeding Methodologies*

A particular feeding practice is required in order to achieve optimal growth. Blind feeding method is typically used for the first 30 to 35 days of cultivation. It is a feed method where feeding amount is given without considering shrimp biomass. This method gives shrimp fry the right nutrition in their early stages of growth. However, if it is not managed properly, it could cause overfeeding and deteriorate the quality of the water [10]. As shrimp grow and gain more weight, feeding methods use calculated approach such as index feeding or feed rate feeding. Index feeding method is formulated based on calculations on shrimp biomass, survival rate, and average weight, whereas feeding rate follows a set value established through research and experience in shrimp culture [7]. Both methods have a similar goal which is optimized feed utilization. In order to maintain shrimp appetite and growth, both approaches would still require close observation of environmental factors like temperature, pH, salinity, and water quality [11].

The index feeding method for shrimp uses percentage indexing calculation. The method considers many parameters, including the age of shrimp in days of cultivation (DoC), the quantity of shrimp in one pond, and the feed index. Before applying this technique, farmers need to determine the goal of average daily growth (ADG) of the shrimp. After the ADG number is decided, it is possible to calculate the feed index percentage according to an equation (1) [6].

$$Index\ (\%) = 2 \times ADG \times 100\% \tag{1}$$

Once the index is decided, the feed quantity can be calculated using the equation (2).

$$Feed(Kg) = \frac{Index(\%) \times DoC \times Num.of\ Larvae}{1000} \tag{2}$$

Meanwhile, the feed rate method calculates shrimp feed based on the average body weight (ABW) and the biomass of the shrimp. The Feed Rate (FR) table from previous observation is used as a reference for this feed rate method. Before determining the feed quantity using this method, farmers need to do sampling to obtain the ABW value. When the ABW number is identified from the sampling process, they can calculate the shrimp biomass using equation (3) [6].

$$Biomass = ABW \times Population \tag{3}$$

After both the ABW and biomass values have been determined, the feed amount can be calculated using the FR Feeding method and its corresponding formula (4).

$$Feed = Biomass \times FR(\%) \tag{4}$$

B. *Monte Carlo Simulation*

Monte Carlo Simulation is a method used to demonstrate how sample data in the simulation may be applied and forecast its distribution. This simulation is conducted using the previous farming and feeding log data. The main idea of the Monte Carlo Simulation is to create a model variable and derive its value from the other variables that are analyzed. Monte Carlo Simulation enables calculating the average feed quantity recommendations and the standard deviation of feed amount [9].

The formula to calculate the average feed quantity is described in equation (5).

$$\mu = \frac{1}{n}\sum_{i=1}^{n} R_i \tag{5}$$

μ represents the mean obtained from the Monte Carlo Simulation. σ represents the standard deviation derived from the Monte Carlo Simulation. n indicates the number of Monte Carlo simulations to be conducted. Ri is the feed quantity recommendation for the i-th iteration.

Equation (6) is used to calculate the standar deviation of the feed quantity.

$$\sigma = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(R_i - \mu)^2} \tag{6}$$

After obtaining the average and standard deviation, the next step is to calculate the confidence interval. Before calculating the confidence interval, it is necessary to define the confidence level and then identify the z-score corresponding to the chosen confidence level using the z-table. The formula for calculating the confidence interval is described in equation (7).

$$CI = \mu \pm z \times \sigma \tag{7}$$

σ represents the standard deviation derived from the Monte Carlo Simulation. z represents the z-score based on the selected confidence level, which can be found in the z-table [12].

III. Design and Analysis

The business process analysis for the system module designed to monitor and calculate shrimp feed using the Monte Carlo algorithm is divided into two aspects. The first aspect addresses input-output data requirements. Input data for the system includes user and role information for system access, master data encompassing suppliers, supplier types, ponds, clusters, feeding rate presets, and feeding rate parameters, as well as feeding entries and active pond data.

The second aspect focuses on functionality. Traditionally, feed calculations are managed using whiteboards and Google Spreadsheets. The system is expected to handle more complex feed recommendation calculations while replacing manual recording methods. Based on the identified needs, a web-based system can provide enhanced functionality for managing complex feed calculations and serve as an effective substitute for manual data tracking.

The system development process has adopted the Monte Carlo algorithm as the primary method for calculating feed recommendations. The web-based system utilizes the ReactJS framework for the frontend and Django for the backend. The Monte Carlo algorithm calculates feed recommendations on the backend, sending the results to the frontend via Application Programming Interface (API)s.

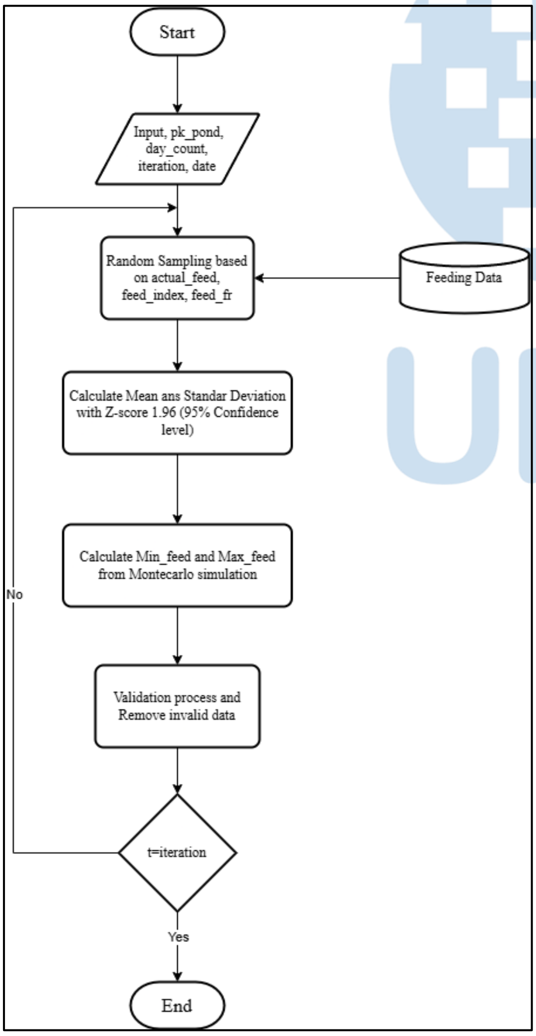

Fig 1. Flowchart of Monte Carlo Simulation

Figure 1 flowchart illustrates the process of analyzing the feeding data in Monte Carlo simulation. The process starts by collecting input parameters such as pond identification (*pk_pond*), cultivation days (*day_count*), iteration count, and reference date. Then it takes a random sample of the feeding data such as including feed quantities, feed index values, and feed rate (FR) number. From the obtain sample, the mean and standard can be calculated. For establishing a confidence level of 95%, a Z-score of 1.96 is used which ensures reliability from a statistical perspective. To support the simulation flowchart illustrated in Figure 1, Table 1 presents the schema of the feeding data utilized during the Monte Carlo analysis.

TABLE I. FEEDING DATA TABLE SCHEMA

Field	Datatype
id	uuid
active_pond_id	uuid
actual_feeding_weight	float
doc	integer
calculated_index	float
feeding_rate_preset_id	uuid
created_by	uuid
created_at	timestamp
updated_at	timestamp
deleted_at	timestamp

The feeding data schema in Table 1 includes a unique identifier `id` for each record, ensuring traceability across datasets. It associates each entry with an `active_pond_id`, which links the feeding activity to a specific pond for localized analysis. The `actual_feeding_weight` field records the total feed dispensed in kilograms, which is used for evaluating efficiency and controlling waste. The doc, or days of culture, tracks the shrimp's age since stocking and is used to adjust feed rates over time. `calculated_index` reflects a derived metric indicating feed per biomass unit, helping checks how much feed is given relative to shrimp growth. The `feeding_rate_preset_id` links to standardized feeding plans, allowing comparison and control across different cultivation setups. Each record is tagged with `created_by` to identify the user or system that logged the data, while timestamps like `created_at`, `updated_at`, and `deleted_at` support auditing, version control, and soft deletion for historical tracking and recovery.

This is followed by determining the minimum and maximum feed rates by the simulator. Invalid data is then filtered out in a validation process. The number of iterations is checked to decide if the loop is continued or end the calculation process. This method is applied to estimate feeding values: Table 1 Feeding recommendations derived from statistical analysis Results gained on the basis of Monte Carlo simulation.

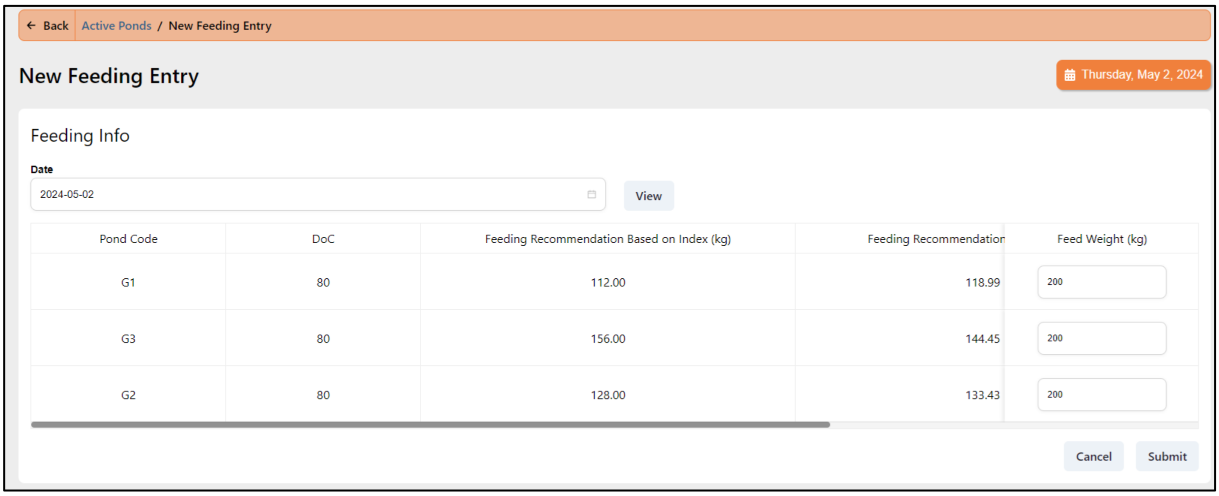

Fig 2. Feeding Entry Page

IV. Implementation and Testing

A testing and evaluation process was conducted after the system had been developed. It has a purpose to determine the accuracy and assess the functionality of the system. The evaluation was divided into two stages: functional testing is used to examine system usability and performance. The second stage is validation testing, which focuses on verifying feed recommendation calculations generated using the Monte Carlo algorithm. These assessments have a purpose to make sure that the system operates well function and provides accurate feed recommendations that are consistent with predefined models.

Figure 2 displays the interface of the feeding entries page, which is used as the input source for the Monte Carlo simulation. Within this page, users can select the specific pond and enter the actual feed quantity on a given Day of Cultivation (DoC). Once the feeding data is submitted, the system uses it as part of the historical dataset to generate projected feed requirements for the next day using Monte Carlo simulation.

At this study, the feed recommendation calculation was tested on a pond labeled H1. It started provide recommended feed quantity for Day of Cultivation (DoC) 32 or before the first shrimp sampling was done. The testing process used feed data from DoC 21 to DoC 31. The confidence level set at 95%, and simulations run with iteration sets of 30, 100, 10,000, and 100,000.

This dataset was chose because feeding during DoC 1 to DoC 20 the feeding process still followed a blind feeding approach. It serves to introduce artificial feed to the shrimp and does not using index or feed rate (FR) methods yet. The minimum iteration count used in this study was based on Sugiyono's suggestion that statistical testing should involve at least 30 iterations [13]. The feed distribution and recommended feeding values based on index and FR methods for pond H1 from DoC 21 to DoC 31 are presented in Table 2.

TABLE II. DATA FEEDING RECOMMENDATION OF DoC 21 - 31

DoC	Actual Feed (Kg)	Recommendation by Index (Kg)	Recommendation by FR (Kg)
21	67	58.8	58.5
22	63	61.6	61.42
23	69	64.4	64.35
24	72	67.2	67.28
25	75	70	70.2
26	78	72.8	73.12
27	81	75.6	76.05
28	84	78.4	78.98
29	87	81.2	81.9
30	90	84	84.82
31	87	86.8	87.75

The data presented in Table .1 was obtained from the developed system. This data was then categorized into multiple scenarios, varying in the number of iterations and the duration of historical feed data used. The number of days refers to the span of feeding data considered prior to Day of Cultivation (DoC) 32 for simulation purposes, while the iteration count represents the number of simulations performed per day. The results of the testing process are detailed as follows.

A. 30 Iteration of Monte Carlo Simulation

The initial testing phase involved running simulations 30 times for each designated number of days. In total, 330 simulations were conducted under this scenario. Upon completing all simulations, feed recommendations were obtained along with the corresponding confidence interval, as presented in Table 3.

TABLE III. RESULT OF 30 ITERATION

Total Days	Minimum Feed (Kg)	Maximum Feed (Kg)
1	87.5000	87.5000
2	83.4376	86.3624
3	80.1359	86.6641
4	76.9458	87.7209
5	75.1825	88.0842
6	72.4937	89.1063
7	68.9931	88.6735
8	65.9086	89.2248
9	61.7309	88.0024
10	63.3541	88.0459
11	63.2646	87.8021

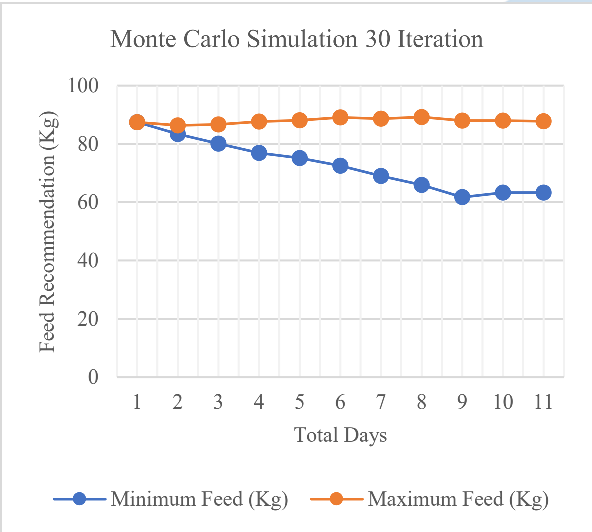

Fig 2. Line Chart of Monte Carlo 30 Iteration

A line chart was generated to facilitate the visualization of feed recommendation results from the Monte Carlo simulation, as shown in Figure 3. The chart illustrates that as the number of days considered increases, the range of recommended feed quantities expands.

Following this visualization, the next step involved comparing the simulated feed recommendations with the actual feed recorded data in Google Spreadsheets. This comparison helps identify the scenario in which the Monte Carlo simulation produces the closest feed recommendation range to the actual feed quantity provided. On Day of Cultivation (DoC) 32, the actual feed quantity administered to shrimp in pond H1 as recorded in the Google Spreadsheets was 86 kg. To generate a feed recommendation using the Monte Carlo simulation, input data from the previous 31 days (DoC 1 to 31) were used from feeding entries in Feeding Data table. This included the historical feeding plan generated using index and feeding rate approach in kilograms. Then later the simulation processed these inputs across 30 randomized iterations, producing a projected feeding plan in range between 83.4376 kg and 86.3623 kg for DoC 32. These results demonstrate a reasonable approximation to previously recorded feeding value, indicating that the simulation can produce statistically supported recommendations that reflect actual feeding behavior in the shrimp farm under dynamic cultivation conditions.

B. *100 Iteration of Monte Carlo Simulation*

After completing the initial testing with 30 simulations, the process was extended to 100 simulations per day. In total, 1,100 simulations were conducted under this scenario. Following the completion of all simulations, feed recommendations were obtained along with their respective confidence intervals, as presented in Table 4.

The line chart in Figure 4 illustrates a trend similar to the previous simulation, where increasing the number of days considered results in a wider range of feed recommendations. However, the chart appears more refined compared to the earlier simulation due to the higher number of iterations, which contributes to a smoother representation of the data.

Following the visualization of the generated range, the next step involved comparing the simulated feed recommendations with actual feeding data recorded in Google Spreadsheets. This comparison helps identify the scenario in which the Monte Carlo simulation produces a feed recommendation range closest to the actual feed quantity administered. According to actual data, the feed quantity provided to shrimp in pond H1 on Day of Cultivation (DoC) 32 was 86 kg. The Monte Carlo simulation scenario with 100 iterations that yielded the closest recommendation considered feeding data from the two days prior to DoC 32, producing a range between 83.6745 kg and 86.6455 kg.

TABLE IV. RESULT OF 100 ITERATION

Total Days	Minimum Feed (Kg)	Maximum Feed (Kg)
1	87.5	87.5
2	83.6745	86.6455
3	80.0827	86.7373
4	77.0679	88.1921
5	75.7052	88.0348
6	71.7429	87.9971
7	69.3862	88.5538
8	66.6448	88.5952
9	63.5393	89.0807
10	61.635	88.1249
11	57.6148	91.4652

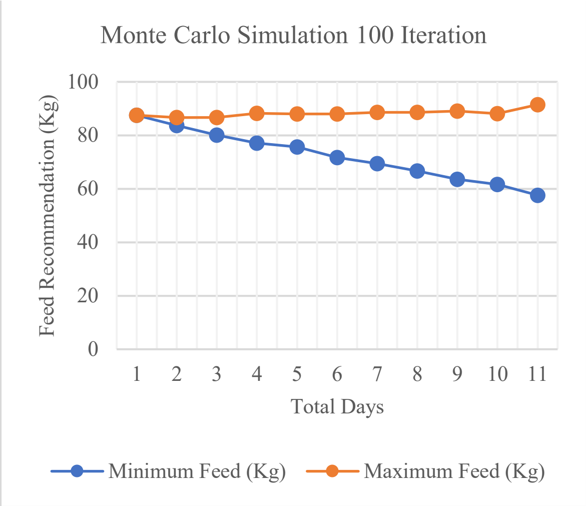

Fig 3. Line Chart of Monte Carlo 100 Iteration

C. *Testing Result Summary*

After conducting all Monte Carlo algorithm testing scenarios, the feed recommendation data that closely aligns with actual feed records from Google Spreadsheets was identified. The complete results are presented in Table 5.

The findings indicate that the Monte Carlo algorithm is applicable for feed recommendation calculations. The scenario that provides the closest recommendation range is based on data from the two days preceding the targeted Day of Cultivation (DoC), with a minimal difference of approximately 3 kg between the minimum and maximum feed recommendations. Additionally, an iteration counts of at least 10,000 ensures stability in the variation of feed recommendation values.

TABLE V. SUMMARY RESULT OF MONTE CARLO SIMULATION

Minimum Feed (kg)	**Maximum Feed (kg)**	**Days of Data**	**Iterations**
83.4376	86.3624	2	30
83.6745	86.6455	2	100
83.4131	86.5953	2	10,000
83.4007	86.598	2	100,000

V. CONCLUSION

Based on this research, it can be concluded that the system developed and implemented using the Monte Carlo algorithm has been successfully designed and built. The system calculates feed recommendations using Monte Carlo based on historical feeding data and provides recommendations using both the index and feed rate (FR) methods.

During Monte Carlo testing, simulations were carried out under various scenarios. Feed recommendations calculated using historical data from the previous two days produced results close to the actual feed quantity, ranging between 83 kg and 86 kg, compared to the actual value of 86 kg. Additionally, the confidence interval showed stable results across iteration ranges from 10,000 to 100,000, as larger iterations incorporated more data variability. Conversely, when iterations fell below 10,000, the results became inconsistent due to limited data variations. Meanwhile, iterations above 100,000 did not yield significantly different results compared to 100,000 iterations, only increasing computational load without improving the accuracy of feed recommendations.

Despite its effectiveness, the simulation system has certain limitations, especially its reliance on manual user input during daily feeding operations. Incorrect entries can lead to inaccurate feed projections, affecting decision-making and system reliability. Additionally, the model is currently dependent on index-based and feed rate calculations derived from historical data, which may not fully capture real-time changes in shrimp behavior or environmental conditions. To achieve more precise feed recommendations, future work should explore the integration of real-time sensor technologies such as automated feeding systems, water temperature monitoring, and pH detection sensors. Therefore allowing the model to dynamically adjust its projections based on current aquaculture conditions.

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