36

41

46

48

Fuzzy mathematics and machine learning algorithms application in educational quality evaluation model

- Jian Wang^{a,*} and Weizhong Zhang^b
- ^a Quzhou College of Technology, Quzhou, China
- ⁶ bZhejiang Normal University, Zhejiang, China

Abstract. Teaching quality evaluation is a complex non-linear system fitting problem under the influence of many factors. The establishment of teaching quality evaluation is to construct a functional relationship between teaching quality evaluation index and teaching effect. In this paper, the authors analyze the fuzzy mathematics and machine learning algorithms application in educational quality evaluation model. Machine learning method has been well applied in complex problems such as classification, fitting, pattern recognition and so on. It can be used to realize a more comprehensive, reasonable and effective evaluation of the classroom teaching quality of university teachers. The simulation results show that the model can well express the complex relationship between the teaching quality evaluation index and the evaluation results. The theoretical values of the evaluation results are in the corresponding confidence interval, which proves that the machine learning algorithm has good reliability for different teaching quality evaluation problems.

Keywords: Fuzzy mathematics, precision contrast, machine learning algorithms, education quality

1. Introduction

8

10

11

12

13

15

18

19

20

23

24

25

27

28

30

31

Teaching is the foundation of a university, and classroom teaching is the most important, core and essential part of teaching, and the main position of personnel training. Reasonable evaluation of classroom teaching quality is a powerful guarantee to improve teaching quality and teaching management level. In order to accurately evaluate the effect of classroom teaching, a reliable evaluation model of teaching quality must be established [1]. However, because teaching includes the dynamic process of teaching and learning, there are many factors affecting the quality of teaching, and the influence degree of these factors on the quality of teaching is different, and there is a complex non-linear relationship

between the evaluation index and the teaching effect, so it is difficult to construct an accurate and reliable mathematical model for the evaluation of teaching quality. Therefore, the construction of mathematical model of teaching quality evaluation has become a hot research topic. The establishment of teaching quality evaluation is to construct the functional relationship between teaching quality evaluation index and teaching effect [2, 3]. At present, there are many methods to evaluate the quality of classroom teaching, such as absolute evaluation, evaluation, relative evaluation, grammar evaluation and comprehensive evaluation. These methods are simple to operate, but they are too subjective. There is a big difference between the evaluation results of these methods and the real situation of teaching quality. In recent years, intelligent algorithms such as fuzzy clustering analysis, grey correlation method, neural network algorithm and support vector machine have been applied to the

^{*}Corresponding author. Jian Wang, Quzhou College of Technology, Quzhou, China. E-mail: wangjian0390@163.com.

52

53

56

57

58

59

61

62

63

64

65

66

67

68

69

70

71

72

73

74

75

76

77

78

79

80

81

82

83

85

86

87

88

90

91

92

93

96

97

98

99

100

101

102

evaluation of teaching quality and achieved certain results. However, the stability of these algorithms needs to be improved, and the reliability of the analysis results can not be achieved [4]. Therefore, how to construct a new teaching quality evaluation model with little subjective influence, high reliability and self-adaptive model parameters has become the current research trend and difficulty. Gauss process (GP) is a new machine learning method based on Gauss and Bayesian learning theory in recent years. Gauss process is a probabilistic kernel learning machine. The algorithm can obtain both the results and the uncertain data. Therefore, the algorithm has been well applied in complex problems such as classification, fitting, pattern recognition and so on. There is no relevant research in the research of teaching quality evaluation. In view of the advantages of GP algorithm and the characteristics of teaching quality evaluation, the application of GP algorithm to achieve a more comprehensive, reasonable and effective evaluation of classroom teaching quality of university teachers is of positive significance to promote the continuous improvement of teaching level and school teaching quality [5, 6].

All along, China has paid more attention to the construction and management of information technology in colleges and universities. In June 1992, in order to strengthen the construction and management of information technology in higher education institutions, ensure the quality of education and scientific research in schools, and improve the efficiency of running schools, the National Education Commission issued the No. 20 Order to give the informatization work procedures for higher education institutions. With the rapid development of China's higher education in these years, the enrollment scale of higher education institutions is constantly expanding, and the construction and management of information technology is becoming more and more important [2]. In 2003, the letter from the Ministry of Education gave the evaluation criteria for professional informatization in higher education institutions (for trial implementation) and emphasized the construction and management of information technology. As an important part of China's higher education, colleges and universities now occupy half of China's higher education. In order to standardize high education information construction and management, make information construction more scientific, and enable the informatization to be built more efficiently and reasonably, it is necessary to carry out systematic performance evaluation of information [7].

The performance evaluation of basic education informatization has become a realistic problem that needs to be studied. Performance appraisal can enable the education management department to have a correct grasp of the future technological development level and its changing trend, thus providing a scientific basis for the basic education information decision-making and reducing the subjectivity and blindness in the basic education informatization decision-making process. Therefore, only under the premise of correctly grasping the direction of technological innovation, the basic education informatization work can develop in the right direction.

103

104

105

106

108

109

110

111

113

114

115

116

117

118

119

120

121

122

123

124

125

126

127

128

129

131

132

133

134

135

136

137

138

139

142

143

144

145

147

148

149

150

151

The main contribution of this paper is analyzed the fuzzy mathematics and machine learning algorithms application in educational quality evaluation model. Machine learning method has been well applied in complex problems such as classification, fitting, pattern recognition and so on. It can be used to realize a more comprehensive, reasonable and effective evaluation of the classroom teaching quality of university teachers. The simulation results show that the model can well express the complex relationship between the teaching quality evaluation index and the evaluation results.

This paper is organized as follows: The related work is introduced in Section II. BP neural network structure was in section III. Fuzzy comprehensive evaluation method designed was in section IV. Parameter processing and model simulation results was in section V. Results evaluation was in section VI Finally, Conclusions are given in Section VII.

2. Related work

The evolution of foreign performance evaluation methods can be summarized into three stages. The first is the cost performance evaluation orientation period, the second phase is the financial performance evaluation orientation period, and the final stage is the innovation performance evaluation orientation period [8]. The period from the early nineteenth century to the beginning of the twentieth century was a period of cost performance orientation, and cost became the only evaluation criterion for measuring performance. Later, along with the need for management and the standard cost system proposed by Hari in 1911, the cost performance evaluation orientation was influenced by the standard cost system and achieved new development. The analysis of the difference between the actual cost and the standard cost during this

206

207

210

211

212

213

216

217

218

219

220

222

223

224

225

226

227

228

229

230

231

233

234

235

236

237

239

240

241

242

243

245

246

247

248

249

251

252

253

254

255

256

period and the implementation level of the standard cost become the main performance evaluation indicators. From the beginning of the 20th century to the 1990 s, it was the period of financial performance evaluation. During this period, financial indicators became the key to evaluating performance [9]. At the beginning of the twentieth century, DuPont built and applied a financial performance evaluation indicator system based on the needs of production management. This is also known as the DuPont financial analysis system, which decomposes financial performance evaluation indicators into asset turnover rate and sales profit rate [10]. Alexandra Wall proposes to use the consolidated financial ratio to evaluate the company's operating status and ability to pay. It consists of seven sub-financial indicators, including fixed asset turnover, current ratio, inventory turnover, etc. [11]. In the 1930 s, based on pure financial indicators, James McKinsey proposed comprehensive indicators based on strategic factors, financial status, business activities and management factors, which made the financial performance evaluation indicators more comprehensive. Based on the qualitative analysis, Jackson Mading added indicators such as organizational structure and enterprise value, which further expanded the scope of indicators and constructed a comprehensive performance evaluation index system [12]. In the twentieth century, based on the performance analysis of more than 30 multinational companies, Melnnes put forward the idea that performance evaluation should be based on the return on investment performance. Subsequently, Parson and Laixig proposed two other important financial indicators, namely operating profit and cash flow. The third stage since the 1990 s is the period of innovation performance evaluation. During this period, performance evaluation has achieved rapid development, and performance evaluation has developed toward comprehensive performance evaluation. At the same time, the original cost indicators and financial indicators can no longer meet the needs of enterprises, and no longer adapt to the rapid development of the economic environment, which is also an important turning point in the development of performance evaluation to performance management [13].

153

154

155

156

157

158

150

160

161

163

164

165

166

167

168

169

170

171

172

173

174

175

176

177

178

179

180

181

182

183

184

185

187

188

189

190

191

192

193

194

195

196

197

198

199

200

201

202

204

The content of performance evaluation has gone through a process from one dimension to multiple dimensions. The earliest performance evaluation values focus on the results, and only a certain quantitative indicator is used to determine the level of performance. Representatives of this stage are Mondi et al., and they use the results of individual or group

work as the sole criterion and believe that performance evaluation is to regularly review and evaluate it [14]. As productivity increases, so does the level of work, and there is more and more collaborative work between employees. People realize that only work results do not reflect the performance of employees or organizations. At the same time, the content of performance evaluation has also begun to expand to multiple dimensions, such as employees' work attitudes and behaviors. Such as A. Longsner believes that performance evaluation should consider the employee's work ability, work status, work adaptability, and consider its value to the organization; Motowadelo and Bauman (1993), while considering the impact of job outcomes on performance evaluation, also began to consider the impact of peripheral factors on performance, such as employees' spontaneous behavior or specific behaviors [15]; Flippo believes that performance evaluation should consider employee personality, work attitude, work results, and from multiple dimensions [16]. Since then, the content of performance evaluation has begun to have a new feature, namely performance management. It began to focus on the application of the evaluation process in HR rather than just focusing on how to get accurate performance evaluation results. Matsuda Kenji believes that performance evaluation is an important part of human resource management, and performance evaluation needs to achieve the purpose of cultivating, guiding and motivating employees through evaluation of employees.

Regarding the method of performance evaluation, foreign scholars have conducted a large number of systematic research, and many methods have been widely used in practice. Baras and Flanagan propose a key event technology approach. That is, by determining the critical time in the employee's work and the evaluation of the critical time determine the employee's performance level. Peter Drueker put forward the famous goal management theory, that is, to achieve the performance level of employees or organizations through the achievement of goals [17]. Robert S. Kaplan and David P. Norton (1992) proposed the Balanced Scorecard (BSC), which proposes to evaluate the performance level of the firm from the perspectives of finance, customers, internal processes, learning and development [18]. Needly (2000) proposed a performance prism approach that includes five dimensions: competence, process, strategy, stakeholder contribution, and satisfaction. In addition, there is a behavioral anchor rating method [19].

258

259

260

262

263

264

265

266

267

269

270

271

272

274

276

277

278

279

282

283

284

285

287

288

289

290

291

292

293

294

295

296

297

298

299

Peng Zhenglong and Sun Hongguang proposed the evaluation of employee performance based on the Analytic Hierarchy Process (AHP) combined with the Fuzzy Comprehensive Method in the article "Research and Application of Enterprise Employee Performance Evaluation Methods". The analytic hierarchy process determines the index weights, and the fuzzy comprehensive method quantifies the indicators and systematically synthesizes them to comprehensively examine and rank the performance levels of employees [20]. Liu Renhuai and Wang Xuegong systematically analyzed the performance evaluation system of a multinational company, analyzed its advantages and disadvantages, and pointed out its reference significance for the construction of performance evaluation system for Chinese enterprises [21-24].

3. Theoretical analysis

3.1. BP neural network structure

BP neural network is a neural network composed of a large number of neurons. The basic characteristics are: nonlinear, distributed storage, fault tolerance, parallel processing and self-organization, and adaptive characteristics. There are dozens of neural network models available, but the existing neural networks can be divided into four categories: forward neural network model, feedback network model, self-organizing network model and mutual network model. The BP neural network is a multilayer feedforward neural network, which includes an input layer, an output layer, and an implicit layer. The neurons on each layer are called nodes or units. In the design of BP network topology, the number of hidden layers and the number of nodes in the hidden layer should be considered. A typical BP neural network structure is shown in Fig. 1. Signal transmission in BP networks includes two aspects: forward propagation of signals and back propagation of errors. That is, the actual output is calculated from the input to the output direction, and the weight and threshold are corrected from the output to the input direction [25].

3.2. Description of BP neural network mathematical model

The three-layer BP neural network is taken as an example for derivation analysis. The first is the forward propagation of the signal, and *net_i* represents

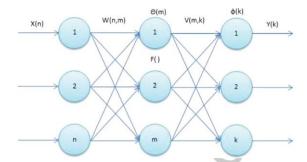


Fig. 1. BP neural network structure topology.

the node of the hidden layer, the input of which is shown below.

$$net_i = \sum_{i=1}^{M} w_{ij} x_j + \theta_i \tag{1}$$

 y_i represents the node output of the hidden layer, which can be expressed as:

$$y_i = \phi(net_i) = \phi\left(\sum_{i=1}^M w_{ij}x_j + \theta_i\right)$$
 (2)

The output layer node can be represented as net_i , and its calculation formula is:

$$net_i = \sum_{i=1}^q w_{ki} y_j + a_k$$

$$= \sum_{i=1}^q w_{ki} \phi \left(\sum_{i=1}^M w_{ij} x_j + \theta_i \right) + a_k$$
 (3)

The node output of the output layer is expressed as o_k , and its calculation formula is:

$$o_{k} = \psi (net_{i}) = \psi \sum_{i=1}^{q} w_{ki} y_{j} + a_{k}$$

$$= \psi \sum_{i=1}^{q} w_{ki} \phi \left(\sum_{i=1}^{M} w_{ij} x_{j} + \theta_{i} \right) + a_{k}$$
 (4)

The weights and thresholds of the layers are adjusted according to the error so that the modified network output can approach the expected value [26].

The error function of the p-th sample can be expressed as E_p , and its expression is as follows:

$$E_p = \frac{1}{2} \sum_{k=1}^{L} (T_k - o_k)^2$$
 (5)

301

304

The expression of the total error function E of the network training samples is as follows:

$$E = \frac{1}{2} \sum_{p=1}^{P} \sum_{k=1}^{L} (T_k^p - o_k^p)^2$$
 (6)

 Δw_{ki} indicates correction of the output layer weight, Δa_k indicates the modified output layer threshold, Δw_{ij} indicates the hidden layer weight, and $\Delta \theta_i$ indicates the modified hidden layer threshold. The above parameter expressions can be expressed as follows:

$$\Delta w_{ki} = -\eta \frac{\partial E}{\partial w_{ki}} \tag{7}$$

$$\Delta a_k = -\eta \frac{\partial E}{\partial a_k} \tag{8}$$

$$\Delta w_{ij} = -\eta \frac{\partial E}{\partial w_{ij}} \tag{9}$$

$$\Delta \theta_i = -\eta \frac{\partial E}{\partial w_{i}} \tag{10}$$

After derivation, the following formula is obtained:

$$\Delta w_{ki} = \eta \sum_{p=1}^{P} \sum_{k=1}^{L} (T_k^p - o_k^p) \psi' net_k y_i$$
 (11)

$$\Delta a_k = \eta \sum_{p=1}^P \sum_{k=1}^L \left(T_k^p - o_k^p \right) \psi' net_k \qquad (12)$$

$$\Delta w_{ij} = \eta \sum_{p=1}^{P} \sum_{k=1}^{L} \left(T_k^p - o_k^p \right) \psi' net_k w_{ki} \phi' (net_i) x_j$$
(13)

$$\Delta\theta_{i} = \eta \sum_{p=1}^{P} \sum_{k=1}^{L} \left(T_{k}^{p} - o_{k}^{p} \right) \psi' net_{k} w_{ki} \phi' (net_{i})$$
(14)

The error signal can be expressed as:

$$\delta_{pk} = \frac{\partial E_p}{\partial net_{pk}} = -\frac{\partial E_p}{\partial o_{pk}} \frac{\partial o_{pk}}{\partial net_{pk}}$$
(15)

$$\delta'_{pj} = o'_{pj} \left(1 - o'_{pj} \right) \sum_{k} \delta_{pk} w_{jk}$$
 (16)

The response function of network training generally adopts the Sigmoid function, which has certain

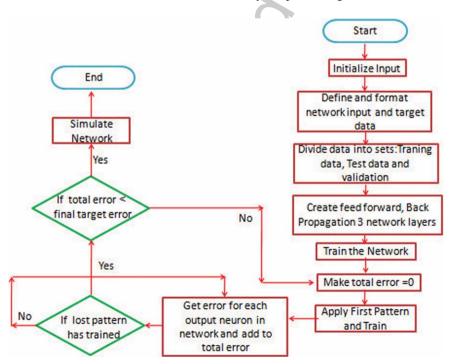


Fig. 2. Flow chart of the BP algorithm program.

306

307

308

310

311

312

313

315

316

317

318

319

320

321

322

323

324

325

326

327

328

330

331

332

333

334

336

337

338

339

341

342

343

344

345

347

348

349

350

351

352

353

threshold characteristics and can be continuously guided. Then, according to the Sigmoid function, the error of the output layer unit and the hidden layer unit can be obtained, and finally the adjusted connection weight and threshold are obtained. The BP algorithm program flow is shown in Fig. 3.2 The BP algorithm is an algorithm often used in neural network training. It is one of the most mature training algorithms for neural networks. At the same time, the BP algorithm has several advantages, the algorithm is simple, the calculation is small, the operation is convenient, and it has strong parallelism [27].

4. Model building

Traditional evaluation methods such as fuzzy comprehensive evaluation method, analytic hierarchy process (AHP) and grey clustering method have human factors. Through the multi-index evaluation method based on neural network, the basic education informatization performance tracking evaluation model is established, and the pre-processed data is input into the set network, and the result can be calculated. This evaluation method is faster and has the following advantages: (1) The BP algorithm has an adaptive function. It finds the intrinsic connection between output and input through training and learning according to the provided data and obtains the solution of the problem. (2) It can handle noisy or incomplete data and has generalization function and strong fault tolerance. (3) In the actual comprehensive evaluation, each factor interacts with each other and exhibits a very complex nonlinear relationship. BP neural network can provide powerful help for dealing with such nonlinear problems. (4) The BP neural network evaluation method does not rely on the empirical knowledge and rules of the problem, reduces the distortion of the results caused by subjective factors in the evaluation process, and the evaluation results obtained are more objective, effective and reliable. Compared with other comprehensive evaluation methods, the comprehensive evaluation method based on BP neural network shows its unique superiority, so it is applied more and more widely in performance evaluation [28].

The key to constructing the BP network model is how to reasonably select the number of hidden layers and determine the number of neurons in the input layer, the hidden layer and the output layer. There are 16 indicators for basic education informatization performance evaluation. Therefore, the number of input layer neurons is (m = 16), and the number of neurons in the output layer (n = 1) is the performance evaluation result. The number of hidden layers should not be too much, and generally one layer is set, which can reduce the network scale and control the training time. At the same time, the selection of the number of neurons in the hidden layer of the BP network should be cautious. If the number of neurons is too small, the network learning accuracy is low, the curve fitting is poor, and the training time is increased. Generally, the more the number of neurons in the hidden layer, the higher the learning accuracy, but the poorer the ability of the network to apply to the unlearned input. In addition, if the number of neurons in the hidden layer is too large, it will increase the training time, and it will cause uncoordinated fitting and lower precision.

354

355

356

357

350

360

361

362

366

367

368

369

370

371

372

373

374

376

377

378

379

380

382

383

384

385

386

388

390

391

392

393

The range of values of neurons in the hidden layer is $L = \sqrt{m+n} + a$, $a \in [0, 10]$ or $\frac{m+n}{2}$. Among them, m is the number of neurons input and n is the number of neurons output. According to the above empirical formula and combined with the content of the research in this paper, the number of hidden layer neurons used for identification can be selected as 5. The BP neural network structure of the basic education informatization performance evaluation index is shown in the figure below.

The attribute value of the evaluation index of the multi-objective comprehensive evaluation is normalized, and the normalized value constitutes the input vector, which is used as the input of the BP network, and the evaluation result is used as the output of the BP network. After that, using a large amount of sample data for training, the BP network can obtain the experience, knowledge, subjective judgment of the evaluation expert and its tendency to importance to the indicator. Thus, the set of weight coefficient values of the trained BP network model is the internal representation of the correct knowledge obtained by the network through adaptive learning. Finally, after the attribute values of the indicators to be evaluated

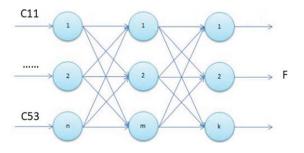


Fig. 3. BP network model for performance evaluation.

are input to the trained BP network, an evaluation index for the evaluation object is obtained. In this way, the expert's experience, knowledge, subjective judgment and its tendency to the importance of the indicator can be reproduced, and the effective combination of qualitative and quantitative can be realized, and the objectivity and consistency of the evaluation can be guaranteed.

5. Model simulation

5.1. Parameter processing

(1) Normalized processing

Normalization has a common method of data processing, such as modeling calculations. First, the basic unit of measurement is unified. The neural network is based on the statistical probability of the sample in the event (probability calculation) and prediction. The normalization is the statistical probability distribution unified between [0, 1]. When the input of all samples is positive, the weights of the input layer and the first hidden layer neurons are either increased at the same time or decreased together, which makes the learning speed of the BP neural network very slow. Therefore, the normalization of the input signal can avoid the situation that the learning speed is very slow and achieve faster network learning speed. The normalization process is to make the input signal of all samples have a mean value close to zero or small compared to their mean square error.

Normalization accelerates the convergence of the training network. The reason for normalization is that the value of the Sigmoid function is between 0 and 1 and the output of the last node of the network is also true. Therefore, it is often necessary to normalize the output of the sample.

(2) Initial value determination

The BP network is a nonlinear system. The initial weight selection is related to whether the learning accuracy reaches the local minimum, whether the function can converge, and the length of training time required. Therefore, in actual work, if the output value of each neuron after initial weighting can be made close to zero, it can be ensured that the weight of each neuron can be adjusted where the Sigmoid excitation function changes the most. If the initial value is too large and f'(x) is very small, it will cause the weighted input to enter the saturation region of the excitation function. If the correction value d of the weight is proportional to f'(x) and $f'(x) \to 0$, then

 $d \rightarrow 0$, which will cause the adjustment to almost come to a standstill. Therefore, in this paper, the initial weight of the BP network is preset between [0–0.1], and the overall maximum value is 0.1 At the same time, the initial threshold is set to be between [0–0.2], which can avoid the difficulty of convergence due to the initial weight and threshold setting being too large. The weights and thresholds are saved in separate files, and each time training is performed, the weights and thresholds can be derived directly from the file for training. After that, initialization is not required, and the weights and thresholds after training are imported directly into the file. However, if the convergence speed is too slow, you need to reset the weights and thresholds.

(3) Input matrix design

The performance appraisal indicator system in the performance evaluation of basic education informatization is divided into five first-level indicators, including information planning and management, infrastructure construction, teaching resources, informatization talents, and teaching applications and it contains 16 secondary indicators. The third chapter has discussed how to determine the weight of the evaluation indicators by AHP. The attribute value of an index of the object to be evaluated is divided into 10 levels, which are 1, 2, 3, 4, 5, 6, 7, 8, 9, and 10. The membership function method is used to normalize the index attribute values, and the corresponding membership degrees are 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, and 1, thus constructing the hierarchical membership matrix of the evaluation index. Then, based on the weight vector and the hierarchical membership matrix, the training sample input matrix of the BP network for calculating the evaluation index can be obtained. The training sample input matrix is shown in Table 1.

Table 1 Input matrix (partial)

		*		
Grade	C11	C23	C41	C53
10	0.0725	0.1423	0.0457	0.0397
9	0.0652	0.1281	0.0411	0.0357
8	0.0580	0.1139	0.0365	0.0318
7	0.0507	0.0996	0.0320	0.0278
6	0.0435	0.0854	0.0274	0.0238
5	0.0362	0.0712	0.0228	0.0199
4	0.0290	0.0569	0.0183	0.0161
3	0.0217	0.0427	0.0137	0.0119
2	0.0145	0.0395	0.0091	0.0080
1	0.0072	0.0142	0.0046	0.0040
Weights	0.0725	0.1423	0.0457	0.0397

Table 2
Comparison of the output of the basic education informatization performance evaluation training sample

The actual measured value	The test value
0.7121	0.721

5.2. Network simulation implementation

The first step is to build a trainable feedforward network. Newff is a function used to build a trainable feedforward network. The new line uses four input parameters: parameter one is the minimum and maximum values of R input vectors; parameter two is an array of the number of neurons per layer; parameter three is the array of transfer function names used by each layer and parameter four is the name of the training function used.

The second step is to initialize the weights. The command init is used to implement network initialization. After the weights and deviations of the network are initialized, the network can begin training.

The third step is network training. 利 Training of BP network is realized by training function train. The train function completes the training process of the BP network based on the preset training parameters, the input vector P of the sample, and the target vector T. The first, second, third, fourth, fifth, sixth, eighth, ninth, and tenth index levels in Table 4.1 were used as sample data for network training, and the seventh indicator level was used for testing. After the end of the training, the seventh indicator level data is selected for numerical test, and the network outputs the test value to verify the simulation accuracy. The network generalization results are shown in Table 2. Obviously, the BP neural network model has high precision, and the BP neural network model is feasible for performance evaluation of basic education informatization.

The fourth step is network simulation. The sim function is used to simulate the BP network. After the data is simulated and calculated, the data is input and tested after the third step of the trained network.

5.3. Case analysis

(1) Input variables

The input variable is also the second-level evaluation index of basic education informatization, which contains a total of 16. They are organization, rules and regulations, development planning, vari-

Table 3 Standards for performance evaluation

Interval	F rating	Result
[0.9,1)	1	Excellent
[0.7,0.9)	2	Good
[0.6,0.7)	3	Qualified
[0.5,0.6)	4	Basically qualified
(0.0.5)	5	Unqualified

ous types of information function rooms, network construction, computer numbers, multimedia class-rooms, digital resource libraries, multimedia software and courseware, e-books, information management talents, information technology teachers, and general teachers, information application capabilities, information technology courses, modern educational technology applications in other disciplines, and information technology research projects.

(2) Output variable

The output variable is also the performance level variable of the basic education informatization. The output vector of the network is represented by F, and the value range of F is [0, 1]. If the output is 0 or 1, the original data is incorrect, and the level of performance is represented by the magnitude of the value between 0-1. Starting from the practicability and ease of operation, the criteria for basic education informatization performance evaluation are divided into five levels, namely, level 1 is excellent, level 2 is good, level 3 is qualified, level 4 is basically qualified, and level 5 is unqualified. The specific ranges of the network output vectors representing the five levels are shown in Table 3.

(3) Normalized processing

This paper selects 20 different levels of colleges, numbered 1, 2, 3,..., 20. Questionnaires were issued and data on their educational informatization were collected according to the scoring rules established in Chapter 3. The normalized data is shown in Table 4.

The data of the 16 evaluation indicators after normalization is used as the BP neural network input vector for basic education informatization performance evaluation. After that, through the training of the BP neural network model trained in the previous article, the network output result can be obtained. The comparison of the output results with the weighted average is shown in Table 5.

According to the above output, the statistical results of 20 schools can be drawn into a statistical chart, and the results are shown in Fig. 4.

The weighted average is plotted as a chart and the results are shown in Fig. 5.

565

567

568

569

570

571

572

574

575

576

577

578

579

580

581

582

583

584

585

Table 4 Normalized data (partial)

			_		
	1	2	3	4	5
C11	0.743	0.523	0.836	0.958	0.979
C12	0.567	0.553	0.658	0.547	0.626
C13	0.801	1.023	0.777	0.846	0.511
C21	0.742	0.856	0.694	0.748	0.568
C22	0.781	0.615	0.857	0.862	0.827
C23	0.765	0.902	0.416	0.769	0.432
C24	0.901	0.796	0.932	0.913	0.768
C31	0.470	0.744	0.799	0.663	0.438
C32	0.870	0.670	0.614	0.564	0.554
C33	0.870	0.521	0.579	0.664	0.870
C41	0.922	0.870	0.841	0.941	0.554
C42	0.591	0.885	0.767	0.849	0.959
C43	0.671	0.857	0.723	0.843	0.825
C51	0.480	0.823	0.648	0.516	0.527
C52	0.653	0.796	0.973	0.836	0.825
C51	0.528	0.666	0.535	0.919	0.878

Table 5
Comparison of output result and weighted average

	F	Weighted average	Relative error
1	0.8066	0.7996	0.91%
2	0.6942	0.6779	2.48%
3	0.9082	0.8976	1.21%
4	0.9283	0.9069	2.43%
5	0.9534	0.9243	3.23%
6	0.6620	0.6715	-1.45%
7	0.6943	0.6922	0.32%
8	0.4945	0.5194	-4.94%
9	0.7732	0.7686	1.82%
10	0.8190	0.8362	-2.12%
11	0.8255	0.8147	1.37%
12	0.8164	0.8410	-3.02%
13	0.6909	0.6788	1.84%
14	0.8048	0.8226	-2.21%
15	0.6080	0.5966	1.98%
16	0.6307	0.6412	-1.53%
17	0.8667	0.6978	-2.94%
18	0.6558	0.8876	-2.41%
19	0.6558	0.6708	-2.31%
20	0.8191	0.8119	0.91%

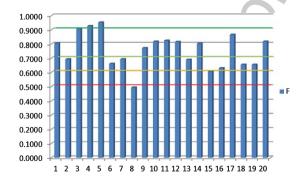


Fig. 4. Distribution profile of performance evaluation.

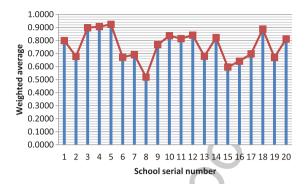


Fig. 5. Statistical graph of weighted average.

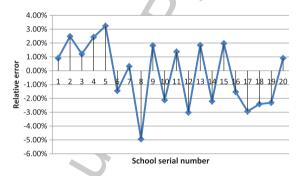


Fig. 6. Statistical graph of relative error.

The relative error is plotted as a chart, and the result is shown in Fig. 6.

Using BP neural network model, the survey data is input into the trained BP neural network to obtain the test result output value. Combining the knowledge and experience of experts, and using the AHP, the weights of the evaluation indicators of the basic education informatization are obtained, and the weighted average of the survey data is obtained, and then compared. As can be seen from Table 5 and Figs. 4–6, the ordering of the two evaluations did not change. This shows that the BP neural network using MATLAB shows high stability in the performance evaluation of basic education informatization, and the result has high reference value. At the same time, the relative error of the results of the evaluation is very small, and none of them exceeds 5%.

6. Analysis of results

By analyzing the influencing factors of basic education informatization performance, combined with the literature research on the basic education informatization performance evaluation, a set of evaluation

587

588

589

591

502

593

594

595

596

597

598

599

600

601

602

603

604

605

606

607

608

609

610

611

612

613

614

615

616

617

618

620

621

622

623

624

625

626

627

628

629

630

631

632

633

634

basic education informatization performance index system in line with China's national conditions is constructed. At the same time, this paper determines the scoring rules of each indicator of performance evaluation, the consultation form of design indicator weight, and calculates the weight of evaluation index based on the collected data. Moreover, the improved BP neural network is applied to the performance evaluation of basic education informatization, and the evaluation model is constructed. In addition, using MATLAB toolbox, the modeling and simulation of basic education informatization performance evaluation based on improved BP algorithm is completed. Finally, the evaluation index is taken as a sample, and the BP neural network is trained, and the trained network is used for case evaluation. The results prove the accuracy and feasibility of the BP neural network performance evaluation method and can provide an important reference for education management decision-making. Of course, since the basic education informatization is a complex system, there are objective differences in the basic education departments of different types, levels, and regions. This paper attempts to use a set of fixed performance evaluation index system to evaluate the information operation performance of the entire basic education department, which has certain subjectivity in the process of setting indicators. These issues are worthy of further study in the future.

This paper focuses on the modeling and implementation of education informatization performance evaluation based on MATLAB. At the same time, the BP neural network learning training toolbox of MAT-LAB is introduced, and the BP network modeling of basic education informatization performance evaluation is completed, the BP network algorithm flow for performance evaluation is given, and the performance evaluation of basic education informatization based on improved BP algorithm is realized. Finally, the model was trained and tested through survey data. The error of test results is within 5%, and the evaluation results have high reference value. It proves that BP artificial neural network based on MATLAB has high stability for performance evaluation of basic education informatization.

7. Conclusion

This paper focuses on the modeling and implementation of educational informatization performance evaluation based on BP neural network tools based on MATLAB. Combined with the content of this study,

the number of hidden layer neurons used for identification can be selected as 5. At the same time, by analyzing the influencing factors of basic education informatization performance, combined with the literature research on the basic education informatization performance evaluation, a set of evaluation basic education informatization performance index system is established. The BP neural network of the performance evaluation index of basic education information normalizes the attribute value of the evaluation index of multi-objective comprehensive evaluation. Moreover, the normalized value constitutes the input vector as the input of the BP network, and the evaluation result is used as the output of the BP network to achieve an effective combination of qualitative and quantitative, and to ensure the objectivity and consistency of the evaluation. In addition, by building a simulation model, data is collected for model simulation runs. The results show that the BP neural network using MATLAB shows high stability in the performance evaluation of basic education informatization, and the result has high reference value. Moreover, the relative error of the results of the evaluation was very small and did not exceed 5%. Therefore, through simulation research, we can know that this research model can be used for the evaluation of college education informatization performance and can provide theoretical reference for subsequent related research.

635

636

637

638

640

641

642

643

645

646

647

648

649

650

652

653

654

655

656

657

658

659

660

661

663

665

666

667

669

670

671

672

673

674

675

676

677

678

679

Acknowledgment

(1) The First Group of Teaching Reform Projects in the 13th Five-Year Plan of Universities in Zhejiang Province, China (2018); Construction and Practice of General Education System in Higher Vocational Education from the Perspective of International Major's Certification (jg20180730); (2) Special planning subject for Institute of vocational education of Quzhou College of Technology (2017); The construction and practice of general education system in Higher Vocational Colleges(VER201701); (3) Project fund for the humanities and social science research of the Ministry of education (2015); National Mathematics and mathematics curriculum reform(15YJA880107).

References

 S. Pereira, A. Pinto, V. Alves, et al., Brain Tumor Segmentation Using Convolutional Neural Networks in MRI Images, *IEEE Transactions on Medical Imaging* 35(5) (2016), 1-1.

732

733

734

735

736

737

738

739

741

742

743

744

745

746

747

748

749

750

751

752

753

754

755

756

757

758

759

760

761

762

763

764

765

766

767

768

770

771

772

773

774

775

776

777

778

[2] A. Dosovitskiy, P. Fischer, J.T. Springenberg, et al., Discriminative Unsupervised Feature Learning with Exemplar Convolutional Neural Networks, *IEEE Transactions on Pattern Analysis & Machine Intelligence* (2016).

682

683 684

685

686

687

688

689

690

691

692

693

694

695

696

697

698

699

700

701

702

703

704

705

706

707

708

709

710

711

712

713

714

715

716

717

718

719

720

721

722

723

724

725

726

727

728

729

730

- [3] S.J. Nowlan and G.E. Hinton, Simplifying Neural Networks by Soft Weight-Sharing, *Neural Computation* 4(4) (1992), 473–493.
- [4] J. Zhang, L. Duan, J. Guo, et al., A Genetic Algorithm-based BP Neural Network Method for Operational Performance Assessment of ATC Sector, *Promet* 28(6) (2016).
- [5] L.L. Peng, A service innovation evaluation framework for tourism e-commerce in China based on BP neural network, *Electronic Markets* 24(1) (2014), 37–46.
- [6] J. Yosinski, J. Clune and Y. Bengio, et al., How transferable are features in deep neural networks? *Eprint Arxiv* 27 (2014), 3320–3328.
- [7] N. Srivastava, G. Hinton, A. Krizhevsky, et al., Dropout: A Simple Way to Prevent Neural Networks from Overfitting, *Journal of Machine Learning Research* 15(1) (2014), 1929–1958.
- [8] D. Silver A. Huang, C.J. Maddison, et al., Mastering the game of Go with deep neural networks and tree search, Nature.
- [9] S. Han, H. Mao and W.J. Dally, Deep Compression: Compressing Deep Neural Networks with Pruning, *Trained Quantization and Huffman Coding*, Fiber 56(4) (2015), 3–7.
- [10] A.K. Jain, J. Mao, K.M. Mohiuddin, Artificial neural networks: a tutorial, *Computer* 29(3) (1996), 31–44.
- [11] Y. Ganin, E. Ustinova and H. Ajakan, et al., Domain-Adversarial Training of Neural Networks, *Journal of Machine Learning Research* 17(1) (2015), 2096–2030.
- [12] T.N. Sainath, B. Kingsbury, G. Saon, et al., Deep Convolutional Neural Networks for Large-scale Speech Tasks, Neural Networks (2014), 64.
- [13] S. Zhang, B. Wang, X. Li, et al., Research and Application of Improved Gas Concentration Prediction Model Based on Grey Theory and BP Neural Network in Digital Mine, *Procedia CIRP* 56(Complete) (2016), 471–475.
- [14] J.Y. Li, Bp Neural Network Optimized by PSO and its Application in Function Approximation, Advanced Materials Research 945–949 (2014), 4.
- [15] S. Gholami-Boroujeny, A. Fallatah, B.P. Heffernan, et al., Neural network-based adaptive noise cancellation for enhancement of speech auditory brainstem responses, *Signal, Image and Video Processing* **10**(2) (2016), 389–395.
- [16] J. Li, J. Feng, W. Wang, et al., Spatial and Temporal Changes in Solar Radiation of Northwest China Based LM-BP Neural Network, *Scientia Geographica Sinica* 36(5) (2016), 780–786.

- [17] S. Gupta, A. Saxena and B.P. Soni, Optimal Placement Strategy of Distributed Generators based on Radial Basis Function Neural Network in Distribution Networks, *Proce-dia Computer Science* 57 (2015), 249–257.
- [18] J. Zhou, Q. Wang, M. Yi, et al., Acoustic emission signal recognition based on wavelet transform and RBF neural network, *Journal of Qingdao University of Science & Technology* 8(3) (2015), 80–85.
- [19] S.M. He and L.W. Liu, Using the Improved Genetic BP Neural Network Algorithm for Lithologic Identification, Advanced Materials Research 1037 (2014), 4.
- [20] P. Roy, G.S. Mahapatra and K.N. Dey, An Efficient Particle Swarm Optimization-Based Neural Network Approach for Software Reliability Assessment, *International Journal of Reliability, Quality and Safety Engineering* 24(04) (2017), 1750019.
- [21] Y. Fei and D. Wen-Bo, Particle swarm optimization-based automatic parameter selection for deep neural networks and its applications in large-scale and high-dimensional data, *Plos One* **12**(12) (2017), e0188746.
- [22] J. Dai Z. Ji and Y. Du, The research of near-infrared blood glucose measurement using particle swarm optimization and artificial neural network, *Journal of Biomedical Engi*neering 34(5) (2017), 713.
- [23] H. Sadeghzadeh, M.A. Ehyaei and M.A. Rosen, Technoeconomic optimization of a shell and tube heat exchanger by genetic and particle swarm algorithms, *Energy Conversion* and Management 93 (2015), 84–91.
- [24] N.N. El-Emam, New data-hiding algorithm based on adaptive neural networks with modified particle swarm optimization, *Computers & Security* 55 (2015), 21–45.
- [25] S. Martin and C. Choi, Nonlinear Electrical Impedance Tomography reconstruction using Artificial Neural Networks and Particle Swarm Optimization, *IEEE Transactions* on Magnetics 2015 1-1.
- [26] H. Zhao, L. Jin, Y. Huang, et al., An objective prediction model for typhoon rainstorm using particle swarm optimization: neural network ensemble, *Natural Hazards* 73(2) (2014), 427–437.
- [27] J. Xiangkui, F. Yongqing and W. Wan, BP Neural Network Camera Calibration Based on Particle Swarm Optimization Genetic Algorithm, *Journal of Frontiers of Computer Science & Technology* 8(10) (2014), 1254–1262.
- [28] A.D. Niros, G.E. Tsekouras, D. Tsolakis, et al., Hierarchical Fuzzy Clustering in Conjunction with Particle Swarm Optimization to Efficiently Design RBF Neural Networks, *Journal of Intelligent & Robotic Systems* 78(1) (2015), 105–125.