CENTIVE
Conference on Electrical Engineering, Informatics,
Industrial Technology, and Creative Media
ISBN: 978-602-53004-0-0

Selection Strategy for Handling Deadstock Products using the Analytical Hierarchy Process (AHP) and Expected Monetary Value (EMV) Method

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Abstract — The accumulation of deadstock on Network Terminal Equipment (NTE) products in the telecommunications company's warehouse has resulted in increased storage costs and financial losses for the Company. This study aims to develop an optimal deadstock-handling selection strategy by integrating the Analytical Hierarchy Process (AHP) and the Expected Monetary Value (EMV). The AHP method is used to determine the weight of the decision criteria (cost, implementation time, and ease of implementation). At the same time, EMV is calculated using a Monte Carlo simulation to evaluate the monetary value of each of eight handling alternatives (re-layout, FIFO strategy, purchase forecast, stock opname, product discount, resale to supplier, sale to Marketplace, and sale with bundling strategy). Data were collected through expert interviews and historical deadstock data from the telecommunications company's warehouse. The analysis shows that the AHP-EMV combination can recommend the best strategy by considering both financial and non-financial factors. The EMV simulation revealed that sales with a bundling strategy provide the highest monetary value of IDR. 288,572,250 compared to other alternatives. This research offers practical contributions in the form of a data-based decision-making framework for deadstock management and policy recommendations for internet service providers.

Keywords – Deadstock, AHP, EMV, Monte Carlo Simulation, NTE.

I. INTRODUCTION

The telecommunications company provides connectivity solutions and telecommunications infrastructure. From year to year, the number of service users continues to grow in line with the growth of internet users, as evidenced by a Databox report by We Are Social showing that Indonesian internet users in 2023 reached 213 million, an increase of 5.45% from the previous year. As a result, the telecommunications company requires greater efficiency and effectiveness in its supply chain management. One of the critical areas within supply chain management is the logistics process [1]. The key logistics processes within a company involve transportation, inventory, and warehousing [2].

The telecommunications company's warehouse supply operation network terminal equipment faces dead stock, which occupies most of the warehouse space and continues to increase each month. Dead stock refers to inventory that has remained in storage for a long period, has not been sold for several months, and ultimately hinders business growth [3]. This inventory becomes unsellable and turns into dead stock due to short-lived trends, damaged goods, or product mismatches with company standards following standardization updates [4].

One product categorized as dead stock in the telecommunications company's warehouse is the Network Terminal Equipment (NTE), which comes in various series. Network Terminal Equipment (NTE) is used as an interface between customers and access networks in telecommunications systems [5]. NTE functions as the termination point between the service provider's network and the customer's equipment, such as modems, telephones, and other devices. The presence of dead stock is detrimental to the Company; aside from being unusable, it continues to accumulate and occupy valuable warehouse space.

According to the warehouse supervisor, losses per region per year range from 2 to 3 billion. With seven regional areas throughout Indonesia, the Company's average total loss reaches 25 billion per year. Based on the researcher's observations, from January to October 2023, the dead stock of NTE products in the telecommunications company's warehouse totaled 800 units, resulting in a total loss of IDR 2,191,769,000.00. The biggest factor affecting this loss is stock bleaching. Dead stock incurs high non-value-added costs, including warehouse costs, maintenance costs to maintain stock quality, and repair costs [6], [7].

As warehouse space for storing the new series of NTEs (fast-moving goods) became increasingly limited, the warehouse could not accommodate the goods to meet monthly requirements. As a result, the Company had to order NTEs every two weeks. This increased costs, including maintenance, handling, and ordering. Previously, the Company only needed to order once every three months. The more frequently the Company orders goods, the more cash flow can be disrupted, and administrative costs can increase.

Several previous studies have discussed handling dead stock using various approaches. Widyatmoko et al. [8] applied root cause analysis, along with process, HR, and technology-based solutions, to material management in the oil and gas industry. Hakim et al. [9] used the House of Risk (HoR) framework to identify the main causes of dead stock in spare parts inventory and prioritize risk mitigation. Li et al. [10] developed a classification and prioritization framework for a decision-rule-based retail system to detect and prevent dead stock early. Sugumaran & Sukumaran [11] utilized a data analytics approach combining ID3 classification and the AdaBoost ensemble algorithm, and sales optimization using linear programming and the UCB algorithm. Sugiono & Alimbudiono [12] used a qualitative approach, including interviews and observations, to identify solutions to deadstock cases in the ceramic industry.

Meanwhile, Ramadhan et al. [13] evaluated drug dead stock in hospitals through a quantitative descriptive approach with a focus on the process of drug selection, planning, storage, and prescribing. However, no research has specifically combined ABC, AHP, Monte Carlo simulation, Expected Monetary Value (EMV), and decision tree methods to determine the optimal strategy for handling deadstock in telecommunications companies. This combination of techniques is a novelty in previous research, enabling more accurate and less risky decisions.

The purpose of this study is to assist management in determining the optimal dead stock handling strategy so that dead stock can leave the warehouse without incurring large losses, using decision trees in decision-making.

II. RESEARCH METHOD

In this study, researchers conducted research at the telecommunications company's warehouse. The object of research is dead stock in the telecommunications company's warehouse, and the subject of this research is the telecommunications company's warehouse. The data collection techniques used are observation, interview, and literature study. Researchers conducted direct observations at a telecommunications company warehouse, conducted interviews with staff regarding problems that occurred in the warehouse, their causes, and the resulting impacts, and conducted literature reviews by collecting data from appropriate articles, journals, and books.

The data sources researchers use are primary and secondary. Primary data for this study are obtained from observations and interviews with staff familiar with the telecommunications company's warehouse situation, including deadstock data on NTE (Networking Terminal Equipment) products. Secondary data from this study are obtained from previous research sources, including literature reviews, data on the growth of internet users, and the results of prior research.

A. ABC Classification

The ABC classification method is a data analysis technique used in inventory management to group goods by value, from highest to lowest. Items with a cumulative capital absorption value of 80% are categorized as class A, 15% as class B, and 5% belong to class C. Category A has the greatest impact on company losses from deadstock [14].

B. Fishbone Diagram

The fishbone method is used to identify the root cause of a problem. With this method, various factors that could cause problems can be identified [15]. After placing the deadstock product series with the greatest impact on company losses, the next step is to draw up a Fishbone Diagram to analyze the root causes of deadstock accumulation in the warehouse.

C. Analytical Hierarchy Process (AHP)

AHP is a general theory that includes steps for determining the scale of pairwise comparisons, both in discrete and continuous forms. This method is used in the decision-making process to select the most suitable alternative [16]. After finding the root cause of deadstock accumulation from the results of the fishbone diagram, the next step is to design criteria and options for handling deadstock by applying the Analytical method.

D. Monte Carlo Simulation

Then, it will perform a Monte Carlo simulation to obtain the average product price from the three pieces of information collected from three respondents. The Monte Carlo method is a statistical simulation technique that uses random numbers to analyze processes with random properties. This method has been applied in various situations where physical measurements are difficult or cannot even be solved through experimental calculations. This procedure works by performing repeated random sampling to produce more accurate predictions [17]. The basis of Monte Carlo simulation is an elemental probability experiment using random samples. This method is divided into five stages [18]:

a. Determine the probability distribution.
b. Calculate the cumulative probability distribution.
c. Determine the random number interval for each variable.
d. Generate random numbers.
e. Create a simulation of the experiment series.

E. Expected Monetary Value (EMV)

The average price obtained from the Monte Carlo simulation is then further analyzed using Expected Monetary Value (EMV) calculations and visualized as a decision tree. The Expected Monetary Value (EMV) method is a statistical approach that calculates the average future expenditure based on the likelihood of a situation occurring. The goal is to maximize the result by multiplying each possible situation by its probability. To calculate the EMV, the following formula can be used [19].

$$\boldsymbol{EMV} = \sum_{j=1}^{n} \boldsymbol{X_{ij}} \times \boldsymbol{P}(\boldsymbol{X_{ij}}) \quad (1)$$

ISBN: 978-602-53004-0-0

Where:

X_{ij} = payoff for outcome *j* under alternative *i*
$P(X_{ij})$ = probability of occurrence of X_{ij}
n = number of possible outcomes

F. Decision Tree

Furthermore, a Decision Tree is a simple, easy-to-understand method for analyzing data and making decisions. Decision trees are created using this approach, which is one of the most common. The tree is classified as a structure consisting of a root node with no inputs. Internal nodes, or test nodes, are nodes other than the root that have at least one input. Meanwhile, the remaining nodes are called leaves and represent the final target of each class [20].

III. RESULT AND DISCUSSION

This study uses existing deadstock data at the telecommunications company's warehouse. Table 1 lists deadstock series for Networking Terminal Equipment (NTE) products.

Table 1. List of deadstock

Product Code	Amount
Item 1	74
Item 2	27
Item 3	87
Item 4	87
Item 5	3
.....	…..
Item 40	2
Item 41	3
Item 42	1
Item 43	1
Item 44	2
Total	800

A. ABC Analysis

ABC classification categorizes products from category A, with the greatest loss impact, to category C, with the least. Category A items accounted for 80% of the overall inventory value, Category B 15%, and Category C 5%.

Table 2. ABC Classification Result

Product Code	Amount	Unit Price	Total Price	Percentage	Cumulative	Classification
Item 1	74	IDR 25,042,500	IDR 1,853,145,000	85%	85%	A
Item 2	27	IDR 2,000,000	IDR 54,000,000	2%	87%	B
Item 3	87	IDR 516,000	IDR 44,892,000	2%	89%	B
Item 4	87	IDR 400,000	IDR 34,800,000	2%	91%	B
Item 5	3	IDR 9,750,000	IDR 29,250,000	1%	92%	B
....	....	....	....	....	....	....
Item 40	2	IDR 250,000	IDR 500,000	0%	100%	C
Item 41	3	IDR 150,000	IDR 450,000	0%	100%	C
Item 42	1	IDR 312,000	IDR 312,000	0%	100%	C
Item 43	1	IDR 310,000	IDR 310,000	0%	100%	C
Item 44	2	IDR 140,000	IDR 280,000	0%	100%	C
Total	800	IDR 51,265,500	IDR 2,191,769,000	100%		

From the ABC classification results above, it is known that NTE deadstock products with the Item 1 series are in the A category. Although the number of units accounts for only 9.25% of the total NTE deadstock, this series accounts for 85% of the total losses caused by NTE product-type deadstock. This shows that Item 1 series has the greatest impact on the Company's losses.

B. Fishbone Analysis

Fishbone diagrams are used to understand the root cause of the problem. This diagram helps in identifying the factors that contribute to the deadstock problem.

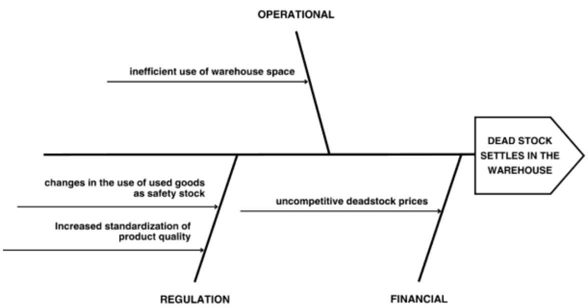

Fig 1. Fishbone Diagram

From the figure above, it is known that three categories of root causes were identified, which are:

a. Operational factors are at the root of inefficient use of warehouse space.

Sub-optimal warehouse management and arrangement can lead to inefficient space utilization. This results in frequently used items becoming difficult to access as space is occupied more by rarely used items or deadstock. The lack of implementation of stock management strategies, such as FIFO or LIFO, can also worsen space utilization efficiency. Therefore, it is necessary to improve warehouse utilization and reduce the accumulation of unproductive goods. The Company can implement several alternative solutions to this problem, such as optimizing the warehouse layout, implementing a more structured stock dispensing system, and conducting regular stock-taking.

b. Regulatory factors with the root cause of policy changes in the use of used goods as safety stock
Changes in the Company's policy regarding the use of used goods as reserves cause goods that have been repaired to no longer be utilized. This resulted in deadstock due to the goods not meeting the new quality standards. The Company's decision to no longer use repaired goods as reserves increases warehouse stock. To overcome this problem, alternative solutions are needed, such as prioritizing the release of old stock first or selling dead stock products to suppliers.

c. Financial Factors
The uncompetitive prices of deadstock goods are one of the main reasons they are difficult to sell. The offered price can't compete with market prices, so deadstock items remain in the warehouse, providing no economic value to the Company. To overcome this problem, several alternative strategies can be implemented, such as offering discounts to customers, selling deadstock products to suppliers, utilizing the Marketplace as a sales channel, and implementing a bundling strategy.

C. Data Analysis with AHP

After determining the products that are the focus of deadstock handling, the next step is to rank the alternatives and criteria using AHP. This process begins with setting criteria and options, then following a hierarchical structure that connects goals, criteria, and alternative solutions. Based on the ABC classification, the product in category A is Item 1, so the research focuses on this product. The three main criteria for handling it, based on the opinions of two team leaders and one warehouse staff member, include price, implementation time, and ease of implementation. Next, eight alternative solutions were evaluated: changing the warehouse layout, removing old stock first, making purchase forecasts, conducting stock-taking, offering discounts to customers, selling products to suppliers, selling in the Marketplace, and implementing a bundling strategy.

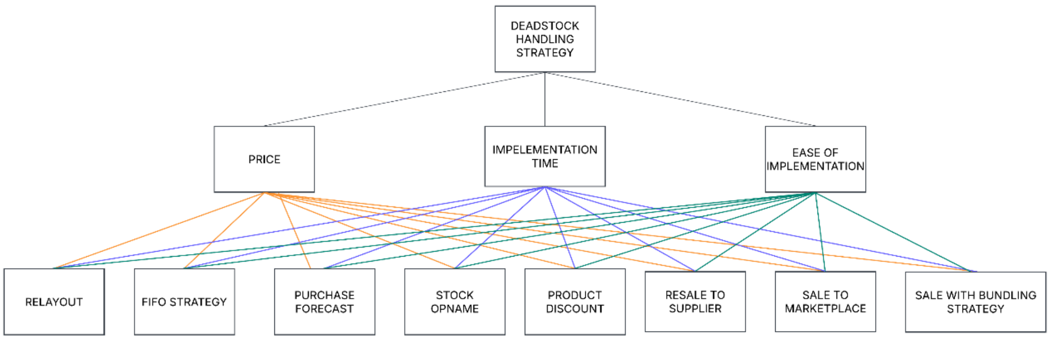

Fig 2. Hierarchy Structure

Next, a questionnaire was developed to collect data from two team leaders and one warehouse staff member. After obtaining the priority weights for criteria and alternatives from each respondent, the weights were averaged and entered into Super Decisions. Priority weights for criteria are compared with the criteria, and the criteria are compared with other options.

Table 3. Pairwise Comparisons result criteria with criteria

Criteria	Normalized value	Idealized value	Inconsistency
Price	0.34454466579798 387	0.629960524 94971799	0,05156
Ease of implementation	0.54693056493577 064	1.0	0,05156
Implementation time	0.10852476926624 55	0.198425131 4954216	0,05156

The table above presents the results of the Pairwise Comparison calculation between criteria. Implementation is the top priority, followed by price, while implementation time has the lowest priority. This comparison shows good consistency with an inconsistency index of 0.05156, still within acceptable limits.

Table 4. Pairwise Comparisons result price criteria with alternative

Criteria	*Normalized value*	*Idealized value*	*Inconsistency*
Stock opname	0.050063	0.181239	0,08496
Product discount	0.039468	0.142884	0,08496
Purchase forecast	0.035707	0.129268	0,08496
FIFO Strategy	0.076925	0.278483	0,08496
Relayout	0.057495	0.208145	0,08496
Sele with bundling strategy	0.199681	0.722881	0,08496
Sele to marketplace	0.264427	0.957276	0,08496
Resale to supplier	0.276229	1.0	0,08496

The table above displays Pairwise Comparisons between price criteria and eight alternatives. Selling deadstock products to suppliers is the most important alternative with a normalized value of 0.276229 and idealized 1.0. Other significant alternatives are selling deadstock on the Marketplace and using a bundling strategy. Alternatives with lower values include removing old stock first, changing the warehouse layout, and conducting stock-taking. Meanwhile, giving discounts to customers and providing purchase forecasts have the lowest priority. This comparison has an inconsistency index of 0.08496, which is still within the limit of 0.1, indicating consistent results. This process helps in selecting the best alternative based on price criteria, focusing on alternatives with higher priority values.

Table 5. Pairwise Comparisons result ease of implementation criteria with alternative

Criteria	Normalized value	Idealized value	Inconsistency
Stock opname	0.076087	0.256239	0,09619
Product discount	0.039843	0.134180	0,09619
Purchase forecast	0.064324	0.216626	0,09619
FIFO Strategy	0.069018	0.232435	0,09619
Re-layout	0.089845	0.302575	0,09619
Sele with bundling strategy	0.296937	1.0	0,09619
Sele to marketplace	0.198898	0.669831	0,09619
Resale to supplier	0.165045	0.555824	0,09619

Table 5 displays Pairwise Comparisons between the ease of implementation criteria and eight alternatives. Selling deadstock products with a bundling strategy is the most important alternative with a normalized value of 0.2969374 and idealized 1.0. Another important alternative is selling deadstock in the Marketplace and selling it to suppliers. Alternatives with moderate priorities include changing the warehouse layout, stock-taking, and removing old stock first. Alternatives with lower priority are giving discounts to customers and providing purchase forecasts. This comparison has an inconsistency index of 0.09619, still within the limit of 0.1, so it is quite consistent.

Table 6. Pairwise Comparisons result Implementation time criteria with alternative

Criteria	Normalized value	Idealized value	Inconsistency
Stock opname	0.089026	0.239504	0,09477
Product discount	0.035423	0.095298	0,09477
Purchase forecast	0.044965	0.120969	0,09477
FIFO strategy	0.053847	0.144865	0,09477
Re-layout	0.024176	0.065041	0,09477
Sale with bundling strategy	0.371710	1.0	0,09477
Sales to marketplace	0.172209	0.463288	0,09477
Resale to the supplier	0.208640	0.561299	0,09477

Table 6 displays the Pairwise Comparisons between the implementation time criteria and eight alternatives. Selling deadstock products with a bundling strategy is the main alternative, with a normalized value of 0.371710 and an idealized 1.0. The next options are selling to suppliers and selling on the Marketplace. Alternatives with moderate priority include stock-taking and removing old stock first. Lower-priority alternatives include providing purchase forecasts, offering discounts to customers, and changing the warehouse layout. The inconsistency index of 0.09477 remains within the 0.1 limit, indicating consistent results. This analysis helps select the optimal deadstock strategy based on the implementation time factor.

Table 7. Results using AHP

Alternatives	Total	Normal	Ideal	Ranking
Stock opname	0.033	0.0792	0.243	4
Product discount	0.015	0.0368	0.113	8
Purchase forecast	0.019	0.0456	0.14	6
FIFO strategy	0.025	0.0606	0.186	5
Re-layout	0.016	0.0397	0.122	7
Sale with bundling strategy	0.135	0.326	1	1
Sales to marketplace	0.081	0.1949	0.598	3
Resale to the supplier	0.09	0.217	0.665	2

Top Ranking provides a clear picture of the best alternative, helping make the best decision. The table above shows the ranking results using the AHP method, with the top three options as follows:

1. Sales with a bundling strategy
   A bundling strategy involves selling deadstock products alongside other products in a single package. This strategy aims to increase sales value by adding the value of different products that may be more in demand or have stable demand. This strategy tops the list because it is considered the most optimal based on the criteria considered.
2. Resale to the supplier
   This strategy is ranked second. Direct sales to suppliers or distributors can accelerate deadstock elimination.
3. Sales to Marketplace
   Selling deadstock products through online marketplaces gives access to a wider market and directly to end consumers. This could be through platforms such as eBay, Amazon, or other Marketplaces. This alternative ranks third, indicating that, in the context of the criteria considered, selling on the Marketplace is the least optimal of the three alternatives.

Thus, the AHP ranking results provide clear guidance in choosing a deadstock sales strategy. The bundling strategy is the best choice, followed by selling to suppliers, and finally, through the Marketplace.

D. Data Analysis with Monte Carlo Simulation

In this study, data were obtained from three respondents, namely two team leaders and one warehouse staff member, who provided information about market prices in favorable and unfavorable situations. A Monte Carlo simulation was used to determine the median and average costs for the three respondents. Simulation tables for each State of Nature, with 30 trials, are essential for helping decision makers visualize the impact of various market conditions on the outcome of a decision or project. Using these tables, decision-makers can design strategies that are more adaptive and responsive to the risks and opportunities arising in a dynamic market environment.

Table 8. Outcome Value Development

Respondent's Position	Alternative	State of Nature	Outcome (IDR)	Probability	Random Number Assignment
Staff Warehouse	Resale to the supplier	Favorable market	967.550.000	0,3	00-29
Team Leader			969.770.000	0,4	30-69
Team Leader			962.000.000	0,3	70-99
Staff Warehouse		Unfavorable market	479.150.000	0,3	00-29
Team Leader			477.300.000	0,4	30-69
Team Leader			479.890.000	0,3	70-99
Staff Warehouse	Sales to marketplace	Favorable market	969.400.000	0,3	00-29
Team Leader			973.100.000	0,4	30-69
Team Leader			973.470.000	0,3	70-99
Staff Warehouse		Unfavorable market	481.925.000	0,3	00-29
Team Leader			482.665.000	0,4	30-69
Team Leader			483.405.000	0,3	70-99
Staff Warehouse	Sale with bundling strategy	Favorable market	1.139.600.000	0,3	00-29
Team Leader			1.145.150.000	0,4	30-69
Team Leader			1.142.930.000	0,3	70-99
Staff Warehouse		Unfavorable market	565.730.000	0,3	00-29
Team Leader			567.395.000	0,4	30-69
Team Leader			564.065.000	0,3	70-99

Table 9. Simulation for each State of Nature

No	RN for altern atif 1	Outcome (+)	Outcome (-)	RN for altern atif 2	Outcome (+)	Outcome (-)	RN for alternat if 3	Outcome (+)	Outcome (-)
1	51	969770000	477300000	71	973470000	483405000	61	1145150000	567395000
2	88	962000000	479890000	50	973100000	482665000	39	1145150000	567395000
3	33	969770000	477300000	59	973100000	482665000	68	1145150000	567395000
4	32	969770000	477300000	58	973100000	482665000	22	1139600000	565730000
5	93	962000000	479890000	23	969400000	481925000	12	1139600000	565730000
					.....				
26	68	969770000	477300000	11	969400000	481925000	21	1139600000	565730000
27	36	969770000	477300000	82	973470000	483405000	2	1139600000	565730000
28	54	969770000	477300000	60	973100000	482665000	31	1145150000	567395000
29	9	967550000	479150000	51	973100000	482665000	41	1145150000	567395000
30	93	962000000	479890000	50	973100000	482665000	45	1145150000	567395000
Average		966995000	478447000		972088667	482640333		1143263000	566118500

E. Data Analysis with EMV

The final calculation is done with the EMV calculation model. In the context of risk evaluation, EMV helps decision makers assess options or projects based on the risks and potential financial rewards associated. The EMV calculation procedure involves multiplying the financial value of each possible outcome by the probability of that outcome occurring, then summing the values.

Table 10. Decision

	Favorable Market (IDR)	Unfavorable Market (IDR)	EMV Favorable market (IDR)	EMV Market unfavorable (IDR)	EMV (IDR)
Probability	0,5	0,5			
Resale to the supplier	966.995.000	- 478.447.000	483.497.500	- 239.223.500	244.274.000
Sale to marketplace	972.088.667	- 482.640.334	486.044.334	- 241.320.167	244.724.167
Sale with bundling strategy	1.143.263.000	- 566.118.500	571.631.500	- 283.059.250	288.572.250

The calculation results show that for the alternative of selling deadstock products to suppliers, the EMV value is IDR. 288,572,250. For the alternative of selling deadstock products in the Marketplace, the EMV is IDR 244,724,167. As for the alternative of selling deadstock products with a bundling strategy, the EMV is IDR. 244,274,000. Of the three alternatives, the EMV for selling deadstock products with a bundling strategy is the largest. This shows that, mathematically or from a risk analysis perspective, this alternative has the potential to yield the most favorable financial results compared to the other two.

F. Decision Tree Depiction

The Decision Tree depiction of the EMV results visually shows the decision options, probabilities, financial values, and the consequences of each decision. This helps decision-makers understand the economic impact of options and simplifies the decision-making process in situations of uncertainty.

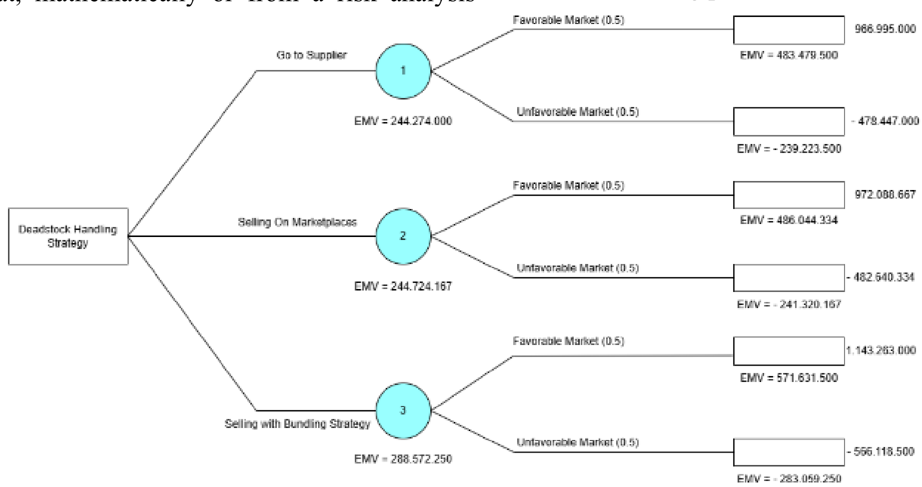

Fig 3. Decision Tree Final

In a Decision Tree, each node represents a possible decision or event. The lines connecting the nodes reflect the potential outcomes of the decision. The financial value of each outcome is described in the nodes, while the probability of each outcome is represented by the lines connecting the nodes.

IV. CONCLUSSION

Based on the results of data processing and analysis regarding the deadstock problem, the following conclusions are obtained:

1. Deadstock products in warehouses are caused by several factors, including operational factors with the root cause of inefficient use of warehouse space, regulatory factors with the root cause of policy change, the use of used goods as safety stock, and increasing product quality standardization, price / financial factors with the root problem of uncompetitive deadstock prices.
2. The AHP analysis yields a proposed approach to handling the deadstock problem, supported by the EMV value and illustrated in a decision tree showing the potential risks of each handling alternative. This makes it easier for decision makers to determine which alternative to adopt.
3. The best alternative with the highest potential financial gain is to sell deadstock products with a bundling strategy, with an EMV value of IDR. 288,572,250.

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