Research Article

Evaluation Method for Diversifying Dynamic Capabilities of Small- and Medium-Sized Enterprises Using a Hybrid Genetic Algorithm

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Focusing on the topic of dynamic capability development and digital transformation of traditional enterprises in the digital economy era, and using traditional manufacturing as an example, this paper examines how small- and medium-sized (SMS) businesses should transform and develop in the digital economy era. Furthermore, in light of the problem that existing models cannot evaluate dynamic nonlinear optimization, a diversified dynamic capability evaluation model of SMS enterprises is developed, and the model is solved using the accelerated genetic value method based on real number coding, while the parameters of the BP network are evaluated using the genetic algorithm. In this study, 100 SMS companies are chosen from a pool of 1000 companies to perform an empirical study. In the empirical study, three different scenarios were employed. The selected dataset is utilized to test BP and GA in the first scenario. In the second scenario, the BP and GA are combined to create a more robust model, which is then evaluated on the specified dataset. This research provides a novel approach that combines the PCA with the acceleration method in the third case. According to the findings of this study, the methodology suggested in this work has an overall evaluation accuracy of 95.6 percent, which is pretty good when compared to other approaches. The model training error and test error, on the other hand, are both lower than those of traditional assessment procedures, according to the data.

1. Introduction

There is no disputing that today's breakthrough technologies have changed the structure of everything, including people's thinking and lifestyle patterns. Some of the revolutionary technologies include the Internet, big data, artificial intelligence (AI), and deep learning. These technologies not only changed the lifestyle of a layman but also changed the way we interact with one another and the way we buy and sell, and, in a nutshell, they put the entire world at our fingertips. Businesses can use these technologies to change their strategic thinking, business processes, organizational structure, and operational model. This allows them to build a value-creation system, with data serving as the primary driving force behind digital transformation. Because of their capacity to collaborate closely in order to produce value, firms will be

better positioned to compete in the market and develop new products and services. During this time of crisis, traditional enterprises are leveraging digital transformation to improve their digital capabilities and respond to the new crown pneumonia epidemic [1, 2]. The digital transformation of enterprises is being driven by three key factors: changes in the macroeconomic environment, more competition in the market, and the customized needs of users. As a result of the rapid speed of technical improvements in the digital domain, businesses that have successfully completed digital transformation are better positioned to adapt to digital changes in the external environment and keep their original market competitive advantages. Traditional businesses are undergoing transformation and development as a result of the rising influence of digital technology on their operations and operations management. Traditional firms are currently

witnessing a rebound in their operations and profitability. In the current situation, there is still a great deal of reliance on the traditional business model, as well as low levels of informatization and digitalization of the workforce. Digital transformation must be elevated to the level of strategic decision-making, and many parts of the organization, such as the organization's structure, production model, and management model, must work together to implement the strategy [3].

The digital transformation of all aspects of the organization is accelerating as traditional enterprises transition away from manufacturing and toward virtualization and networking. In order to establish the dynamic capabilities of companies to adapt to the rapid development of the digital economy as well as technological changes in the industry, traditional businesses must implement a digital transformation strategy and invest in independent research and development as well as digital technology innovation because of the impact and change brought about by information technology (IT) on traditional business models [4, 5]. However, the transition to digital technologies will not be easy for traditional businesses, and the digital technologies developed as a result of this process will have a substantial impact on the decision-making and business models of conventional warfighters in the future. The objective of digital transformation has been established as a high priority for enterprise management. However, there is a scarcity of theoretical and empirical studies on how businesses go about experiencing a digital transformation, as well as knowledge on how enterprises might go about undergoing digital transformation through acquiring dynamic capabilities in the field. Therefore, because of the disruptive character of digitization, this research claims that the theoretical framework of dynamic capacities can be used to investigate the digital transformation of conventional industries, which is supported by empirical evidence. The digital economy has ushered in the requirement for firms to have dynamic capabilities through the development, implementation, and modification of their business models.

As a result of the growth of the interconnected wind, the field of organizational design has rapidly progressed from internal design difficulties such as centralization to business model design centered on cross-border transactions. When businesses that use business model design introduce innovative and efficient business models, the creation, transfer, and acquisition of business value are made easier for everyone involved in the value chain. Designing a company's business model is now recognized as a critical instrument for enhancing efficiency within the organization [6, 7].

SMS enterprises must devote more attention to the creation of their business models. According to the logic behind this, startups are less hampered by route dependency and organizational inertia than established businesses. Consequently, organizational performance is frequently contingent on the design of cross-border organizational structures. DELA's revolutionary production and distribution methods were the first to provide a nonintegrated and flexible business model, which had a profound impact on the profit model of the computer industry. Regardless of

whether an entrepreneurial company mimics and imitates an existing business model, the business model must be adjusted to the specific market positioning of the company. This has resulted in the importance of the topic of an entrepreneurial business model building being recognized both academically and practically [8–13].

A large number of researchers have looked into the evaluation of the dynamic capabilities of firms that diversify. Even if certain achievements have been made, the rating system is more prone to human error and subjective experience than most of the other evaluation methods. It is not possible to include all essential data and machine learning models. In particular, researchers are interested in the algorithm feature extraction and classification process, since it does not require human intervention and can quickly extract implicit characteristics from the sample dataset. The inherent reliance on subjective judgment or experience judgment, the weight of methods such as analytic hierarchy process (AHP), fuzzy comprehensive evaluation, and differential equation analysis (DEA), among others, results in a lack of long-term perspective and a failure to take into account sustainable development as a result of their design [10, 11, 14–17]. The effects of these changes will be felt for a long time. Furthermore, because of these approaches, it is impossible to determine the level of diversification.

The basic contributions of the paper are as follows:

(1) To address this nonlinear optimization issue, the genetic algorithm (GA) and the back-propagation neural network (BPNN) are used, which take into consideration the complexity and multivariate nature of the problem to be solved.

(2) The evaluation of multiple dynamic capabilities of enterprises in an urban area of the United States is carried out using nearly 100 SMS enterprises in an urban area of the United States.

(3) The goal of this paper is to provide an innovative method for the evaluation of businesses, as well as a theoretical basis for governments and businesses to formulate various policies.

The rest of the paper is organized as follows: Section 2 describes the related work done in the literature on the chosen topic. The methodology followed in this research work is discussed in Section 3. Section 4 presents the proposed model's findings and draws a comparison between the proposed model's findings and those of various current models. Section 5 finally concludes the theme of the whole paper.

2. Related Work

An organization's internal and external resources and capacities are dynamically integrated, coordinated, configured, and reconstructed to actively react to external market changes. It consists of three components: the ability to detect possibilities, the ability to acquire opportunities, and the ability to reconstruct one's assets.

In entrepreneurial environments, dynamic capacities can be classified into three categories. Opportunity perception

ability refers to an entrepreneurial firm's capacity to discover opportunities in the outside environment. Startups must continually scan, analyze, and research technologies and marketplaces in order to detect and uncover possibilities, which motivates them to invest in R&D and predict possible customer needs, market structures, and competition. To identify the potential for growth, discover opportunities, and adapt effectively to changes in the environment, you must be able to perceive the large picture as an entrepreneur [8, 9, 18].

The ability of entrepreneurial businesses to seize possibilities is referred to as opportunity acquisition ability. A specific business model is required to implement the entrepreneurial enterprise's new products, processes, or services in order to capitalize on the identified market opportunity. An enterprise system's purpose is to create a corporate operation model that enables the monetization of opportunities [19, 20]. Entrepreneurial businesses with a strong capacity for opportunity acquisition will aggressively modify organizational and operational strategies to accelerate the transition of business prospects into products and services.

Asset reconstruction ability refers to the ability of entrepreneurial enterprises to restructure their resources and skills. When entrepreneurial businesses successfully identify and buy opportunities, their assets and performance improve. Entrepreneurs must improve their ability to transfer and reallocate resources as goals are implemented and the market environment changes. Asset recovery startups can find underlying links between assets and utilize them to their maximum potential. The ability to reconstruct assets stimulates the synergistic influence of assets, which improves the efficiency with which resources are utilized and the effectiveness of organizations [5, 7, 21].

It is important to note that, in the entrepreneurial management environment, the risk and complexity of new businesses are both higher than those in more established corporations. New entrepreneurial enterprises have challenges due to limited resources and a lack of market understanding. Entrepreneurship cannot afford to disregard the need for risk management. Because of the interconnection of rules, markets, technology, and the supply chain, there are risks associated with entrepreneurial activities. Risk management has evolved into an entrepreneurial venture in order to ensure a consistent supply of goods and services. Successful risk management and operation are vital to the activities and healthy growth of an entrepreneurial company's risk control competence. Companies with good risk management capabilities can change fast, deliver high-quality products and services at lower management costs, and increase their market competitiveness [2, 4].

Manufacturing firms in many nations have been caught in a quandary of swinging back and forth in the present trend as a result of a variety of global developments, including the global financial crisis, the rise of environmental awareness, and changes in international relations. The obvious advantages of its manufacturing enterprises' low cost and high output are no longer available due to the constant restraints placed on their previously uncontrolled production methods by-laws, agreements, international consensus,

and other regulations, particularly for developing countries that have always prioritized the three highs and one low. The most straightforward technique for improving the competitiveness of the industrial chain is to integrate two or more industries into a single one. Huawei, a well-known Chinese firm, is an example of this. The company's business plan incorporates a number of companies, including semiconductor manufacturing, mobile phone sales, and intelligent services. The company has demonstrated its prominence in the manufacturing industry through a strong brand, multifield cooperation, and self-sufficiency [6, 9].

Academics have long argued about digital transformation and determining an organization's dynamic capabilities. Some academics define digital transformation as the application of cutting-edge digital technology by firms to improve customer experience and channel operations or establish new business models. Other academics define digital transformation as an organizational transformation and change in the digital economy that integrates digital technology and business processes, emphasizing that digital transformation focuses on transformation rather than change so that enterprises can start from scratch and adopt a comprehensive organizational approach. Digital technology provides both opportunities and hazards that must be capitalized on. Many others, on the other hand, believe that business strategy, not technology, is the key to digital transformation. Digital technology is changing the dynamic capabilities of firms in ways that previous strategic breakthroughs did not. Regardless of their executive team's internal drive to support the digital transformation of their business model, structure, and process, incumbent firms will face significant challenges. The most difficult issue is how to reconcile the organization's existing skills with external rivals. The relationship between digital capabilities and their formation is important to break free from the route dependence of the past. Researchers in strategic management are increasingly turning to the dynamic capabilities research paradigm to explain how organizations adapt to rapidly changing markets and technologies. To remain competitive, incumbent firms must undergo digital transformation and strategic change.

Data, computing, interaction, and connection are commonly viewed as a combination of these four technologies, allowing for a fundamental transformation of an enterprise's strategy, operational processes, and capacity, as well as products and services, via business networks. The basic concept underpinning digital technology's layered modular architecture is that digital products may also become platforms because two firms can compete on the same layer at the same time. Before it can work on a greater level with the digitalization and transformation of education, a new business model is required to examine how the organization generates value for consumers, transmits value, and profits from it [10, 14, 15]. They form a potent mechanism that increases firm performance while also providing value to the organization's clientele.

Developing a realistic evaluation approach and model is critical for assessing the dynamic potential of enterprise diversification. Numerous Chinese and foreign academics have

undertaken significant research on this subject. Certain researchers have produced a fuzzy comprehensive evaluation model based on the type and level of elements and indicators that affect a company's ability to grow, as have previous fuzzy comprehensive evaluation models. As a result, the system's cost and robustness will be reduced [11, 16, 17]. Other academics have used the theory of complex system adaptability to create a model of the dynamic mechanism of company sustainable development based on the pyramid support mechanism [12, 13, 22, 23]. Firms can improve their dynamic capacity by using a self-evaluation model based on essential aspects and a three-level indicator system. The dynamic capacities of businesses can be quantified using DEA models established by a number of scholars. Several scholars have added the Balanced Scorecard to circumvent the current evaluation index method, which exclusively considers financial data. To assess the dynamic capabilities of small- and medium-sized businesses, some researchers created a regional difference coefficient conversion model based on the TOPSIS approach [24–29], [30]. Researchers improved the gray correlation degree evaluation of small- and medium-sized enterprises in the east and west by combining the theory that the slopes of two vectors are related to degrees to address the issue of uncoordinated development of dynamic capabilities of enterprises caused by regional differences and external environmental factors. This method is mainly used to test the logic and applicability of the experimental method.

In the static coverage research stage of techniques such as AHP, fuzzy comprehensive assessment, DEA, and others, there are several concerns with subjective judgment weight or judgment weight based on experience. These strategies tend to be short-term in nature and rarely consider the possibility. As a result, this paper develops an evaluation model for the dynamic diversification capability of SMS enterprises, employs the accelerated genetic value method based on real number coding to solve the model, and employs the GA to optimize the parameters of the BP network to achieve a better evaluation effect.

3. Proposed Methodology

According to the concept of dynamic capability and on the basis of the viewpoints of scholars such as literature [15, 19, 21], this paper uses the five dimensions of investment and income, solvency, profitability, management capability, and capital to form the dynamic development capability of enterprises. We selected 20 relevant indicators. The idea of constructing the model is to first simplify the index data of the 20 dimensions of the sample by the principal component analysis (PCA) method and reduce the dimension to obtain n-dimensional principal components ($n < m$) as the input of BPNN. The number of neurons in the input layer of the BPNN is n, the number of neurons in the hidden layer is $k = 2n + 1$, and the number of neurons in the output layer is 5, which represents different levels of enterprise diversified dynamic capabilities. The GA is used to optimize the weights and thresholds of the BP neural network during the model training phase. The model framework proposed in this paper is shown in Figures 1–3.

In order to handle and analyze high-dimensional nonlinear and nonnormal data in a more robust, anti-interference, and accurate manner, the projection pursuit model defined by Kruiskeal must be used. Analysis of high-dimensional observations is carried out by searching for feature projections of the higher dimensions into the lower dimensions of the data. The purpose of this paper is to develop an enterprise dynamics model based on the characteristics and advantages of projection search that can be used to assess enterprise dynamics. The stepwise process of the method followed in this paper is described below.

Step 1. The sample metrics standardization: Since the dimensions of each indicator value are not uniform, the following methods should be used to normalize the data. Equation (1) shows the positive indicator, while equation (2) shows the inverse indicator.

$$x(i, j) = \frac{x^*(i, j) - x_{\min}(j)}{x_{\max}(j) - x_{\min}(j)}, \tag{1}$$

$$x(i, j) = \frac{x_{\max}(j) - x^*(i, j)}{x_{\max}(j) - x_{\min}(j)}. \tag{2}$$

Step 2. Project index function calculation: The projection index function $Q(a)$, as indicated in equation (4), is established by first calculating the projection value $z(i)$ as stated in equation (3). The projection pursuit model forms the best projection direction by projecting high-dimensional data into a low-dimensional subspace.

$$z(i) = \sum_{j=1}^{p} a(j)x(i, k), \tag{3}$$

$$Q(a) = S \times D \tag{4}$$

where D is the local density and S is the standard deviation and they are defined by equations (5) and (6), respectively:

$$D = \sum_{i=1}^{n} \sum_{j=1}^{n} (R - r(i, j)) \times u(R - r(i, j)), \tag{5}$$

$$S = \sqrt{\frac{\sum_{i=1}^{n} \left(z(i) - 1/n \sum_{i=1}^{n} z(i)\right)}{n - 1}}. \tag{6}$$

In equation (5), variable R is the window radius of D.

Step 3. The optimization of the projection index function: The main purpose of solving the problem of maximizing the projection exponential function is to estimate the optimal projection direction. Equations (7) and (8) show the process of the projection index function optimization.

$$\max Q(a) = S \times D, \tag{7}$$

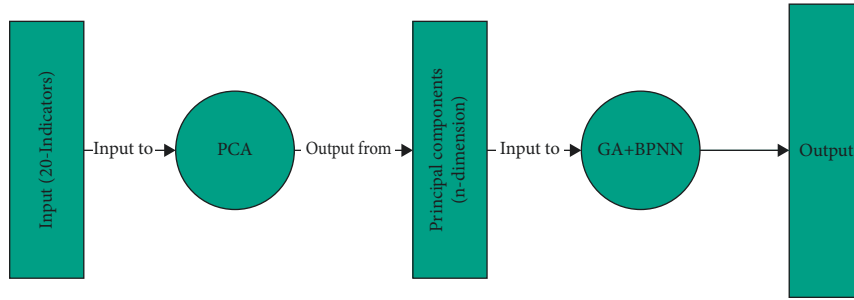$$\text{s.t.} \sum_{j=1}^{p} a^2(j) = 1. \tag{8}$$

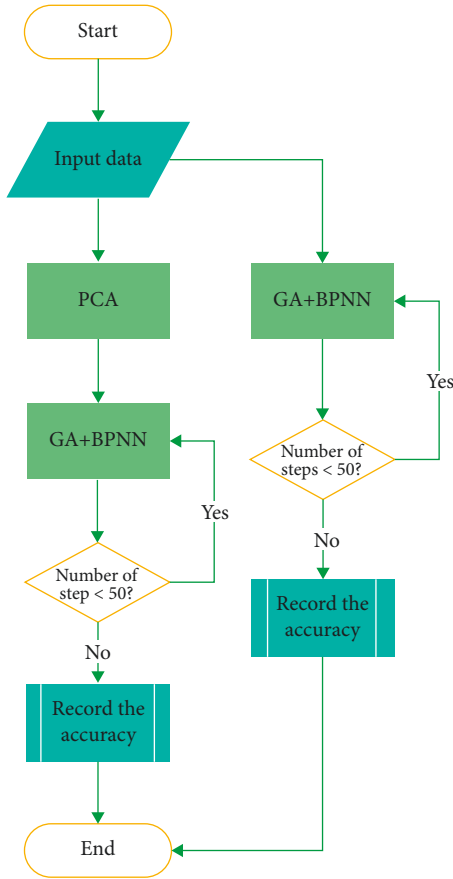FIGURE 1: Abstract level model for the proposed method.

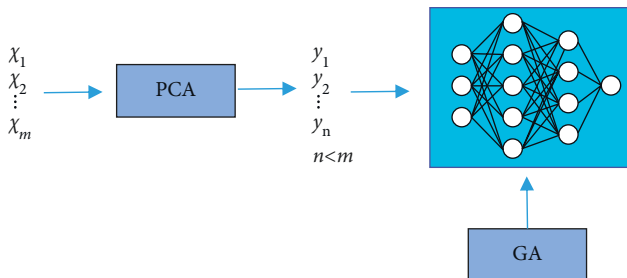FIGURE 2: Flowchart for the proposed method.

FIGURE 3: Structure of the proposed genetic algorithm.

Step 4. Obtain the projection value of each sample according to the best projection direction.

The challenge of determining the best projection direction is a nonlinear optimization problem with a number of well-established solutions. Given the uncertainty in the initial point set, an algorithm such as SCE-JUA can converge to its global optimal solution; however, if the initial point set is erroneous, the algorithm can run into the problem of local convergence, which can be very frustrating. The chaotic optimization strategy is capable of dealing with this problem effectively while not adding any more complexity to the system under consideration. The establishment and selection of objective functions as well as punitive factors, on the other hand, are extremely difficult to accomplish. As well as inspiring many specialists and scholars, natural events have resulted in the development of a diverse spectrum of innovative concepts. Intelligent optimization techniques such as GA, particle swarm optimization (PSO), and simulated annealing (SA) are among the most widely used today. It is easy to slip into a local optimum while using these algorithms because of their early convergence in real operation, and their big amount of computation results in a slow operation speed owing to a large number of calculations. As a starting point for determining the ideal projection direction, this research uses the reasonably mature GA + BPNN combination. When it comes to dealing with the projection pursuit problem, this research advises that a hybrid genetic algorithm (HGA) be used. As a result of this method, the algorithm becomes more efficient. The process of optimizing has become considerably faster and more efficient, enabling a more rapid arrival at the optimal solution to be achieved.

First, this paper optimizes the encoding process of variables as shown in the following equation:

$$x(j) = a(j) + y(j)(b(j) - a(j)). \tag{9}$$

Then we define the fitness function as given in the following equation:

$$\text{Fit}(y(i, j)) = k(1 - k)^{i-1}, \tag{10}$$

where k is a hyperparameter and its value is $0 < k < 1$.

Individuals are then chosen for the next generation. A fresh pair of chromosomes is selected in each rotation, and the first-generation population creates a total of N replicated chromosomes to establish a new generation of humans. Cross the parent population to get the second generation,

and then mutate to get a new one. Note that GA's selection, hybridization, and mutation are generally done sequentially. As a result, essential information is often lost in the subsequent genetic operation as a result of this. In this study, the selection, hybridization, and mutation procedures are all done in parallel, which means that the search domain of the approach is generally bigger than GA, resulting in a more likely and accurate optimal solution.

In addition, iterative evolutionary processes are employed. The progeny of selection, hybridization, and mutation are ranked according to the value of the fitness function. Individual appraisal, selection, crossbreeding, and mutation of the parent are repeated for each of the first (n-k) individuals identified as outstanding offspring.

Finally, do a rapid processing operation. For the following generation of optimization variables, the interval between the first and second generations of outstanding individuals should be used. Search algorithms are limited in how many times they can evolve since too many evolutions will damage their ability to find the optimal individual objective function value or to attain the stipulated acceleration timings.

4. Results and Discussion

The empirical analysis in this paper is based on a network of 100 SMS firms that were recruited from a national database. The dynamic capacity of these SMS enterprises is tagged, and labels are obtained using the method outlined by Ellonen et al. [20] to identify the businesses' dynamic capabilities. The data points of 80 businesses are chosen for the training set, whereas the data points of 20 businesses are chosen for the testing set. This article divides dynamic capacity into five types, each of which is addressed in further depth. For each risk level, the output results from the five neurons in the output layer of the model show the probability value of the examined sample for each of the five risk levels. The level of hazard associated with an evaluation result is indicated by a neuron with a greater probability value.

To begin, the performance of the hybrid genetic algorithm described in this research is evaluated in this study. Feature extraction in this paper is accomplished through the use of principal component analysis (PCA), as illustrated in Figures 4 and 5. The impacts of PCA on the training set of the approach are shown in Figures 4 and 5. The abscissa of the figure reflects the number of iterations, while the ordinate represents the inaccuracy in the model's training. Incorporating PCA into the model leads to a near-zero error in the 16th generation, and subsequent iterations have no effect on this outcome. After 23 iterations, the error in the model that does not employ PCA stabilizes, despite the fact that it is much bigger than the error in the model that does use PCA as shown in Table 1.

Figure 6 shows a comparison between the two approaches: the first one is the GA alone and the second one is the GA combined with PCA.

Further, we tested the performance of the algorithm in this paper on the training set and the test set. In this paper, the precision rate and the recall rate were selected as the
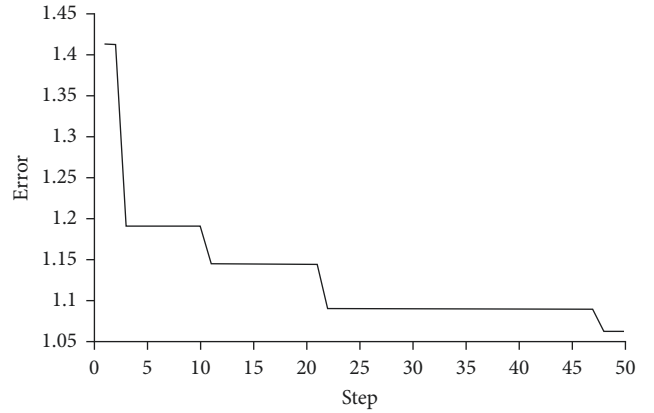

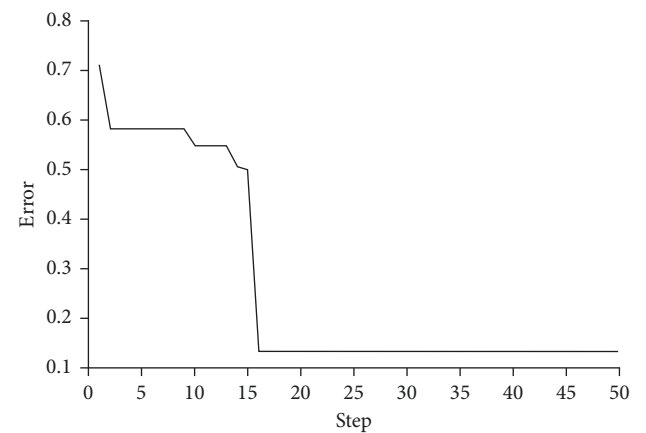
FIGURE 4: Training loss of hybrid GA model without PCA.

FIGURE 5: Training loss of hybrid GA model with PCA added.

TABLE 1: Error rate of GA with and without PCA.

Number of steps	Error rate for GA	Error rate for PCA + GA
0	1.43	0.71
5	1.20	0.60
10	1.15	0.58
15	1.15	0.50
20	1.15	0.15
25	1.10	0.15
30	1.10	0.15
35	1.10	0.15
40	1.10	0.15
45	1.10	0.15
50	1.08	0.15

evaluation indicators. The experimental results are shown in Figure 7. It can be seen that, on the training set, the accuracy and recall rate of the algorithm in this paper can reach more than 95%. Although the performance of the algorithm degrades on the test set, the values of both metrics are higher than 93%.

To judge the quality of the model, a corresponding comparison algorithm is needed. This paper selects BP, GA, and BP + GA as the comparison algorithms and tests the performance of the two algorithms in terms of precision and recall. The experimental results are shown in Figure 5. It can
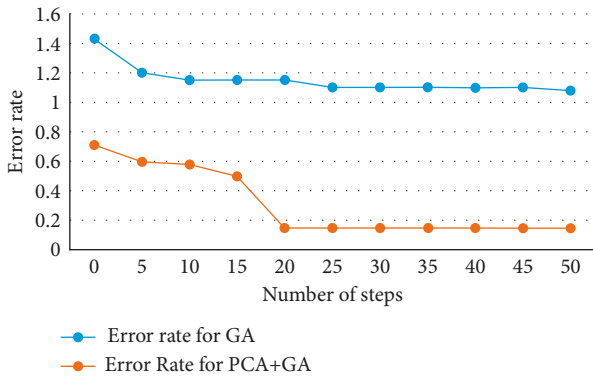
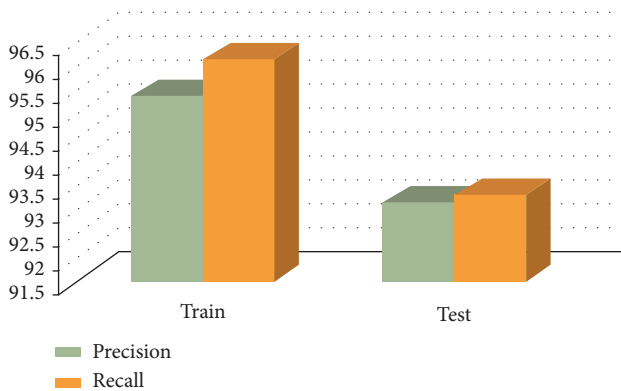Figure 6: Comparison between error rates of GA with and without PCA.

Figure 7: Results of the proposed method on the training set and test set.
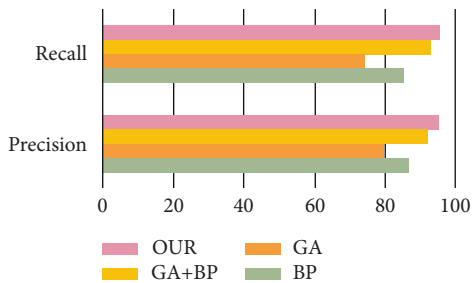

Figure 8: Comparison of results of different algorithms on two indicators.

be seen from Figure 5 that the BP and GA algorithms are less effective than BP + GA and the approach presented in this study. The BP + GA method combines the powerful nonlinear representation ability of BP with GA, so the performance has been improved to a certain extent. On the basis of BP + GA, the approach followed in this paper integrates PCA and acceleration methods and has the best performance.

5. Conclusion

This study looks at how small- and medium-sized firms should change and grow in the digital economy, with a focus on dynamic capability development and digital transformation of conventional organizations. Using traditional manufacturing as an example, this paper examines how SMS businesses should transform and develop in the digital economy era. An enterprise-wide dynamic capability evaluation model for SMS enterprises is developed as an additional consideration in light of the problem that existing models are incapable of evaluating dynamic nonlinear optimization. The model is solved using the accelerated genetic value method based on real number coding, with the genetic algorithm being used to evaluate the parameters of the BP network. In order to conduct an empirical study, 100 SMS firms are selected from the pool of 1000 firms. Three alternative situations were used in the empirical investigation. In the first scenario, the selected dataset is used to evaluate BP and GA. The BP and GA are integrated in the second scenario to build a more robust model, which is then tested on the chosen dataset. In the third situation, this paper proposes a new methodology that combines the PCA with the acceleration method. The outcomes of this study suggest that the ultimate evaluation accuracy of the methodology proposed in this work is 95.6 percent which is quite good as compared to other followed approaches. On the other hand, the model training error and test error are both less than those of conventional evaluation approaches, according to the findings.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that there are no conflicts of interest.

Acknowledgments

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