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Environmental Cost Control of Manufacturing Enterprises via Machine Learning under Data Warehouse

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Abstract: Environmental cost refers to the cost paid by enterprises to reduce environmental pollution and resource depletion in production and operation. To help enterprises reduce environmental costs, a manufacturing environmental cost control algorithm based on machine learning is proposed. The probabilistic neural network is used to classify the current environmental cost control level of different manufacturing enterprises. Then, the particle swarm optimization (PSO) algorithm is improved to build a multi-objective backbone PSO algorithm for multi-objective decision-making, which is used in the selection of environmental cost control methods. The experimental results show that there is a strong correlation between the original data classification and the proposed probabilistic neural network, and the correlation reaches 96.1%. PSO performance test results show that the algorithm has the best performance, the best stability, and the shortest time needed to find the optimal solution set when the initial particle number is 140 and the number of iterations is 60. Based on the comprehensive experimental results, the following conclusions are drawn. Enterprises should strengthen collaboration and cooperation with customers, suppliers, and waste-profiting enterprises, so as to well control environmental costs. To sum up, the proposed model provides some references for the adoption of machine learning in environmental cost control of manufacturing enterprises.

Keywords: data warehouse; environmental cost control; machine learning; manufacturing enterprise

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Citation: Li, X.; Ma, C.; Lv, Y. Environmental Cost Control of Manufacturing Enterprises via Machine Learning under Data Warehouse. *Sustainability* **2022**, *14*, 11571. https://doi.org/10.3390/su141811571

Academic Editor: Andreas Kanavos

Received: 28 July 2022
Accepted: 9 September 2022
Published: 15 September 2022

1. Introduction

With the advent of the era of global economic integration, China's manufacturing industry is facing increasingly fierce competition. The competitors of manufacturing enterprises may come from domestic or foreign countries. Effective corporate cost control can help companies survive and develop better, and resist the impact of external competition [1]. Environmental cost control is an important part of enterprise cost control. Since China's reform and opening up, the economy has developed rapidly, which has also brought tremendous pressure to the environment. The global temperature rises, and the destruction of the ozone layer occurs from time to time. In addition, the environment is an indivisible public resource, and the control of environmental costs can effectively prevent the spread of the "tragedy of the commons". Therefore, the control of environmental costs can effectively mitigate the degradation of environmental functions and enhance the protection of public resources. At present, the emergence of such problems has triggered most people's thinking on environmental issues [2]. China has now become a world-class "manufacturing power", and the development of the manufacturing industry has promoted the process of industrialization and enhanced China's comprehensive national power. However, the manufacturing industry has a large energy consumption and high environmental cost. With the "made in China" going global, controlling environmental costs has become a common problem faced by Chinese manufacturing enterprises. Therefore, how to develop the economy under the premise of protecting the environment has become a difficult problem for many manufacturing enterprises and government departments with high pollution, high consumption, and high emission [3]. According to the data released by the National Bureau of Statistics in 2020, China's total energy consumption was 498,000 million tons of standard coal, of which the total energy consumption of the manufacturing industry was 268,426 million tons of standard coal, accounting for 53.9% of the total. High energy consumption is inevitably accompanied by high pollution and high costs. Due to the short time of implementing a low-carbon economy in China, manufacturing companies have less practical experience in environmental cost control. The practical experience of environmental cost control in manufacturing enterprises is relatively scarce. The high cost of manufacturing enterprises is the key factor affecting their competitiveness. Therefore, strengthening the research on environmental cost control of manufacturing enterprises provides practical guidance for environmental cost control of manufacturing enterprises in a low-carbon economy. The level of environmental cost control of enterprises should be improved, and the economic benefits of manufacturing enterprises should be increased in the implementation of a low-carbon economy. Thus, manufacturing enterprises are motivated to actively develop a low-carbon economy, and their competitive position in the international market is enhanced.

2. Literature Review

At present, experts have put forward corresponding ideas to solve this problem. Liu used the conjugate analysis theory in extenics to analyze the components of the manufacturing cost of an enterprise's products. The extension theory-related knowledge was utilized to give the steps of product manufacturing cost control analysis. Through system modeling, extension analysis, extension transformation, evaluation decision, etc., the corresponding product manufacturing cost control strategy was obtained [4]. Yuan believed that the iron and steel industry, as the industrial base of China, is an industry with high energy consumption, high pollution, and high emission. Moreover, its pollution of the environment is extremely serious. For this reason, the author analyzed and summarized the problems in cost management of the steel industry environment in detail. In addition, corresponding suggestions were put forward according to the problems summarized [5]. Fu believed that there is a close relationship between the socio-economic development of the river basin and water environment protection. Therefore, he integrated the bidirectional causality between economic activities and water environment improvement accordingly and put forward the corresponding theoretical model [6]. Liu believed that China's manufacturing industry is facing new challenges under a new background at the current moment of the arrival of the new era of socialism. The manufacturing sector is a stabilizing force for China's real economy. Therefore, computer-aided technology should be reasonably applied to effectively control and manage the cost of enterprises and improve the core competitiveness of enterprises [7]. From the perspective of supply chain logistics, Mo analyzed the logistics cost structure of enterprises. In view of the current logistics cost problems, the supply chain logistics cost control strategy was formulated, to provide feasible suggestions for the cost control of current logistics enterprises [8]. Cadavid pointed out that with the advent of Industry 4.0, the rich availability of data, high computing power, and large storage capacity make machine learning methods an attractive solution to the challenges of manufacturing. Therefore, the latest development of ML-production possibility curve (PPC) technology is introduced through the systematic analysis of 93 recent research and adoption literature. The first objective is to provide a methodological definition for the implementation of ML-PPC and to propose a mapping of scientific literature classifications to determine further research perspectives. To achieve the first goal, the ML technologies, tools, activities, and data sources required for the implementation of ML-PPC are reviewed. The second objective is developed by analyzing the use cases for I4.0 and the features being addressed. The results show that 75% of the potential research areas for ML-PPC are barely explored or not referred to at all [9].

Based on a review of the existing literature, it was found that there are still some shortcomings in the existing studies. Specifically, in terms of research content, the current research on environmental cost management of domestic enterprises mostly stays in the discussion of relevant relationships and theoretical model construction but has not yet conducted an in-depth analysis from the practical and realistic level. From the perspective of enterprise types, research on enterprise cost control has mostly focused on industrial enterprises, and not enough attention has been paid to other types of enterprises such as manufacturing (Table 1). This study will make up for the lack of existing literature and analyze how to achieve environmental cost control in manufacturing companies based on realistic data and specific cases. Based on this, a probabilistic neural network is introduced to classify manufacturing enterprises with different environmental cost control levels, to utilize data warehouse and machine learning to study the environmental cost control of manufacturing enterprises. Moreover, an optimized backbone particle swarm optimization (PSO) target is proposed to select different environmental cost control methods. It is hoped that this research can provide a stable model for the adoption of machine learning in the environmental cost control of manufacturing enterprises.

Table 1. Review of representative literature.

Title	Authors	Research Summary	Research Methodology	Research Innovations	Research Deficiency
Extension Analysis of Manufacturing Cost and Construction of basic-elements Model	Liu et al. (2019) [4]	It analyzes the components of the product manufacturing cost of the enterprise by using the conjugate analysis theory in extenics.	System modeling, extended analysis	This article starts from the production of this product, through the extension of the entire life cycle of the product.	It is only limited to macro cost analysis and no corresponding solution is proposed.
Research on Environmental Cost Management Problems and Countermeasures of China's Iron and Steel Enterprises	Yuan et al. (2020) [10]	It analyzes the problems that may exist in the environmental cost management of the steel industry, and then proposes targeted recommendations.	Theoretical model construction	The necessity of environmental cost control is analyzed theoretically.	There is no detailed analysis from the practical level, and there is insufficient attention to other types of enterprises.
Equilibrium cost of water environmental protection based on watershed sustainability	Fu et al. (2019) [6]	It presents a theoretical pattern of economic activities and water environmental improvement by incorporating their bidirectional causality relationship.	Data statistical analysis	The correlation between economic activities and water environment improvement was analyzed.	No feasible environmental improvement scheme is proposed.
Cost Control Analysis of Manufacturing Enterprises Based on Computer Aided Technology	Liu et al. (2020) [7]	It discusses the importance of computer aided technology for enterprise cost control.	Theoretical model construction	The importance of computer technology to enterprise cost control is analyzed theoretically.	There is no detailed analysis from the practical level.
Logistics Cost Control from the Perspective of Supply Chain	Mo et al. (2020) [8]	It provides feasible suggestions for the current internal control of logistics enterprises, namely cost control.	Theoretical model construction	The importance of cost control in logistics enterprises is analyzed theoretically.	There is no detailed analysis from the practical level.
Machine learning applied in production planning and control: A state-of-the-art in the era of industry 4.0.	Cadavid et al. (2020) [9]	It provides an initial systematic review of publications on machine learning applied in production planning control.	Text analysis	Through the analysis of the text, it is proved that 75% of the ML-PPC domain has not been discussed.	Only from the perspective of text, the results are not further discussed.

The first section of this research expounds on the concept of the environmental cost of China's manufacturing industry, summarizes the work of others, and puts forward the work direction of this research. In the second section of this research, the research status of environmental cost control in manufacturing enterprises is described. The environmental cost factor control classification based on a probabilistic neural network is proposed, and then the multi-objective backbone PSO algorithm is proposed. Finally, the evaluation index of this research is explained. The third section of this research describes the algorithm and dataset used in this research. In the fourth section of this research, the performance of the probabilistic neural network classification algorithm and multi-objective backbone PSO algorithm is tested, and an example is given for verification. The fifth section of this research summarizes the research work of this research and points out the shortcomings of the work of this research and the future research direction.

3. Enterprise Environmental Cost Accounting Using Product Life Cycle Method

3.1. Adoption of Artificial Intelligence in Manufacturing Enterprises

Manufacturing is a relatively complex process. The manufacturing of a product requires multiple processes. Nowadays, manufacturing companies are using a variety of methods to improve their production efficiency and quality. With the continuous development of science and technology, big data and artificial intelligence have solved the problem of massive data collection and storage. Many companies are beginning to try to use artificial intelligence algorithms to help them complete their work. As a new driving force of industrial transformation, artificial intelligence has become the focus of government development. The integration of artificial intelligence and manufacturing belongs to the category of intelligent manufacturing and has great potential. According to the data predicted by the consulting company, by 2035, the adoption of artificial intelligence will increase the manufacturing industry by nearly four trillion US dollars, with an annual growth rate of more than 5%. The fundamental purpose of the integration of artificial intelligence and manufacturing is to improve efficiency and reduce costs. At present, artificial intelligence has been applied to a certain extent in the field of intelligent manufacturing. Common areas are classified into product life cycle areas and key element areas. The adoption of artificial intelligence in the field of intelligent manufacturing often revolves around specific issues such as product quality inspection and process optimization, which provides the managers and staff of the enterprise with optimized decision-making for reference to improve the profit of the enterprise. Typical adoptions of artificial intelligence include predictive maintenance, dynamic intelligent scheduling, intelligent online detection, and energy consumption and environmental analysis. With intelligent online detection as an example, intelligent online detection is based on product photos collected by sensors. Computer artificial intelligence algorithms are employed to detect defective and defective products, thereby improving the quality and speed of product inspection. With cotton textile enterprises as an example, the implementation of this adoption can greatly reduce the rate of defective products. The scrap rate of products can also be reduced by analyzing the causes of defective products, and product design and production processes can be optimized to further reduce test costs.

3.2. Environmental Cost Control for Manufacturing Enterprises

The development of manufacturing enterprises has a decisive influence on the development of China's industrial industry. The cost control characteristics of manufacturing are classified into three aspects. The first point is strong implementation. The environmental cost of manufacturing enterprises exists in all business links of the enterprise. In the context of big data and the Internet of Things, with the continuous advancement of geospatial data acquisition and retrieval, the amount of available geospatial data is increasing. Therefore, a new data management architecture is needed. A building information model (BIM) big data storage-management solution based on a hybrid storage architecture of Web VRGIS is proposed by Lv [11]. Therefore, environmental costs should be controlled in the design link, R&D link, development link, procurement link, and after-sales service link. The second point is that the cost of breaking the law is high. An important provision in the relevant environmental laws of China is to require companies to lower their pollution standards by charging high pollution fees. The third point is high environmental costs. According to the data from China's Environmental Protection Statistics Bureau, the economic loss caused by the pollution of manufacturing enterprises in China accounts for the difference in the overall pollution [12]. However, there are often the following three problems in the environmental cost control of manufacturing enterprises in China. First, manufacturing enterprises often only use a single environmental cost control method in environmental cost control, which greatly reduces the effectiveness and effectiveness of enterprise cost control. Second, manufacturing enterprises fail to integrate different environmental cost methods, and the cost control methods and numbers used by different enterprises are different. This approach will lead to repeated use of cost control methods or offsetting the effects of different control methods. Third, manufacturing enterprises all take themselves as a unit to carry out independent environmental cost control. Moreover, they have not coordinated with upstream and downstream enterprises that have management with the enterprise to jointly carry out cost control [13]. For a manufacturing enterprise, maximizing benefits is only one of the purposes of implementing environmental cost control. The ultimate goal of environmental cost control is realizing coordinated and stable development of economic, environmental, and social benefits. The coordinated development of economic benefits, social benefits, and environmental benefits is maximizing economic benefits, that is, to obtain relatively more profits with a relatively small investment [14]. For manufacturing enterprises, it refers to carrying out green production and sales and implementing reasonable waste utilization to reduce environmental costs, so as to reduce business costs and maximize economic benefits. The maximization of social benefits means that manufacturing enterprises increase the utilization rate of resources and reduce the waste of resources, so as to carry out sustainable development and harmonious development. Maximizing environmental benefits refers to actively taking measures to reduce waste water, waste gas, and waste discharge in the production stage, thereby maximizing environmental benefits [15,16].

3.3. Control Classification of Environmental Cost Factors under Probabilistic Neural Network

The probabilistic neural network is a feedforward neural network constructed according to the principles of probability and statistics, and its basic model is Radial Basis Function (RBF) [17]. Probabilistic neural networks have the advantages of a simple learning process, fast training speed, accurate classification, and strong fault tolerance. Bayes' rule can make better judgments on the data in the input space and has an accurate guiding effect on the selection of data [18]. Therefore, Bayes' rule is the theoretical basis for realizing probabilistic neural networks.

The posterior density $\pi(\theta|x)$ in Bayes' rule is shown in Equation (1).

$$\pi(\theta|x) = \frac{\pi(\theta)f(x|\theta)}{\int \pi(\theta)\, f(x|\theta)d\theta} = \frac{h(x|\theta)}{m(x)} \tag{1}$$

In Equation (1), $f(x|\theta)$ is the sample density, $\pi(\theta)$ is the sample distribution, $h(x|\theta)$ is the joint distribution, and $m(x)$ is the marginal distribution.

Bayes in the neural network is written in the form shown in Equation (2).

$$\pi(\lambda|X) = \frac{\pi(\lambda)f(X|\lambda)}{\int \pi(\lambda)f(X|\lambda)d\lambda} \tag{2}$$

In Equation (2), λ is the model parameter and X is the dataset.

The decision function $d(x)$ in Bayes' rule can be expressed in the form shown in Equation (3), and the value range of the decision function is $[-1, 1]$.

$$d : X(X \subset R^n) \to y = \{-1, 1\} \tag{3}$$

The loss function is an important way to measure whether the prediction is accurate or not [19]. It has a close relationship with the decision function and can be expressed in the form shown in Equations (4) and (5).

$$l(x, y, d(x)) = 1(y - d(x)) \tag{4}$$

$$l(\beta) = \begin{cases} 0 & \beta = 0 \\ 1 & others \end{cases} \tag{5}$$

The meaning of y in Equations (4) and (5) is the output of the function.

Expected risk is an index to evaluate the promotion ability of the decision function [20]. The expected risk of the decision function is the Riemann-Stieltijes integral of the loss function with respect to the probability distribution as shown in Equation (6) [21].

$$R[d] = E[l(x, y, d(x))] = \int l(x, y, d(x))dP(x, y) \tag{6}$$

The general network structure based on a probabilistic neural network is shown in Figure 1.

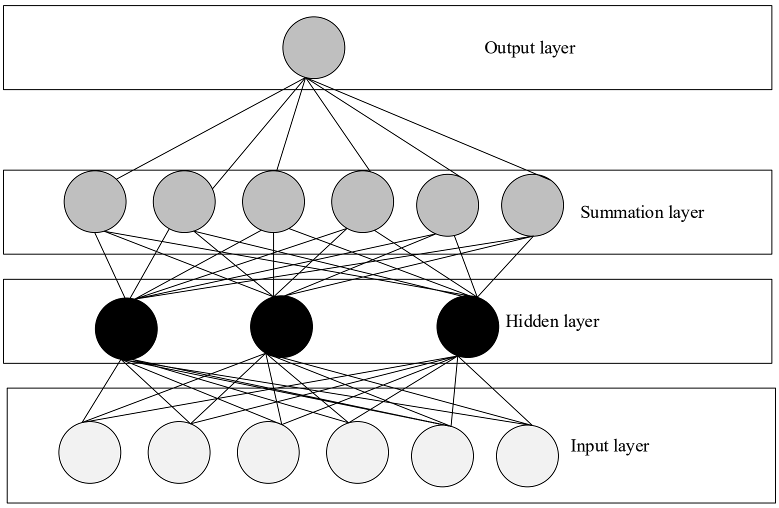

Figure 1. Basic structure of the probabilistic neural network.

Figure 1 presents that the basic probabilistic neural network consists of an input layer, a pattern layer, a summation layer, and an output layer [22]. Based on the above analysis, with the probabilistic neural network as the basis, the correlation coefficient is deemed as the core indicator of element division, and the four element types are taken as the factors affecting the division, and the model is established [23]. The TensorFlow framework designs the structure of a probabilistic neural network and designs the transfer function, calculation error, and training parameters in the network [24].

4. Methods and Datasets

4.1. Bare-Bones Particle Swarm Optimization

PSO is a random search algorithm based on group collaboration inspired by birds foraging [25]. The algorithm has the characteristics of the clear concept, easy implementation, and fast convergence speed, and is widely adopted in the field of decision-making optimization [26]. However, the solution speed and accuracy of the current commonly used

PSO are largely dependent on the value of the inertia weight and learning factor. When multi-objective optimization problems are performed [10], it is difficult to easily obtain better values of inertia weights and learning factors [27]. For this reason, related researchers have proposed a bare-bone PSO (BPSO) that uses Gaussian distribution sampling to replace the inertial weight parameters and learning factor parameters in the standard PSO [28], which solves the problem of inconvenient parameter setting in the original algorithm [29].

The expression of particle velocity in the multi-objective bare-bone PSO is shown in Equation (7).

$$X_{i,j}\ (z+1) = \begin{cases} N\left(\frac{r_3 Pbest_{ij}(z)+(1-r_3)Gbest(z)}{2}\right), \left|Pbest_{ij}(z) - Gbest(z)\right| & U(0.1) < 0.5 \\ Gbest(z) & otherwise \end{cases} \tag{7}$$

In Equation (7), i is the total number of the particle group, $Pbest_{ij}(z)$ is the best position of the particle itself, r_3 is the radius of the particle group.

The speed update bit is shown in Equation (8).

$$V_{i,j}\ (z+1) = \begin{cases} N\left(\frac{Pbest_{ij}(z)+Gbest(z)}{2}\right), \left|Pbest_{ij}(z) - Gbest(z)\right| - X_{i,j}(z) & U(0.1) < 0.5 \\ Gbest(z) - X_{i,j}(z) & otherwise \end{cases} \tag{8}$$

For discrete position variables, the position update of the particles is shown in Equation (9).

$$X_{i,j}\ (z+1) = \begin{cases} 1 & V_{i,j}(z+1) = max\{V_{i,j}(z+1)\},\ \forall_j \in \{1,\ 2,\ \ldots, n\} \\ 0 & otherwise \end{cases} \tag{9}$$

In the multi-object bare-bone particle swarm [30], it is still necessary to find the global optimal position of the particle and the local optimal position of the particle [31]. The expression of the local optimal position of the particle is shown in Equation (10).

$$Pbest_i\ (z+1) = \begin{cases} Pbest_i & (F(Pbest_i\ (z)) \prec F(X_i(z+1)) \\ X_i\ (z+1) & otherwise \end{cases} \tag{10}$$

Subsequently, the optimal position of each iteration is updated according to the local optimal position of the particle. If the performance of the previous fitness value is better than the performance of the current fitness value, the previous fitness value is used. Otherwise, the current fitness value is used [32]. To update the global best position of the particle, the researchers propose to use the sigma to find the global best position of the particle [33]. The principle is assigning σ_i to the coordinates (($f_{1,i}$,$f_{2,i}$)) of each solution, and all the solutions on the line $f_2 = \alpha f_1$ have the same σ. Therefore, σ can be defined as the form shown in Equation (11).

$$\sigma = \frac{f^2{}_1 - f^2{}_2}{f^2{}_1 + f^2{}_2} \tag{11}$$

For the optimization of the three objectives, sigma is defined as the form shown in Equation (12).

$$\sigma = \begin{pmatrix} f_1^2 - f_2^2 \\ f_2^2 - f_3^2 \\ f_3^2 - f_1^2 \end{pmatrix} \Big/ \left(f_1^2 + f_2^2 + f_3^2\right) \tag{12}$$

The basic steps of the multi-objective bare-bone PSO are shown in Figure 2.

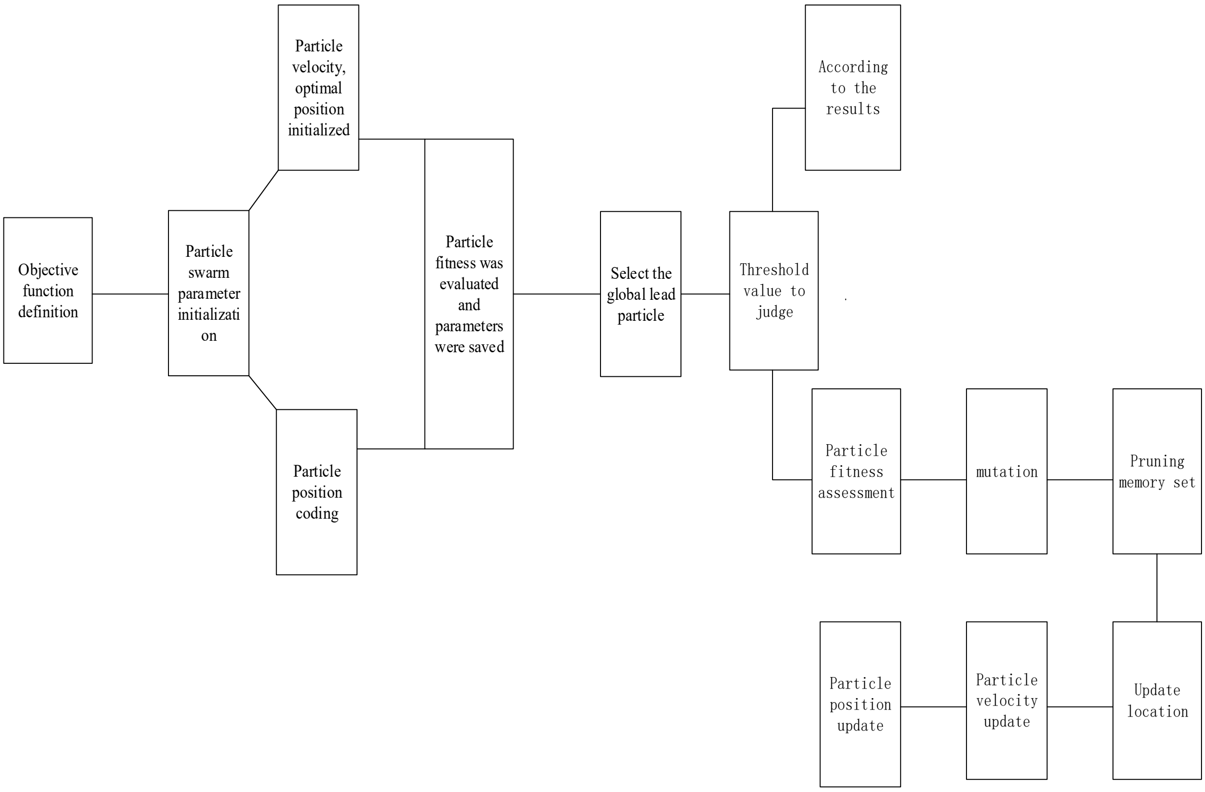

Figure 2. Multi-target bare-bone PSO framework.

Based on the above analysis, it is found that the multi-objective PSO can accurately and efficiently solve the two-objective optimization problem, and the algorithm solution set accurately converges to the Pareto front end. This algorithm can solve discontinuous functions, and the solution set of the algorithm and the exact solution of discontinuous functions are highly consistent. The multi-objective bare-bone function has obvious advantages in solving high-dimensional optimization problems, and can efficiently solve multi-objective optimization problems. Therefore, multi-objective PSO can be employed to construct a manufacturing enterprise's environmental cost control decision-making model to solve the multi-objective optimization problem of manufacturing enterprises' environmental cost control [34,35].

Based on the above analysis, the environmental cost control synergy equation is established as shown in Equation (13).

$$Y = a_0 + a_1 X_1 + a_2 X_2 + \varepsilon \tag{13}$$

In Equation (13), X_1 is the collaboration with the supplier, X_2 is the collaboration with the customer, Y is the coordinated control effect of dependent variable cost control, a_0 is a constant term, a_1, a_2, a_3 is the coefficient of each variable, and ε is a random error term.

For external recycling companies, waste will be passed on to downstream companies as raw materials. In this case, the degree of environmental cost coordination X_3 with waste-utilizing companies is particularly important for manufacturing enterprises' environmental cost coordination. The regression analysis system is as shown in Equation (14).

$$Y = a_0 + a_1 X_1 + a_2 X_2 + a_3 X_3 + \varepsilon \tag{14}$$

In Equation (14), a_0 is a constant term and a_1, a_2, a_3 is a regression coefficient.

4.2. Evaluation Indicators of Decision Model Formation and Dataset Overview

To describe the performance indicators of the algorithm in a multi-objective problem, three measurement factors need to be considered, which are as follows [36]. First, the distance of the Pareto front of the non-dominated solution set. Second, the distribution of the non-dominated solution set to the Pareto front. Third, the degree of coverage of the non-dominated solution set to the Pareto front. The current common performance evaluation indicators are classified into three categories. The first category is taken to evaluate the degree of approximation between the obtained solution and the global Pareto optimal frontier of the problem and to illustrate the convergence of the algorithm [37]. The second category is taken to evaluate the diversity performance index of the non-inferior solution. The third category is taken to evaluate the comprehensive performance indicators of convergence and diversity. In this research, the maximum coverage (MS) shown in Equation (15), the spacing (s) shown in Equation (16), the generation distance (GD) shown in Equation (19), and the diversity shown in Equation (20) are utilized to test the performance of the multi-target bare-bone PSO.

Maximum coverage represents the non-dominated solution set. The two most distant solutions determine the maximum range of the set. The value of maximum coverage (*MS*) is closely related to the performance of the algorithm. The larger the value, the better the performance of the algorithm.

$$MS = \sqrt{\sum_{m=1}^{M} [\max(f_m^n) - \min(f_m^n)]^2} \quad \forall_n \in \{1, 2, \ldots, N\} \tag{15}$$

N in Equation (15) means the number of non-dominated solutions, and M is the number of objective functions.

The function of the spacing (S) is describing the distribution of the vector. The smaller the value of the spacing, the more uniform the distribution of the solution and the better the performance of the algorithm. In addition, the non-dominated solution vector can be measured by comparing the value of S with the solution that converges to the actual Pareto front.

$$S = \sqrt{\frac{1}{N} \sum_{i=1}^{N} \left(\overline{d} - d_i\right)^2} \tag{16}$$

$$d_i = min_{l=1 \wedge l \neq i}^{N} \left(\sum_{m=1}^{M} \left| f_m^i - f_m^l \right| \right) \tag{17}$$

$$\overline{d} = \sum_{i=1}^{N} \frac{d_i}{N} \tag{18}$$

In Equations (16)–(18), d_{i} is the minimum value of the sum of absolute differences of each objective function value between the i-th solution and all N non-dominated solutions. The meaning of $\overline{d}$ is the average of all d_{i}.

The generation distance represents the distance between the currently searched non-dominated solution vector and the Pareto optimal solution set. The smaller the value of the generation distance, the better the performance of the algorithm.

$$GD = \frac{\sqrt{\sum_{i=1}^{N} q_i^2}}{N} \tag{19}$$

In Equation (19), q_i is the non-dominated and the Euclidean distance between solutions.

The diversity index is used to test the distribution range of the solution. If the diversity is strong, the algorithm can continuously search for unknown areas.

$$\Delta = \frac{d_f + d_l + \sum_{i=1}^{N-1} \left| d_i - \bar{d} \right|}{d_f + d_l + (N-1)} \tag{20}$$

$$\bar{d} = \frac{\sum_{i=1}^{N-1} d_i}{N-1} \tag{21}$$

In Equations (20) and (21), d_f and df_l is the Euclidean distance between the extreme value in the non-dominated solution and the boundary solution.

The pseudo-code of the algorithm proposed is shown in Figure 3.

```
// Function: particle swarm optimization algorithm pseudo code.
// Note: this example aims at the minimum value of the problem
// Parameter: n is the population size
procedure PSO
  for each particle i
  Initialize velocity Vi and position Xi for particle i
  Evaluate particle i and set pBesti=Xi
  end for
  gBest=min(pBesti)
  while not stop
    for i=1 to N
     Update the velocity and position of particle i
     Evaluate particle i
    if fit (Xi) <fit (pBesti)
      pBesti=Xi;
    if fit(pBesti)<fit(gBest)
     gBest=pBesti;
 end for
end while
print gBest
end
```

Figure 3. Pseudo-code proposed.

The manufacturing enterprises listed in Shanghai and Shenzhen A-share markets are selected as the research samples. Stockstar (http://www.stockstar.com/) (accessed on 7 April 2021) manufacturing enterprises listed companies are taken as analysis objects. The data of 325 manufacturing enterprises (source: China Business Information Network) are selected as the sample for analysis in this research. To ensure the accuracy of the data, all the data in the sample have been proofread three times to avoid the operation error fundamentally. The data used in this research are shown in Table 2.

Table 2. Datasets used in this research (part).

Number	The Goal of Cost Reduction Jointly Achieved by the Enterprise	Reduce the Cost of Raw Materials	Reduce the Cost of Production and Operation within the Manufacturing Enterprise	Improve the Efficiency of Internal Operations of Manufacturing Companies	Improve the Environmental Management Performance of Manufacturing Enterprises	R&D Personnel Should Be Familiar with Relevant Knowledge	Suppliers Supply Environmentally Friendly Materials to Manufacturing Companies	Reach Long-Term Cooperative Relationship with Waste Enterprises	Provide Technical Support for Environmental Protection Technology
1	0.87	0.67	0.21	0.33	0.45	0.89	0.87	0.21	0.88
2	0.66	0.88	0.29	0.44	0.98	0.88	0.86	0.77	0.89
3	0.91	0.86	0.43	0.67	0.89	0.77	0.89	0.79	0.67

5. Results and Discussion

5.1. Probabilistic Neural Network Classification Test Results

The environmental cost control data of 400 manufacturing enterprises are selected as the experimental dataset. According to its environmental cost control level, the company is classified into five grades, which are represented by 5, 4, 3, 2, and 1, respectively. The probabilistic neural network training set and test set are divided at a ratio of 8:2, and the results are shown in Figure 4.

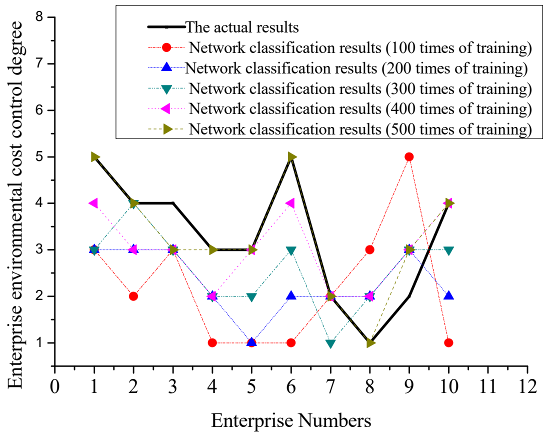

Figure 4. Probabilistic neural network classification results.

Figure 4 shows the test results of the environmental protection control level of the enterprise after training the same probabilistic neural network with the same parameters 100 to 500 times.

Figure 4 shows that when the number of network training times is small, the probabilistic neural network has a large deviation in the classification results of the environmental protection control level of the enterprise. After the network is trained 300 times, the deviation between the network classification result and the real result is reduced. The deviation between the network classification result and the real result of the network training 500 times is the smallest.

The performance of the probabilistic neural network is further analyzed, and the results of the regression analysis experiment on the probabilistic neural network are shown in Figure 5.

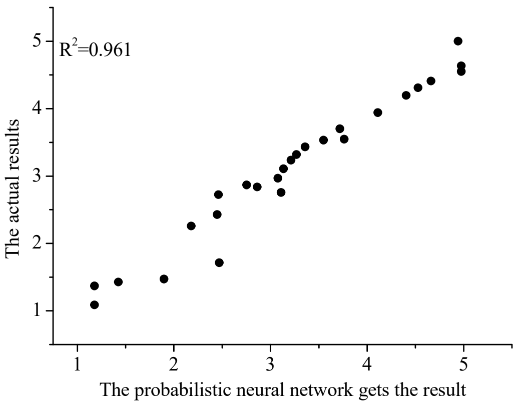

Figure 5. Classification regression analysis.

Figure 5 shows that there is a strong correlation between the original classification results and the probabilistic neural network classification structure. Moreover, the correlation is calculated to be 96.1%, suggesting that it is feasible to use the probabilistic neural network constructed to classify the environmental cost control level of enterprises. However, it can be inferred from the characteristics of the probabilistic neural network that if the sample size of the experimental data is increased. The correlation will be further improved, and the constructed model is also applicable in actual situations.

5.2. Regression Analysis

Table 3 shows the analysis results of the synergies of environmental costs.

Table 3. Analysis of unary linear regression results.

Independent Variable	Coefficient	Y
	X_1	
Constant	3.322	
F test		33.67
DW test		1.411
T	5.9	
	X_2	
Constant	3.422	
F test		36.67
DW test		1.461
T	6.29	
	X_3	
Constant	3.432	
F test		32.67
DW test		1.491
T	6.21	

Table 3 shows that the synergy X_1 between manufacturing enterprises and suppliers is two-tailed significant at the level of 0.001, suggesting that the higher the degree of synergy between manufacturing enterprises and suppliers, the more obvious the synergy effect of environmental cost control. Therefore, it is recommended that manufacturing enterprises need to strengthen collaborative cost control with suppliers to reach strategic cooperation. From the results of the T-test, the T-test value of the fit degree of collaboration with suppliers is 5.9, the value of T-test of the fit degree of collaboration with waste enterprises is 6.21, and that with customers is 6.29. The value of the T-test of the fit degree in collaboration with customers is the highest, indicating that the cost coordination control between manufacturing enterprises and customers occupies the main position in all collaborative control. The higher the cost synergy between the enterprise and the customer, the greater the environmental cost synergy. Therefore, manufacturing enterprises should strengthen communication and cooperation with customers. Moreover, the synergy between manufacturing enterprises and waste-use enterprises has obvious significance at the level of 0.01, which proves that the higher the degree of cost coordination control between manufacturing enterprises and waste-use enterprises, the greater the synergy effect of environmental cost control. Therefore, strengthening cooperation with waste-utilizing enterprises is conducive to the development of environmental cost control and coordination benefits.

5.3. Performance Test of Multi-Objective Bare-Bone PSO

From the previous database, six companies with similar situations are selected to study the performance of the decision-making model. The initial particle number of the model is 80–180, the particle dimension is 55, and the maximum external storage capacity is 25. Every five iterations is an interval, and the maximum number of iterations is 120.

Figure 6 illustrates the changes in the maximum coverage and the number of particles and the number of iterations.

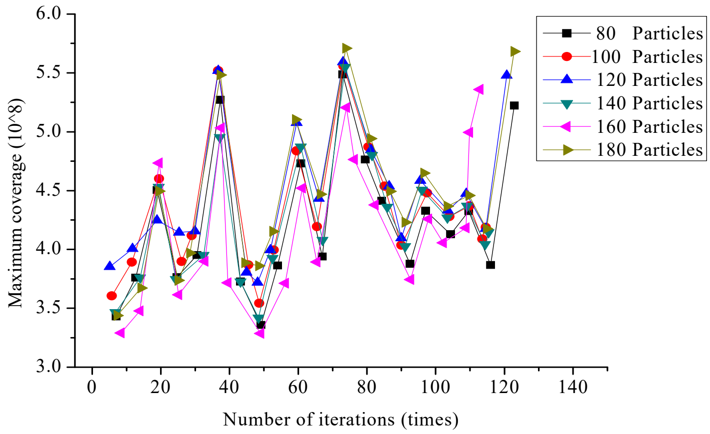

Figure 6. Maximum coverage under different particle numbers and different iteration times.

Figure 6 shows that the maximum coverage reaches its first peak when the number of optimized particle swarm optimization iterations is 30, and then gradually decreases and fluctuates between 5.3×10^8 and 4.8×10^8. When the number of iterations is 65, the maximum coverage value reaches the second peak. When the number of iterations is 125, the maximum coverage is close to the maximum. The maximum coverage has no obvious relationship with the number of particles. However, from the experimental results, when the number of iterations is 65 and the number of particles is 180, the maximum coverage has the largest value.

Figure 7 shows the changes in the spacing and the number of particles and the number of iterations.

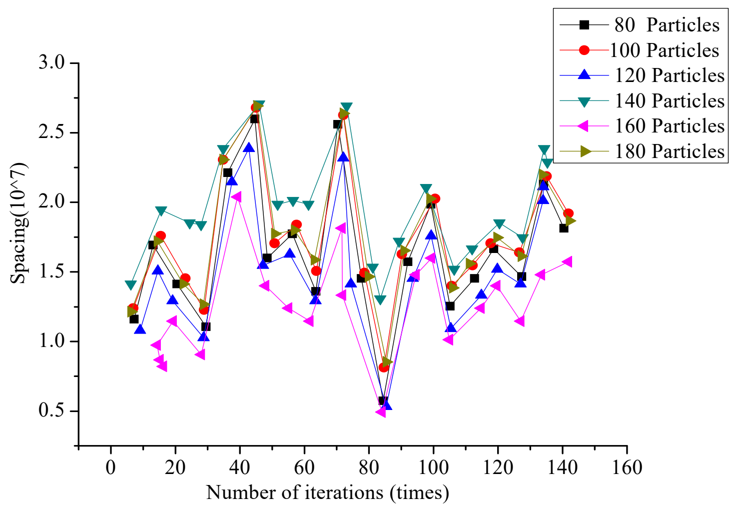

Figure 7. The spacing under different particle numbers and different iteration times.

Figure 7 shows that when the algorithm is iterated 65 times, the distant peaks. The more the number of initial particles, the more the distance. When the algorithm is iterated 85 times, the value of the spacing parameter is the smallest, the fewer number of particles, the smaller the spacing, which indicates that the distribution of the solution is the most uniform after 65 iterations.

Figure 8 shows the variation diagram of the generation distance and the number of particles and the number of iterations.

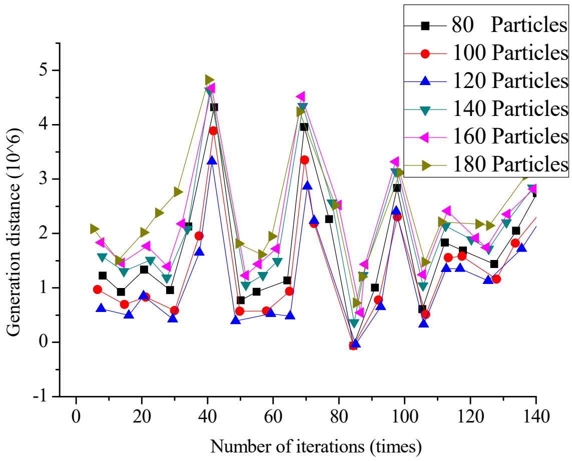

Figure 8. Generation distance under a different number of particles and a different number of iterations.

Figure 8 shows that the value of the generated distance is minimized after 60 iterations of the algorithm. The generation distance reaches a local maximum when the algorithm is iterated 35, 55, and 75 times. It can be stated that the distance to the Pareto optimal solution is the closest at 60 iterations, and the optimal solution is most likely to be obtained at 60 iterations.

Figure 9 shows the variation diagram of the diversity and the number of particles and the number of iterations.

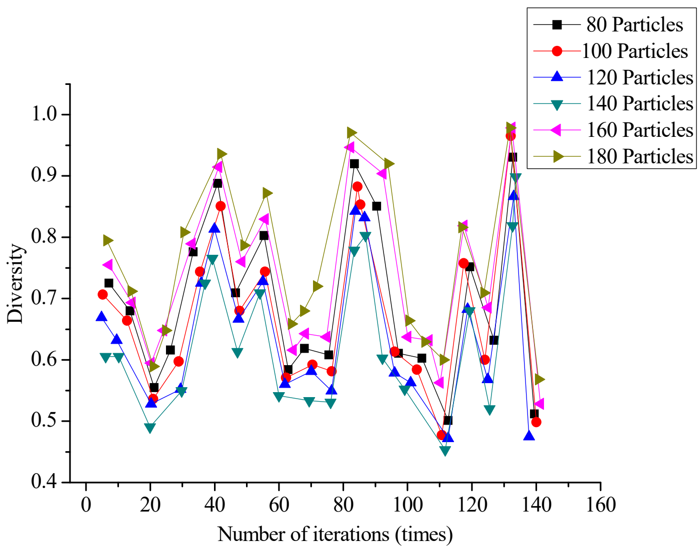

Figure 9. The diversity under different particle numbers and different iteration times.

Figure 9 shows that the fluctuation range of the various indicators is [0.55, 0.85]. During the 140 iterations of the algorithm, 3 relatively high positions are achieved, namely 30, 65, and 95 iterations, indicating that the algorithm has a strong global search capability. When the diversity index reaches a relatively high point, the algorithm has a greater possibility of obtaining the optimal solution. According to the change trends in Figure 5 to Figure 8, although the number of initial particles and the number of iterations of the algorithm is different, the performance indicators of the algorithm fluctuates within the range of the average value. It is proven that the algorithm has good stability and excellent optimization ability. However, considering the optimality and stability of the algorithm, it is found that when the initial particle number is 140 and the number of iterations is 60, the algorithm has the best performance and stability, and the time required to find the optimal solution set is the shortest.

5.4. Comparison of Algorithms

The algorithm proposed and the algorithm proposed by Chen were tested in the machine learning database proposed by the University of California, Irvine. In the experiment, the particle swarm number (N) of each PSO algorithm was selected as 100, and each algorithm carried out at least 100 iterations. Each algorithm was run 50 times. The experimental results show that the accuracy of the algorithm proposed is 2.6% higher than that of the original PARTICLE swarm optimization algorithm and 2.0% higher than that of the original ID3 algorithm. It is 1.5% higher than the algorithm proposed by Chen et al. The accuracy of the algorithm proposed here is better than the original PSO algorithm, the original ID3 algorithm, and the algorithm proposed by Chen et al. The above experimental results verify the rationality of the algorithm proposed and its guiding role in environmental cost control. The algorithm proposed improves the level of environmental cost control, improves the green degree, and environmental protection intensity of enterprise production and operation, and maintains the long-term and healthy development of enterprises [38].

In order to better test the performance of the algorithm proposed, this research tests and compares the proposed algorithm with the classical PSO algorithm, QPSO (Quantum particle swarm optimization algorithm) algorithm, and the algorithm proposed by Chen et al. in the machine learning database proposed by the University of California, Irvine. In the PSO algorithm, $c_1 = c_2 = 2$, the weight coefficient gradually decreases from 0.9 to 0.3, the number of particles is 40, and the algorithm iteration number is 4000 times. The expansion and contraction coefficient of the QPSO algorithm gradually decreases from 1 to 0.6, the number of particles and iterations of the algorithm proposed is the same as that of the PSO algorithm. The parameter setting of the algorithm proposed by Chen et al. is 40 particles and 4000 iterations. The parameter setting of the algorithm proposed is the same as that proposed by Chen et al. The performance comparison results of the four algorithms are shown in Figure 10.

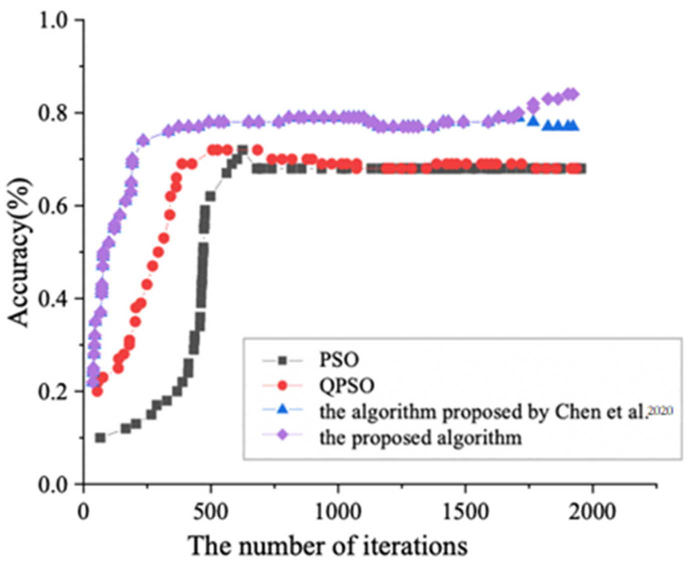

Figure 10. Algorithm comparison [38].

Experimental results show that the accuracy of the algorithm proposed is 2.6% higher than that of the PSO algorithm, 2.0% higher than that of the QPSO algorithm, and 1.5% higher than the algorithm proposed by Chen et al. Compared with other algorithms, the algorithm proposed not only improves the quality and precision but also speeds up the convergence of the algorithm. Experimental results verify the rationality of the algorithm proposed and its guiding role in environmental cost control. The algorithm proposed improves the level of environmental cost control, optimizes the greenness and environmental protection intensity of enterprise production and operation, and maintains the long-term healthy development of enterprises.

5.5. A Case Analysis of Environmental Cost Control of Company A

To further verify the performance of the algorithm proposed, the environmental cost control of paper *Company A* is taken as an example to illustrate the usage of the algorithm constructed.

Company A is a company established in the 1990s and belongs to the paper manufacturing industry. The main reasons why *Company A* needs to implement environmental cost control are classified into internal reasons and external reasons. In terms of internal reasons, the company has mastered the production status of the products at the current stage, and the company's managers have improved the company's management level. In terms of external reasons, it is caused by the promotion of the national government and the pressure of competition in domestic and foreign markets. Enterprise environmental cost control based on internal reasons has four stages. The first stage is the product design research stage, in which *Company A* first established a new type of professional R&D team. The environmental protection and greenness of its products provide some technical guarantees. To minimize the environmental cost of the product throughout its life cycle, *Company A* uses green design thinking in the research and design phase of the product and implements a novel type of green ecological design method. The flow chart of the green ecological design method is shown in Figure 11.

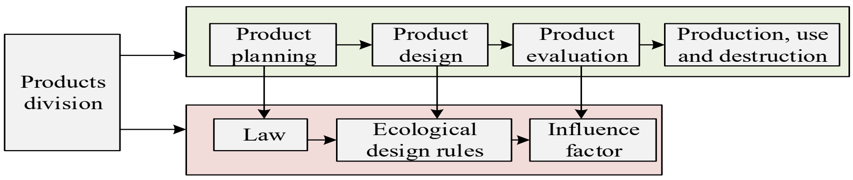

Figure 11. *Company A*'s ecological design flow charts.

The second stage is the activity stage of the procurement stage. After the product design plan is determined, *Company A* selects appropriate suppliers according to the "green ecological concept" and purchases the raw materials that need to be purchased. When purchasing, *Company A* incorporates environmental cost factors into the purchasing plan and sets strict environmental standards when purchasing raw materials. It purchases according to the standard and does not purchase raw materials that do not meet the standard. Moreover, it checks the purchase order from time to time and finds out the problems in it in time. The third stage is the production and operation stage. The main measures taken by *Company A* for cleaner production have two manifestations. The first manifestation is that the company proactively adopts technology that minimizes pollution. To improve the greenness and environmental protection of its products, *Company A* organizes production technicians to develop new processes. For example, *Company A*'s research and adoption project—easy to decompose molecular membrane material technology, which has been widely used in environmental protection, is a kind of material that has been developed not long ago. The second type is that *Company A* actively promotes resource-saving process technology to reduce the environmental pollution generated in the production process. Most companies use resource conservation and improve resource utilization in the production process to reduce resource consumption. *Company A* improves the production efficiency of the enterprise by introducing new production processes and reduces the waste of resources. The fourth stage is the sales and after-sales stage. *Company A* advocates green marketing. Its main manifestation is the implementation of green packaging design for the company's products and strengthening the recycling rate of packaging. In the waste stage of products, recycling disposal is implemented to fundamentally reduce the pollution rate of the environment. The main measures are the following 3 aspects. First, the company actively uses environmentally friendly packaging materials to replace the original traditional packaging materials. It uses environmentally friendly packaging for the inner packaging, which can be used multiple times, which improves the utilization rate of the packaging and reduces the rate of waste of resources. Second, *Company A* makes economic adjustments to the price compensation methods for product recycling, mainly to give downstream companies corresponding discounts when recycling products. Third, to strengthen the protection of the ecological environment and the green construction of the city, the company conducts compliant disposal of hazardous waste.

5.6. Threats to Vadility

5.6.1. Threats to the Internal Validity

Internal validity refers to the extent to which the study design can attribute changes in the dependent variable to changes in the independent variable. The internal validity threat in this study comes mainly from the implementation of the multi-objective backbone PSO algorithm and the implementation of scripts for the analysis and evaluation of all experimental results. To effectively reduce these internal validity threats, for the multi-objective backbone PSO algorithm, we use Gaussian distribution sampling to replace the inertia weight parameters and learning factor parameters in the standard PSO [28], which solves the problem of inconvenient parameter settings in the original algorithm. After analysis, it is found that the multi-objective particle swarm optimization algorithm can converge to the Pareto front-end accurately and can solve the multi-objective optimization problem effectively. In addition, to ensure the accuracy of the data, all the data in the samples were proofread three times to fundamentally avoid operational errors.

5.6.2. Threats to the External Validity

External validity refers to the representativeness or generalizability of the study results. Specifically, it refers to the extent to which the study results can be generalized to similar scenarios. In this study, the environmental cost control data of 400 manufacturing companies were selected as the original experimental data set. The classification regression analysis proved that the probabilistic neural network constructed in this study is feasible for classifying the level of environmental cost control of enterprises. It can also be inferred from the characteristics of the probabilistic neural network that if the sample size of the experimental data is increased, the correlation will be further improved and the constructed model will apply to the real situation. In addition, the performance test of the algorithm was conducted in this study, and the experiments proved that the algorithm has good stability and optimization ability. Compared with other algorithms, this algorithm not only improves the quality and accuracy of the algorithm but also accelerates the convergence speed, which is a guide for enterprise environmental cost control. In the future, we will continue to study the environmental cost control mechanism of the algorithm for other types of enterprises.

6. Conclusions

China is a major manufacturing country in the world. Since the reform and opening up, China has attracted the inflow of many global manufacturing industries, which has led to the rapid development of China's manufacturing industry. The healthy development of manufacturing enterprises has a critical impact on the development of China's economy. However, the manufacturing industry uses energy and raw materials from the natural environment to carry out production activities and then discharges wastewater, exhaust gas, and waste into the natural environment, which is one of the most serious industries in terms of pollution. Therefore, how to control the environmental cost of manufacturing enterprises, improve the market competitiveness of manufacturing enterprises and achieve a balance between economic and environmental benefits is a serious challenge for Chinese manufacturing enterprises at present. It is found that the current manufacturing enterprises in China usually adopt a single environmental cost control method and have not yet formed an integrated environmental cost control mechanism. This greatly reduces the effectiveness of cost control. In addition, manufacturing enterprises take themselves as the unit to carry out independent environmental cost control. No coordination mechanism has been formed between enterprises, between enterprises and customers, or between enterprises and the government.

Based on this, this paper conducts an integrated study on the environmental cost control of manufacturing enterprises in China. A probabilistic neural network is introduced to classify manufacturing firms with different levels of environmental cost control, and an improved PSO algorithm is used to select the method of environmental cost control. Experiments show that probabilistic neural networks can achieve multi-level environmental cost control and effectively help industry managers to choose the appropriate environmental cost control method according to their situation, and provide more accurate decision models for environmental cost control in manufacturing enterprises using machine learning technology. This study analyzes the synergistic effect of environmental costs between manufacturing enterprises and suppliers, customers, and waste enterprises. The results of the analysis show that the synergy effect between manufacturing companies and suppliers is significant, which indicates that the higher the degree of synergy between them, the more significant the synergy effect of environmental cost control. The synergy effect between manufacturing companies and waste companies also showed significant results. From the results of the *T*-test, the highest *T*-test value was found for the degree of cooperation between manufacturing enterprises and customers, indicating that the coordinated cost control between manufacturing enterprises and customers dominates all synergistic effects.

Based on the results of the study, we propose the following recommendations. First, a synergistic cooperation mechanism should be established between manufacturing companies, customers, and waste companies. The synergistic cooperation among enterprises will form an environmental protection effect and take joint measures to deal with environmental problems, thus achieving a win-win situation. In addition, there is an inseparable cooperation relationship between enterprises themselves. The synergistic mechanism can enable enterprises to strictly control environmental costs at all stages of product production, supply, and recycling. This will greatly save the cost of traditional ex-post control and jointly achieve a win-win situation for both economic and environmental benefits.

Secondly, manufacturing enterprises should establish a cost control mechanism for the whole life cycle of products. From the acquisition of raw materials, production of products, distribution of products, and recycling of waste, the costs in each stage should be collected. Thus, the environmental cost of the product life cycle is formed and the environmental cost in each stage is controlled. From the acquisition of raw materials, as far as possible to choose environmentally friendly materials, choose materials that can be recycled again, not only for the benefit of the environment but also to improve the utilization rate of materials and reduce the cost of expenditure. The production process of products should be clean production. The adoption of clean production includes the use of clean energy, the implementation of clean production methods, and the production of clean products. The implementation of cleaner production not only reduces the production cost of enterprises and realizes the change of economic growth mode, but also greatly reduces environmental pollution and alleviates the burden of enterprises in managing the environment so that enterprises can obtain double benefits [39]. The management of waste generated during the production of products follows the idea of a circular economy and recycling them again. The environmental cost of an enterprise is incurred throughout the entire production and operation activities. The stages of product development, production, sales, and recycling of waste may all have an impact on environmental quality. The environmental cost control of the whole life cycle can be adjusted from the previous control afterward to control before, during, and afterward at the same time.

Finally, this study proposes an environmental cost control model for manufacturing enterprises that responds to the goal of digital products and services proposed by the Chinese government. Machine learning technology provides a more accurate detection model for environmental cost control in manufacturing enterprises, which is also useful for the development of other heavy and light industrial enterprises.

But there are certain deficiencies. Based on the analysis of the performance of the model, this research only takes the initial particle swarm number and the number of iterations as the research object but does not consider the influence of other parameters on the performance of the model, such as particle dimension and external storage capacity. Meanwhile, it is difficult to obtain data on the external environmental cost of enterprises, because the accounting process of the external environmental loss cost needs to be determined according to the market conditions when the business occurs. Therefore, in the follow-up research work, the research will focus on the measurement of external environmental costs, which needs long-term attention and exploration. In the empirical process of the model, since this research only obtains the environmental cost data of enterprises in three years for the empirical test, the sample size needs to be expanded for further study, and the fitting degree of the model needs to be further discussed.

Author Contributions: Conceptualization, X.L. and C.M.; methodology, C.M.; software, C.M.; validation, X.L., C.M. and Y.L.; data curation, C.M.; writing—original draft preparation, X.L. and C.M.; writing—review and editing, X.L., C.M. and Y.L.; project administration, Y.L. All authors have read and agreed to the published version of the manuscript.

Funding: This study is funded by the Key Project of Vocational Education Research Center of Chengdu University (Project Approval No. CDZJZX2022A02), China under the project entitled "Research on the Practical Characteristics and Path Optimization of the Integrated Development of Industry and Education Cities in the Twin Cities Economic Circle of Chengdu and Chongqing Region". Funder, Y.L.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Not applicable.

Conflicts of Interest: The authors declare no conflict of interest.

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