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OPTIMIZING THE DECISION-MAKING OF ENTERPRISES IN THE PRODUCTION PROCESS BASED ON DECISION TREE MODELS

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Abstract: In the enterprise's production activities, the enterprise's production efficiency is the key to whether the enterprise to obtain the maximum benefit, efficient production efficiency is the enterprise to the good development of the top priority, on this basis, due to the enterprise's decision-making directly affects the efficiency of the enterprise's organization and management, whether to make the optimal decision can be a direct impact on the enterprise's production efficiency.Therefore, this paper proposes the basic model of enterprise optimization production process based on decision tree model algorithm. Firstly, the model is established through the establishment of hypothesis testing and the method of cost-profit; secondly, combined with the principle of multi-recursive optimization algorithm and the overall optimal solution of which any step is optimal, it is applied to the construction of the model of decision-making problem in the enterprise's production process, and the basic sampling method is proposed, and the validity is determined through the method of proposing a specific sampling scenario; lastly, some basic conditions are assumed, and using the established Decision Tree Model algorithm to give the corresponding sampling scheme, by comparing the cost required to make the decision, the results can be derived as a result of the optimal solution in a specific scenario can be depicted by Fig. 5; in the specific conditions of the enterprise decision-making results in the optimal decision-making scheme for the inspection of spare parts 1, spare parts 2, spare parts 3, and semifinished products 1 but the semifinished products 1 is not disassembled; for spare parts 4, spare parts 5, Spare part 6 and semi-finished product 2 are tested but semi-finished product 2 is not disassembled; Spare part 7 and spare part 8 are tested and semi-finished product 3 is not tested and disassembled; only finished products are tested and unqualified finished products are not disassembled, and finished products that are returned from customers are not disassembled.The advantage of the decision tree model is that it does not require data preprocessing, it can directly deal with numerical and categorical features, reducing the complexity of data preprocessing and at the same time has a very strong adaptability, able to deal with complex nonlinear relationships, and can to a large extent to capture the complex patterns in the data. Most of the traditional enterprises in the decision-making process there are many problems, this paper will be the decision tree model used in the production of enterprise decision-making, can be more accurate, fast and efficient for the enterprise to make the right decision, can improve the accuracy of the enterprise decision-making, especially in dealing with the small amount of data in the problem. Decision tree is a very intuitive model, extensive in-depth study of the decision tree model can help to improve the efficiency of decision-making and prediction accuracy in the fields of finance, health care, marketing and manufacturing, etc., and at the same time, it can optimize the decision-making algorithms, improve the performance of the algorithms to promote the explanatory and transparency of the algorithms.
Keywords: Decision tree model; Local optimization; Hypothesis testing; Sampling test

1 INTRODUCTION

Since the implementation of the reform and opening-up policy, China has continued to develop and grow amidst competition in the global market, a process that has not only witnessed profound changes in Chinese economic system, but has also reflected Chinese ability to adapt to the international business environment. With the increase in market openness and the expansion of foreign trade, domestic and foreign enterprises are actively exploring diversified strategies to enhance their competitiveness, among which, improving the decision-making efficiency of enterprises has gradually become an important way to improve their competitiveness. As a representative of Chinese high-tech enterprises, Huawei was engaged in the production and sale of communication equipment in the early stage, but with the process of globalization, it faced considerable competitive pressure, in order to alleviate the external competitive pressure, Huawei has made decisions such as globalization strategy and optimization of organizational structure through independent innovation, and through the implementation of the decisions, it has not only taken a dominant position in the domestic market, but has also succeeded in moving towards the global market, which have directly contributed to its standing out in the fierce competition and eventually established a strong corporate competitivenessTherefore, there is an urgent need to optimize and improve the decision-making efficiency of enterprises.

At present, there are many studies on enterprise decision-making model at home and abroad, Zhang et al. proposed that the C4.5 algorithm in decision tree model is one of the decision tree algorithms[1], which has the advantages of easy to understand, high accuracy, etc., and compared with the predecessor ID3 algorithm, the concept of information gain rate is added, and the system takes the decision tree algorithm as the core technology, obtains the scientific, reliable and accurate information of the project management, and realizes the visualization of the data, which can assist enterprises to establish a good management system in the era of big data, Li and others applied the decision tree model based on machine learning to industrialized risk management decisions[2], showing good results, Lee C S and others pointed out that in the business big analytical model[3], the decision tree model is not one of the most important models, but it is really one of the most simple and intuitive models used to analyze data, Bian et al. proposed a novel school-enterprise cooperation mechanism based on decision tree model[4], Lu H et al. applied the research on decision tree modeling to water resources and water quality detection and proposed two novel hybrid decision tree-based machine learning models to obtain more accurate short-term water quality prediction results[4], Masood et al. proposed a novel system centered on CIMOSA Enhanced Integrated Modeling Framework that can be used to facilitate the transfer of driven decision models in manufacturing firms[5], Sishi M et al. stated that a business process is a structured set of activities with understandable sequences and dependencies to produce a desired outcome[6]. Optimization of these processes is critical and Decision Tree (DT) is a tool that supports decision making by mapping the possible outcomes of a set of interrelated choices through a tree-structured modeling approach, Sarker I H developed a scenario-aware predictive model based on decision tree learning[7]. Compared to the above decision models for different situations and approaches, the decision tree model based on the principle that any step of the overall optimal solution is optimal is more stable and accurate in corporate decision making. The principle of optimality means that the decision maker should always choose the best decision at each stage of the decision problem, conditional on the best behavior thereafter, and is the basis of many optimal dynamic decision theories[8]. It is worth mentioning that the number of decisions in a business can often be too large to be listed individually, so there is a need to find a more accurate and simpler way to reduce the overall number of decisions while ensuring their accuracy.

hrough the analysis of the previous research of scholars at home and abroad, this paper establishes a basic model for optimizing enterprise decision-making based on the decision tree model and the principle that any step of the overall optimal solution is optimal. In order to reduce the number of decisions required by the enterprise, this paper analogizes the number of decisions to the number of sampling tests, and ensures the accuracy of decision-making on the basis of reducing the number of decisions through the mathematical modeling method of hypothesis testing[9]. The main content of the paper can be summarized as follows: firstly, the basic principles of the decision tree model and hypothesis testing are introduced, and a mathematical model of hypothesis testing is proposed based on the principle that any step of the overall optimal solution is the optimal solution; then the model is applied to the sampling method of a specific scenario to determine its effectiveness.

2 RIEF DESCRIPTION OF THE APPLICATION METHODOLOGY

2.1 Basic Decision Tree Model

Decision tree model is an ancient and traditional modeling approach, which can be traced back to the 1960s, and in the 1980s, with the key algorithms ID3, CART and C4.5 proposed decision tree model gradually tends to mature. Currently, decision trees have a wide range of applications in both machine learning and artificial intelligence[10], and decision tree model building techniques have been widely used to build classification models.Ghiasi M M et al. applied decision tree modeling to the diagnosis of coronary artery disease[11], and decision tree model building techniques have been widely used to construct classification models. Decision tree models are divided into two main processes[12]: the construction process and the classification process, the construction process usually starts from an empty tree, and the appropriate decision nodes are deduced through the corresponding computation; the classification process has to categorize new instances with only all their attribute values, starting from the root of the construction tree and following a path that corresponds to the observed values of the attributes in the nodes inside the tree. The previously mentioned algorithms ID3, CART and C4.5 differ in the selection of decision nodes, and this paper focuses on the basic process of ID3 (information gain).

The essence of ID3 algorithm is information gain, in order to explain the information gain more rationally, the concept of “entropy” is introduced here. Entropy is considered to be used to describe the degree of inaccuracy of a random variable in mathematical statistics, and its formula is:

$$H(X) = -\sum_{i=1}^{n} p_i \, log_2 \, p_i \tag{1}$$

where X represents the random variable and $H(X)$ is the determined value of entropy. The value of entropy is zero when the probability is 0 and 1, when the uncertainty of the random variable is the lowest; the value of entropy has a maximum value when the probability is 0.5, when the uncertainty of the random variable is the highest[13]. Considering that most of the studies are basically two variables, the joint probability distribution of two different variables is:

$$P\left(X = x_i,\ Y = y_j\right) = p_{ij}, i, j = 1,2, \cdots n \tag{2}$$

X、Y represent two basic variables.

The concept of conditional entropy is introduced here, i.e., the entropy of event Y occurring under the condition that event X has occurred, which is given by.

$$H(Y|X) = \sum_{i=1}^{n} p_i H(Y|X = x_i) \tag{3}$$

conditional entropy has the same mathematical properties as entropy, when the probability is more certain then the value of conditional entropy is smaller, when the probability tends to 0.5, the value of conditional entropy is larger.
Based on the model expression above, the information gain is represented by the reduction of uncertainty in the information Y that can be obtained after the condition X is known, where the reduction of entropy is the information gain.
If we denote the information gain of feature A on the training set D as $g(D, A)$, it is calculated as:

$$g(D, A) = H(D) - H(D|A) \tag{4}$$

the overall idea of ID3 algorithm is to calculate the information gain of each feature quantity from the training set, compare and select the largest information gain, take it as a pivot point of the decision tree, and finally construct a complete decision tree model through the constant repetition of the above methods. The specific model building process is given by the following figure:

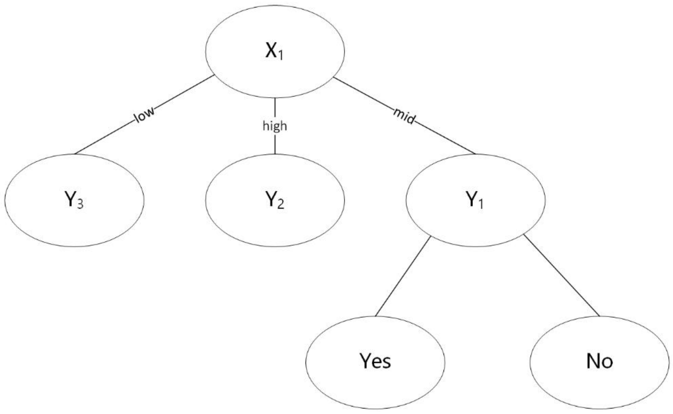

Figure 1 Decision Tree Decision Process

It can be clearly seen through the above Figure 1, first of all, through the calculation of information gain to find out the root node with the largest information gain is recorded as X_1, through this node to calculate the conditional entropy of the remaining events under the conditions of X_1, to find out the information gain for the middle of the event Y_1 as the second node, through the node can be very good to make the best decision, and finally, when a new event needs to be decided, it can be decided through the above obtained conditions for decision making. Of course, in general, the decision tree will be more complex, this paper only as the simplest example.

2.2 Hypothesis Testing Fundamentals

The basic steps of hypothesis testing and its applied principles are[14-15]:
(i) The original hypothesis H_0 as well as the alternative hypothesis H_1 are formulated with full consideration and utilization of the background according to the actual situation and the requirements of the problem;
(ii) Based on the specifics of H_0, choose the appropriate statistical test size, i.e., the total sample size N, and require that the specific probability distribution of N be determined provided that H_0 holds;
(iii) Given a significance level of $\propto$, identify the corresponding small probability event and determine the corresponding rejection domain;
(iiii)Make a specific sample, calculate the specific value of the corresponding statistical test quantity based on the sample value, and from this value determine whether the sample value falls in the rejection domain.
In order to minimize the number of firms sampled, the total number of samples to be tested should first be determined before sampling can be carried out. Therefore, this paper adopts the method of normal approximation, for the total number of samples N, there is the following formula:

$$N = \frac{Z^2 \cdot p_0 \cdot (1 - p_0)}{E^2} \tag{5}$$

P_0 is the probability, Z is the corresponding quantile of the normal distribution, and E is the corresponding error.

3 PRINCIPLE DERIVATION

3.1 Availability of a Basic Sampling Program

For the selection of E, in the formula established above, Z、P_0 are all determined values, so the functional relationship between N and E can be established, in order to find out the optimal error rate, through the mathematical knowledge, as well as the minimization of the objective function model, the function should be taken to the largest value of the slope as the optimal error rate, after finding out the optimal error, you can carry out the next step of the calculations, where this paper demonstrates that The confidence level is 95% and 90% two cases.

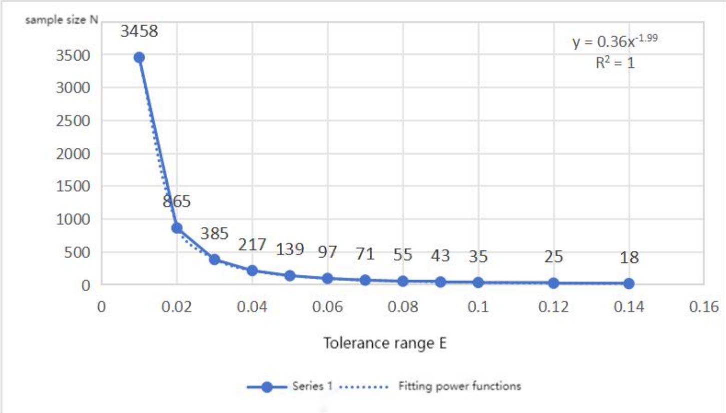

Figure 2 Error Versus Sample Size for a 95% Confidence Level

According to Figure 2, it can be seen that with 95% confidence level N and Esatisfy the relationship equation:

$$N = 0.36E^{1.99} \tag{6}$$

in order to find out the optimal error rate, through mathematical related knowledge, and minimizing the objective function model, the value with the largest slope of this image should be taken as the optimal error, which can be derived as E=0.1;

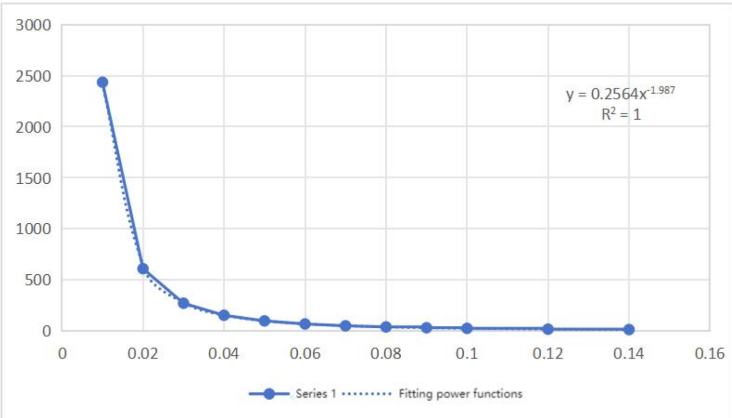

Figure 3 Error Versus Sample Size for a 90% Confidence Level

According to Figure 3, it can be seen that at a confidence level of 90% N and E satisfy the relationship equation:

$$N = 0.256E^{1.987} \tag{7}$$

in the same way as in the first case, the value with the largest slope of this image serves as the optimal error, which is still E = 0.1. After finding the optimal error, the solution of the problem becomes very simple, and the final result required by the statement of the problem can be given by discussing the following two cases.

1. Constructing hypothesis tests:

Original hypothesis H_0, alternative hypothesis H_1

2. Calculation of sample size

Using the normal approximation of distribution method described above, the specific sample size can be calculated using the previous equation (5)

3. Sampling modeling

Since it is a P_0 small probability event, we use a normal distribution to model it. Assuming that the samples are randomly drawn in the sample, using the normal distribution, we can get the minimum number of samples in the sample with P_0 probability.

3.2 Scenario-Specific Optimal Decision Problems

In order to better verify the effectiveness of the model, this paper simulates the establishment of the enterprise production process decision-making problem. Two kinds of spare parts and finished product defective rate is known:

(1) Whether or not the part (Part 1 or Part 2) is tested; if a part is not tested, the part will go directly to assembly; otherwise, the detected nonconforming part will be discarded;
(2) Whether to test each piece of assembled finished product, if not, the assembled finished product directly into the market; otherwise, only qualified finished products enter the market;
(3) Whether to disassemble the detected unqualified finished products, if not, directly discard the unqualified finished products; otherwise repeat steps (1) and (2) for the disassembled spare parts;
(4) For non-conforming products purchased by users, the enterprise will exchange them unconditionally and incur certain exchange losses (such as logistics costs, enterprise reputation, etc.). Repeat step (3) for returned nonconforming products.
In this paper, the enterprise production process of each stage of the decision-making ideas are mainly whether to spare parts 1 for testing, whether to spare parts 2 for testing, whether to assemble the finished product for testing, for the customer returned to the unqualified products whether to exchange, the basic ideas flow chart is as follows:

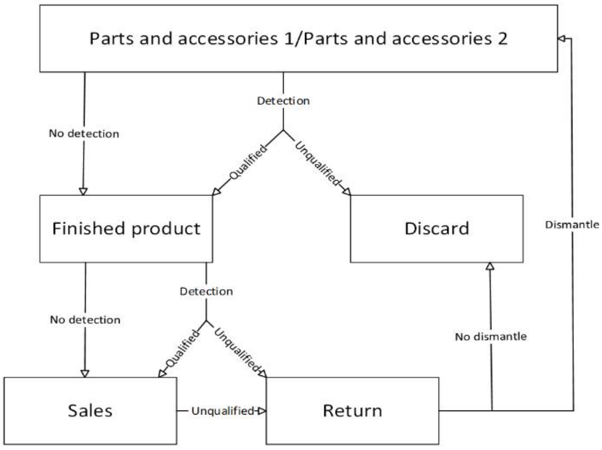

Figure 4 Decision-Making Process for parts 1 and 2

With the help of the Figure 4, we can intuitively observe the interrelationship between the decisions and the sequence of decisions. In order to let the enterprise make the optimal decision, this paper starts from the basic profit model, firstly calculates the decision cost in each decision situation, according to the basic relationship between the decisions obtained from the flow chart, re-establishes the cost model, and finally uses the algorithm of the decision tree model to calculate the corresponding optimal decision in different situations.
To simplify the difficulty required for decision tree modeling, the decisions are first carefully divided as follows:

1. Whether or not to test part1
2. Whether or not to test part2
3. Whether the finished product is tested
4. Whether to disassemble the detected substandard products
5. Whether the returned nonconforming products are disassembled or not

We introduce the decision variable X_i , where i= 1, 2, 3, 4, 5,when X_i=0,it means no testing,when X_i=1,it means testing.Analysis of the decisions made, for the newly established first three decisions, that is, on parts 1, 2 and finished products whether to test this, these three whether to test there is no necessary connection between, therefore, can be considered that these three cases are independent of each other; if the implementation of decision 3, then to the user's hands must be complete that is, there is no need to implement the decision 5, on the contrary, it is necessary to implement decision 5 implementation.
After the above analysis of the type of situation, a wide range of decision-making types are streamlined, for each situation, basically can be streamlined into the following 16 basic decision-making scenarios, in order to be more convenient to record the decision-making scenarios, this paper takes the form of the representation of the $(x_1, x_2, x_3, x_4, x_5)$, through the value of the x_i to indicate whether to carry out the decision-making, and each bracketed number before the first decision on behalf of the first few kinds of decision-making, the 16 basic decision-making scenarios as follows for demonstration (Table 1):

Table 1 16 Decision-Making Methods

1.(0,0,0,0,0)	2.(1,0,0,0,0)	3.(0,1,0,0,0)	4.(1,1,0,0,0)
5.(0,0,1,0,0)	6.(1,0,1,0,0)	7.(0,1,1,0,0)	8.(1,1,1,0,0)
9.(0,0,1,1,0)	10.(1,0,11,0)	11.(0,1,1,1,0)	12(1,1,1,1,0)
13.(0,0,0,0,1)	14.(1,0,0,0,1)	15.(0,1,0,0,1)	16.(1,1,0,0,1)

Now you need to establish the cost - profit function, the annex describes the finished product defective rate is the assembly of the second rate, according to the question stem conditions, as long as there is a failure of spare parts, the finished product is also unqualified, so it can be associated with the real finished product defective rate should be

greater, so this paper first consider the calculation of the finished product of the actual rate of defective, so far, the following begins to describe the process of modeling.
The actual defective rate of finished products:

$$p=(1-x_1)p_1+(1-x_2)p_2-(1-x_1)(1-x_2)p_1p_2 \tag{8}$$

the number of non-conforming finished products is:

$$N_{f3}=N_f-N_f\cdot(1-p) \tag{9}$$

the number of qualified finished products is:

$$N_{f2}=N_f\cdot(1-p) \tag{10}$$

spare parts1 purchase cost:

$$C_{p1}=C_1\cdot N_1 \tag{11}$$

spare parts2 purchase cost:

$$C_{p2}=C_2\cdot N_2 \tag{12}$$

finished assembly costs:

$$C_a=a\cdot N_f \tag{13}$$

spare parts 1 Inspection costs:

$$C_{d1}=x_1\cdot d_1\cdot N_1 \tag{14}$$

spare parts 2 Inspection costs:

$$C_{d2}=x_2\cdot d_2\cdot N_2 \tag{15}$$

finished product testing costs:

$$C_{fi}=x_3\cdot d_f\cdot N_f \tag{16}$$

disassembly costs:

$$C_d=x_4\cdot e(p_f\cdot N_{f2}+N_{f3}) \tag{17}$$

processing of returned costs:

$$C_r=x_5(I+C_1+C_2+a)\cdot(p_f\cdot N_{f2}+N_{f3}) \tag{18}$$

in the description of the topic, for Decision 4 and Decision 5, when choosing to implement on Decision 4 or Decision 5, there is a possibility to return Decision 1, Decision 2 or Decision 3, so the iterative problem may occur, so this paper adopts the recursive method to calculate the recursive profit in the recursive process rp.
Then the total income is:

$$T_r=s\cdot(N_f-(p_f\cdot N_{f2}+N_{f3}))+rp \tag{19}$$

the total cost is

$$T_r=s\cdot(N_f-(p_f\cdot N_{f2}+N_{f3}))+rp \tag{20}$$

the total profit objective function is:

$$W=T_r-T_c \tag{21}$$

the model is brought into the algorithm of the decision tree model, in which the eigenvalues are selected as Decision 1 to Decision 5 assumed in the previous paper, and the target variables are selected as the total profit objective function model established in this paper.
In order to visualize the optimal decision-making in the six cases more visually, more detailed graphs of the curves are plotted in this paper:

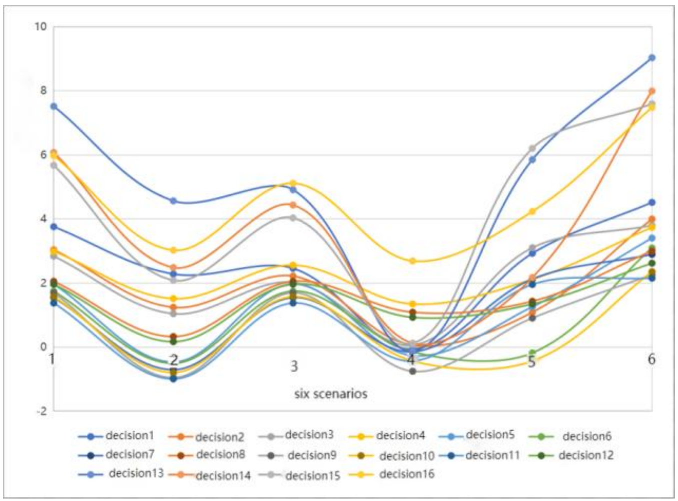

Figure 5 Visual Model of Decision-Making

The above Figure 5 shows the final profits of the sixteen different decision scenarios in each case. From the graph, it can be seen that in each case, the decision scheme corresponding to the point with the highest final profit is the optimal decision scheme for that case.

3.3 Determination of Business Decisions under Specific Conditions

Suppose that the finished product consists of n spare parts, assembled through m processes, and the defective rate of each spare part, semi-finished product and finished product is known. The introduction of the mathematical concept of semi-finished products makes the production process to go through the process, and increase the number of spare parts to , therefore, consider the optimization of the decision tree model, based on the overall optimal solution of the overall optimal principle of the optimum of any step, the complex decision-making steps will be split into parts to semi-finished products and semi-finished products to the finished product of the m steps, and production process of the production process of the decision-making scheme flowchart, the establishment of the diagram of the optimal solution of each step of the mathematical model. Mathematical model. In the case of knowing the defective rate of spare parts, semi-finished products and finished products, this paper firstly gives the analysis of the following figure:

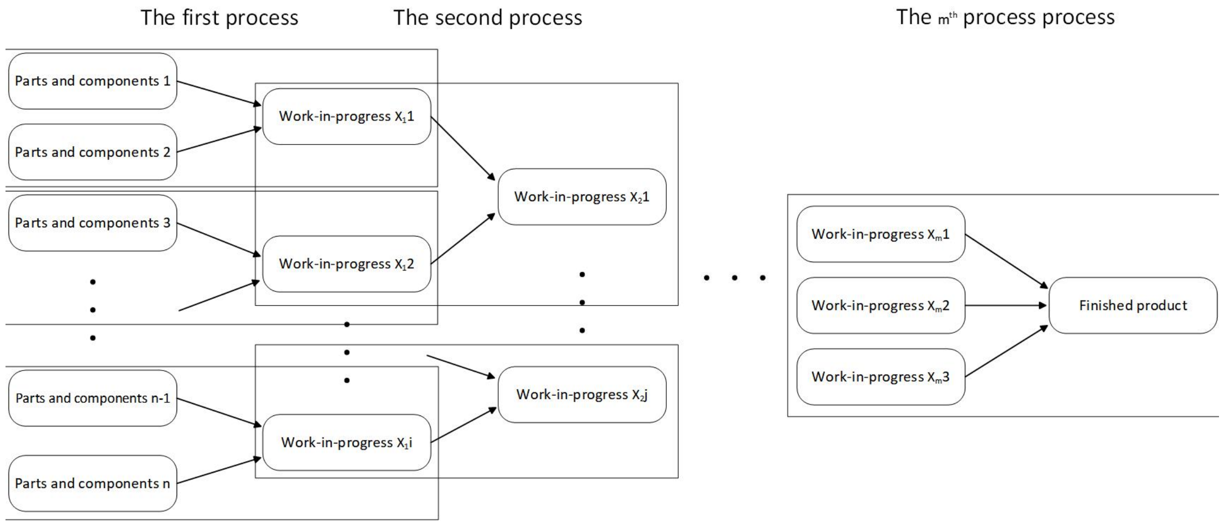

Figure 6 Specific Steps in Decision-Making

As shown in Figure 6 considering the variety of processes, this paper is based on the principle of local optimization, using the model of decision tree, the steps of the process are split step by step, and the optimal solution is sought for each process of assembling spare parts into semi-finished products. The principle of optimization shows that when a solution to a problem requires more than one step to make decisions to achieve a certain result[16], then each of these decisions must be the optimal decision in its corresponding state, in turn, the optimal decision-making is applied to this problem, should be composed of semi-finished parts in step one of the optimal decision-making.

Following 3.2 careful division of decisions, here we divide them into:

1.Whether the spare parts are tested
2.Whether semi - finished products x_{1i} are tested
3.Whether or not testing of non - conforming semi - finished products x_{1i} is carried out
4.Whether returned semi - finished products x_{1i} are dismantled
5.Whether semi - finished product x_{2j} is tested
6.Whether to dismantle substandard semi - finished product x_{2j}
7.Whether returned semi - finished product x_{2j} is dismantled
m.Whether the finished productis tested
m+1.Whether to dismantle substandard finished products
m+ 2.Whether the returned finished productis disassembled

For the values of the decision variable x_i, under the conditions of this question, i ranges from $1-m+1$. The specific mathematical model is as follows:

$$Frist\ process\ costs = N_K\sum_{i=1}^{K} C_K + x_1\sum_{i=1}^{K} d_K + a_{zf1} + x_2 d_{f1} + x_3 e_{zf1} + x_4 I_{zf1} \tag{22}$$

$$Second\ process\ costs = a_{zf2} + x_5 d_{zf2} + x_6 e_{zf2} + x_7 I_{zf2} \tag{23}$$

$$Mth\ process\ costs{=}a_{zfm} + x_m d_{zfm} + x_{m+1} e_{zfm} + x_{m+2} I_{zfm} \tag{24}$$

through the derivation of the above formula, it can be concluded that in order to satisfy the optimal decision-making conditions, the assembly process of semi-finished product 1 should make the lowest cost decision-making, i.e., decision-making 16, in which the decision-making situation is as follows: spare parts 1, spare parts 2, spare parts 3, and semi-finished product 1 are inspected, but semi-finished product 1 is not disassembled; the assembly process of semi-finished product 3 should make the decision-making process at the lowest cost, i.e., decision-making 4. In this case, the decision is: to test parts 7 and 8, and not to test and disassemble semi-finished product 3.

The decision making on whether to test the finished product or not is carefully divided, and the decision making that needs to be done for this process is divided into:

15. Whether the finished product is tested
16. Whether to dismantle substandard finished products
17. Whether the returned finished product is disassembled

Decision-making in the process of semi-finished products to finished products, after the analysis of the decision tree model, can be divided into the following four kinds of decision-making programs, the representation follows the expression of problem two, at this time the value of i is 15-17, four kinds of decision-making programs are shown below (Table 2):

Table 2 4 Decision-Making Methods

1.(0,0,0)	2.(1,0,0)	3.(1,1,0)	4.(0,0,1)

The equation for the decision making process from semi-finished product to finished product is shown below:

Finished assembly costs:

$$C_a = a \cdot N_f \tag{25}$$

finished product testing costs:

$$C_{fi} = x_{15} \cdot d_f \cdot N_f \tag{26}$$

disassembly costs:

$$C_d = x_{16} \cdot e(p_f \cdot N_f) \tag{27}$$

processing of returned costs:

$$C_r = x_{17}(I + 88 + a) \cdot (p_f \cdot N_f) \tag{28}$$

total cost:

$$T_c = C_{fi} + C_d + C_r \tag{29}$$

provided that the model function of the cost is known, substituting the model established above into the decision tree modeling algorithm yields a visual graph of all the decisions made in the case:

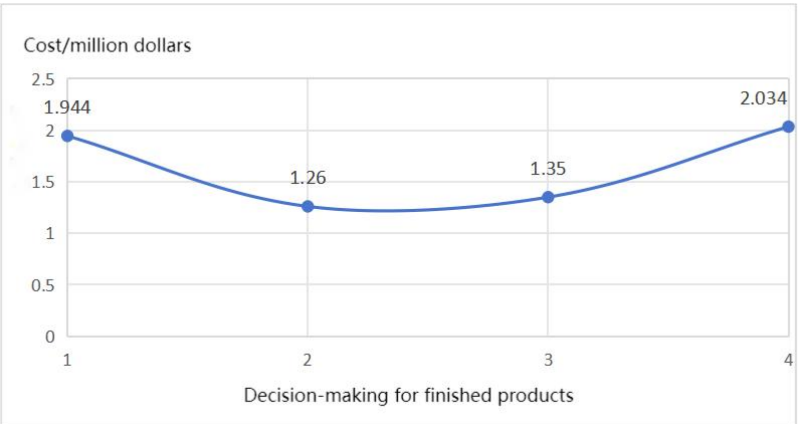

Figure 7 Decision-Making Situation for Finished Products

As shown in Figure 7, in order to meet the optimal decision-making conditions, should make the lowest cost decision-making that is decision-making 4, at this time, the decision-making situation is: only the finished product testing, the unqualified finished product is not disassembled, and returned from the hands of the customer's finished product is also not disassembled.

In summary, the optimal decision-making scheme is to test parts 1, parts 2, parts 3 and semi-finished product 1 but not disassemble semi-finished product 1; to test parts 4, parts 5, parts 6 and semi-finished product 2 but not disassemble semi-finished product 2; to test parts 7 and 8 and not to test and disassemble semi-finished product 3; to test only the finished product, and not to disassemble the unqualified Finished products are not disassembled, and finished products returned from customers are not disassembled.

After obtaining the locally optimal solution, the mathematical model of the cost can be obtained based on the decision situation as:

$$N_k = \times \sum_{i=1}^{8}(C_i + d_i) + V \times \sum_{j=1}^{3}(C_{fi} + d_{fi}) + V_z{}' \times (C_f + d_f) \tag{30}$$

4 CONCLUSION

Enterprise decision-making is a core component of enterprise management, which involves all levels from strategic planning to daily operations. Effective decision-making can help enterprises cope with complex business environments, optimize resource allocation, enhance competitiveness and achieve sustainable development. Therefore, the accuracy of the final results of decision-making and the efficiency of decision-making can directly affect the development results of enterprises.

This paper starts from the perspective of optimizing enterprise decision-making, firstly introduces the accuracy and reasonableness of the decision tree model in decision-making application, and establishes the corresponding enterprise decision-making model according to the specific scenarios of enterprise decision-making needs; then verifies and calculates the newly established model through the decision-making problems of specific scenarios, in the process of which the decision-making problem is transformed into the sampling detection problem, and the basic principles of mathematical statistics are used to simplify the problem; finally gives the specific conditions of enterprise decision-making, adopts the principle that any step is optimal based on the overall optimal solution, and gives the corresponding conclusions. The problem is simplified; finally, the specific conditions of enterprise decision-making are given, and the principle that any step is optimal based on the overall optimal solution is adopted to make the localization optimal, and the corresponding conclusions are given. The results show that the calculation method established in this paper in 3.2 with the decision tree model algorithm as the core, while drawing conclusions, also according to the test program that comes with the algorithm to calculate that the mean square deviation value of each of the optimal decisions obtained is less than 1%, so this is a great help to the reliability of the model. Decision tree model has obvious advantages in the problem of enterprise decision-making, it optimizes the cumbersome steps in enterprise decision-making, and makes the enterprise decision-making problem clearer and clearer.

Decision tree modeling can be useful in finance, healthcare, marketing and manufacturing, especially in dealing with small amounts of data. In finance, it can be used to assess the credit risk of an individual and select a better investment portfolio, predicting the return and risk through the future; in medicine, it can be used to a large extent to help patients with diagnosis of illnesses and medical assistance; and in technology research, it can be used to provide training value and research significance to machine learning or data mining algorithms. In research, it can be used to provide training value and research significance to machine learning or data mining algorithms.

COMPETING INTERESTS

The authors have no relevant financial or non-financial interests to disclose.

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