Hu *Journal of Cloud Computing* (2023) 12:81
https://doi.org/10.1186/s13677-023-00396-9

Journal of Cloud Computing:
Advances, Systems and Applications

RESEARCH

Open Access

Optimal urban competitiveness assessment using cloud computing and neural network

Rong Hu[1*]

Abstract

In the network economy domain, urban competitiveness refers to the comparison between cities in terms of competition and development. It is the ability to gain competitive advantage under different factors. The evaluation of urban competitiveness will help cities to learn from each other, and provides reference for the government to enhance urban competitiveness. Unlike various studies in the literature exploiting only the non-linear characteristics of urban competitiveness, this paper selects BP (Back Propagation) network as the main framework for evaluation. A Genetic Algorithm BP (GABP) network based on genetic optimization is utilized. The weights are optimized besides the crossover mutation of GA algorithm. To compensate the slow prediction in the stand-alone mode, this work proposes a MapReduce (MP) based method; MR-GABP via cloud computing. The model ensures effective urban competitiveness evaluation with improved convergence speed and threshold generation speed. The systematic experiments conducted verify effectiveness of the method while the results obtained reveal that performance of the method is better than the other methods in terms of accuracy and recall yielded as 95.1% and 92.6% respectively.

Keywords Urban competitiveness, MapReduce based assessment, Enhanced GABP algorithm, Cloud computing, Neural network

Introduction

The term urban competitiveness in the context of the network economy refers to a city's capacity to manufacture goods and deliver services that cater to local, national, and international consumers. It is a way to enhance the residents' incomes and to attain improved living conditions. Followings are the three main facets of its meaning. First, the competition theme is cities, treated as an enterprise. The competition between cities in a region is equivalent to the market competition between enterprises. Second, urban competitiveness is affected by many factors such as economy, society, culture and policy where development is gradual. Third, urban competitiveness is essentially the ability to optimize resources in the region. Its purpose is to promote the high-speed operation and sustainable growth of the economy and to create more wealth. Urbanization and regional progress are intertwined processes that mutually constrain and shape one another. As a result, increasing urban competitiveness mostly requires regional resource integration and optimization. Efficiency of business functions has a direct bearing on the competitiveness of metropolitan areas. On the contrary, as the carrier of enterprise competitiveness, the city's political, economic and social environment also has a great impact on enterprise competitiveness [1–5].

The competitiveness of a city mainly reflects the comprehensive competitiveness of the city. Its strength is the result of the interaction of various factors in the environment. These together form a unified organic whole. It can be said that urban competitiveness is result of combined forces. Therefore, improving the competitiveness of cities is a systematic project and must proceed from the overall situation. In the process of urban operation, various factors affecting urban development are always changing, and the composition of urban competitiveness

*Correspondence:
Rong Hu
litchihu@mail.ynu.edu.cn
[1] Yunnan University, Yunnan 650091, China

is also changing. Therefore, only by constantly following the changes of the external environment and constantly revising and improving, can the urban competitiveness be kept at a high level. To study urban competitiveness, we must first determine a certain region, a certain period of time, and a certain competitor. With the different selection factors, even the same city has different levels of competitiveness in different development periods. Therefore, urban competitiveness is a relative rather than an absolute concept. As the city is an open system, it can develop by exchanging various materials, technologies, funds, etc. with the outside world. The evaluation indicators of urban competitiveness will also change with the passage of time hence, urban competitiveness is an open and non-closed loop system [6–10]. The key factors affecting urban competitiveness include human resource, culture, economics, environment, and politics. There is a strong relationship of competitiveness at different levels. The levels of competitiveness are interrelated, rather interdependent. As shown in Fig. 1, a low level competitiveness like that of sector or firm is in the sphere of urban competitiveness which in turn is a part of national competitiveness.

This work uses neural networks to evaluate urban competitiveness under the network economy. The neural network consists of numerous nodes that are linked together and incorporates numerous nonlinear components. Training a neural network involves a continuous process of fine-tuning the network's parameters, which is why a big number of nodes require a huge number of parameters. A large amount of training data is also typically required while training a neural network. Since neural networks require extensive amounts of training data and time-hungry processing, it is better to use the cloud technology instead. Multiple cloud nodes can engage in neural network computing at the same time, and the cloud computing platform can store a vast amount of training data in a dispersed manner. A cloud-based neural network can be trained much faster than its single-computer counterpart. Additionally, it can accommodate large amounts of training data. However, in cloud computing, hardware vendors no longer dictate the parameters within which application services are operated. By abstracting information and resources into a cloud, users do not need to know the details of the cloud, nor do they need to have cloud computing expertise. New, dynamic and scalable IT services can be provided with little management effort [11–15].

Unlike other statistical methods, this paper selects BP network as the main framework for evaluation with the following contributions:

1. Aiming at the problems of BP network, a GABP network based on GA optimization is established to optimize weights of BP network through the selection, crossover and mutation of GA algorithm.
2. This paper proposes MR-GABP based on cloud computing to evaluate the urban competitiveness under the network economy, so as to improve the convergence speed and threshold generation speed of BP network.
3. Systematic experiments are conducted to verify the advantages.

In a nutshell, the optimal evaluation method proposed has a vital role in the development of economy and urban living. The method may be used for sightseeing competitiveness in various related domain like urban infrastructure, tourism, security, industry and national economy.

Rest of the paper is organized as; sec. 2 analysis the related literature about urban competitiveness. The following section (Sect. 3) explains the proposed method. Experimental analysis is conducted in Sect. 4. In the last section; summary for the whole paper is presented.

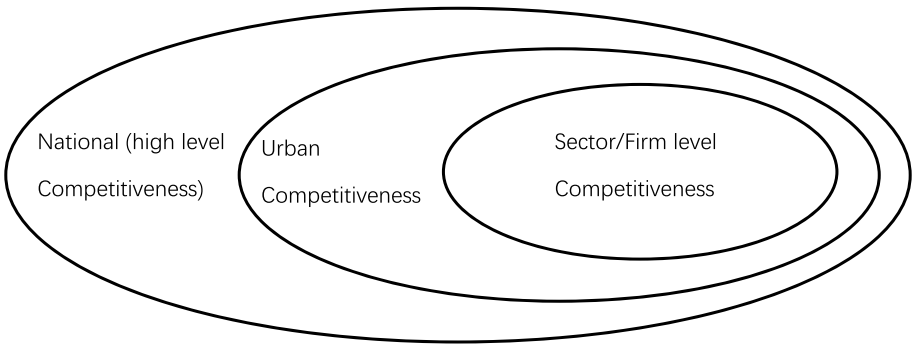

Fig. 1 Competitiveness at different levels

Related Work

According to the literature [16], a city is more competitive if it generates more income and jobs than its neighboring cities. According to the literature [17], urban competitiveness is defined as the degree to which a city can generate and sell goods and services that are superior to those of competing cities. As stated in [18], the key to a city's competitiveness is whether it can attract more investment and talent migration while retaining existing talents and investment. There is a growing body of research [19] that suggests global economic integration has a direct impact on a country's cities' ability to compete on the global stage. According to the literature [20], urban competitiveness is defined as the degree to which a city generates its own wealth and helps its surrounding area generate even more social wealth when compared to other cities in the same or similar market. In a nutshell, the production capability, quality of life, social growth, and external impact of a city are all reflected in its competitiveness. A review of the literature [21] reveals that despite its apparent intuitive connotation, the idea of urban competition is not simple to fully grasp. Literature [22] summarized the influencing factors of urban competitiveness into economic determinants and strategic determinants, and built an evaluation model of urban comprehensive competitiveness accordingly. Literature [23] summarized the characteristics that a competitive city must have six aspects: high-quality life, attractive environment, high-quality services, competitive policies, human resources, and urban taste.

Literature [24] emphasizes that urban competitiveness is affected by both internal and external factors. It is believed that comprehensive economic strength, industrial competitiveness, enterprise competitiveness and technological competitiveness are the four internal factors that affect the level of urban competitiveness. These factors are affected by financial environment, government behavior, infrastructure, national quality, openness, urban environment and other basic factors and environmental factors. In [25], emphasis is paid on industry level competitiveness for national competitiveness. Literature [26] discusses the global competitiveness rankings of countries by focusing on national competitiveness as the primary study object. As stated in [27], a city's ability to compete in the global economy is linked to the political stability of the country in which it is located. It is believed that the highlight of the urban competitiveness model, the national policies, and human resources are increasingly important for urban competitiveness [28]. However, it is really difficult to quantify these important factors at present. Literature [29] treats the city as a whole and consciously develops its core competitive advantages. Literature [30] pointed out that under the impetus of economic globalization, changes in domestic economic, and political management, network management has increasingly become an element of urban comprehensive competitiveness.

Competitiveness is driven by key factors called determinants [31]. The determinants mainly affected by national circumstances [32]. Assets like human resources and technology and processes like management and operational process are the determinants of competitiveness as stated by [31]. The concept of urban competitiveness in a chronological order is presented in Table 1.

These researches systematically introduce and analyze the urban competitiveness, and use some methods to quantitatively evaluate the urban competitiveness. However, there are fewer researches in the literature about the use neural network and cloud computing to this task. Hence this work is to utilize neural network for urban competitiveness.

Genetic algorithm back propagation methodology

Aiming at the problems of BP network, a GABP network based on GA optimization is established. This optimizes the weight of BP network through the selection, crossover and mutation of GA algorithm. As the process of evaluation of urban competitiveness is typically time-consuming in stand-alone mode, this study proposes MR-GABP via cloud computing. The method ensures urban competitiveness evaluation by improving the convergence speed and threshold generation speed of BP network.

Table 1 The concept of urban competitiveness

Author(s)	Concept presented
Webster and Muller [33]	Urban competitiveness is the competence of an urban area to feasibly generate products and to provide a market place for the exchange of goods and services
Kostiainen [34]	It is the ability to absorb culture, and people besides offering efficient ways for the flow of information, technology, and organizations
PK Kresl [35]	It is the measure that how an urban area is superior to other cities in terms of culture, environment, economy and politics
J Sinkiene [18]	It is the ability of the dwellers of an urban area to keep and continue a competitive environment for economy and market

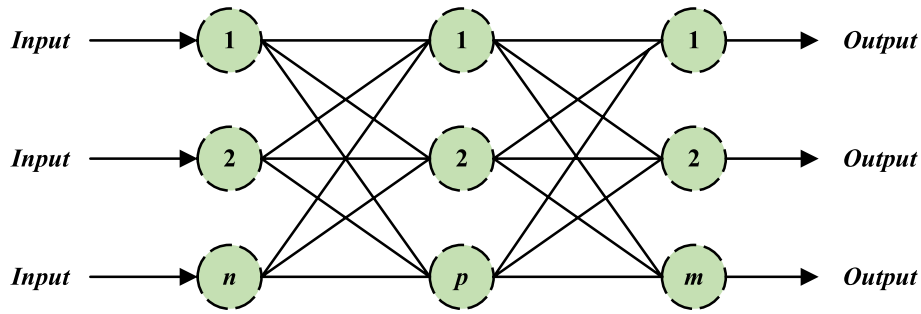

Fig. 2 The BP Neural Network structure

Back propagation network

Due to the highly parallel processing mechanism of BP, it is suitable for building complex nonlinear models. BP has been widely and successfully applied in pattern recognition and classification, intelligent fault diagnosis, image processing, prediction and fitting and other fields. The calculation method of BP network is similar to the function of biological neuron. The typical topology structure of BP network model is generally three layers, as demonstrated in Fig. 2.

Forward data flow calculation and back propagation of error signal are the two main components of a BP network. All of the machine's operational signals are forwarded through the network in the following sequence: input layer concealed layer and output layer. Each layer of neurons can only influence the layer above it, and information cannot be sent from one layer to another. If the result of autonomous steering's forward propagation does not match expectations, the error signal will be sent backwards. The gradient descent technique of the error function is implemented in the weight vector space. A set of weight vectors is searched dynamically and iteratively by alternating between the two processes. This completes the process of information extraction and storage by minimizing the sum of squares of the network's error function.

$$y_i = f\left(\sum_{i=1}^{N} w_i x_i + b_i\right) \tag{1}$$

$$L = f(y_i, t_i) \tag{2}$$

In the BP, error (E_i) at a particular weight w_i is computed as;

$$E_i = \frac{\delta E_{total}}{\delta w_i} \tag{3}$$

The net weight 'w' and bias 'b' is then computed as,

$$w = w - \Delta w \tag{4}$$

$$b = b - \Delta b \tag{5}$$

As an evaluation model of urban competitiveness, BP network has many advantages like the nonlinear mapping capability. Only three layers of perfect BP network are needed to realize the mapping function of machine learning from input to output. Furthermore, it may closely approximate any nonlinear continuous function. Secondly, the self-learning and adaptability are achieved. Simply put, a BP network is supervised learning with a lot of data. When fed a significant amount of unique data, it can learn to map inputs to desired outcomes across multiple samples. This will store the learning content in weight of the network in real time and automatically adapt to the update. Another advantage is the generalization ability of BP. The generalization ability refers to the ability of neural network to recognize the sample set outside the training set. As an important indicator of a computing model, generalization ability reflects the ability of BP network to apply learning results to a new environment. Lastly, because of the fault tolerance if the network suffers external damage, it will not cause serious consequences to the overall training results.

However, BP network itself still has shortcomings and defects. First of all, because of the low learning rate and convergence speed, BP network is costlier in terms of training time. When the input data is large and the problem is relatively complex, the BP network may take several hours to train. Secondly, the objective function is easy to fall into local minima. BP network can converge to the minimum value, but the minimum value cannot be guaranteed to be the global minimum value. Third, the selection of hidden layers and nodes is not known theoretically. It is generally obtained through repeated tests and empirical formulas. Therefore, it is necessary to use data for training in advance to select appropriate hidden layers and neurons, which increases learning burden.

Genetic algorithm back propagation algorithm

The linear characteristic of BP neural network makes it suitable to minimize the subjective factors typically occurred in traditional models. However, BP networks suffer from the problem of the objective function easily falling into the local minimum. Genetic algorithm is a random search technique effective for global optimization. The genetic algorithm is used to find the best weights for the BP network if the weights between the input and hidden layers and the weights between the hidden and output layers are utilized as the initial population. This can effectively avoid the objective function of BP neural network falling into local minimum.

GA is a heuristic search algorithm via principle of biological evolution in nature and the natural law of survival of the fittest. After obtaining information about the search contents the algorithm intends to optimize the search process and to get the optimal solution. It mimics the processes of natural selection and genetic inheritance, including reproduction, gene crossover, and mutation. Each iteration involves keeping some solutions in reserve and picking the best ones from the population based on some metric. These individuals are then crossbred using genetic operators to provide a fresh set of potential answers. To achieve convergence, you should iterate until the convergence index is reached. Like biological evolution, the GA algorithm produces offspring that are capable to thrive in their new surroundings than the original population. The natural genetic mechanism of a genetic algorithm can be broken down into two distinct processes: natural selection and random search. Conventional optimization techniques provide a deterministic test solution sequence based on the gradient or higher order statistics of a single metric function. The best answer is found through a genetic algorithm that mimics the process of natural evolution. The process does not require certain gradient information, so this coding technology is applied to a certain number string. This digital string can also be called chromosome, simulating the evolution process of the population composed of these strings. As in biological inheritance, chromosomes in the body need to be combined and exchanged regularly. Genetic algorithm also goes through the same process to generate a new optimized individual. The GA pipeline is demonstrated in Fig. 3.

If the weights of BP network are selected, crossed and mutated by a GA, the optimal solution of weights can be obtained. The algorithm proposed in this paper is named as GABP algorithm. The steps of using GABP to evaluate urban competitiveness are as follows. First, randomly initialize the population. At the beginning of genetic algorithm, these parameters need to be transformed into population individuals. Then code the individuals to generate real number strings one by one. Here, binary encoding is adopted. Second, establish fitness function. In this paper, the inverse of the sum of the absolute errors of the predicted value and the expected output of the BP network is used as the fitness.

$$F = 1/L \tag{6}$$

Formula for absolute error and individual fitness is shown in Eqs. 7 and 8 respectively. In the equations, N is the data sample or population of individual i. x_i is the individual data sample and $\widehat{x_i}$ is the average data sample.

$$f_i = k\sum_{i=1}^{n} AE_i \tag{7}$$

$$AE = \frac{1}{N}\sum_{i=1}^{N}\left|x_i - \widehat{x_i}\right| \tag{8}$$

Third, individual selection of the population. It is necessary to select individuals of the population as parents for heredity. The fitness value of each individual is calculated, and the probability of the individual being selected as the genetic subject is calculated. The higher the fitness, the greater the percentage. Then the probability of being selected is greater, and vice versa.

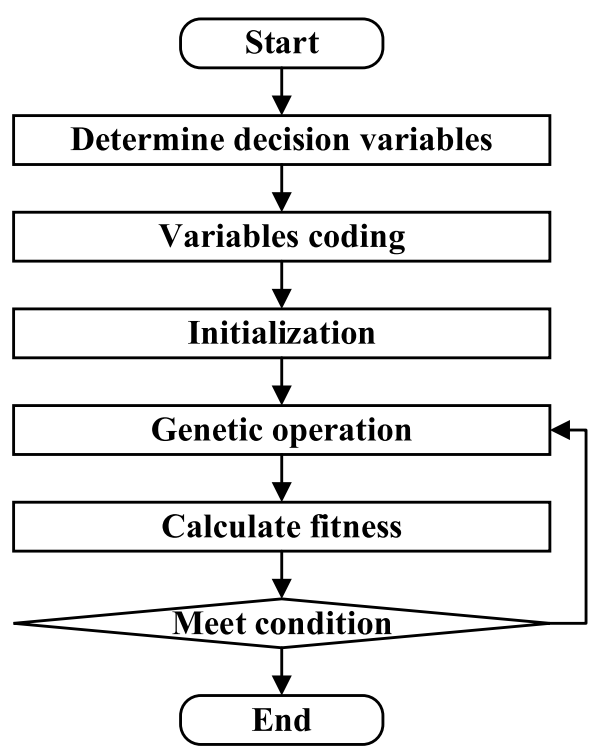

Fig. 3 GA pipeline

$$P_i = F_i / \sum_k F_k \tag{9}$$

Fourth, carry out individual crossover. In the process of crossover, every two individuals need to exchange part of information through crossover probability to form two new individuals. Fifth, carry out mutation operation. In order to increase the diversity of the population, individual genes are mutated with a relatively small probability of variation. Sixth, after the previous steps are completed, the fitness function value is calculated again. Judge whether the fitness value of the new individual meets the end condition of the algorithm. If it is satisfied, it is considered that the most suitable individual is obtained after multiple inheritance, that is, the weight value of output optimization. Otherwise, go back to step 3 to continue iteration. Seventh, according to the optimized weights, establish the topology of BP network, learn training samples, and get the model. Test the test sample, get the results, analyze the error, and compare.

MapReduce Genetic Algorithm Back Propagation with Cloud Computing

Cloud computing is a computing model that integrates parallel computing, distributed computing, grid computing and other computing technologies. It has good application in big data and complex computing. Its basic principle is to use distributed technology to aggregate a large number of local or non-local computing servers to form a cluster and provide computing services for users.

For large data sets, distributed storage and parallel computing can be implemented, both on large-scale clusters. This can greatly improve the operation efficiency and save time. Moreover, MapReduce's framework shields the underlying implementation details, reducing the implementation difficulty. MapReduce includes Map and Reduce functions. The task of the MapReduce programming framework is to accept job requests through the job submission node. Then Mapper and Receiver are sent by the jobtracker process to the idle tasktracker process. The jobtracker process is also responsible for monitoring the execution status of this process. The tasktracker process completes the task after receiving it. The task processing process of MapReduce model is demonstrated in Fig. 4.

In the MapReduce calculation model, the input data to be calculated is automatically separated into multiple independent data blocks. This allows each Map function to be directly used for calculation, and ensures that it can perform the calculation task in parallel. For users, because Hadoop has its own simple segmentation mode, MapReduce's segmentation mode can be fully transparent. However, you can also specify the division mode yourself. When each Map task receives a data block, the Map task starts the job. First, the InputFormat class of the Map task will map the data block, while the Mapper class is defined by the user. Then the OutPutCollect class combines these key value pairs to obtain. Finally, it is written to the disk in the form of SequenceFile. After the Map task is completed, an intermediate result will be formed. The intermediate results will be classified by the patitioner class, and each intermediate result will be merged and stored according to the key value according to the HashParitioner method [36]. Then send the data of these key value pairs to the Reduce task. The Reduce task receives the intermediate result data from each Map node and sorts them by key value. This combines the same key value data pairs to ensure that each key value is unique and valid. Then output to HDFS through the OutputCollector class. The architecture of MapReduce is shown in Fig. 5.

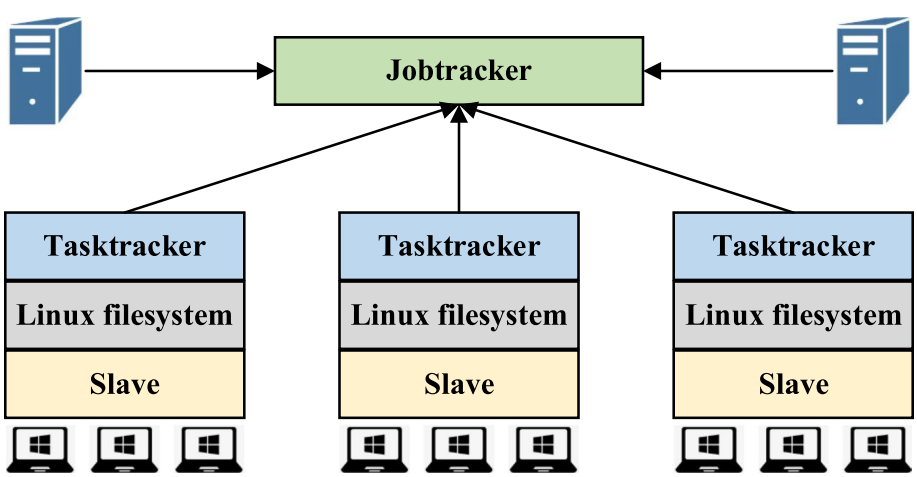

Fig. 4 MapReduce task processing

Being sequential in nature, with greedy algorithm a choice made in a step depends on what is done in the previous. The MapReduce implementation is preferred because with MapReduce, in a particular round an individual action is performed. Hence MapReduce is suitable for distributive setup.

The main method of GABP is to take the weight of BP network as the initial population of genetic algorithm. The fitness value of each population individual is calculated according to the fitness function, and the individuals with high fitness value are selected as the parent individuals for breeding the next generation. This pair of parent individuals cross according to a certain cross probability to generate new individuals. The mutation operation is performed on the new individual to judge whether the obtained individual meets the requirements. In this process, if there are many individual data of the selected population, the calculation of fitness is time-consuming. Therefore, this paper uses piece genetic algorithm to build MR-GABP, and uses Map function to calculate the error of each individual. This is followed by the basic operation of the genetic algorithm in the Reduce function.

The population individual information of the genetic algorithm is used as the input of the Map function. Individual information is a real number string formed by real number coding of BP network parameters. The function needs to calculate the training error of each individual to generate key value pairs. By generating key value pairs through Map function output, the key value pairs related to fitness can be converted. Reduce function needs to merge key value pairs. In order to avoid the situation that the best individual is eliminated, the individual with the highest fitness value will be directly transformed into the next generation. Then the roulette algorithm is used to select individuals to enter the next generation. The selected individuals should perform crossover operation according to a certain crossover probability, and the uniform crossover method is used here. In order to ensure genetic diversity, the process of variation is also needed. Since real coding is used, crossover cannot change all weights, so it is necessary to increase the mutation probability appropriately.

In the data partitioning phase, the input massive training sets are read from the distributed file system of cloud computing. The training set is divided through the underlying mechanism of MapReduce programming framework. Different training subsets are allocated to command nodes, and key value pairs generated from training sets are used. Map function is responsible for dividing the generated key value pairs into input component key value pairs and expected output component key value pairs. After the weight value is obtained, the local gradient change of the weight value can be obtained by back propagation. Each connection weight of the network is calculated by backpropagation respectively. MapReduce will temporarily save the key value pairs generated each time in the running local file system. Variables are treated as inputs by functions for local reduction. To facilitate the reduce operation, you need to collect data with the same key. The final key value pair generates a key value pair for each reduce, and switches this back to the command node. The weight is updated, and the input layer, hidden layer, hidden layer and output weight matrix are put into the configuration file of the Hadoop platform for the second MapReduce operation. After iterating

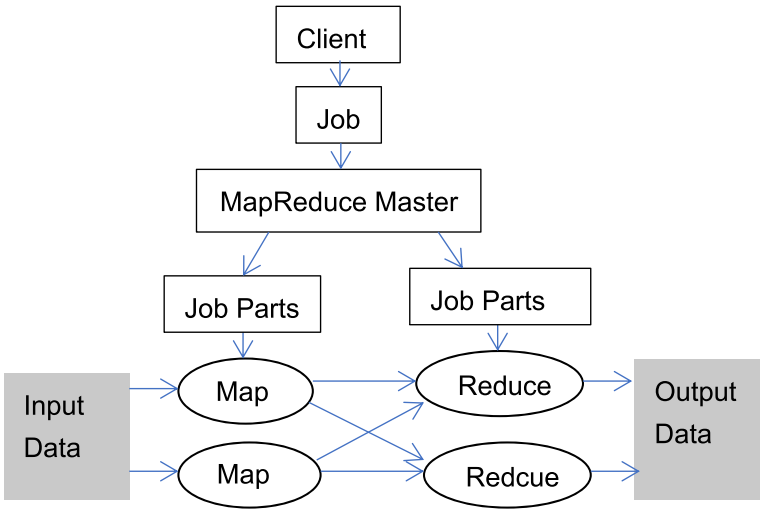

Fig. 5 The architecture of MapReduce

MapReduce for several times, if the weight value is based on stability and does not change significantly, and the calculated error meets the requirements, the training can be ended. The cloud computing platform is demonstrated in Fig. 6, and the MR-GABP architecture is demonstrated in Fig. 7.

Experiment

This paper first collects the urban competitiveness data under the network economy to build the data needed for MR-GABP network training and testing. The dataset is obtained from the cloud-based HDFS [37]. Two thirds of the data set is selected as training set and one third as test set. The key influencing variables used in the evaluations include; security (food and financial), natural and clean air, agriculture, density of population, tourism, regional plans and natural resources. The urban competitiveness evaluation indicators are demonstrated in Table 2.

Firstly, the training situation of MR-GABP network is analyzed, and the analysis object is the loss change in training. The change of loss with training iteration is demonstrated in Fig. 8.

From change trend of loss curve, with increase for training iteration, overall loss gradually decreases and finally converges.

To further verify feasibility for MR-GABP to evaluate urban competitiveness under the network economy, this paper compares MR-GABP with other methods based on SVM, Adaboost and DBN. Random forest is not included in the analysis due to its insensitivity to the basic

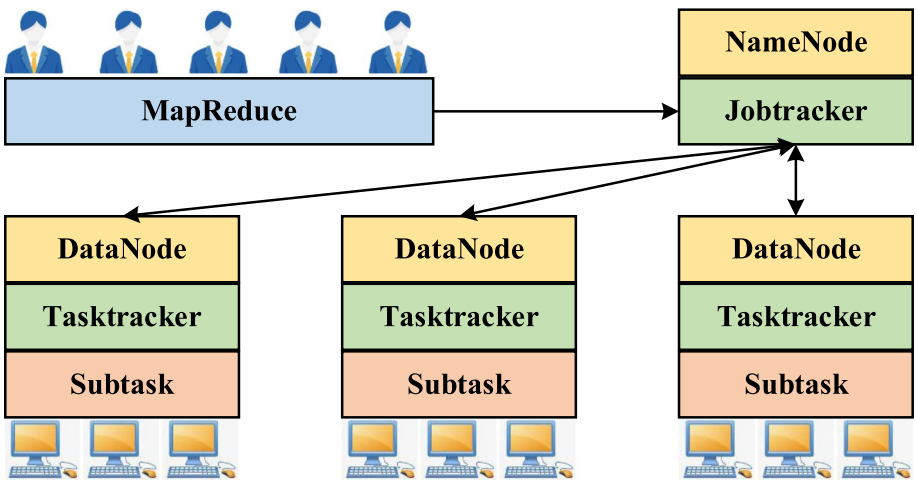

Fig. 6 The cloud computing platform

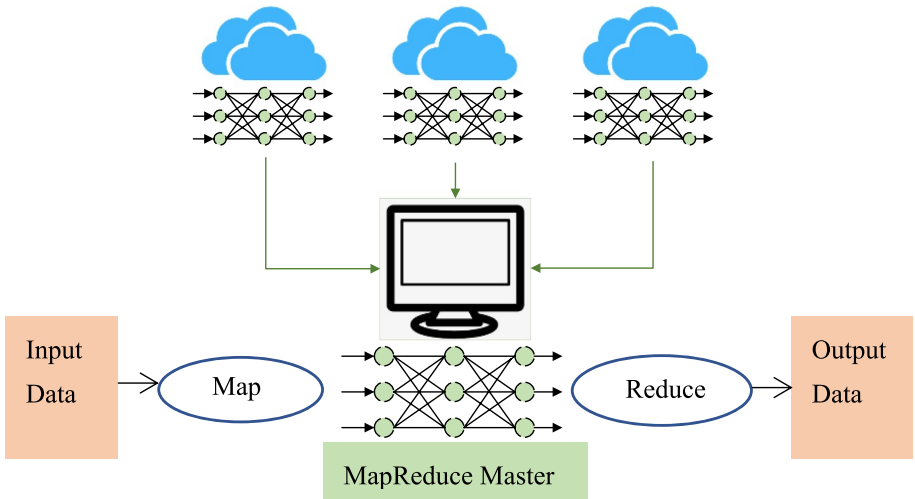

Fig. 7 The MR-GABP architecture

Table 2 Urban competitiveness evaluation indicators

Symbolic representation	Primary Indicator	Secondary Indicator
X1	Economic competitiveness	Per capita income
X2	Public finance	Average income
X3	Social system	Extents of norms and values
X4	Enterprise competitiveness	Productivity and cost
X5	Financial system	Consumer prices
X6	Infrastructure	Community development
X7	Ecological environment	Average annual temperature
X8	Educational level	Highest degree

competitiveness factors [38], including soft and hard factors [2, 39]. Outcomes of the analysis is shown in Table 3.

MR-GABP network in this paper can achieve the highest accuracy and recall. This can effectively verify the superiority of MR-GABP network in the evaluation of urban competitiveness under the network economy. Outcomes of the analysis reveals that SVM is least sensitive while MR-GABP is most sensitive to the indicators presented in Table 1. Moreover, the key factors affecting urban competitiveness include economics, environment, and culture.

This method uses GA to optimize BP. To verify feasibility, this paper compares performance of the model without and with GA, and the experimental results are demonstrated in Fig. 9.

Table 3 Comparison with different methods

Method	Accuracy	Recall
SVM	90.1	88.1
Adaboost	91.4	89.2
DBN	92.7	90.5
MR-GABP	95.1	92.6

From the comparison data in the figure, after using GA strategy to optimize BP, the accuracy and recall indicators can be improved accordingly. This further verifies the feasibility of using GA to optimize BP network.

In MR-GABP network, hidden layer nodes are not fixed. To select the optimal hidden node, this paper conducts experiments for different parameters, as demonstrated in Table 4.

As clear from Table 4, the accuracy and recall increases with the increase in the number of hidden nodes. However, after further increase from 12 nodes, the accuracy and recall decreases slightly. It is not difficult to see that the performance of MR-GABP network first rises to the peak, and then gradually declines. When the modified parameter is set to 12, the model can obtain the best accuracy and recall. Hence the number of hidden nodes is set to the optimal 12 in the layers.

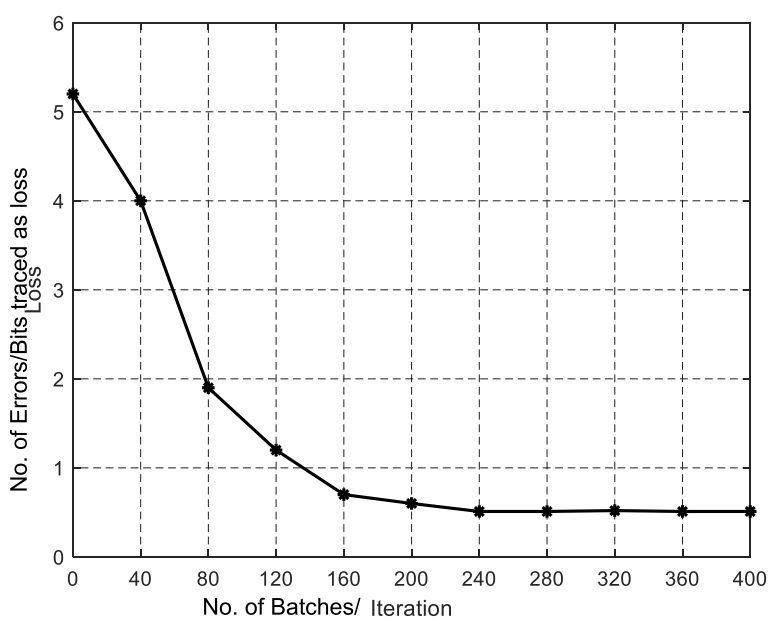

Fig. 8 Training loss of MR-GABP

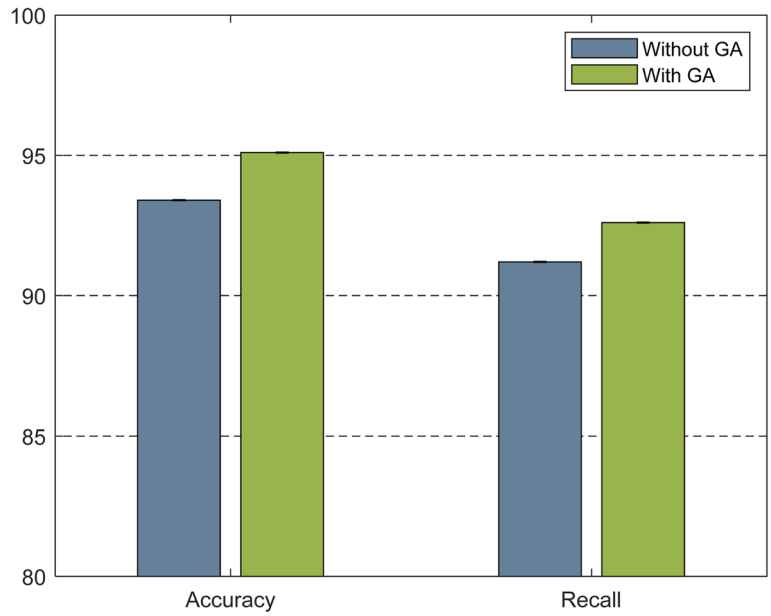

Fig. 9 Evaluation on GA

To compare the advantages of MR-GABP algorithm in the case of large amount of data, this paper records the prediction time by increasing the size of data. This compares the training time of the stand-alone GABP algorithm with the training time of the MR-GABP algorithm on the cloud computing cluster. Results are demonstrated in Fig. 10.

As clear from Fig. 10 in case of MR-GABP, variation in training time is negligible while increasing the size of training set (as denoted by red line). Unlike MR-GABP, with GABP the training time nearly increases linearly with the increase in the training set (illustrated by blue line). This demonstrates that the training time of MR-GABP running on the cloud cluster does not change much. However, with the increase of the number of training sets, the training time of single GABP algorithm is also increasing. In terms of sustainability in urban area other aspects, such as [40], may also be considered and treated using cloud computing and deep or machine learning methods which could be picked by practitioners or automatically using some smart mechanism, such as discussed in [41].

Table 4 Analysis of hidden nodes for urban competitiveness

Node	4	8	12	16	20
Accuracy	93.1	94.2	95.1	94.5	93.8
Recall	91.6	91.3	92.6	91.9	91.5

Conclusion

In the domain of network economy, urban competitiveness originates from international competitiveness. The research on international competitiveness mainly focuses on the four levels: national, industrial, enterprise and product competitiveness. With the rapid development of global informatization and economic integration, cities are not only playing an increasingly important role in global activities and local affairs, but also competing with each other. In this increasingly fierce competition, the decline or prosperity of a city is closely related to the weakening or strengthening of its comprehensive competitiveness. The research on urban competitiveness under the network economy has become the focus of domestic and foreign academia and policy makers. In view of the non-linear characteristics of urban competitiveness, different from the statistical analysis methods have been proposed in the literature. By selecting BP network as the main framework for evaluation, this paper proposes GABP network to optimal evaluation. The weight of BP network is optimized through selection, crossover and mutation of GA algorithm. To overcome the slow processing of stand-alone mode, the cloud based MR-GABP network method is proposed to improve the convergence speed and threshold generation speed of BP network.

Although, with the use of BP, weights are adjusted in the right direction and global optimization is achieved

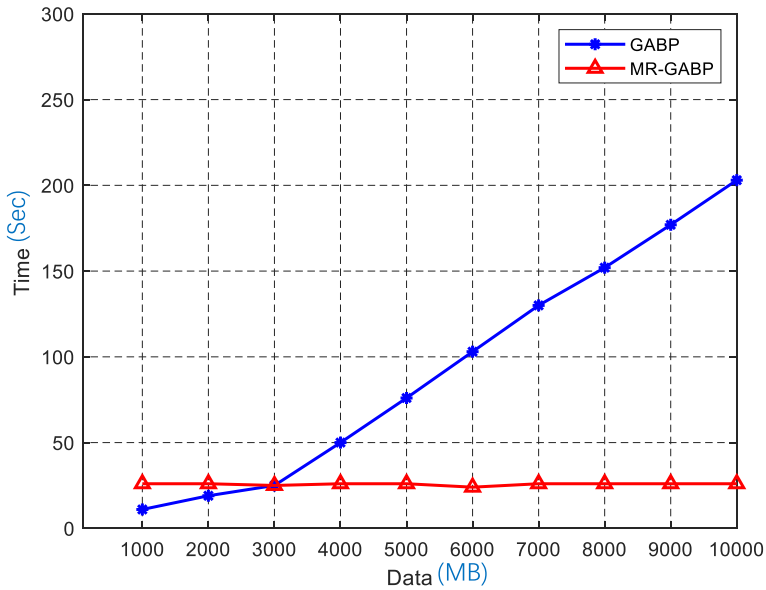

Fig. 10 Analysis of GABP and MR-GABP

using GA, the mixing of GA and BP adds sensitivity to weights and in computational complexity. Moreover, the Hadoop MapReduce model is good for batch processing and real time processing is not supported. As our future direction, the model will be enhanced to overcome or minimize impact of the said issues.

Acknowledgements
The authors would like to thank anonymous referees for their valuable suggestions and comments.

Conflict of interest
The authors declare no conflict of interest exists.

Authors' contributions
Rong Hu:Investigation, conceptualization, methodology, funding acquisition, resources, software, validation, formal analysis, writing—review and editing. The author(s) read and approved the final manuscript.

Funding
Not applicable.

Availability of data and materials
The datasets used during the current study are available from the corresponding author on reasonable request.

Declarations

Competing interests
The authors declare no competing interests.

Received: 21 October 2022 Accepted: 26 January 2023
Published online: 22 May 2023

References

1. Ghahremani H, Afsari Bajestani S, McCarthy L et al (2021) Transformation of urban spaces within cities in the context of globalization and urban competitiveness. J Urban Plan Dev 147(3):05021026
2. Sgambati S, Gargiulo C (2022) The evolution of urban competitiveness studies over the past 30 years a bibliometric analysis. Cities 128:103811
3. Song M, Xie Q (2021) Evaluation of urban competitiveness of the Huaihe River eco-economic belt based on dynamic factor analysis[J]. Comput Econ 58(3):615–639
4. Pei J, Zhong K, Li J et al (2022) PAC: Partial Area Clustering for Re-Adjusting the Layout of Traffic Stations in City's Public Transport. IEEE Transactions on Intelligent Transportation Systems
5. Liu X, Ni P, Niu F et al (2021) Research on the coordinated development of global urban economic competitiveness: based on a sample of 1007 cities. Complexity 2021:1–2
6. Garcia-Alvarez-Coque JM, Roig-Tierno N, Sanchez-Garcia M et al (2021) Knowledge drivers, business collaboration and competitiveness in rural and urban regions. Soc Indic Res 157(1):9–27
7. Yin S (2022) Construction of Cities' E-Commerce Competitiveness BRMS Model from the System Perspective. Forest Chemicals Review 1:1549–1568
8. Yazdan Panah P, Ezatpanah B, Beygbabaye B (2021) Assessing the Affecting Geographical Factors of the Urban Development Competitiveness Based on Strategic Scenario Planning (Case Study: West Azerbaijan Province). Geography (Regional Planning) 12(1):511–534
9. Shih WYC, Agrafiotis K (2022) Aesthetic Capitalism and Sustainable Competitiveness in Urban Artisanal Networks. Handloom Sustainability Cult Entrepreneurship Cult Luxury 1:295
10. Delshad A (2021) The Model of Smartness' Effect on Competitiveness of Tourism Urban Destination in Iran. Geogr Territorial Spat Arrangement 11(38):49–70
11. Alouffi B, Hasnain M, Alharbi A et al (2021) A systematic literature review on cloud computing security: Threats and mitigation strategies[J]. IEEE Access 9:57792–57807
12. Bello SA, Oyedele LO, Akinade OO et al (2021) Cloud computing in construction industry: Use cases, benefits and challenges. Autom Constr 122:103441

13. Ibrahim IM (2021) Task scheduling algorithms in cloud computing: A review. Turkish J Comput Math Educ (TURCOMAT) 12(4):1041–1053
14. Vinoth S, Vemula HL, Haralayya B et al (2022) Application of cloud computing in banking and e-commerce and related security threats. Mater Today Proc 51:2172–2175
15. Cao K, Hu S, Shi Y et al (2021) A survey on edge and edge-cloud computing assisted cyber-physical systems. IEEE Trans Industr Inf 17(11):7806–7819
16. Jiang Y, Shen J (2010) Measuring the urban competitiveness of Chinese cities in 2000. Cities 27(5):307–314
17. Charnock G, Purcell TF, Ribera-Fumaz R (2014) City of Rents: The limits to the B arcelona model of urban competitiveness. Int J Urban Reg Res 38(1):198–217
18. Bruneckiene J, Guzavicius A, Cincikaite R. Measurement of urban competitiveness in Lithuania. Engineering Economics, (2010);21(5)
19. Esmaeilpoorarabi N, Yigitcanlar T, Guaralda M (2016) Place quality and urban competitiveness symbiosis? A position paper. Int J Knowl Based Dev 7(1):4–21
20. Lember V, Kalvet T, Kattel R (2011) Urban competitiveness and public procurement for innovation. Urban studies 48(7):1373–1395
21. Bruneckiene J, Činčikaitė R, Kilijonienė A (2012) The specifics of measurement the urban competitiveness at the national and international level. Inžinerinė ekonomika 23(3):256–270
22. Li X (2020) Cultural creative economy and urban competitiveness: How one matters to the other. J Urban Aff 42(8):1164–1179
23. Zhao Q, Xu H, Wall RS et al (2017) Building a bridge between port and city: Improving the urban competitiveness of port cities. J Transp Geogr 59:120–133
24. Shen J, Yang X (2014) Analyzing urban competitiveness changes in major Chinese cities 1995–2008. Appl Spat Anal Policy 7(4):361–379
25. Guo H, Liu X, Li Y et al (2015) Comparison analysis and evaluation of urban competitiveness in Chinese urban clusters. Sustainability 7(4):4425–4447
26. Carvalho L (2012) Urban competitiveness, u-city strategies and the development of technological niches in Songdo, South Korea[M]//Regional Development: Concepts, Methodologies, Tools, and Applications. IGI Global 1:833–852
27. Pine AM (2015) Social reproduction and urban competitiveness: How Dominican bodegueros use the care economy. City Society 27(3):272–294
28. Zhang S (2013) Urban competitiveness and public housing[J]. Asian Soc Sci 9(5):94
29. CORBOŞ RA, Popescu RI (2013) Study regarding Theatres' Role in Increasing Urban Competitiveness. Adm Public Manag Rev 1(20):13–19
30. Ni P, Kamiya M, Ding R (2017) Global Urban Competitiveness: General Analysis[M]//Cities Network Along the Silk Road. Springer, Singapore, pp 31–50
31. Siudek T, Zawojska A (2014) Competitiveness in the economic concepts, theories and empirical research. Acta Scientiarum Polonorum Oeconomia 13(1):91–108
32. Eskerod P, Hollensen S, Morales-Contreras MF, Arteaga-Ortiz J (2019) Drivers for pursuing sustainability through IoT technology within high-end hotels—an exploratory study. Sustainability 11(19):5372
33. Webster D, Muller L. Urban competitiveness assessment in developing country urban regions: The road forward. Urban Group, INFUD. The World Bank, Washington DC, (2000);17:47
34. Kostiainen J (2002) Learning and the'Ba'in the Development Network of an Urban Region. Eur Plan Stud 10(5):613–631
35. Kresl PK (2007) Planning cities for the future: the successes and failures of urban economic strategies in Europe[M]//Planning Cities for the Future. Edward Elgar Publishing
36. Kabiljo I, Karrer B, Pundir M, Pupyrev S, Shalita A, Presta A, Akhremtsev Y (2017) Social hash partitioner: a scalable distributed hypergraph partitioner arXiv preprint arXiv:1707.06665
37. Shvachko K, Kuang H, Radia S, Chansler R (2010) The hadoop distributed file system. In IEEE 26th symposium on mass storage systems and technologies (MSST). pp 1–10
38. Croes R, Ridderstaat J, Shapoval V (2020) Extending tourism competitiveness to human development. Ann Tour Res 80:102825
39. Komasi H, Hashemkhani Zolfani S, Prentkovskis O, Skačkauskas P (2022) Urban Competitiveness: Identification and Analysis of Sustainable Key Drivers (A Case Study in Iran). Sustainability 14(13):7844
40. Ali, Rahman, Farkhund Iqbal, and Muhammad Sadiq Hassan Zada. "Multicriteria Decision Making for Carbon Dioxide (CO 2) Emission Reduction." *Scientific Programming* 2022 (2022).
41. Ali R, Lee S, Chung TC (2017) Accurate multi-criteria decision making methodology for recommending machine learning algorithm. Expert Syst Appl 71:257–278

Publisher's Note