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Marketing Decision Support System Based on Data Mining Technology

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Abstract: With the continuous development of business intelligence technology, the application research of decision support systems (DSSs) is deepening. In China, the work in this area started relatively late, and there are few DSS research cases to assist in marketing decision-making. Currently, marketing decision support systems have shortcomings in data integration, historical data, query functions, and data analysis. This article analyzes the characteristics of marketing decision-making, discusses the application of data warehouse, OLAP, and data mining technology in marketing decision support systems, and designs a marketing decision support system based on data mining technology. The system uses a BP neural network to conduct data mining marketing forecasting. A three-layer network model for marketing prediction is established, with sales time, product price, and customer purchasing power as network inputs and output as the sales volume of a certain type of product in different locations. The test results show that the average absolute percentage error of this method is 15.13%, and the prediction accuracy is high. Research shows that with the continuous development of data mining technology, the system cannot only help users conduct scientific and reasonable marketing decision-making analyses, making the marketing decision-making process more scientific and reasonable, but also can bring new ideas to enterprise decision-makers, promoting the continuous improvement and progress of the system.

Keywords: data mining (DM); marketing decisions; decisions support system (DSS)

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1. Introduction

With the gradual transformation of China's economic system from a planned economy to a market economy and the deepening of reform and opening up, the business activities of enterprises are in a rapidly expanding three-dimensional strategic space. Enterprises have been pushed into a complex and volatile business environment [1]. There are many factors involved in the marketing system, including both internal and external factors, and all these factors are developing and changing without exception. Therefore, the marketing strategy and combination of the enterprise should be able to make corresponding adjustments in time with the changes of the internal and external environment of the enterprise. Finally, effective measures should be taken to ensure the implementation of the marketing plan [2].

The traditional management information system is mainly aimed at the daily structured problems, with the main goal of improving the operational efficiency of enterprises, and strengthens management by converting a large amount of data into valuable information [3]. With the progress of society and the development of technology, people are no longer just satisfied with obtaining a variety of information and simply using information, but want to make use of this information to help enterprises make decisions at a deeper level, combining modern information technology with marketing concepts to help enterprise leaders make scientific marketing decisions to meet the requirements of market competition [4].

The development of DM technology provides strong support for enterprises to improve their decision-making ability. Experts, data warehouses, data mining, online analytical processing, and other technologies can not only help users make structured quantitative decisions, they can also help users to make semi-structured and unstructured qualitative decisions, which can greatly improve the effectiveness of decision-making by senior managers [5,6]. DM can automatically process a large amount of raw data in the database through preset algorithms. It uses various methods and means to extract necessary and meaningful patterns from a large amount of data, excavate the specific relationship between objects, find out people's answers to the required questions, and serve decision-making [7]. DM is a specific step of knowledge discovery. The so-called knowledge discovery refers to the whole process of discovering useful knowledge from data, while DM is the process of extracting patterns from data with special algorithms [8,9]. The main methods and techniques used to obtain these results include statistics, cluster analysis and pattern recognition, classification of decision numbers, artificial neural network and genetic algorithm, rule induction, and visualization techniques [10]. DM can help decision-makers make more scientific decisions by converting original data into comprehensive data and providing analysis tools for multi-dimensional analysis of data [11]. DM is based on the use of new information about consumers and the market and their mastery [12,13].

At present, the marketing decision support system still has deficiencies in data integration, historical data, query function, and data analysis. There are few domestic research cases of decision support systems (DSSs) for auxiliary marketing decision-making, so this paper constructs a marketing decision support system based on data mining technology. The system collects, processes, and stores all kinds of information related to marketing decisions according to users' habits and requirements for solving problems, and makes use of mathematical models, expert experience, and knowledge discovered through data mining to conduct scientific and reasonable marketing decision analysis. The results of this study are conducive to a more scientific and reasonable marketing decision-making process, thus improving the efficiency of market management.

The overall structure of this paper consists of five parts. Section 1 introduces the background and significance of marketing DSSs, and then introduces the main work of this paper. Section 2 mainly introduces the related work of DSSs. Section 3 analyzes the concept and model of DM and designs the framework of marketing DSSs. In Section 4, the simulation experiment is carried out and the conclusion is drawn. Section 5 is a summary of the full text. The innovation of this paper is that the marketing decision support system proposed in this paper can solve the problem of information asymmetry in the game with other companies and sales agents in sales. It adopts a message mechanism, which allows managers to obtain the information of rival companies and the pre-determined agent team first, and know all the sales in the next few days, so as to take the lead in the whole sales game.

2. Work Related to Decision Support System

A decision support system (DSS) is a scientific tool to assist decision-making in a specific form. It provides decision-makers with a working environment that combines knowledge, initiative, creativity, and information processing ability, and combines qualitative and quantitative methods through human–computer dialogue. It helps decision-makers analyze problems, explore decision-making methods, and conduct evaluation, prediction, and optimization. The traditional decision support system combines the model base and the relational database. The relational database can only carry out simple processing and inquiry operations on the data. The information obtained from it cannot meet the current decision support. The model base cannot meet the dynamics and complexity of decision-making. The independent design mode of the two bases lacks internal unity. The traditional decision support system cannot meet the needs of decision support, prompting people to find new solutions.

Jamalian E. et al. put forward that the management decision-making process with decision-makers as the core subject should be subject to information and intelligence, design and planning, and selection decision. In this process, in order to better identify problems and finally deal with the results of decision-making, it is necessary to complete the determination of factors influencing decision-making and the collection, analysis, and processing of data in the information stage [14]. Wang Y. et al. put forward the three-part structure of DSSs, which defined the basic components of DSSs and greatly promoted the development of DSSs. In the late 1980s and early 1990s, DSSs began to combine with expert systems to form intelligent DSSs [15]. Miller J. et al. put forward that at present, most query systems used by marketing management departments of enterprises are based on OLTP technology, and the characteristics of OLTP determine that it is not suitable for the increasingly developing marketing DSSs [16]. Othman S. B. et al. put forward that in the process of final decision-making, we should evaluate these n schemes again, select the one with strong operability that is most conducive to achieving the decision-making goal, and start to implement it. As each link of decision-making has its own emphasis, the process is complicated, but at the same time, there is no denying that the three are inextricably linked, interdependent, and influential [17]. Pablo et al. put forward that although it started late, the application and development of DSSs in China is relatively fast. For example, the DSS developed by the Institute of Systems Engineering of Huazhong University of Science and Technology for resource allocation and freight car distribution supports the strategic decision of population and economic development and has achieved good results in practical application [18]. Koowrocki K. et al. put forward that the existing marketing DSSs can only provide the existing information, lacking the functions of data analysis and mining, unable to find the business rules hidden behind the data, and also unable to realize real-time monitoring and risk prediction [19]. Mccoy C. et al. pointed out that in China's telecom industry, the research on DSSs is in the ascendant. Zhejiang Telecom, Qingdao Telecom, Xiamen Telecom, Fujian Mobile Bureau, Guangdong Institute of Telecom Science and Technology, Zhongda Xintai High-tech Company, Neusoft Software Co., Ltd. and other telecom companies and software companies are all developing telecom DSSs [20]. Zhang S. proposed that the decision-making of decision-making managers is based on the analysis and calculation of databases in many aspects, and OLTP can no longer meet the needs of decision-makers. In addition, OLTP is mainly used to complete transactional processing, which usually requires a lot of update operations and requires high response time [21].

Although the application of DSSs has achieved initial results, there are not many successful examples, especially traditional DSSs. The data show that the DSSs successfully put into use abroad only accounts for approximately 30% of the total R&D, and the same is true in China [22]. There are many reasons for the failure of DSS development, but there are two main reasons. First, traditional DSSs can only provide data-level support in the process of auxiliary decision-making. However, the data needed for practical decision-making are often distributed and heterogeneous, which limits the adaptability of the system and does not meet the needs of the decision-making process. Secondly, the traditional DSS requires the decision-makers not only to have professional domain knowledge, but also to have higher knowledge of the DSS construction model, which makes it difficult for the decision-makers to understand and accept [23]. With the emergence of data warehouses, online analytical processing, and data mining technology, a new generation of decision support system based on DW, OLAP, and DM has been proposed. Because of the inherent connection and complementarity among the three, combining them to design a new DSS architecture, that is, a solution based on data warehouses and using data mining and OLAP tools as means, can give full play to their respective advantages. Utilizing the massive data existing in the enterprise to mine valuable knowledge and rules can provide more effective support for decision-making. The new decision support system is data-driven, which is less difficult to develop. It makes up for the shortcomings of traditional DSSs, and has become a hot direction of the development of decision support system.

Through the organic combination of DM technology and DSSs, this paper designs a set of intelligent DSSs, and applies it in marketing. Specifically, the decision support system extracts, transforms, and loads various business data related to marketing decisions according to the theme, and establishes a unified, standardized, and highly shared comprehensive theme data center. On this basis, OLAP and data mining technology are used to analyze data from multiple perspectives and extract potential knowledge from them, so as to establish an efficient marketing decision support system [24]. The system provides assistant decision support for management and decision-makers in new product development, product pricing, market maintenance and development, competitor analysis, customer relationship management (CRM), marketing goal formulation, product promotion, advertising promotion, performance evaluation, employee management, and many other aspects related to marketing decisions, and lays a solid foundation for enterprise development and market development.

3. Method

(1) The concept and model of DM

DM is a process of mining interesting knowledge from a large amount of data stored in databases, data warehouses, or other information bases. To put it more popularly, we extract the parts we need from a lot of data and ignore the useless parts. DM is a good method of knowledge extraction [25]. DM enables valuable knowledge, rules, or high-level information to be extracted from the relevant data sets of the database, making the large-scale database serve as a rich and reliable resource for decision-making. The core technologies of DM are artificial intelligence, machine learning, statistics, etc. However, a DM system is not a simple combination of multiple technologies, but a complete whole. It also needs the support of other auxiliary technologies. The main methods and technologies used include statistics, cluster analysis and pattern recognition, decision tree classification, artificial neural network and genetic algorithm, rule induction, and visualization technology. The typical knowledge pattern extraction methods of data mining include classification, concept description deviation detection, and sequential pattern and association rule discovery. It can complete a series of tasks such as data collection, preprocessing, data analysis, and result expression, and finally present the analysis results to users [26]. The data extraction layer processes the original data and obtains some valuable data. On this basis, the information extraction layer uses a variety of data analysis tools to extract useful information for decision-making from the data. OLAP and DM are powerful tools for information extraction. The purpose of establishing a data warehouse is to provide the OLAP system with processed data. OLAP is characterized by inquiry and analysis and provides real-time and accurate information according to the decision-maker's demand for information. OLAP can quickly, consistently, and interactively access various possible information views, providing a favorable means for decision support. The key problem in the implementation of OLAP is how to organize the comprehensive data in the data warehouse to meet the needs of multi-dimensional data analysis of client users. At present, there are mainly two organization modes: multi-dimensional OLAP (MDOLAP) and relational OLAP (ROLAP). MDOLAP takes multi-dimensional database as the core and displays data in a multi-dimensional way. It can intuitively express the "one to many" and "many to many" relationships in the real world, and its multi-dimensional concepts are clearly expressed. ROLAP's comprehensive data organization mode takes relational database as the core and uses two-dimensional tables in relational database to organize data and express multidimensional concepts. Its data organization adopts star pattern. The ROLAP-oriented data organization pattern with the sales analysis in marketing analysis as the theme is shown in Figure 1.

Each topic in the data warehouse corresponds to a star schema structure, which is composed of fact tables and several dimension tables. Each record in the fact table contains a pointer to each dimension table, through which multidimensional data can be linked.

The data warehouse design of the system adopts star pattern. Therefore, the OLAP design of the system adopts ROLAP mode [27].

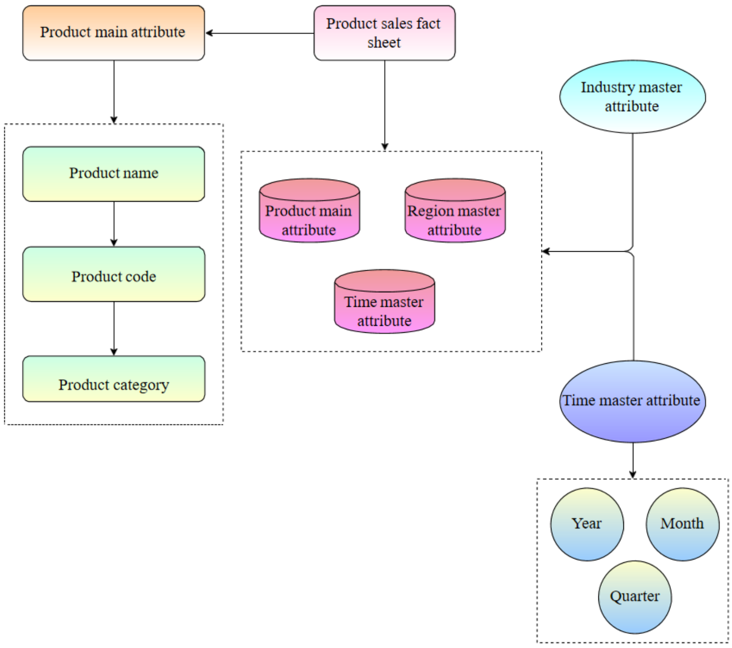

Figure 1. OLAP data organization model for DM sales analysis.

The classification analysis of the decision tree is mainly to train the decision tree or Bayesian neural network through the transaction samples in the transaction database to form the classification rules for the sample points in the sample. It can explain the main and secondary attributes that form classification differences in the samples and can classify and predict the samples with set attributes according to the classification rules in the decision tree. The system uses ID3 algorithm, a representative algorithm based on information gain theory, to realize decision tree analysis. Decision tree analysis can obtain the levels and categories of various influencing factors and the resulting sales level. The tuple data of the training set are marked as D class, assuming that D class is marked with M different values, and the M different values represent M different classes, which are marked as $C_i = (i = 1, 2 \ldots m)$ in turn. A set of tuples in C_i class is denoted by C_i, d. $|D|$ represents the number of data in a tuple.

The expected information required in C_i is Formula (1):

$$Info(D) = -\sum_{i=1}^{m} \log_2(Pi) \tag{1}$$

$Info(D)$ is the entropy of D. P_i represents the probability that data belong to each tuple, and pi is calculated as $|C_{i,D}|/|D|$. The tuple of data is supposed to be divided by A, and A will obtain V different results after dividing the tuple, in which each division has a value aj; thus, the information of A can be obtained, as shown in Formula (2):

$$Info_A(D) = -\sum_{j=1}^{v} Info(D_j) \tag{2}$$

The information gain metric is used to select test attributes on each node of the tree. This metric is called attribute selection metric or split goodness metric. Select the attribute with the highest information gain or maximum entropy compression as the test attribute of the current node. This attribute minimizes the information and quantity required for sample classification in result division and reflects the minimum randomness of division. Assuming that the original information demand is $Info(D)$ and the new information demand is $Info_A(D)$, the information gain is the difference between them, as shown in Formula (3):

$$Gain(A) = Info(D) - Info_A(D) \tag{3}$$

The information gain rate normalizes the information gain by using the split information ‖ value. Information classification is similar to $Info(D)$, and is defined as Formula (4):

$$SplitInfo_A(D) = -\sum_{j=1}^{v} \log_2 \frac{|D_j|}{|D|} \tag{4}$$

This value represents the information generated by dividing the training data set D into v divisions corresponding to v outputs of the attribute A test.

Select the attribute with the maximum gain rate as the split attribute, as shown in Formula (5):

$$GainRation(A) = \frac{Gain(A)}{SplitInfo(A)} \tag{5}$$

Let D_k be the distance from a sample to the K nearest neighbor. For a homogeneous Poisson process and $x \in [0,\ \infty]$, there is Formula (6):

$$P(D_K \geq x) = \sum_{k=0}^{k-1} 1 - F_{D_K}(x) \tag{6}$$

Then its distribution probability density is Formula (7):

$$f_{D_K}(x) = \frac{dF_{D_K}(x)}{dx} \tag{7}$$

The maximum likelihood estimation of parameter λ is Formula (8):

$$\overset{\wedge}{\lambda} = \frac{K}{\pi \sum\limits_{i=1}^{n} d} \tag{8}$$

where d is the $K - NN$ distance of the i sample; n is the number of random samples.

As mentioned above, the decision tree obtained through data set training can continuously subdivide the sales market according to the impact of various factors on sales in different levels of markets.

(2) Architecture design of marketing DSSs

The marketing decision support system designed in this paper can solve the problem of information asymmetry in the game with other companies and sales agents in sales. It adopts a message mechanism, so that managers can obtain the information of rival companies and the pre-determined information of the agent's team first, and can know all the sales in the next few days, so as to take the lead in the whole sales game. The business involved in the sales management system is relatively confidential. If it is directly placed on the public network, it is obviously not safe enough. Users on the public network using VPNs to connect to the company's intranet to access the sales management database and its applications is a better choice. The operating environment of the marketing DSS is shown in Figure 2.

After the decision-maker sends the decision request command, the data mining tool uses the data warehouse, model base, and knowledge base to complete the data mining process. The data warehouse management system is triggered by data mining tools to obtain task-related data from the data warehouse and generate auxiliary patterns and relationships. After these patterns and relationships are analyzed and evaluated, some data that are considered to be of interest are provided to decision-makers through human–computer interaction systems, and some discoveries are added to the knowledge base for new knowledge discovery and knowledge evaluation.

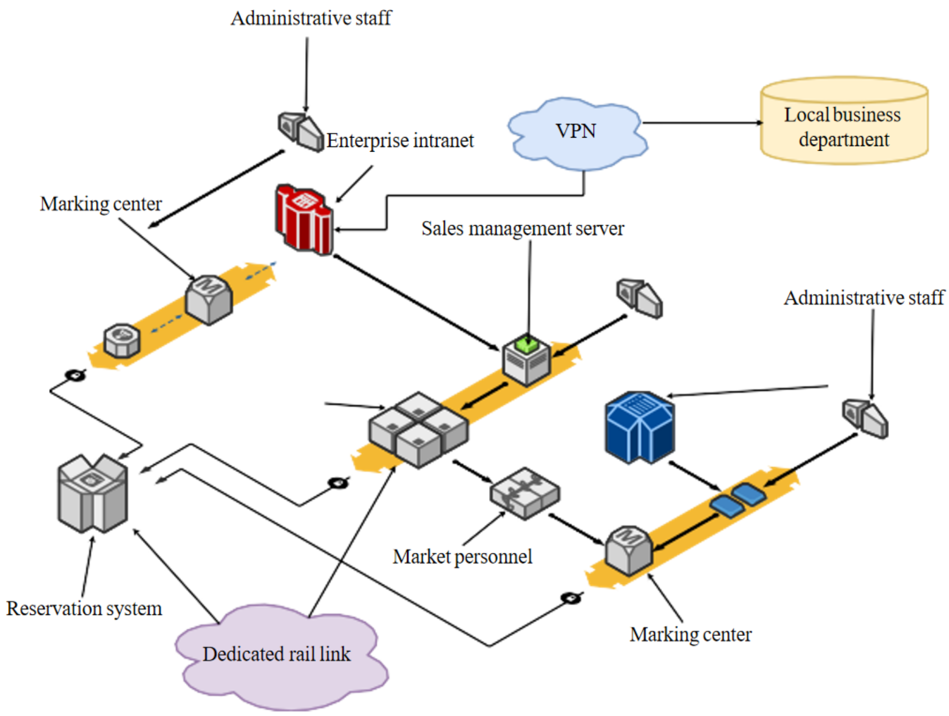

Figure 2. Operating environment of marketing decisions support system.

According to the design objectives of the system, marketing DSSs can be divided into six levels according to functions: basic data, data extraction, data warehouse, information extraction, information presentation, and system management.

(1) Basic data

The basic data layer covers a large amount of basic data accumulated by the marketing management department, including historical data and business data stored in many business system databases such as the sales management system, customer relationship management system, and cost management system.

(2) Data extraction

The data extraction layer performs preliminary processing on the basic data from the database, which is an efficient data processing factory that transforms the basic data from application-oriented to subject-oriented.

(3) Data warehouse

After the data are processed and purified by the extraction layer, they need to be stored in the data warehouse to directly face data analysis and data mining. The establishment of a data warehouse is not to replace the database, but to establish a more comprehensive and complete information application to support high-level decision analysis.

(4) Information extraction (OLAP analysis, data mining)

The data extraction layer initially processes the original data to obtain some valuable data, while the information extraction layer uses a variety of data analysis tools to extract information useful for decision-making from the data. For example, by analyzing the customer's purchase frequency, purchase volume, and recent purchase time, we can predict the future purchase behavior and calculate the customer's career value. The visualization tools in data mining can effectively detect the development trend hidden in the data. In marketing decisions, trends can be used to evaluate marketing plans and predict future sales.

(5) Information display

The information display layer is responsible for displaying the analysis results for users and can analyze and use the displayed data again to form the final analysis report.

(6) System management

It provides security management for users, permissions, passwords, etc., of the entire system, and completes the publishing of multi-dimensional analysis models, data mining models, customized reports, and other functions.

A DSS is a comprehensive and integrated system that makes use of database and human–computer interaction to organically combine multiple models and assist decision-makers to make scientific decisions. It is developed on the basis of a management information system and operational research. A DSS not only needs the relevant data of all departments within the whole enterprise, but also needs the relevant data of external enterprises and competitors. To automatically discover the potentially important relationships between things, DM is necessary. By measuring the distance of the attribute characteristics that affect the sales expenses, each point in the data set is allocated to a cluster. Here, the allocation principle is the principle of proximity, that is, the data points are allocated to that cluster when the European distance from the central point is small.

DM technology provides powerful tools such as neural networks and genetic algorithms, which can find and classify deviations in time. If the deviation is found to be an abnormal reaction, the marketer can take effective measures to prevent this abnormal reaction. If a change is found, further search for information is required. Competition lies not only in price, but also in quality, timeliness, product customization, and customer support. Organizations must quickly and frequently change their operation modes, reorganize their processes and structures, empower employees, and innovate. Decision support technologies, such as expert systems, enable people who lack knowledge to make good decisions.

At present, the vast majority of enterprise data is distributed and non-integrated. A DSS needs to integrate these scattered data, which is very complex work, and the data processing efficiency is very low. In addition, the DSS generally does not analyze detailed data, and decision analysis is mainly conducted for various summary data. After extracting, converting, and loading various business data related to marketing decisions according to the subject, a unified, standardized, and highly shared comprehensive subject data center is established. On this basis, OLAP and DM technologies are used to analyze the data from multiple perspectives and extract potential knowledge, so as to establish an efficient marketing DSS. The DSS architecture system formed by the combination of a data warehouse and data mining eliminates the problem of data inconsistency within the system. Due to the inherent unity, this new structure solves the problem of mutual connection. Data mining is to use a series of data mining methods and models to mine and analyze the data in a data warehouse and OLAP, find the potential laws and knowledge in the data, and use these laws and knowledge to make predictions. A DSS with this architecture can fully explore information, truly show the essence of information, and show the transformation of the DSS design concept from model-driven to data-driven, and the development difficulty is small.

4. Analysis and Discussion of Marketing Experiment Simulation Results

(1) Prediction of data mining in decision support systems

Sales prediction is to analyze sales volume and sales profit through data mining technology to predict future development trends. There are many data mining algorithms used for sales prediction. This article introduces an artificial neural network method for sales prediction, designs a data mining model for sales prediction, and validates it with data from a sales data warehouse to obtain a better data mining model for sales prediction. BP networks are currently the most widely used neural network with strong mapping ability, which can achieve arbitrary nonlinear mapping between input and output. To establish a sales forecast model using the BP network, first of all, the factors that affect the sales forecast and sales historical data should be used as input parameters. Then, the predicted sales data are used as output parameters to establish a network model. When making a prediction, you can input the prediction time and calculate the sales value for the predicted time based on the network model. In order to validate the BP sales prediction network model, part of the sales data was extracted from the database FoodMart 2000 provided by Microsoft and converted into the sales data warehouse we created as simulation data. Select the sales information of the enterprise's food products in 2020 after being summarized on a monthly basis, take the data of the first eight months as a training sample, and the data of the ninth month as a verification sample.

The network inputs are the sales time of the product, the predicted monthly average price of the product, the average revenue of the customer who purchased the product, and the monthly sales volume of the product in different regions. The sales volume of goods in different regions in the next month is used as the output of the network. In order to determine the length of historical data used for network input, this article selects the historical data length by comparing experimental results. The historical data length takes the historical sales volume and its influencing factors in the previous 1, 2, and 3 months, and compares the prediction accuracy of the three groups. Select the best group and use the length of historical data used as the network input for this type of product.

Using the artificial neural network toolbox of MATLAB, a three-layer BP network prediction model with a hidden layer is constructed. The number of input neurons in the network is 27, 54, 81, and the number of output neurons is 24. The number of neurons in the hidden layer is determined experimentally. The activation functions of the hidden layer and the output layer are the hyperbolic tangent function tansig and the linear function purelin, respectively. Momentum term coefficient mc = 0.95; learning rate lr = 0.01; error_goal = 0.00001; iteration number epoch = 10,000; premnmx normalization processing is performed on the input data before network training. The training method combines the additional momentum method and the adaptive learning rate method.

By training and verifying the third group of network models, the results show that when the number of hidden layer neurons is 10, the training effect is better, so this article selects the number of hidden layer neurons as 10. Through training three sets of models, the average absolute percentage error results of training times and validation samples under different models are shown in Table 1.

Table 1. Result of difference model training and test.

Model Structure (Input Layer-Hidden Layer-Output Layer)	Learning Times	MAPE of the Sample
27-10-24	345	17.41%
54-10-24	356	16.52%
81-10-24	332	15.13%

Through the validation of three sets of models of the BP sales prediction network, the average absolute percentage error of the three sets of validation samples is less than 20%, which is a good prediction model, indicating that using a BP neural network for sales prediction is feasible. From the perspective of prediction accuracy, the accuracy of the first three months of historical data length is significantly higher than that of the other two groups. Therefore, this article selects the third group of models as the BP network model for sales prediction, which is used to predict sales data.

(2) Consistency test between simulation results and actual data

Based on the data in 2015, this paper simulates the number of franchise stores and corporate profits of direct selling companies in this enterprise from 2016 to 2021, and then compares that with the historical data to test the validity of the model. The specific results are shown in Tables 2 and 3, respectively.

Table 2. Quantity model inspection of franchised stores.

Particular Year	2016	2017	2018	2019	2020	2021
Actual value (number)	405	415	451	491	582	612
Predicted value (number)	401	412	425	464	572	874
Relative error (%)	+0.97%	−1.84%	−6.03%	−5.45%	−1.65%	+43.23%

Table 3. Enterprise profit model test.

Particular Year	2016	2017	2018	2019	2020	2021
Actual value (PCs.)	6.6	10.34	13.55	20.3	28.11	41.7
Predicted value (PCs.)	6.8	10.0787	14.1791	20.0744	29.0744	43.525
Relative error (%)	+2.98%	−2.61%	+7.82%	−1.61%	+3.38%	+4.12%

As can be seen from Table 2, the number of franchise stores of direct selling enterprises from 2016 to 2021 is 405, 415, 451, 491, 582, and 612, respectively. The predicted values of the system dynamics model are approximately 401, 412, 425, 464, 572, and 874. The prediction error of this index will reach 43.23% in 2021, and the error in other years will be basically within 6%. This shows that the fitting degree of this model is also good, and the model is effective.

As can be seen from Table 3, the corporate profits of direct selling enterprises from 2016 to 2021 are, respectively, CNY 660 million, CNY 1034 million, CNY 1355 million, CNY 2.03 billion, CNY 2811 million, and CNY 4.17 billion. The predicted values of the system dynamics model are CNY 680 million, CNY 100,787 million, CNY 14,179.1 million, CNY 207,744 million, CNY 290,744 million, and CNY 4352.5 million. Except for 2018, the absolute value of the error in other years is less than 5%. The relative error between the predicted value and the actual value in 2018 is 7.82%, which is within the acceptable range. It can be explained that the consistency test between the simulation results and the actual data has been verified.

(3) Single factor analysis of simulation results

In this experiment, the promotion investment is changed in steps of 0.01 within the range of [0.21, 0.24], and the change of enterprise profit is shown in Figure 3.

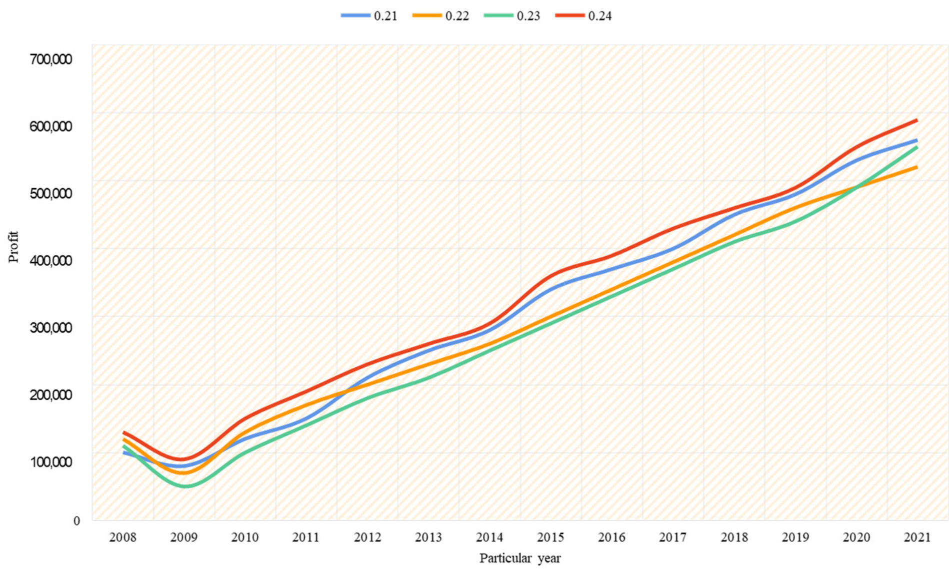

Figure 3. Change curve of enterprise promotion investment coefficient.

As can be seen from Figure 3, vertically, each curve shows that in the simulated 14 years, except for the slight decline in the enterprise profit in the first year, the enterprise profit in the following years is increasing year by year, and the increasing curve is close to the index curve. For horizontal comparison, the five curves represent different promotion investment ratios. It can be seen from the five curves that the promotion investment coefficient is positively correlated with the enterprise profit. With the increase in promotion investment, the enterprise profit increases. In the simulation year 2008–2017, with the increase in the promotion investment coefficient, from 0.21 to 0.26, the enterprise profit also increased correspondingly, but not significantly, from 1.82 billion to 4.35 billion; in the forecast year 2018–2021, the input coefficient will increase from 0.22 to 0.26, and the corporate profit will increase from 4.54 billion to 5.948 billion. This is because the enterprise profit curve is similar to the exponential increasing curve. In the forecast year, the slope of the curve is larger and the enterprise profit increases more.

Change the product input within the range of [0.21, 0.24] in steps of 0.01, and the change of enterprise profit is shown in Figure 4.

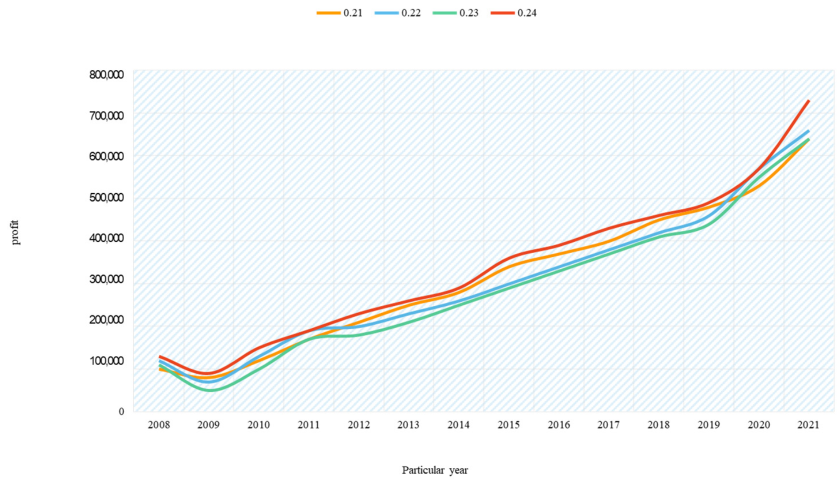

Figure 4. Change curve of enterprise product input coefficient.

As can be seen from Figure 4, vertically, each curve shows that in the simulated 14 years, except for the slight decline in the enterprise profit in the first year, the enterprise profit in the following years is increasing year by year, and the increasing curve is close to the index curve. For horizontal comparison, the five curves represent different product input proportion values. It can be seen from the five curves that the product input coefficient is positively correlated with the enterprise profit. With the increase in product input, the enterprise profit increases. In the simulation year 2008–2017, with the increase in the product input coefficient from 0.21 to 0.24, the enterprise profit also increased correspondingly, but not significantly, from 1.87 billion to 4.45 billion; in the forecast year 2018–2021, the input coefficient will increase from 0.23 to 0.26, and the corporate profit will increase from 4.968 billion to 7.12 billion. With the increase in the product input coefficient, the enterprise profits also maintain a corresponding growth, but the growth rate is not significant.

Change the channel input within the range of [0.05, 0.07] in steps of 0.15, and the change of enterprise profit is shown in Figure 5.

As can be seen from Figure 5, vertically, each curve shows that in the simulated 14 years, the enterprise profit increases year by year with the increase in years, and the increasing curve is close to the index curve. By horizontal comparison, the five curves represent different promotion investment ratios. It can be seen that under different channel investment coefficients, the enterprise profits basically remain unchanged.

In order to validate the marketing decision support system, this article finally forecasts the sales volume of goods in different regions in October 2020. Start with network model training. According to the prediction time and product type, the system will automatically extract the sales information of such products from the data warehouse, launch the background MATLAB simulation platform, and conduct BP prediction model training, learning, and detection. Then, the trained network model is saved for prediction. In the prediction interface, predictions are made based on the prediction time and product type, and the results are output in data and graphical form. As sales information in data warehouses changes, network models should also be updated in a timely manner. The output prediction results are also stored in the form of data tables for decision-making. The BP neural network model training is shown in Figure 6.

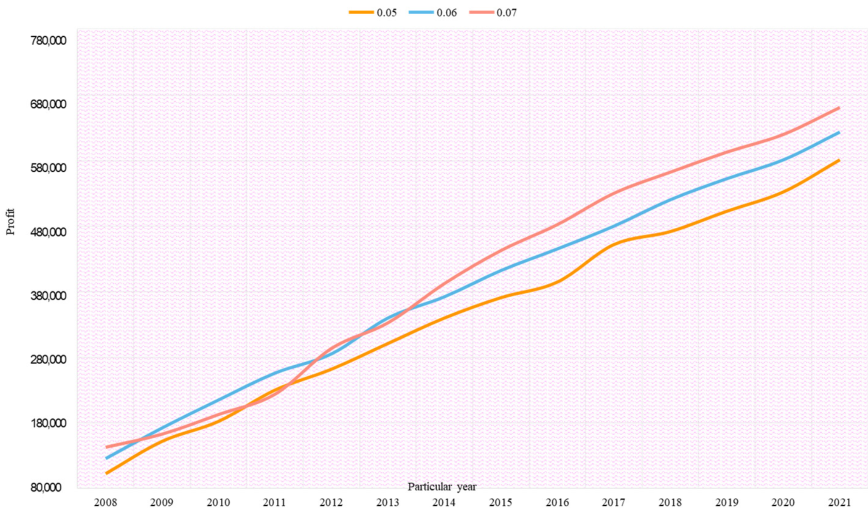

Figure 5. Change curve of enterprise channel input coefficient.

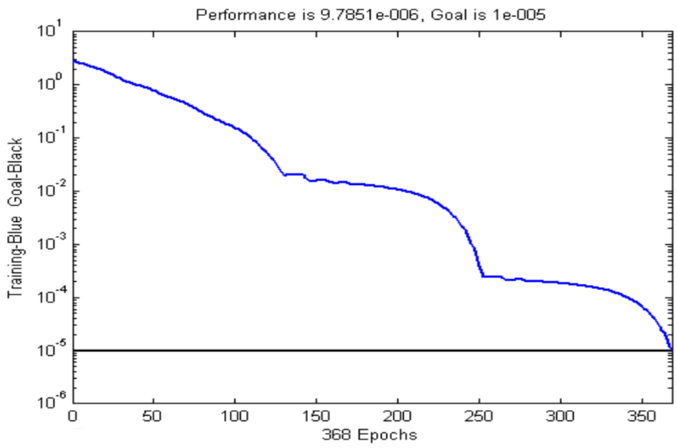

Figure 6. BP neural network model training.

The BP neural network model sales prediction is shown in Figure 7.

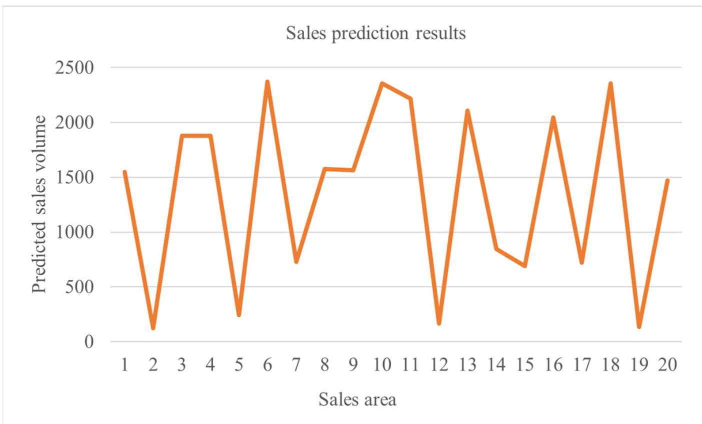

Figure 7. BP neural network model sales prediction.

From the above verification, it can be concluded that the functional modules of this system can meet the expected requirements; the accuracy of sales volume and sales profit predicted based on BP model is high, which can help enterprises formulate scientific and reasonable decision-making plans.

5. Conclusions

The marketing decision-making process is a market-oriented management decision-making process that involves product decision-making, price decision-making, proposal decision-making, and other factors. The marketing decision support system based on a data warehouse designed in this paper can effectively support management decisions in this complex process. The system uses a BP neural network to conduct data mining marketing forecasting. A three-layer network model for marketing prediction is established, with sales time, product price, and customer purchasing power as network inputs and output as the sales volume of a certain type of product in different locations. The test results show that the average absolute percentage error of this method is 15.13%, and the prediction accuracy is high. Marketing decision support systems based on data mining technology can effectively discover marketing knowledge hidden in data, and better meet various decision-making needs in marketing.

As the establishment of a marketing decision data warehouse is also a continuous improvement process, it is necessary to study more marketing decision models and data mining algorithms that conform to marketing characteristics. In addition, the real-time research of marketing decision support systems needs to be strengthened.

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