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Using BP Neural Networks to Prioritize Risk Management Approaches for China's Unconventional Shale Gas Industry

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Abstract: This article is motivated by a conundrum: How can shale gas development be encouraged and managed without complete knowledge of the associated risks? To answer this question, we used back propagation (BP) neural networks and expert scoring to quantify the relative risks of shale gas development across 12 provinces in China. The results show that the model performs well with high predictive accuracy. Shale gas development risks in the provinces of Sichuan, Chongqing, Shaanxi, Hubei, and Jiangsu are relatively high (0.4~0.6), while risks in the provinces of Xinjiang, Guizhou, Yunnan, Anhui, Hunan, Inner Mongolia, and Shanxi are even higher (0.6~1). We make several recommendations based on our findings. First, the Chinese government should promote shale gas development in Sichuan, Chongqing, Shaanxi, Hubei, and Jiangsu Provinces, while considering environmental, health, and safety risks by using demonstration zones to test new technologies and tailor China's regulatory structures to each province. Second, China's extremely complex geological conditions and resource depths prevent direct application of North American technologies and techniques. We recommend using a risk analysis prioritization method, such as BP neural networks, so that policymakers can quantify the relative risks posed by shale gas development to optimize the allocation of resources, technology and infrastructure development to minimize resource, economic, technical, and environmental risks. Third, other shale gas industry developments emphasize the challenges of including the many parties with different, often conflicting expectations. Government and enterprises must collaboratively collect and share information, develop risk assessments, and consider risk management alternatives to support science-based decision-making with the diverse parties.

Keywords: shale gas; risk assessment; BP neutral networks; environmental impacts

1. Introduction

China has become the top energy consumer in the world [1]. At the same time, China is facing intense international and domestic pressure to reduce the greenhouse gas and other emissions resulting from its primarily coal-based energy system [2–4]. Given these twin pressures of increasing energy demand while controlling emissions, the development of China's shale gas industry has emerged as a strategic national priority [5]. In Table 1, we compare the shale gas reserves, resource potential, and status of industry development in China, the United States, and Canada.

Table 1. Comparison of shale gas development in China, the United States, and Canada.

	China	United States	Canada
Depths of shale gas deposits	3000–8000 m	A few hundred to 3000 m	1000–5000 m
Resource potential (reserves)	134.4 trillion m^3 [1]	141.6–169.9 trillion m^3	68.3 trillion m^3 [2]
Recoverable resource potential	25.1 trillion m^3 [1]	24.4 trillion m^3	16.2 trillion m^3
History of the development	Since 2009	More than 80 years	A few decades, behind only the United States
Market conditions	Transition from monopoly to competition	Robust competition	Emergence of market competition
Investment (through 2014) Volumes produced in 2015	\$3.76 billion 5.2 billion m^3	Unknown 432.3 billion m^3	Unknown 68.2 billion m^3

Source: Adapted from Zhao et al. [6], Sun [7], EIA [8] and Mlada [9]. [1] Excluding Qinghai-Tibet; [2] Western Canada only.

Shale gas development in China can be divided into two main phases: the benchmarking phase (1990–2005), which involved observing, summarizing and evaluating shale gas industry development in North America; and the local study phase (2006–present), which involves preliminary assessments of shale gas resource potential and the identification of favorable development areas, applying internationally developed technologies for tight gas exploration, characterization, modeling, and exploitation in the Chinese context [10]. As a result, substantial exploration and production breakthroughs have been made in the Chinese shale gas industry since 2009 [11].

According to China's Shale Gas Resources Report issued in May 2015, China's shale gas geological resource potential is 134.4 trillion m^3, which is almost twice the amount of conventional natural gas resources in China; recoverable reserves are estimated at 25.1 trillion m^3 (excluding those in the Qinghai-Tibet) [11]. The shale gas resource distribution in China is illustrated in Figure 1. Seven provinces—Sichuan, Xinjiang, Chongqing, Guizhou, Hunan, Hubei and Shanxi—account for 68.9% of the nation's total reserves [12].

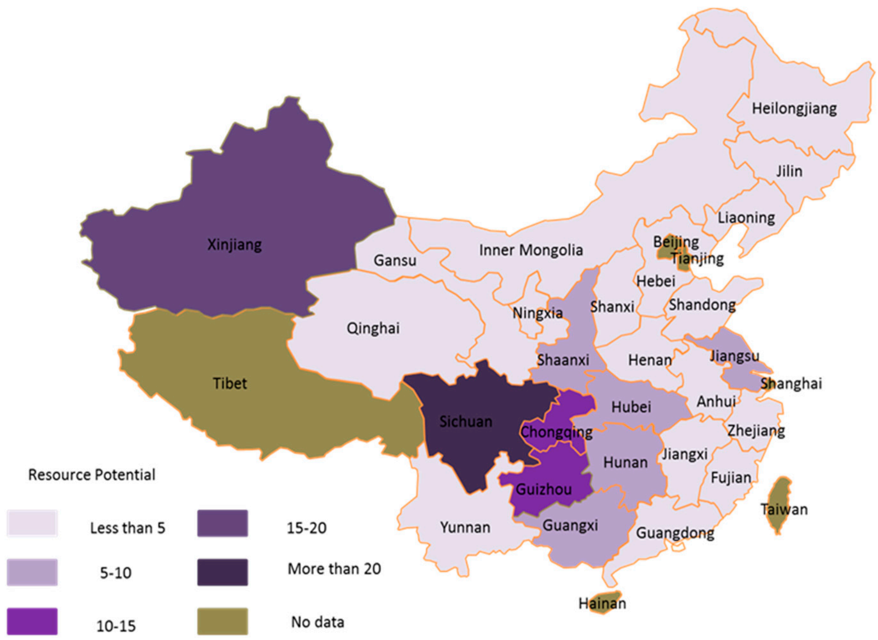

Figure 1. Shale gas resource potential in China's provinces (trillions of m^3) [12,13].

Although developing China's shale gas resources could help address the growing need for cleaner energy, production trails other countries (Table 1). To catalyze this process, in its 12th Five-Year Plan issued in March 2012, China articulated its first national development plan for shale gas, including priorities and objectives for 2011–2015, and an outlook to 2020. The plan called for the completion of basic research and an assessment of China's shale gas resource potential and its distribution, a selection of a batch of shale gas prospect areas (about 30–50) and favorable target areas (about 50–80), implementation of several shale gas exploration and development areas, development of exploration technology and equipment suited to China's geological conditions, and initial achievement of scale production by 2015. Shale gas production goals were 6.5 billion m^3 in 2015 and 60–100 billion m^3 by 2020. To attract foreign investment, in December 2011, the Foreign Investment Industry Guidance Catalogue reclassified foreign investments in shale gas exploration and development in the form of joint ventures with Chinese partners as "encouraged", thereby providing foreign investors some tax and administrative benefits. Additionally, Sichuan, Chongqing, Guizhou, Hunan, Hubei, Yunnan, Jiangxi, Anhui, Jiangsu, Shannxi, Henan, Liaoning, and Xinjiang were defined as key provinces, without providing detailed instructions as to how this development was to occur. In terms of environmental issues, the plan only required the supervision and control of vegetation destruction, water pollution, and the recycling of fracturing fluid.

Given the complex geological conditions [6] and limited experience with relevant shale gas exploration and production technologies, the industry struggled to achieve the shale gas targets set out in the 12th Five-Year Plan [14]. First, shale gas had not been well characterized and proven; only a few blocks within the Sichuan Province basin had proven reserves [11]. By the end of 2014, only 21,818 km of 2D seismic and 2134 km^2 of 3D seismic tests had been completed, mainly in the Fuling block (in Chongqing Province) and Changning-Weiyuan blocks (in Sichuan Province) [11]. By contrast, no 2D seismic exploration had been performed in provinces such as Shaanxi. Second, the costs of exploration and production proved much higher than anticipated; as a result, some state-owned oil companies, such as China Petrochemical Corporation (Sinopec) and China National Petroleum Corporation (CNPC), managed to produce a small amount of shale gas, but with huge deficits. For instance, by the end of 2013, Sinopec and CNPC reported the total investment of $370 million and $640 million, respectively, but produced only 2.58 billion cubic feet and 2.47 billion cubic feet, respectively, resulting in short-term losses of about $1 billion on their shale gas projects [15]. Third, some bid-winning non-oil-and-gas enterprises, such as Chongqing Energy Investment Group Limited Corporation, struggled to meet their shale gas exploration and production targets because they lacked the necessary expertise and investments in reservoir characterization [12,13]. Fourth, some international oil companies have divested their shale gas assets in China (e.g., Shell and ConocoPhillips) [16]. As a result, shale gas development is mainly being left to the state-owned oil and gas companies. Further, by regulation, produced shale gas cannot be sold freely in the Chinese energy market and its price remains uncompetitive with conventional gas. The Chinese government provides subsidies to companies that produce shale gas, but the margins are still tight. Thus, international oil companies are choosing other, more profitable projects.

Taking these issues into consideration, the national energy administration of China has modified the shale gas production target for 2020 from 60–100 billion m^3 to 30 billion m^3, and the Ministry of Land and Resources has repeatedly postponed the third round of bidding for shale gas prospecting rights [14,17]. This suggests that China's production targets have not reflected the operating and regulatory environment, and that the policies made by the Chinese government have not catalyzed the desired development. Underlying this is insufficient characterization of shale gas resources and the risk associated with their development.

We make three contributions to the extant literature. First, we extend and deepen the risk assessment system for China's provincial shale gas industry by considering resource, economic, technical, environmental, and social and policy risks (with 16 subordinated tertiary indicators). Second, we leverage experts' evaluations of shale gas development risks for 12 different provinces in China.

Third, we extend the use of BP neural networks by demonstrating that this approach can be used to quantitatively estimate the risks associated with shale gas development in different regions of China.

The rest of this paper is organized as follows. In Section 2, we review prior research and describe how we identified and selected risk indicators and developed our risk assessment system for China's provincial shale gas industry. In Section 3, we introduce our methodology and data. In Section 4, we present and discuss our results before making some policy suggestions in Section 5.

2. Developing the Risk Assessment System

While research on the risks associated with conventional energy and renewable energy in China has been comprehensive, risks associated with shale gas development were not considered until 2012 when production began. Previous work on shale gas has identified the risks associated with geological conditions [18,19], technology [20,21], yield prediction [22–24], and strategic and government policy [6,25–27], yet less attention has been paid to overall industry development risks [5,28–30]. Processing of minerals is associated with a number of development risks, including various economic, environmental and social issues [31]. These risks have prompted members of the shale gas industry to engage in the sustainability debate. The ideal way to deal with these potential risks generally is through a combination of enhanced socioeconomic growth and development, and improved environmental protection and pollution prevention [32]. This indicates insufficient breadth in the research on shale gas development risk; scholars typically focus on one or two specific industry risks [33–42], rather than engaging in a comprehensive analysis of all risks. It also indicates an insufficient depth of analysis, with most risks being assessed qualitatively rather than quantitatively [33–41]; quantitative analysis supports more complex assessment [43] and evaluative tradeoffs amongst a range of diverse risks [44]. Quantitative evaluations of China's shale gas industry development risks are scarce and province-scale analysis is absent, yet necessary to analyze site-specific information (e.g., local environmental conditions or community characteristics) [5]. The most recent research summarizes scientific activities in terms of who is engaged in research and what they are researching [45,46], but does not provide a comprehensive analysis of development risks. For instance, according to Feng [47] (p. 23):

> "Currently, environmental supervision regarding shale gas development in China mainly references the regulations and technical guidelines developed for conventional resources ... These policies do not fully consider the specific environmental issues brought by this new mineral resource. [Further], the authorities have yet to consider environmental protection, ecological and human health impacts when selecting sites for shale development, and no research has been conducted on pollution levels from China's shale developments."

To address this gap, we analyze the resource, economic, technical, and environmental risks associated with China's provincial shale gas development, using back propagation (BP) neural network modeling. Neural network analysis is used for "categorization and ... prediction problems, particularly when there are a large number of inputs which are related in nonlinear ways" [48]. Indeed, neural networks outperform traditional statistical methods, especially for problems with incomplete data, when inputs and constraints are related in complex, nonlinear ways [49,50]. Feed-forward back-propagation is a well-known learning algorithm for training neural networks, which can supplement existing theoretical analyses and decision-making processes.

The risks discussed in this paper are on an industry level and are not specific to a particular shale gas project. The risks can be divided into internal industry risks (i.e., resource potential, economic, technical and environmental) and external socio-political risks such as China's domestic policy system and international geopolitical factors. The shale gas industry in China is in an early stage, so data are relatively scarce. However, since the shale gas and conventional oil and gas industries share many characteristics in terms of exploration and production, transportation and downstream markets, we consulted experts (see Figure 2) to identify risks. Figure 2 illustrates how we developed a neural network-based risk assessment system for shale gas development in China. We discuss the preparation of our training data, development of our neural network, and the simulation of the relative risks in the next section.

The advantage of expert-based models is that they do not require inventory data for model training; however, the disadvantage is the subjectivity of experts' judgments about the importance of conditional factors. To improve the reliability of our model, we selected a committee of 12 experts in the shale gas field. Since state-owned oil companies are currently engaged in shale gas exploration and development [15], we selected one expert from each of the research institutions of five state-owned petroleum enterprises, namely Sinopec (China Petrochemical Corporation) Exploration and Development Research Institute, Sinopec Economic and Technology Research Institute, China National Petroleum Corporation (CNPC) Exploration and Development Research Institute, CNPC Economic and Technology Research Institute, and China National Offshore Oil Corporation (CNOOC) Energy Economic Research Institute. We also selected an expert from a foreign-funded enterprise (i.e., Schlumberger) and an expert from a private enterprise (i.e., Anton Oilfield Services Group) because these two companies play an important role in providing the engineering and technical services for China's shale gas industry [51]. Since scholars from China University of Petroleum (Beijing), Southwest Petroleum University and Yangtze University have published many papers about shale gas [10], we chose experts from each of these three universities. Finally, we selected one expert from each of the two research institutions engaged in long-term research on China's shale gas industry: Oil and Gas Resources Research Center of China Geological Survey and China Energy Website [51].

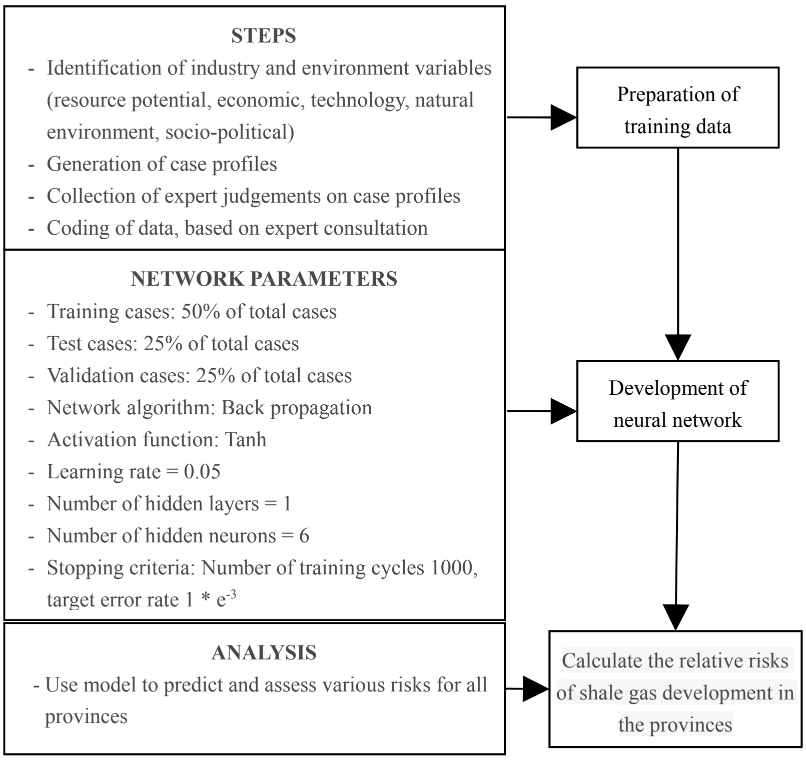

Figure 2. Development process for the neural network-based risk assessment system.

A comprehensive risk evaluation system is key to ensuring that the evaluation results are practical and reliable. Therefore, system development should not only follow general principles such as being scientific, comprehensive, quantitative and feasible, but also include research findings related to industrial risk index systems in China and elsewhere. While considering inter-industry differences, we primarily focused on the research findings of energy-related risk index systems and the feasibility of their application in the shale gas industry (see Table 2). Since our focus is on the risks associated with shale gas industry development, we focused first on three representative studies on this topic: Guo et al. [52], Yu [53] and Krupnick et al. [5]. Second, we considered studies related to coal, the dominant source of conventional fuel energy in China. However, since coal is abundant, the technology is mature, the market is completely competitive, and the regulatory system is established, the risks related to the industry are less applicable. Third, we reviewed literature related to the development of the renewable energy industry (i.e., biomass and solar) because there are similarities in terms of national policy support, market competition, environmental impacts, and technical requirements for industry development. Importantly, we did not consider literature related to the nuclear industry because it is completely different in terms of developmental stage, technology, regulation, and long-term, immeasurable risks [54].

Table 2. Representative risk index system of energy industry.

Researcher	Target Industry	Index System	Indexes Relevant to the Shale Gas Industry
Hou [55]	Biomass	Supply abundance, supply stability, technical maturity of energy conversion technologies, update rate of relevant equipment, technical maturity of energy storage technologies, market demand, public awareness, price competitiveness, legislation, tax preference, subsidies, industrial development management, natural disasters and environmental changes	Technical maturity of energy conversion technologies, technical maturity of energy storage technologies, market demand, price competitiveness, legislation, etc.
Zhang et al. [56]	Photovoltaic power generation	Industry scale, supply and demand, revenue capability, technical R&D, cost structure, policy system, concentration level, resource potential, cost comparison, manufacturing energy consumption, electricity price change, competition pattern, external dependence, macro economy, financial market, product structure, technology tendency	Supply and demand, technical R&D, resource potential, electricity price change, etc.
Chi [57]	Solar photovoltaic	Technical maturity, technical level, independent R&D capacity, raw material supply, product supply and demand, market competition, industrial policies, industrial standards	Technical maturity, raw material supply, industrial standards, etc.
Guo et al. [52]	Shale gas	Geological condition, recoverable reserves, resource prospect, international collaboration, independent R&D, talent team, technology & equipment, production cost, environment rehabilitation cost, operation revenue, pipeline construction, environment deterioration, ecological balance, environmental evaluation system, industry standards, preferential policies	Geological condition, recoverable reserves, technology & equipment, production cost, pipeline construction
Yu [53]	Shale gas	Resource risk, technical risk, water consumption risk, environmental risk, capital investment risk	Resource risk, technical risk, water consumption risk, environmental risk, capital investment risk
Krupnick et al. [5]	Shale gas	Lack of water resources, water pollution, air pollution, soil pollution, community disruption, earthquake, lack of legislation, insufficient regulation	Lack of water resources, water pollution, air pollution, soil pollution, lack of legislation, insufficient regulation

Drawing on our experts' suggestions and findings in the literature, we identified representative and quantifiable indicators of risks associated with shale gas development. For example, production cost, which is a type of economic risk, is taken directly from Guo et al. [52]. However, we identified price competitiveness as a sole indicator of market risk, while Hou [55] also considered market demand. In China, unconventional shale gas directly competes with conventional gas. Since there is no significant difference in terms of production quality, consumers only care about price, not the origins of the gas. As shown in Table 3, our risk assessment system includes five types of secondary indicators, namely resource risk, economic risk, technical risk, environmental risk, social and policy risk (with 16 subordinated tertiary indicators).

Table 3. Indicators of the provincial shale gas development risks.

Target Layer A	Criterion Layer B	Index Layer C
Comprehensive evaluation of shale gas industry development risks (A)	Resource risks (B1)	Resource prospects (C11) Geological conditions (C12) Resource reserves (C13)
	Economic risks (B2)	Production costs (C21) Capital risk (C22) Market risk (C23)
	Technical risks (B3)	Technology equipment (C31) Infrastructure (C32)
	Environmental risks (B4)	Water consumption (C41) Water pollution (C42) Air pollution (C43) CO_2/CH_4 emissions (C44) Other damage (C45)
	Social-policy risks (B5)	Industrial standards (C51) Preferential policies (C52) Long-term planning (C53)

3. Methodology and Data

3.1. BP Neural Network

There are several different risk evaluation methods, among which the analytic hierarchy process (AHP), grey system evaluation method, data envelopment analysis (DEA), fuzzy mathematics comprehensive evaluation method, the multi-objective decision and expert evaluation method [58–65] are relatively mature. BP neural networks are one of the most commonly used and most mature artificial neural network methods [66–71]. Information processing is divided into forward data calculation and back learning (namely the back propagation of error signals and correction of relative values) to approximate a given expected output. A trained network can be used to predict the target variable. This method is believed to be most applicable to simulation of the correlation of inputs and outputs [72]. Funahashi [73] proved that the three-layer network with just one hidden layer is sufficient to express any continuous function with any required accuracy, assuming an adequate number of hidden layer nodes. The artificial neural network can estimate any function in a broad category and reveal the nonlinear relationship that exists in the data sample [74,75]. BP neural networks are widely used in risk assessment and security pre-warning systems in various industries [72,76–79]. The basic mechanism is shown in Figure 3.

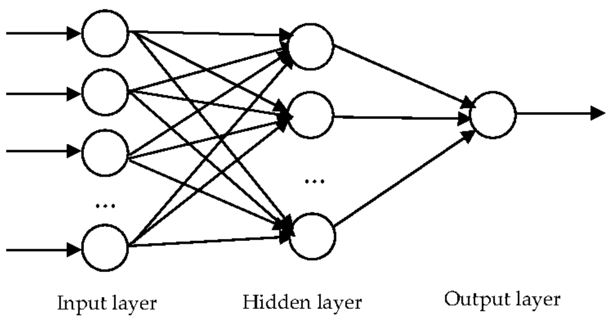

Figure 3. Three layers of a BP neural network.

Figure 3 illustrates the three layers of a BP neural network: the input layer, the hidden layer, and the output layer. Two nodes of each adjacent layer are directly connected via a link. Each link has a weighted value representing the degree of relationship between two nodes [80]. Suppose that the number of input layer neurons is n, the number of hidden layer neurons is p, and the number of output layer neurons is m. We can infer a training process described by the following equations to update these weighted values, which can be divided into two steps:

Step 1: Hidden layer stage. The output of the hidden layer neurons can be calculated as follows:

$$x_i^1 = f\left(\sum_{j=1}^{n} w_{ij}^0 x_j + w_{i0}^0\right),\ i = 1, 2, \ldots, p \tag{1}$$

where $\sum_{j=1}^{n} w_{ij}^0 x_j + w_{i0}^0$ represents the weighted sum of n input layer neurons; w_{ij}^0 is the weight coefficient reflecting the influence level of the input layer neuron j on the hidden layer neuron i; w_{i0}^0 is the threshold value of the hidden layer neurons i; and $f(x)$ is a non-memory nonlinear excitation function used to change the output of neurons.

Step 2: Output layer stage. Similarly, the output of the output layer neurons is:

$$y^k = f\left(\sum_{j=1}^{p} w_{jk}^1 x_j^1 + w_{k0}^0\right),\ k = 1, 2, \ldots, m \tag{2}$$

Moreover, the error function of neurons in the output layer is defined as:

$$\mathrm{E} = \frac{1}{2}\sum_k \left(d^k - y^k\right) \tag{3}$$

where d^k is the target value. The error value at every node in the former layer is calculated layer-by-layer using back propagation and corrected using the following weighted correction formula:

$$\Delta w_{ij}^m = \eta \delta_j^m y_i^{m-1} \tag{4}$$

where η is the learning rate and δ_j^m is the error signal.

Prior to following these steps, data should be normalized to overcome problems arising from the different physical significances and dimensions of the input and output data. Since we used a Tanh activation function, we chose an interval of (−1, 1) for normalization purposes. The following formula is commonly used:

$$P_i = 2 \times \frac{I_i - I_{min}}{I_{max} - I_{min}} - 1 \tag{5}$$

where I_i represents the input or output data, and I_{min} and I_{max} are the minimum and maximum values of input or output data, respectively.

Thus, in this paper: (a) the input layer neurons correspond to the 16 risk evaluation indicators, that is, n = 16; (b) in the output layer, one neuron reflects the risk level, (i.e., m = 1); and (c) the number of hidden layer neurons, p, is usually determined from experience, by the convergence speed and error optimization during the training process, or by the following two formulas [67]:

$$k < \sum_{i=0}^{n} C_p^i,\ \text{if}\ i > p,\ C_p^i = 0 \tag{6}$$

$$p = \sqrt{n + m} + a \tag{7}$$

where k represents the sample number and a is an integer of the interval (1,10). Based on Formula (6), $4 \leq p$. Moreover, based on Formula (7), $6 \leq p \leq 14$. Different precision results are shown in Table 4.

As shown in Table 4, the R-values for the training, validation and testing samples are all greater than 0.9 as the number of neurons in the hidden layer changes from 6 to 14 after the network training process, which indicates that the network output is strongly associated with the target expectation. Meanwhile, MSE does not decrease significantly as the number of neurons in the hidden layer increases. Since the precision of the model is satisfactory, having six hidden layer nodes reduces the complexity of the network.

Table 4. Different precision results for different numbers of neurons in the hidden layer.

Network	Number of Neurons in the Hidden Layer	Training Algorithms	Training		Validation		Testing	
			R	MSE	*R*	MSE	*R*	MSE
1	6	LM	0.996	0.004	0.980	0.073	0.980	0.034
2	7	LM	0.973	0.066	0.948	0.099	0.997	0.191
3	8	LM	0.989	0.044	1.000	0.242	0.980	0.071
4	9	LM	0.999	0.008	0.999	0.269	0.939	0.214
5	10	LM	0.973	0.078	0.995	0.118	0.995	0.064
6	11	LM	0.988	0.056	1.000	0.005	0.974	0.127
7	12	LM	0.949	0.046	0.997	0.168	0.935	0.170
8	13	LM	0.967	0.029	0.986	0.103	0.994	0.256
9	14	LM	0.986	0.023	1.000	0.091	1.000	0.240

Note: R measures the correlation between the output and target values. A value close to 1 indicates a close relationship; 0 represents a random relationship. MSE is the mean squared error, which is the average squared difference between output and target. Lower values are better; 0 indicates no error.

We trained the constructed risk assessment BP network model using the MATLAB neural network toolbox. Taking early stopping into consideration, we randomly divided the samples into training (50%), validation (25%), and testing (25%) subsamples. The target error requirements are satisfied in these different situations through the MATLAB simulation. The BP algorithm has a reliable basis, discrete derivation, high accuracy and universality. We adopted the improved Levenberg–Marquardt (L-M) algorithm, which combines the gradient descent method and the Gauss-Newton algorithm, where the "tansig" function is used as the transfer function, and the "train lm" function is used as the training function. We used a 1000-cycle training process with a 5% learning rate and target error of $1 \times e^{-3}$.

3.2. Input and Output Data

To assess risks associated with shale gas exploration and development in China, we used data from the 12 Chinese provinces where relevant activities are under way. We used actual or virtual values as inputs for risk indicators in accordance with the practical shale gas conditions of each province (e.g., 1 = existing; 0 = not existing).

For each province, we determined the values for: (a) resource prospects based on the amount of proven recoverable reserves; (b) geological conditions based on the area of the favorable shale gas play (10^4 km^2) [12]; and (c) resource reserves based on the amount of technical recoverable reserves. Since data related to production costs are lacking, we used interval scales (i.e., >3.1, 2.8~3.1, 2.5~2.8, 2.2~2.5, and <2.2) to reflect relative costs in China [81]. Using an average value of about 2.49 RMB/m^3, the corresponding values for each interval are 1, 0.9, 0.8, 0.7 and 0.6, respectively; the accuracy of production cost values were verified by the expert committee. We determined the values for capital risk based on the cumulative capital investment made by each province. Market risk values reflect the value of the natural gas price divided by the shale gas price, based on the provincial gate station price of natural gas inventory and the tax-included factory price at the break-even point based on data from the National Development and Reform Commission [17,82]. We determined technology and equipment values based on the number of shale gas technical patents from the Patent Search and Analysis of State Intellectual Property Office (SIPO) [83]. Infrastructure values are based on pipeline network density (km/km^2), and water consumption values are based on data from the Aqueduct Water Risk Atlas issued by the World Resources Institute [84]. We used virtual values for water pollution, air pollution, greenhouse gas emissions, and other damages (noise pollution and earthquake risk), preferential policies and long-term planning based on the data from each province's department of environmental protection. We determined values for industrial standards based on the number of oil and gas inspectors from the Ministry of Land and Resources in each province [85]. We present the input source data in Table 5.

Table 5. Shale gas development risk indicators and their values of different provinces.

Province	Sichuan	Xinjiang	Chongqing	Guizhou	Hubei	Hunan	Shaanxi	Jiangsu	Inner Mongolia	Yunnan	Shanxi	Anhui
Resource prospects/(10^9 m^3)	0	0	134.74	0	0	0	0	0	0	0	0	0
Geological conditions/(10^4 km^2)	43.24	4.01	7.56	4.23	7.91	1.30	10.00	5.07	1.65	2.34	0.64	0.05
Resource reserves/(10^{12} m^3)	27.50	16.01	12.75	10.48	9.48	9.19	7.17	5.33	3.29	2.14	2.14	2.12
Production cost	0.6	0.8	0.6	0.7	0.8	0.8	0.7	0.8	0.8	0.7	0.9	0.8
Capital risk/(10^8 RMB)	55.0	0	130.90	3.20	1.07	1.76	7.20	0	0	13.00	1.70	1.00
Market risk	0.87	0.68	0.87	0.89	0.98	0.98	0.75	1.06	0.75	0.89	0.96	1.03
Technology equipment/(ea)	25	0	12	0	15	0	25	16	0	0	1	0
Infrastructure/(km/km^2)	0.027	0.006	0.081	0.007	0.014	0.005	0.026	.037	0.002	0.003	0.032	0.013
Water consumption	0.38	10.97	0.01	0.11	0.01	0.16	1.74	0.04	11.61	0.06	2.22	0.04
Water pollution	1	1	1	1	1	1	1	1	1	1	1	1
Air pollution	1	1	1	1	1	1	1	1	1	1	1	1
CO_2/CH_4 emissions	0	0	0	0	1	0	1	1	1	0	0	0
Other damage	1	1	1	1	1	1	1	1	1	1	1	1
Industrial standards/(ea)	13	15	11	11	10	11	18	15	18	3	16	7
Preferential policies	1	1	1	1	1	1	1	1	1	1	1	1
Long-term planning	1	1	1	0	1	0	1	0	1	0	0	0
Risk score	0.40	0.60	0.40	0.60	0.55	0.65	0.50	0.55	0.65	0.60	0.65	0.60
Normalized risk score	0.6	1	0.6	1	0.2	1	0.6	−0.2	0.6	0.2	−1	−1

As for the output layer, the risk values were determined by expert scoring, considering 16 input layer C indices at the same time. Here, we divided shale gas industry development risks into four levels, low risk, relatively low risk, relatively high risk and high risk, respectively, corresponding to the intervals of (0, 0.2), (0.2, 0.4), (0.4, 0.6), and (0.6, 1). The output source data can be seen in Table 5. The normalized processing results for the data in Table 5 are shown in Table A1 in Appendix A.

4. Results and Discussion

The results of one trained neural network are shown in Figure 4. The correlation coefficient between the output and target values for the training sample is 0.99878, which indicates the BP neural network training grid is satisfactory. The correlation coefficients for the validation and testing samples are 0.9922 and 0.98938, respectively, which shows that the trained BP neural network grid and prediction accuracy of the neural network on the sample are both satisfactory, and overfitting phenomenon did not happen [72].

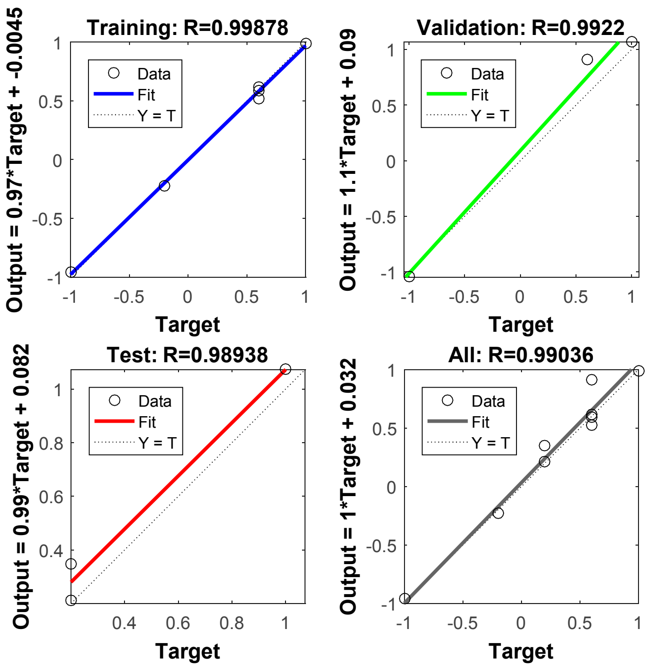

Figure 4. Training, validation, testing, and full sample regression curves.

The above neural network has been trained, which means it has already satisfied the target error of $1 \times e^{-3}$ mentioned in Section 3.1. As shown in Figure 5, for the whole sample, the error between the prediction output values and the target values are small. The error is minimal in the training sample, and a little bit larger in the validation and testing samples, but still well below the accepted threshold of 10% [86]. The figure represents a visual representation of the degree of membership associated with the shale gas industry development risk level.

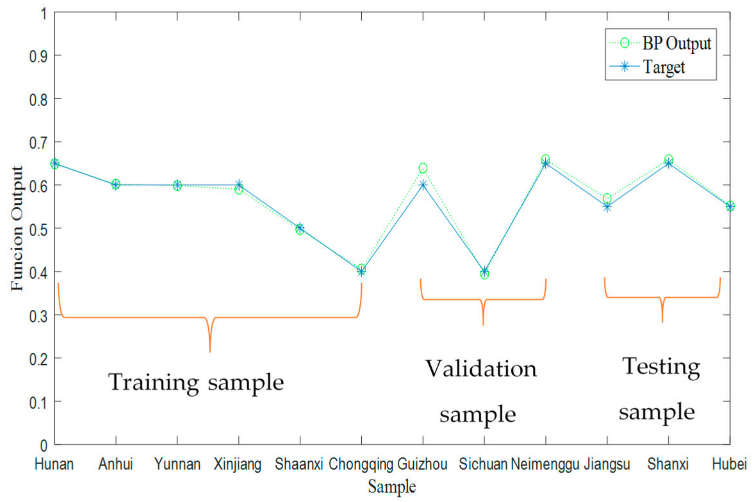

Figure 5. BP network predicted output and expected output.

Figure 6 is a more intuitive expression of the prior figure. The relative error between the predicted output value of the BP neural network and the target value can be seen clearly. Although the curve has higher amplitude fluctuation, the value of the fluctuation is small. It reveals that the error between network output and target value is small (less than 7%).

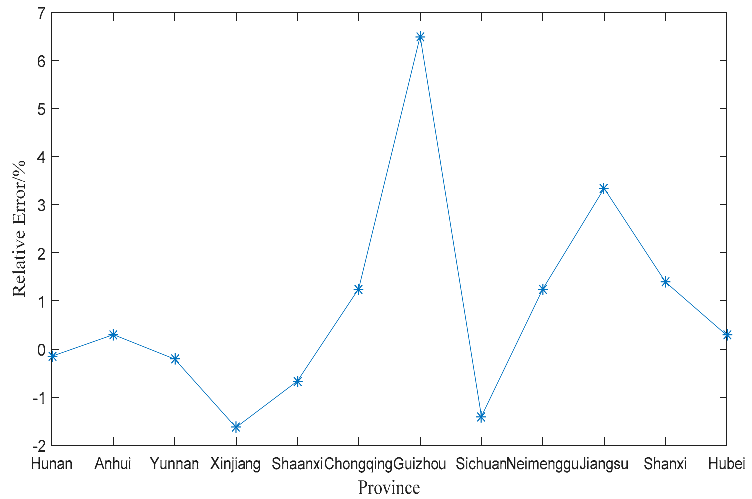

Figure 6. Relative error of BP neural network output and expected output.

We present detailed results for the provinces comprising our validation and testing samples in Tables 6 and 7, respectively. Relative to the four risk levels mentioned before (see Section 3.2), the model results correspond closely with the expected results, indicating that the trained network has excellent generalization capacities [72], and hence, can be used to monitor and evaluate risks of shale gas development in China at the provincial-level.

Table 6. Results for validation sample.

Province	Guizhou	Sichuan	Inner Mongolia
Expected risk value	0.60	0.40	0.65
Model risk value	0.6390	0.3944	0.6581

Table 7. Results for testing sample.

Province	Jiangsu	Shanxi	Anhui
Expected risk value	0.55	0.65	0.55
Model risk value	0.5684	0.6519	0.5516

After the network model is trained, the prediction process is simplified, requiring only monitoring data for the risk assessment target sample to produce results. After building this system model based on the corresponding provincial risk index data, the overall risks of the shale gas industry can then be assessed. Although the BP neural network method has some challenges (primarily related to small sample size), it is a novel research approach that can be used to design a risk assessment system for the emerging shale gas industry in China. In the future, researchers can build on this study and others to improve the method and the risk assessment system.

5. Policy Recommendations for China's Provincial Shale Gas Industry Development

Our efforts have yielded several findings. First, shale gas development in China is associated with high levels of risk, due to delayed exploration and production efforts and immature market and regulatory structures. Some provinces have relatively high levels of risk (Sichuan, Chongqing, Shaanxi, Hubei, and Jiangsu), while other provinces have even higher levels of risk (Xinjiang, Guizhou, Yunnan, Anhui, Hunan, Inner Mongolia, and Shanxi) based on varying levels of regulatory support at the provincial level. We recommend that more attention be paid to environmental, health, and safety issues. In the provinces with highest levels of risk, demonstration zones can be used to test new technologies in China's complex geological conditions, and China's regulatory structures can be adapted to ensure that risk management is tailored to each province [13]. For example, since water is more limited in Chongqing than in Sichuan [84], fiscal policies related to water pricing require greater attention in Chongqing.

Second, the differences between China and other shale gas producing countries such as the United States and Canada should be noted. Such differences include China's extremely complex geological conditions and resource depths that prevent direct application of North American technologies and techniques. Thus, technology research and development and resource exploration and production should be expanded to improve risk management and environmental protection. BP neural networks can be used to quantify the relative risks posed by shale gas development, and hence, risk management priorities. Our approach could be used to optimize the allocation of resources, technology and infrastructure in shale gas development to minimize resource, economic, technical, and environmental risks in China.

Finally, development of the shale gas industry involves many parties [87] with different and sometimes conflicting expectations [54,88], thus, broad-based risk management efforts are required. The government should strengthen the supervision of resources, market and environmental protection to ensure that risks are minimized. Oil and gas companies should enhance research and development activities and improve their identification, assessment, and risk management options. Implementing these recommendations will support collective contributions to data collection and sharing, as well as risk assessment and management activities to support for science-based decision-making.

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Appendix A

Table A1. Normalized processing results.

Province	Sichuan	Xinjiang	Chongqing	Guizhou	Hubei	Hunan	Shaanxi	Jiangsu	Inner Mongolia	Yunnan	Shanxi	Anhui
Resource prospects	−1	−1	−1	−1	−1	−1	−1	−1	−1	−1	−1	1
Geological conditions	−0.8940	−0.9421	−1	−0.9727	−0.6360	−0.9259	−0.8064	−0.5393	−0.8166	−0.7675	1	−0.6522
Resource reserves	−0.9984	−0.4429	−1	−0.9984	−0.4200	−0.9078	−0.3412	−0.6021	0.0946	−0.7470	1	−0.1623
Production cost	−0.3333	0.3333	0.3333	1	0.3333	0.3333	−0.3333	−0.3333	0.3333	0.3333	−1	−1
Capital risk	−0.8014	−0.9731	−0.9847	−0.9740	−0.9837	−1	−0.9511	−0.8900	−1	−1	−0.1597	1
Market risk	0.1053	0.5789	0.8421	0.4737	0.5789	−0.6316	0.1053	−0.6316	−1	1	-2.22×10^{-16}	-2.22×10^{-16}
Technology equipment	−1	−1	−1	−0.92	0.2	−1	−1	1	−1	0.28	1	−0.04
Infrastructure	−0.9747	−0.9241	−0.7215	−0.2405	−0.6962	−1	−0.8734	−0.3924	−0.8987	−0.1139	−0.3671	1
Water consumption	−0.9914	−0.9741	−0.9948	−0.6190	−1	1	−0.9828	−0.7017	0.88975	−0.9948	−0.9362	−1
Water pollution	1	1	1	1	1	1	1	1	1	1	1	1
Air pollution	1	1	1	1	1	1	1	1	1	1	1	1
CO_2/CH_4 emissions	−1	−1	−1	−1	1	1	−1	1	−1	1	−1	−1
Other damage	1	1	1	1	1	1	1	1	1	1	1	1
Industrial standards	−1	0.0667	−0.4667	0.73333	−0.0667	1	0.0667	1	0.6	0.6	0.3333	0.06667
Preferential policies	1	1	1	1	1	1	1	1	1	1	1	1
Long-term planning	−1	−1	−1	−1	1	1	−1	1	1	−1	1	1
Risk score	0.6	1	0.6	1	0.2	1	0.6	−0.2	0.6	0.2	−1	−1

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