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IASB Framework: Construction of Data Asset Accounting System Based on PO-BP Model

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Abstract

This study aims to construct a data asset accounting system based on the International Accounting Standards Board (IASB) framework, addressing the challenges in identifying, measuring, and reporting data assets within traditional accounting systems. By integrating the Political Optimization (PO) algorithm with the Back Propagation (BP) neural network, we propose a novel PO-BP model to enhance the accuracy and efficiency of data asset valuation. The PO algorithm optimizes the weights and biases of the BP neural network, improving its global search and local development capabilities. Experimental validation using open-source datasets demonstrates that the PO-BP model outperforms traditional models (e.g., BP, GWO-BP, and SSA-BP) in terms of convergence speed, prediction accuracy, and stability, achieving an average relative error of 0.2292% and a coefficient of determination R^2 of 0.9957. This study innovatively combines the PO algorithm with BP neural network, offering a robust technical approach for data asset value assessment. The findings provide significant theoretical support for advancing data asset accounting and practical guidance for enterprise decision-making during digital transformation. Future research will explore the model's adaptability to diverse industry data and dynamic market environments.

Keywords: IASB Framework; BP Neural Network; Intelligent Optimisation; Data Asset Accounting System.

1. Introduction

In the era of the digital economy, data is regarded as an important factor of production, and its value is increasingly important in business decision-making and financial reporting [1]. The framework of the International Accounting Standards Board (IASB) provides a theoretical basis for accounting for data assets. As a new production factor, there is no doubt about the business value of data [2]. The current academic research on the concept of data and data assets, the characteristics of data and the definition of ownership, the scope and type of data capitalization, the measurement method of data assets and how to reflect them in the enterprise balance sheet, etc., has not yet formed a consensus both at home and abroad, and it still belongs to the period of preliminary research, and these issues are important for the accurate evaluation of the contribution of data as a key factor of production to the growth of enterprise value in the context of digital transformation is of vital importance [3]. The construction of the data asset accounting system helps extend the development of the relevant theoretical research on data assets, helps investors get more objective financial information, improves the enterprise's ability to manage data assets, and promotes the rationality and normality of data market transactions [4]. Therefore, the study of accurate and objective scientific data asset accounting system construction method is a very meaningful research link for the field of data asset accounting.

Despite the growing recognition of data as a critical asset in the digital economy, existing research on data asset accounting remains underdeveloped [5]. Current studies have not yet established a unified framework for the identification, measurement, and reporting of data assets within traditional accounting systems [6]. Gaps persist in understanding how to accurately evaluate the contribution of data assets to enterprise value growth, particularly during

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digital transformation [7]. Moreover, there is a lack of empirical research and case studies that apply advanced methodologies to data asset accounting. This study addresses these gaps by proposing a novel data asset accounting system based on the IASB framework. We integrate the Political Optimization (PO) algorithm with the Back Propagation (BP) neural network to construct a PO-BP model, which enhances the scientific rigor and practical applicability of data asset valuation [8]. Through experimental validation, this study demonstrates the model's superior performance in convergence speed, prediction accuracy, and stability, providing a robust technical approach for data asset accounting and supporting enterprise decision-making.

The current research on the construction method of data asset accounting systems mainly adopts the literature research method and case study method [9]. Data asset accounting system construction research content is mainly divided into data asset recognition, data asset measurement, data asset recording, data asset reporting, and other aspects of the content [5, 10]. After the study of data asset literature content, it can be found that the current data assets still belong to an emerging topic, mainly in the following aspects [11, 12]: 1) the accounting treatment of data assets in all aspects is still limited to the traditional accounting framework; 2) not all data can meet the conditions for the recognition of assets; 3) the lack of data asset accounting case studies. To solve the construction of a data asset accounting system, combined with data asset accounting data, this paper studies the construction of a data asset accounting system and case analysis based on an improved machine learning algorithm.

To address the deficiencies of the current data asset accounting system construction method, this paper integrates the intelligent optimization algorithm and neural network to suggest a data asset accounting system construction method that is based on the PO-BP model and operates within the IASB framework. The primary contributions of this paper are (1) the identification of the IASB framework concept, the formulation of the research idea, and the development of the data asset accounting system; (2) the integration of the political optimization algorithm and BP neural network to create a data asset accounting value assessment model based on the PO-BP algorithm; and (3) the validation of the proposed method through the analysis of data asset accounting data.

The first section serves as the introduction, detailing the background of data assets as a crucial production element, elucidating the theoretical and practical importance of their accounting, and specifying the research topics and objectives. The second part is the research design and system construction, which defines the core concept of data assets, proposes the accounting flow of data asset recognition, measurement, recording, and reporting based on the IASB framework, and constructs a systematic accounting system. The third part focuses on the value assessment model based on the political optimization algorithm (PO) and BP neural network (BP) and details the design idea, optimization mechanism, and implementation process of the PO-BP model. The fourth part is an arithmetic example analysis, which compares the performance of the PO-BP model with other comparative algorithms through experimental validation of open-source datasets, highlighting its advantages in convergence speed and prediction accuracy. Finally, the fifth part is the conclusion and outlook, which summarises the research results, points out the limitations of the existing research and proposes the future research direction to provide the path support for the continuous development of data asset accounting.

2. Research Design and System Building

2.1. Definition of the Concept and Analysis of the Research Base

2.1.1. IASB Framework Concept

The definition of an asset, as described in the IASB's Conceptual Framework for Financial Reporting, is "a resource that is expected to provide economic benefits to an enterprise, is owned or controlled by the enterprise, and arises from an enterprise's past transactions or events." This definition offers criteria for the identification and evaluation of data assets [13].

2.1.2. Definition and Classification of Data Assets

Following the IASB paradigm, a data asset is defined as a data resource owned or managed by an entity, anticipated to yield economic advantages [14, 15]. Data assets can be classified into the following categories (Figure 1): 1) raw data: original unprocessed data; 2) processed data: data that have been processed and analyzed; 3) derived data: new data generated based on raw and processed data; and 4) data tools: software tools used for data processing and analysis. Figure 1 provides a foundational framework for identifying and measuring different types of data assets, which is essential for their subsequent accounting treatment.

Figure 1. Classification of data assets

2.1.3. Recognition and Measurement of Data Assets

The recognition of data assets should satisfy the following conditions [16, 17]: 1) the enterprise owns or controls the data resources; 2) the data resources can bring future economic benefits; and 3) the cost of the data resources can be measured reliably.

Data assets can be measured using the following methods [18]: 1) cost approach: based on the cost of acquiring or producing the data asset; 2) fair value approach: based on the price that a market participant would receive to sell the asset in an orderly transaction; and 3) income approach: based on the present value of the expected future economic benefits of the data asset.

The concept of recognition and measurement of data assets is shown in Figure 2. This conceptual framework ensures that data assets are accurately identified and measured, aligning with international accounting standards and providing a basis for their inclusion in financial statements.

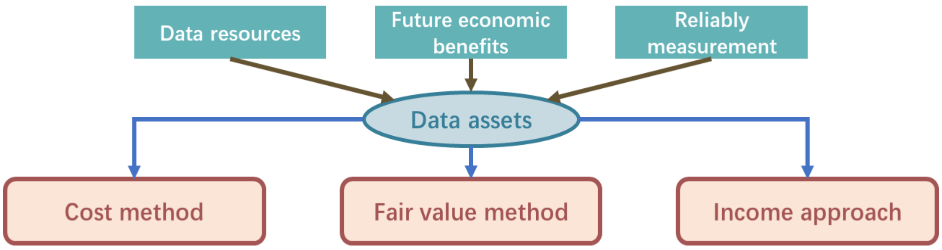


Figure 2. Data asset recognition and measurement concepts

2.1.4. Accounting for Data Assets

The accounting treatment of data assets is based on three main aspects: initial measurement, subsequent measurement, amortization, and impairment [19], as shown in Figure 3 which involve initial measurement, subsequent measurement, amortization, and impairment. 1) Initial measurement; 2) Subsequent measurement; 3) Amortisation and impairment.

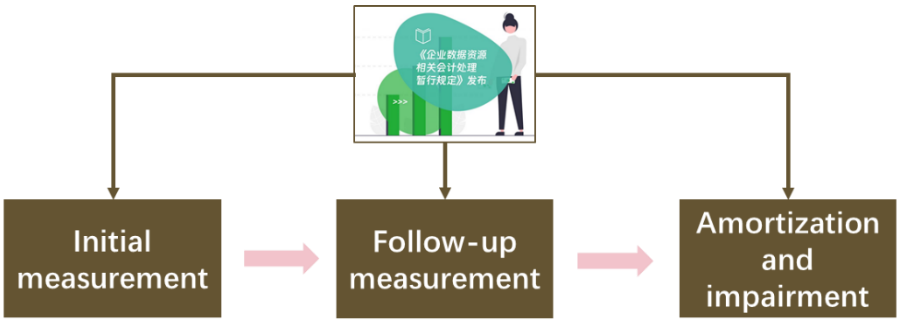


Figure 3. Accounting treatment of data assets

2.1.5. Presentation of Data Assets

Data assets should be presented separately in the balance sheet and the following information should be disclosed in the notes [20]: 1) Classification and description of data assets; 2) Measurement methods and assumptions; 3) Amortisation policy and provision for impairment; and 4) Economic benefits and risks of data assets (Figure 4).

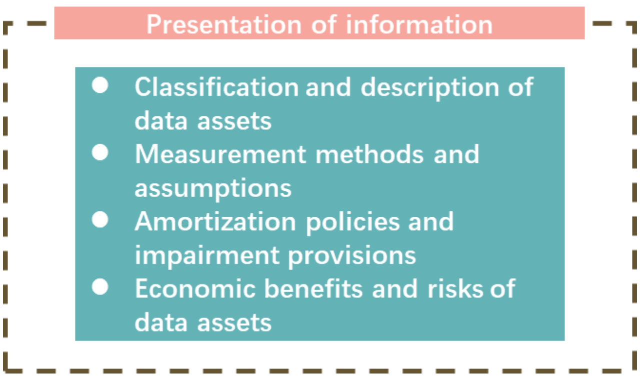


Figure 4. Presentation information for data assets

2.1.6. Valuation of Data Assets

Valuation of data assets is an important part of accounting [21]. Valuation methods can include market, income, and cost methods [22]. Enterprises should choose appropriate valuation methods according to the characteristics of data assets and the market environment (Figure 5).

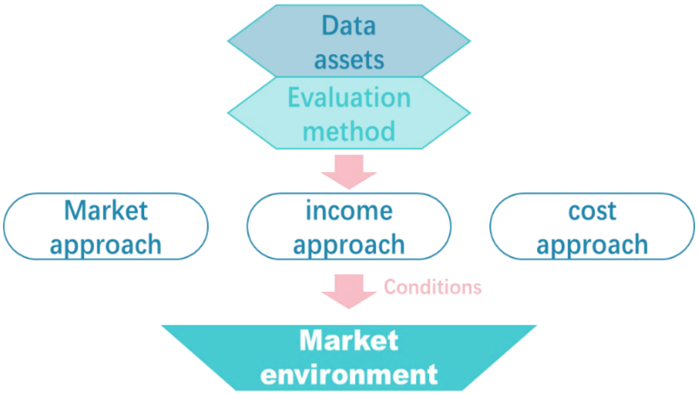


Figure 5. Methods for valuing data assets

2.2. Research Idea Design

The research idea of this paper is shown in Figure 6. The research mainly consists of the recognition, measurement, recording, and reporting of data assets. It is based on the reference to the existing literature, combined with the IASB conceptual framework of asset recognition, measurement, recording, and reporting of the relevant content and supplementing the recording link to form a research idea on accounting for data assets [23].

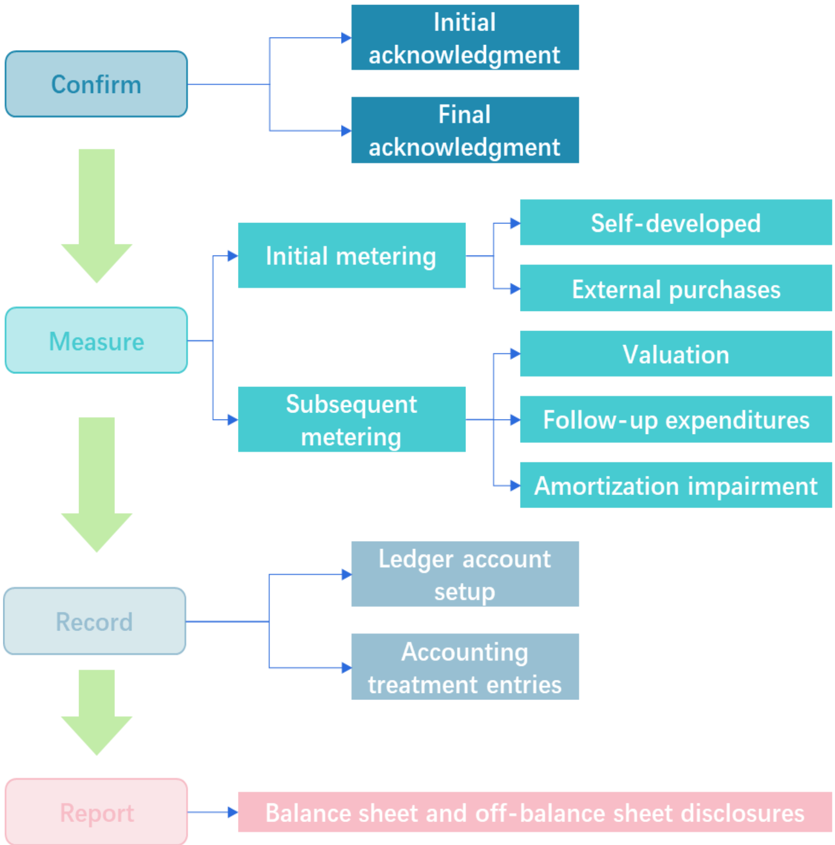


Figure 6. Research idea map

2.3. Construction of Data Asset Accounting System

Using the IASB conceptual framework and previous research, this paper builds an enterprise data asset accounting system that includes recognizing, derecognizing, measuring, recording, presenting, and disclosing data assets [24]. Figure 7 shows this specific accounting system. Figure 7 illustrates that the recognition of data assets encompasses initial recognition and derecognition; the measurement of data assets consists of initial measurement and subsequent measurement; the documentation of data assets primarily includes records of recognition and initial measurement, records of subsequent measurement, and reports on data assets; finally, the presentation and disclosure of data assets are primarily indicated by the presentation location and the number of items presented.

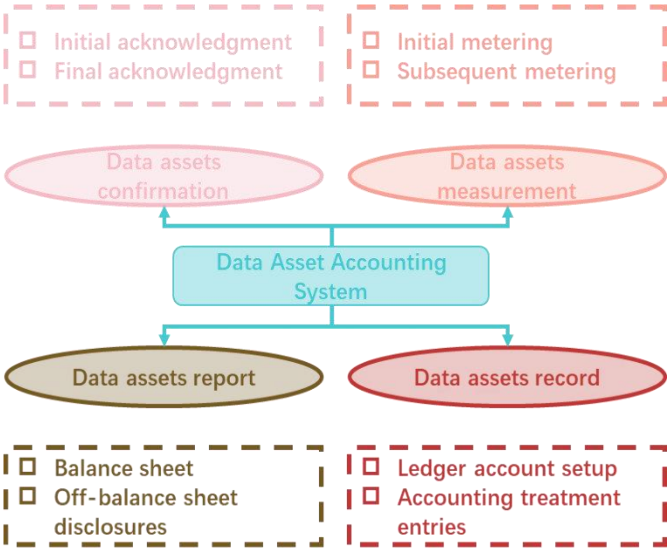


Figure 7. System construction diagram

3. Construction Method of Data Asset Accounting System Based on PO-BP Model

3.1. Political Optimization Algorithms

The Political Optimizer (PO) was introduced in 2020 by Askari et al. [13]. The algorithm is derived from the multi-stage political process. Politics possesses varied interpretations throughout diverse circumstances. The Political Optimization (PO) algorithm is a novel meta-heuristic optimization algorithm inspired by the multi-stage political process, particularly the mechanisms of election campaigns, party switching, and parliamentary affairs within a multi-party democratic system. It simulates the behavior of politicians and parties to balance global exploration and local exploitation capabilities, making it suitable for solving complex optimization problems. In PO algorithms, a country's political system serves as a reference to emulate politicians' behavior for the sake of optimization.

Multi-party democracy is a political system that encompasses a variety of social dimensions, including the formation of parties and the allocation of constituencies, election campaigns, party switching, inter-party elections, cabinet formation, and parliamentary affairs (see Figure 8).

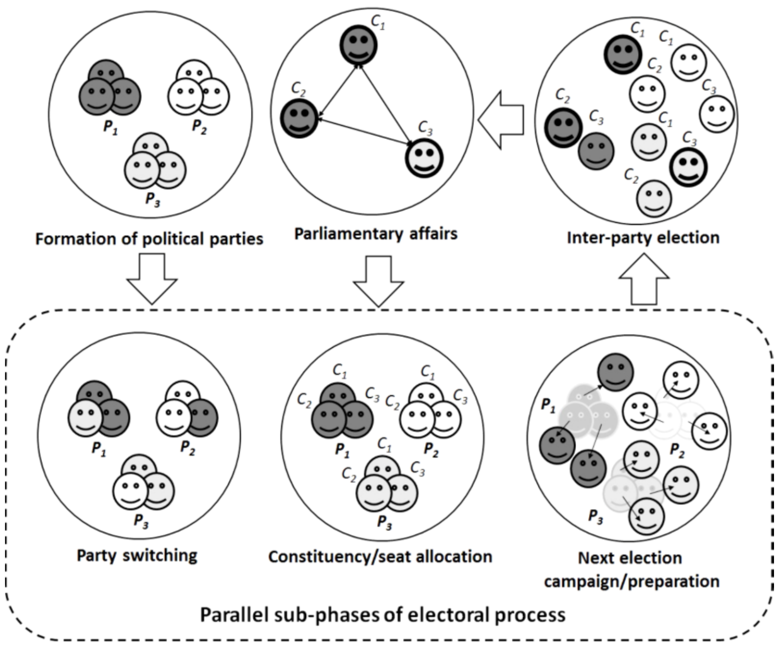


Figure 8. Illustrative map of the multi-stage political process

Where P_i represents the members of the ith party, C_i represents the members who participated in the election in the ith constituency, the color of the face distinguishes the members of one party from the others, and the bolded face denotes the winner of the constituency marked by that face.

The PO's sources of inspiration include the following four domains: 1) The electoral process, wherein candidates solicit votes; 2) intra-party collaboration and competition; 3) the analytical conduct of electoral candidates aimed at enhancing their performance based on prior electoral experiences; and 4) the interaction and collaboration among victorious candidates to govern post-election.

3.1.1. Party Building and Constituency Allocation

Divide the whole group into n parties, each P_i consisting of n candidates/parliamentarians, each of which is a candidate solution (d-dimensional).

$$P = \{P_1, P_2, P_3, \cdots, P_n\} \tag{1}$$

$$P_i = \{p_i^1, p_i^2, p_i^3, \cdots, p_i^n\} \tag{2}$$

$$p_i^j = \left[p_{i,1}^j, p_{i,2}^j, p_{i,3}^j, \cdots, p_{i,d}^j\right]^T \tag{3}$$

In addition to the role of an MP, a candidate solution also plays the role of an election candidate. Suppose there are n constituencies and the jth MP of each party contests the election from the jth constituency. C_i.

$$C = \{C_1, C_2, C_3, \cdots, C_n\} \tag{4}$$

$$C_j = \{p_1^j, p_2^j, p_3^j, \cdots, p_n^j\} \tag{5}$$

After the parliamentary elections (inter-party elections), the most suitable MPs are elected as party representatives:

$$q = \underset{1 \le j \le n}{\arg\min} f\left(p_i^j\right), \forall i \in \{1, \cdots, n\} \tag{6}$$

$$p_i^* = q_i^q \tag{7}$$

The set of all political party leaders is represented by the P^* shown:

$$P^* = \{p_1^*, p_2^*, p_3^*, \cdots, p_n^*\} \tag{8}$$

After the election, the winners of all constituencies become MPs. C^* denotes the set of all MPs and C_i^* denotes the winner of the j th constituency:

$$C^* = \{c_1^*, c_2^*, c_3^*, \cdots, c_n^*\} \tag{9}$$

3.1.2. Campaigning (Exploration and Development)

This phase aids candidates in improving their electoral performance. Three aspects of this phase's delineation: 1) proposing a novel position updating strategy, the Recent Past Position Updating Strategy (RPPUS), by leveraging prior elections; 2) charting the electoral influence of party leaders by revising the positions of MPs about party leaders, and 3) conducting a comparative analysis of constituency victors by adjusting the positions of candidates about constituency winners.

$$p_{i,k}^j(t+1) = \begin{cases} m^* + r\left(m^* - p_{i,k}^j(t)\right) & p_{i,k}^j(t-1) \le p_{i,k}^j(t) \le m^* \text{ or } p_{i,k}^j(t-1) \ge p_{i,k}^j(t) \ge m^* \\ m^* + (2r-1)\left|m^* - p_{i,k}^j(t)\right| & p_{i,k}^j(t-1) \le m^* \le p_{i,k}^j(t) \text{ or } p_{i,k}^j(t-1) \ge m^* \ge p_{i,k}^j(t) \\ m^* + (2r-1)\left|m^* - p_{i,k}^j(t-1)\right| & m^* \le p_{i,k}^j(t-1) \le p_{i,k}^j(t) \text{ or } m^* \ge p_{i,k}^j(t-1) \ge p_{i,k}^j(t) \end{cases} \tag{10}$$

$$p_{i,k}^j(t+1) = \begin{cases} m^* + (2r-1)\left|m^* - p_{i,k}^j(t)\right| & p_{i,k}^j(t-1) \le p_{i,k}^j(t) \le m^* \text{ or } p_{i,k}^j(t-1) \ge p_{i,k}^j(t) \ge m^* \\ p_{i,k}^j(t-1) + r\left(p_{i,k}^j(t) - p_{i,k}^j(t-1)\right) & p_{i,k}^j(t-1) \le m^* \le p_{i,k}^j(t) \text{ or } p_{i,k}^j(t-1) \ge m^* \ge p_{i,k}^j(t) \\ m^* + (2r-1)\left|m^* - p_{i,k}^j(t-1)\right| & m^* \le p_{i,k}^j(t-1) \le p_{i,k}^j(t) \text{ or } m^* \ge p_{i,k}^j(t-1) \ge p_{i,k}^j(t) \end{cases} \tag{11}$$

3.1.3. Switching Parties (Balancing Exploration and Exploitation)

This phase in politics coincides with the election campaign; however, in the PO algorithm, it occurs after the election campaign. An adaptive parameter λ, referred to as the party switching rate, is defined, which starts at $\lambda_{\max}$ and decreases linearly to 0 with the iterative process.

$$q = \underset{1 \le j \le n}{\arg\max} f\left(p_r^j\right) \tag{12}$$

3.1.4. Elections (Adaptation Assessment)

The election serves as an evaluation of the qualifications of all candidates contesting in a constituency, culminating in the declaration of a winner:

$$q = \underset{1 \le i \le n}{\arg\min} f\left(p_i^j\right) \tag{13}$$

$$c_j^* = p_q^j \tag{14}$$

3.1.5. Parliamentary Affairs (Development and Convergence)

The government is established following the inter-party elections. This stage is represented by Algorithm 4, where each MP is positionally updated based on a randomly selected MP and replaced if better.

The PO algorithm pseudo-code consists of four parts; Algorithm 1 is the PO subject, Algorithm 2 is the campaign, Algorithm 3 is switching parties, and Algorithm 4 is parliamentary business (see Tables 1 to 4).

Table 1. Pseudo-code of PO algorithm

Algorithm 1: PO Algorithm Main Framework

```
Inputs: party conversion rate and maximum number of iterations
Output: final population P
Initialize the population P;
Calculate the fitness values of individual members, set up individual
leaders as well as the parliamentary election population C;
t = 1; λ = λmax;
While t<= Tmax do
Ptemp = P; f(Ptemp) = f(P);
For each p do
For each d do
Execute campaigns to update individuals;
End for
End for
Implement switching partisan strategies;
Implementation of the election phase;
P(t-1) = Ptemp; f(P(t-1)) = f(Ptemp);
λ=λ-λmax\λmin;
t= t+1;
End while
```

Table 2. PO algorithm campaign strategy pseudo-code

Algorithm 2: PO algorithm campaign phase

```
Input: population P with optimal individuals
Output: Updated population individuals p
If f(pi(t))<=f(pi(t-1)) do
For k=1:d do
Updating Individuals Using a Parliamentary Winner Strategy;
End
Else
For k=1:d do
Using leader strategies to renew individuals;
End
End if
```

Table 3. PO algorithm switching party policy pseudo-code

Algorithm 3: PO algorithm switching party phase

```
Inputs: population P and party switching rate λ
Output: new population P;
For each p do
For each d do
sp= Random numbers;
If sp<λ then
r is a random integer between 1 and n;
Calculate to determine q;
swap(pr, pi);
End
End for
End for
```

Table 4. PO algorithm parliamentary transaction policy pseudo-code

Algorithm 4: PO Algorithm Parliamentary Affairs Phase

```
Input: members C* who optimally participate in the election with population P;
Output: new population P;
For j= 1:n do
r is a random number from 1 to n and r≠ j;
a is a random number between 0 and 1;
Update c*; calculate the adaptation value;
If f(cnew*)<=f(cj*) do
cj*=cnew*;
f(cj*) = f(new*);
i is an index of the election winner's party;
f(pj) = f(new*);
Check for transgressions;
End if
End for
```

The PO algorithm enhances global search capability through its multi-stage optimization mechanism, including campaigning, party switching, and parliamentary affairs. During campaigning, the algorithm explores new solutions by updating positions based on historical data, expanding search space coverage. Party switching introduces diversity by adaptively transferring members between parties, preventing premature convergence. Parliamentary affairs refine solutions through local exploitation, ensuring high-quality results. Compared to GWO, which may struggle with local optima trapping, and SSA, which can exhibit reduced optimization ability in later stages, PO's balanced exploration and exploitation make it more robust for complex optimization tasks.

3.2. BP Neural Network

The BP Neural Network [25] is a multi-layer feed-forward neural network characterized by the forward propagation of signals and the backpropagation of errors which is a type of multi-layer feed-forward artificial neural network that replicates the architecture of a human brain neural network, consisting of an input layer, one or more hidden layers, and an output layer, with neurons in each layer fully interconnected. It operates through a forward propagation process, where signals are transmitted from the input layer to the output layer, and a back propagation process, where the error between the predicted and actual outputs is calculated and used to adjust the weights and biases of the network, thereby enabling it to learn from data and make predictions. It replicates the architecture of a human brain neural network, comprising an input layer, one or more hidden layers, and an output layer, with neurons in each layer interconnected in a fully linked configuration, as seen in Figure 9.

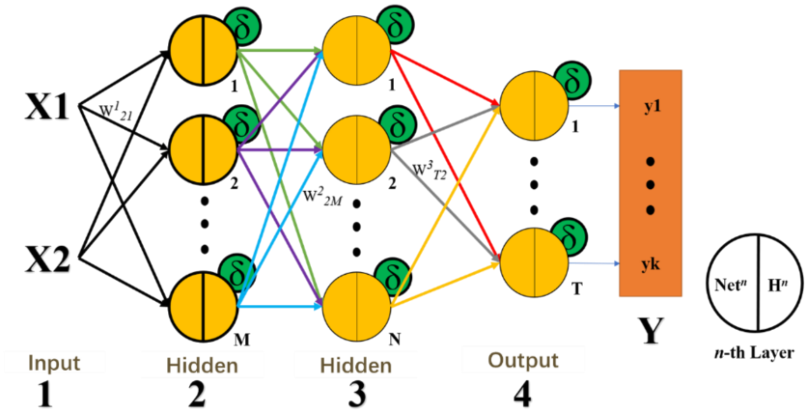


Figure 9. Structure of BP neural network

The operational principle of a BP neural network is primarily categorized into the forward propagation phase and the backpropagation phase.

3.2.1. Forward Propagation Process

The input layer receives the stimuli and transmits the signal to the hidden layer. The hidden layer transmits the stimuli to the output layer according to the weights and interconnection rules of the neurons. In a simple three-layer BP neural network, the relationship between the input vector X, the hidden layer input vector H_{invout}, and the output layer output vector Y, can be expressed as:

- Hidden layer input: $H_{\text{input}} = W_1 X + b_1$ (W_1 is the weight matrix from the input layer to the hidden layer, b_1 is the deviation vector of the hidden layer);
- Hidden layer output: $H_{\text{output}} = f(H_{\text{invuit}})$ (f is the activation function, such as the commonly used Sigmoid function $f(x) = 1/(1 + e^{-x})$);
- Output layer input: $Y_{\text{input}} = W_2 H_{\text{output}} + b_2$ (W_2 is the weight matrix from the hidden layer to the output layer, b_2 is the deviation vector of the output layer);
- Output layer output: $Y = f\left(Y_{\text{input}}\right)$.

3.2.2. Backpropagation Process

The output layer compares the results and if it does not match the desired output, the error is backpropagated. The input error is ascertained by the weights connecting the output layer to the hidden layer and those linking the hidden layer to the input layer; modifying these weights can alter the error. The idea of adjusting the weights is to keep the error shrinking and the amount of weight modification is proportional to the amount of negative gradient decrease in the error [26].

$$\delta_2 = (Y - T) f'\left(Y_{\text{input}}\right) \tag{15}$$

$$\delta_1 = \delta_2 W_2^T f'\left(H_{input}\right) \tag{16}$$

where, δ_2 is the error of the output layer, T is the desired output vector, f' is the derivative of the activation function, and δ_1 is the error of the hidden layer.

3.3. Construction of Data Asset Accounting Value Assessment Model Based on PO-BP Network

3.3.1. Analysis of PO-BP Structure

To enhance the BP network's capacity to address the data asset accounting value assessment issue, this study uses the PO algorithm to optimize the BP network structure's characteristics; the particular structure is depicted in Figure 10.

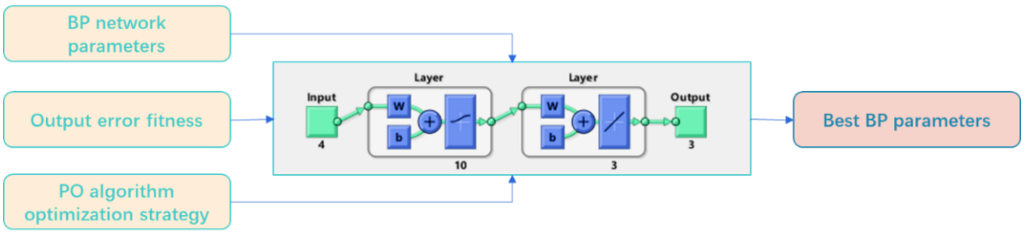


Figure 10. Structure of PO-BP neural network

Figure 10 illustrates that the PO algorithm employs real number encoding for the parameters of the BP network structure (including the weight matrices from the input layer to the hidden layer and from the hidden layer to the output layer, as well as the bias vectors for both the hidden and output layers) as decision variables while utilizing the output layer's error as the fitness value to formulate the PO-BP neural network optimization process.

3.3.2. Data Asset Accounting Value Assessment Model Construction

The input of the PO-BP neural network structure is the index value of the data asset accounting system, and the output is the value assessment value of the data assets, and the data asset accounting dataset is used to train and optimize the PO-BP, to obtain the value assessment model of the data asset accounting, and the specific construction process is shown in Figure 11.

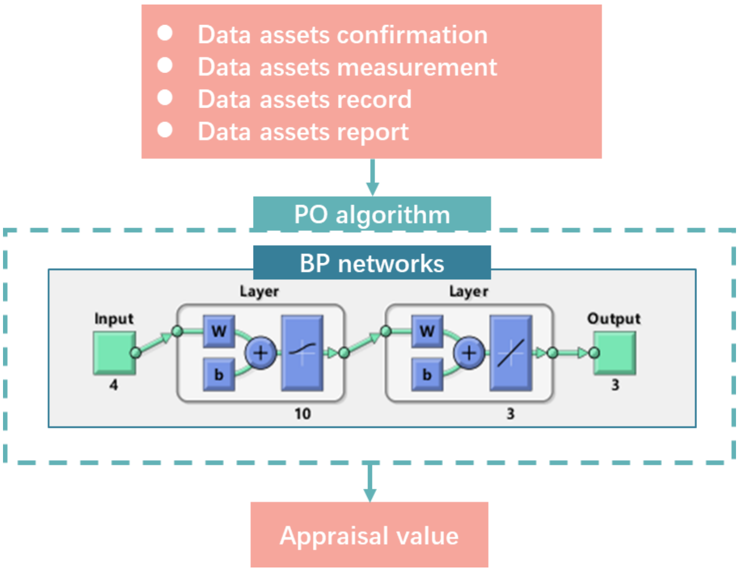


Figure 11. PO-BP neural network constructs data asset accounting value assessment model

4. Calculus Analysis

4.1. Parameter Setting

To verify the performance of the PO-BP data asset accounting value assessment model, this paper uses the open source dataset on the public data asset accounting network [27]. This study randomly partitions the dataset into a training set, testing set, and validation set at a ratio of 8:1:1. The configuration of this experimental environment is shown in Table 5.

Table 5. Experimental environment

No.	Experimental environment	Configure
1	Operating system	Windows 10
2	GPUs	NVIDIA GeForce MX150
3	CPU	Intel(R) Core(TM) i5-8250U
4	Python	3.6
5	Deep learning frameworks	Pytorch
6	Coding format	UTF-8

The comparison algorithms used in this paper are BP, GWO-BP, and SSA-BP, and the specific parameter settings are shown in Table 6.

Table 6. Parameter settings of the algorithm

No.	Methodologies	Condition setting
1	BP [28]	The learning rate is 0.001, the number of hidden layer nodes is 30, the optimizer is Adam, and the network epochs are set to 80
2	GWO-BP [29]	The number of hidden layer nodes is 30, the number of populations is 20, the number of optimization iterations is 80, a = 2, and the control parameters are linearly decreasing.
3	SSA-BP [30]	The number of hidden layer nodes is 30, the number of populations is 20, the number of optimization iterations is 80, ra=1, pc=0.7, pm=0.1
4	PO-BP	The number of hidden layer nodes is 30, the number of populations is 20, the number of optimization iterations is 80, and the λ parameter decreases linearly.

The PO-BP model demonstrates flexibility and adaptability in handling non-monetary or qualitative data assets. By converting qualitative features such as uniqueness or strategic importance into numerical indicators, the model effectively incorporates these aspects into its valuation framework. This capability allows the model to address diverse data asset characteristics across different contexts. The model's design ensures it can adapt to various data types, making it suitable for comprehensive data asset accounting. Its ability to integrate both quantitative and qualitative dimensions enhances its practical application in real-world scenarios. In the open-source dataset used for this study, the value of data assets is quantified through a combination of proxy variables and expert judgment.

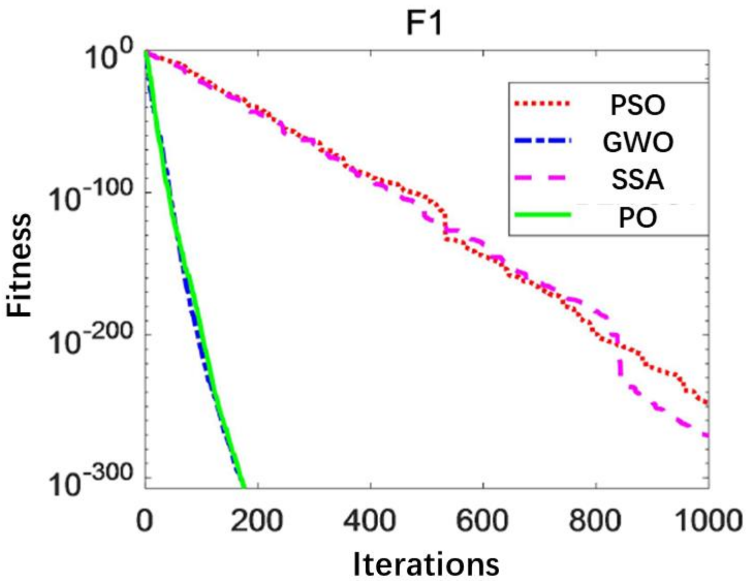
Proxy variables include metrics such as market transaction prices, cost of acquisition, and historical performance data, which provide objective numerical representations of data asset value. Expert judgment is incorporated through consultations with domain experts who assess the strategic importance and potential economic benefits of the data assets. These quantification methods ensure that the dataset accurately reflects the diverse value dimensions of data assets, providing a robust foundation for training and validating the PO-BP model. This approach balances objectivity and subjectivity, ensuring the dataset's reliability for the valuation task.

4.2. Performance Analysis of the PO Algorithm

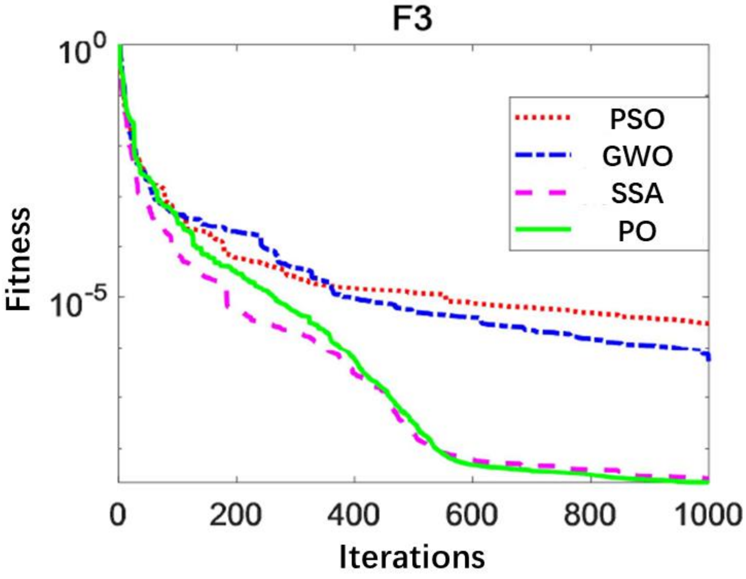
The F1, F3, F5, and F6 functions are optimized using the PSO [31], GWO, and SSA algorithms as comparison algorithms in this paper to verify and analyze the optimization performance of the PO algorithm. The specific results are illustrated in Figure 12. As can be seen from Figure 12, in the optimization of the F1 function, the PO algorithm and the GWO algorithm show faster convergence speeds, with PO slightly outperforming GWO, indicating that it has a stronger global search capability in the early iterations. On the F3 function, the PO algorithm not only achieves higher convergence accuracy but also shows a more stable optimization trend during the iteration process, which is superior to the fluctuating performance of the other compared algorithms.

In the analysis of the F5 function, the PO algorithm always maintains the leading edge during the whole iteration process, and its convergence curve continues to decline, indicating that the PO algorithm can effectively avoid falling into the local optimum. In addition, on the F6 function, the PO algorithm shows a rapid decline at the beginning of the iteration and surpasses the SSA algorithm in the middle and late stages, finally reaching the best optimization accuracy.

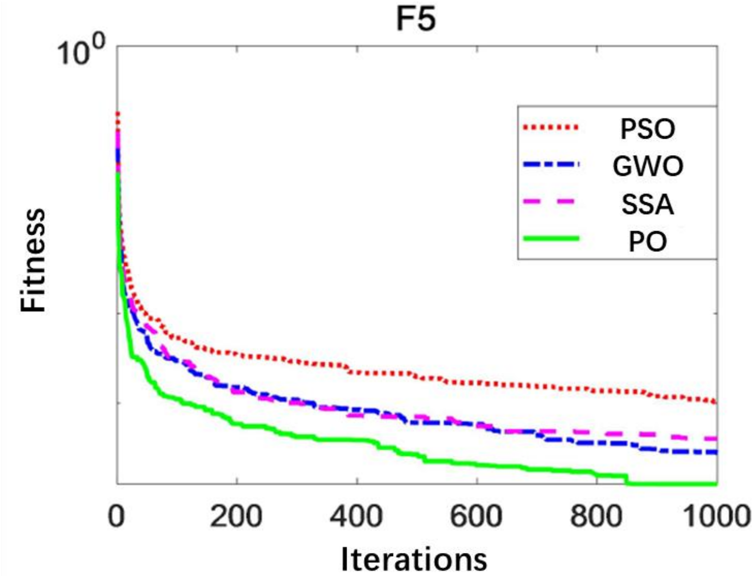
Taken together, the excellent performance of the PO algorithm on different objective functions is attributed to its unique multi-stage optimization mechanism, including operations such as campaigning, switching parties, and parliamentary affairs, which effectively balances the algorithm's global exploration and local exploitation capabilities. Meanwhile, the dynamic parameter tuning of the PO algorithm further enhances its adaptability, enabling it to demonstrate significant advantages in complex optimization tasks. In contrast, the PSO and GWO algorithms converge slowly on some functions and are prone to fall into local optimums, while the SSA algorithm performs better but is slightly inadequate on some functions (e.g., F6).



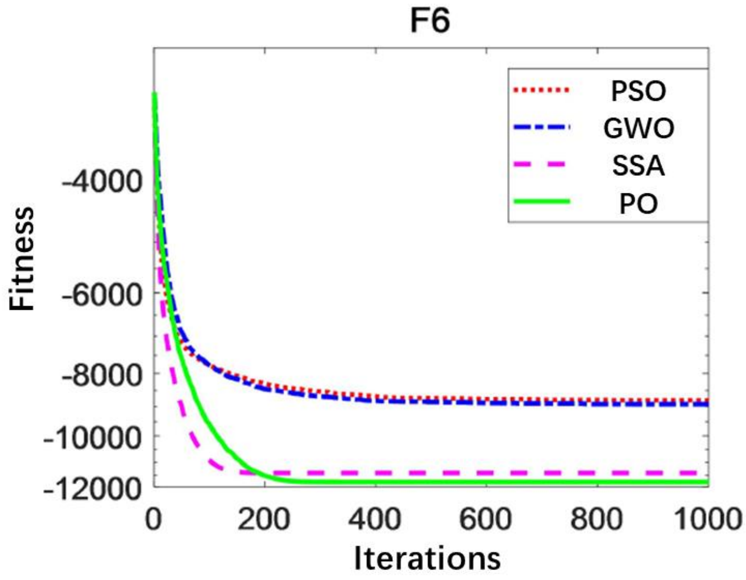
(a) F1



(b) F3



(c) F5

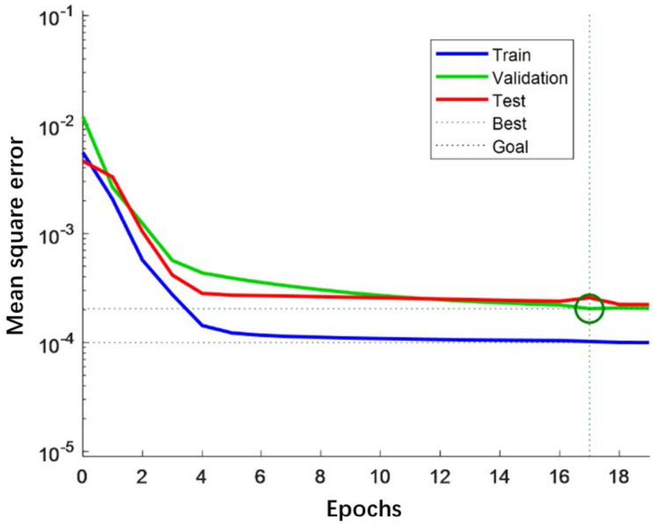


(d) F6

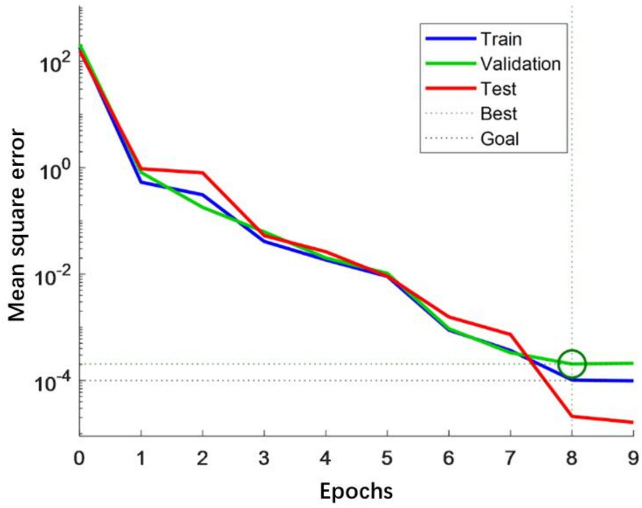
Figure 12. Convergence curve analysis of the PO algorithm

4.3. Value Assessment Analysis

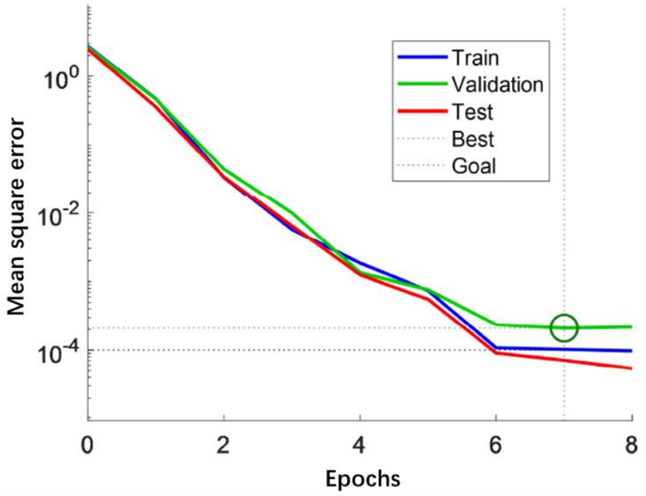
To validate the efficacy and superiority of the PO-BP algorithm in the valuation of data asset accounting within the IASB framework, this paper adopts the BP, GWO-BP, and SSA-BP models as the comparison algorithms to analyze and compare the data of the data asset accounting system under the IASB framework, and the specific results are shown in Figure 13 and Table 7.



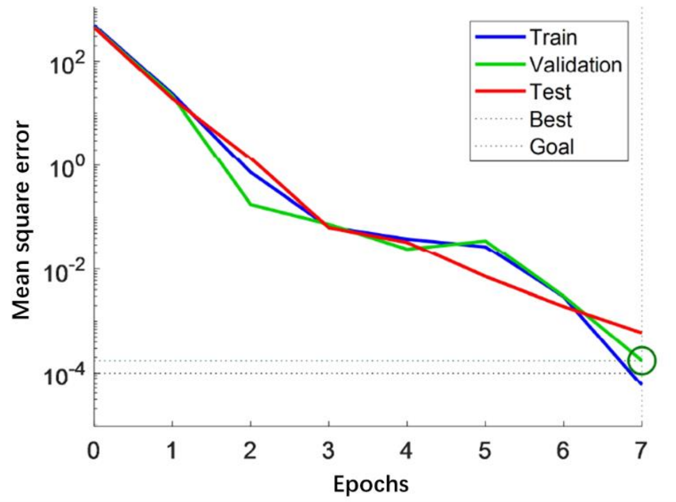
(a) BP



(b) GWO-BP



(c) SSA-BP



(d) PO-BP

Figure 13. Error curves for different value assessment models

Figure 13 shows the error curves of the data asset accounting value assessment models based on different algorithms (BP, GWO-BP, SSA-BP, and PO-BP), from which the performance differences of the models can be analyzed intuitively. The BP model has a slower convergence of error and has not yet reached a higher accuracy after several training sessions, which indicates that its optimization ability and stability are weaker. The GWO-BP model is better than the BP model in terms of convergence speed and accuracy, but its error curve tends to stabilize after a rapid initial decline, and there may be a situation of falling into a local optimum. The GWO-BP model is better than the BP model in terms of convergence speed and accuracy, but its error curve tends to stabilize gradually after the initial rapid decline, and there may be a situation of falling into the local optimum. The SSA-BP model shows better error convergence and higher prediction accuracy and reaches the convergence state after the 7th training, but the optimization ability is weakened in the subsequent training.

In contrast, the PO-BP model exhibits the best performance, with its error decreasing rapidly in the first few training sessions and continuing to be optimized in subsequent training sessions, eventually reaching the lowest error level (average relative error of only 0.2292%). This performance indicates that the PO algorithm effectively improves the weights and bias optimization capability of the BP network, giving it stronger global search and local convergence capabilities. Overall, the PO-BP model outperforms other comparative models in terms of convergence speed, prediction accuracy, and stability, which verifies its significant advantages in the problem of assessing the accounting value of data assets.

Table. 7 Comparative results of value assessment of different models

Arithmetic	Average relative error	Coefficient of determination R^2
BP	1.4648	0.9453
GWO-BP	0.9258	0.976
SSA-BP	0.6058	0.9952
PO-BP	0.2292	0.9957

The comparative results of the value assessment of BP, GWO-BP, SSA-BP, and PO-BP models are given in Table 7. In terms of relative error, the average relative error of prediction of the BP model is 1.4648%, the average relative error of prediction of the GWO-BP model is 0.9258%, and the average relative error of prediction of the SSA-BP model and the PO-BP model is 0.6058 and 0.2292%, respectively, which is significantly lower than the first two models. It can be proved that the SSA-BP model and PO-BP model have higher prediction accuracy compared with the other two traditional models. Where the coefficient of determination R^2 is the model's goodness of fit to the data set, from its value it can be seen that the BP network optimized based on the political optimization algorithm has the highest coefficient value and the best fit to the data.

5. Conclusions

This paper investigates the construction method of a data asset accounting system based on the PO-BP model under the framework of the International Accounting Standards Board (IASB) by combining the political optimization algorithm (PO) and BP neural network (BP). The main contents of the research include the definition, classification, recognition and measurement, accounting treatment, presentation and disclosure of data assets, etc., and the superiority of the method in the value assessment of data asset accounting is verified through experimental analysis.

- Proposes a PO-BP data asset accounting system based on the IASB framework, which clarifies the standards for data asset recognition and measurement and solves the problem of insufficient traditional accounting methods.
- Using the PO algorithm to optimize the structural parameters of the BP neural network, an efficient value assessment model is proposed, and the results show that the PO-BP model outperforms the traditional models (e.g., BP, GWO-BP, SSA-BP) in terms of prediction accuracy and convergence speed.
- Tested with open-source datasets, the PO-BP model performs well in terms of error control (average relative error of only 0.2292%) and goodness-of-fit (coefficient of determination R^2 of 0.9957), which proves the validity and usefulness of the model.

The PO-BP model shows broad applicability across different industries, particularly in technology and finance sectors. In technology, data assets are characterized by high volume, velocity, and variety, requiring models with strong processing capabilities for large-scale, dynamic datasets. The PO-BP model's efficiency and adaptability make it suitable for real-time decision-making and trend prediction. In finance, data assets like market trends and customer transaction records demand high precision and reliability. The model's accuracy in valuation and risk assessment can support investment decisions and regulatory compliance. Its flexibility allows customization to meet industry-specific needs, making it a versatile tool for data asset management.

Although this paper has made important progress in the research of data asset accounting, it still has certain deficiencies and needs further improvement. First, the open-source dataset used for experimental validation is relatively homogeneous, and the lack of adaptability analysis of diverse industry data and internationalization scenarios limits the wide applicability of the model. Therefore, more actual industry or multinational datasets can be introduced in the future to test the robustness and generalization ability of the model in different data environments. Second, the study did not fully consider the dynamic change of data asset value over time and the market environment, which may lead to the lack of accuracy of the valuation results for long-term prediction. To this end, time series analysis or dynamic modeling methods can be combined to enhance the model's adaptability to dynamic changes in data assets. In addition, the research is dominated by experimental data and lacks the validation of actual enterprise cases, which may affect the effectiveness of the model's promotion and application in practice. It is suggested that the feasibility and practical value of the model in practice can be further tested in the future by developing real case studies in cooperation with enterprises. Finally, the combination of data asset accounting with blockchain and big data technology can also be explored to enhance the transparency and efficiency of data asset management from the technical level, and the international applicability under different accounting standards can be studied to expand the theoretical depth and application breadth of the study.

6. Declarations

6.1. Data Availability Statement

The data presented in this study are available in the article.

6.2. Funding

The author received no financial support for the research, authorship, and/or publication of this article.

6.3. Institutional Review Board Statement

Not applicable.

6.4. Informed Consent Statement

Not applicable.

6.5. Declaration of Competing Interest

The author declares that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

7. References

[1] dos Santos Cardoso, V. R., & de Britto, P. A. P. (2024). Relationship between the informativeness of accounting assets and the systematic risk of Brazilian companies. Revista de Educação e Pesquisa em Contabilidade (REPeC), 18(1), 5. doi:10.17524/repec.v18i1.3322.

[2] Pembayun, F. (2023). Implementation of Financial Accounting System at The Regional Finance and Asset Management Agency of Banten Province. Journal of Applied Business, Taxation and Economics Research, 2(4), 451–459. doi:10.54408/jabter.v2i4.195.

[3] Ahn, M. (2023). The Market's View on Accounting Classifications for Asset Securitizations. International Journal of Financial Studies, 11(3), 91. doi:10.3390/ijfs11030091.

[4] Wang, J., Peng, B., Huang, L., & Chen, K. (2024). Tracing offshore marine ecosystem asset changes based on physical accounting: A case of Xiamen Sea Area. Ocean & Coastal Management, 259, 107420. doi:10.1016/j.ocecoaman.2024.107420.

[5] Fan, J. I. N. (2023). Research on Integrating Data Assets into Accounting Discipline System. Journal of Modern Accounting and Auditing, 19(4), 101-112.

[6] Li, Y. (2024). Concepts, Accounting Treatment and Pricing of Data Assets. Journal of Economic Insights, 1(1), 26–40. doi:10.70693/jei.v1i1.93.

[7] Williams, L. D. (2021). Concepts of Digital Economy and Industry 4.0 in Intelligent and information systems. International Journal of Intelligent Networks, 2, 122–129. doi:10.1016/j.ijin.2021.09.002.

[8] Yan, F., Jiao, K., Nie, C., Han, D., Li, Q., & Chen, Y. (2023). Fast Prediction of the Temperature Field Surrounding a Hot Oil Pipe Using the POD-BP Model. Processes, 11(9), 2666. doi:10.3390/pr11092666.

[9] Zeng, Y., & Wu, C. (2022). An Exploration of the Existing Problems of Enterprise Asset Restructuring Accounting, the Causes, and Their Countermeasures. Proceedings of Business and Economic Studies, 5(5), 20–24. doi:10.26689/pbes.v5i5.4102.

[10] Tuan, D. A. (2024). The Effect of Felt Accountability on User Satisfaction with Accounting Information. Emerging Science Journal, 8(2), 732–743. doi:10.28991/ESJ-2024-08-02-023.

[11] Baillie, R. T., Calonaci, F., & Kapetanios, G. (2022). Hierarchical time-varying estimation of asset pricing models. Journal of Risk and Financial Management, 15(1), 14. doi:10.3390/jrfm15010014.

[12] Meister Ko. Freitag, R. (2022). Sociolinguistic repositories as asset: challenges and difficulties in Brazil. Electronic Library, 40(5), 607–622. doi:10.1108/EL-02-2022-0025.

[13] Askari, Q., Younas, I., & Saeed, M. (2020). Political Optimizer: A novel socio-inspired meta-heuristic for global optimization. Knowledge-Based Systems, 195(11), 105709. doi:10.1016/j.knosys.2020.105709.

[14] Yue, W. U., Xingyu, L. I. A. N. G., & Danhong, T. U. (2024). Research on neural network-based prediction method of diesel engine piston ring set scuttling. Internal Combustion Engine Engineering, 45(06), 60-70. doi:10.13949/j.cnki.nrjgc.2024.06.007.

[15] Gray, P., & Zhong, A. (2022). Assessing the usefulness of daily and monthly asset‐ pricing factors for Australian equities. Accounting & Finance, 62(1), 181-211. doi:10.1111/acfi.12786.

[16] Pereira, M. C., & Gouveia, A. F. (2022). An economic estimate of capital stock at the firm level for Portugal (No. o202204). Lisboa, Portugal.

[17] Park, D., Lee, J., & Park, H. (2024). The asset‐ pricing implications of carbon risk in Korea. Journal of International Financial Management & Accounting, 35(1), 7-35. doi:10.1111/jifm.12190.

[18] Galakis, J., Vrontos, I., & Xidonas, P. (2022). On tree-structured linear and quantile regression-based asset pricing. Review of Accounting and Finance, 21(3), 204-245. doi:10.1108/RAF-10-2021-0283.

[19] Tseng, K. (2022). Learning from the Joneses: Technology spillover, innovation externality, and stock returns. Journal of Accounting and Economics, 73(2–3), 73. doi:10.1016/j.jacceco.2022.101478.

[20] Luo, C. (2022). Will the Change from Four to Three Classifications of Financial Assets Lead to a Substitution of Accrual Earnings Management for Real Earnings Management? Open Journal of Accounting, 11(01), 1–20. doi:10.4236/ojacct.2022.111001.

[21] Kang, H., Dou, W., Chen, L., Han, L., Sui, X., & Ding, Z. (2024). A surface water resource asset accounting method based on multi-source remote sensing data. Frontiers in Environmental Science, 12, 1473419. doi:10.3389/fenvs.2024.1473419.

[22] Barton, D. N. (2023). Value 'generalisation' in ecosystem accounting-using Bayesian networks to infer the asset value of regulating services for urban trees in Oslo. One Ecosystem, 8(8), e85021. doi:10.3897/oneeco.8.e85021.

[23] Crosato, L., Domenech, J., & Liberati, C. (2024). Websites' data: a new asset for enhancing credit risk modeling. Annals of Operations Research, 342(3), 1671–1686. doi:10.1007/s10479-023-05306-5.

[24] Kaiser, M. J. (2023). Worldwide oil and gas asset retirement obligations circa 2021. Extractive Industries and Society, 14, 101229. doi:10.1016/j.exis.2023.101229.

[25] Xia, J., Lü, E., Xiquan, W., & Minglin, C. (2024). Prediction of the operation level of agricultural mechanization based on wavelet analysis and BP neural network. Journal of Chinese Agricultural Mechanization, 45(12), 312–318. doi:10.13733/j.jcam.issn.20955553.2024.12.045.

[26] Feng, Z., Yang, L., Liu, M., & Li, X. (2024). Research on damage identification of truss structures based on BP neural network. Journal of Architecture and Civil Engineering, 41(6), 41–48. doi:10.19815/j.jace.2022.12049.

[27] Liu, D. e. (2024). The refined management of medical finance combined with information technology construction. Expert Systems, 41(6), 13151. doi:10.1111/exsy.13151.

[28] Huang, H. L., Cai, J., & Liu, Y. (2024). Optimal robot path control based on improved Hopfiled network. Computer Measurement and Control, 32(11), 204-210. doi:10.16526/j.cnki.11-4762/tp.2024.11.028.

[29] Zhan, W., & Chunxin, C. (2024). Post-earthquake transitional resettlement phase emergency material demand prediction based on GWO-BP. Chinese Journal of Safety Science ,34(10), 17-23. doi:10.16265/j.cnki.issn1003-3033.2024.10.0131.

[30] Li, H., Zhang, Q., Sze, Y. K., & Yan, F. (2024). Sparrow algorithm to improve BP neural network for 4D trajectory prediction. Science Technology and Engineering, 24(31), 13635-13641.

[31] Zhang, P. Y., & Wu, B. F. (2024). Research on the prediction model of driven pile bearing capacity based on PSO algorithm optimized BP neural network. Water Resources Science and Cold Zone Engineering, 7(11):62-65.