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Quantum Neural Networks Based Performance Evaluation Model of Bus Rapid Transit System

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Abstract: Bus Rapid Transit (BRT) system is the emerging transportation system in recent years. Currently it is difficult to value the performance of such a complicated BRT system. To solve the issue, a new evaluation model of BRT system based on Quantum Neural Networks (QNN) was proposed. The specific structure and the training arithmetic of the quantum neural networks are established for the performance evaluation of BRT system. Based on the determined evaluation indexes including society and environment, technical performance, corporate benefits and passengers' satisfaction etc., the proposed model is utilized to obtain the comprehensive evaluation of BRT performance in Hangzhou city. The experiment result showed that the QNN method could evaluate the performance of BRT system easily and rapidly.

Key words: BRT, quantum neural networks, performance evaluation model, training arithmetic, evaluation Index

INTRODUCTION

In recent years, Bus Rapid Transit (BRT) system has been popularized rapidly at home and abroad as an effective way to ease traffic congestion. In China, the BRT was deployed for only a short time. The construction and development of BRT system brings a lot of benefits in society, economy and environment, but the subsequent potential risk has emerged and been concerned by the public and the policy makers. It is absolutely necessary to research on the performance evaluation system for BRT. It will support the operation department of BRT to evaluate operation status timely and accurately, find out the existing problems and provide us the better decision for planning, constructing and managing the BRT system.

The research on evaluation system of BRT has been reported both domestic and abroad publication. Generally, the common evaluation methods include economic analysis method, expert evaluation method, fuzzy comprehensive evaluation method, analytic hierarchy process method and so on (Zhang *et al*., 2007; Mao, 2009; Zhou and Yang, 2006). However, there are various problems in these existing methods, such as too much subjectivity in score assignment which will cause unreasonable weight distribution, too confined application range which will cause deviation of evaluation result for complex object with many indexes. Moreover, due to the obvious complexity and fuzziness of evaluation factors, the inconsistency between subjective motive and objective effect, it is difficult to find an appropriate evaluation method which is objective and easy to popularize.

As we know, to a certain extent, neural network could overcome above defects with its own features such as simulation of human thinking, non-linear transformation, self-organizing learning and so on (He *et al*., 2008). However, once the traditional Artificial Neural Network (ANN) method is applied to BRT evaluation system, there are still some deficiencies as follows:

- Firstly, for the complexity of BRT performance evaluation, the ANN model is too simple in network structure to cope with such a complicated issue. Consequently its learning speed usually become very slow and even catastrophic amnesia arises sometimes
- Secondly, there is short of enough learning samples provided by BRT system for neural network. The evaluation results need to be used to not only export comprehensive score or category, but also obtain the condition of elements and search for improved objective to optimize the construction and operation of BRT system. Therefore, a new performance evaluation model of BRT based on Quantum Neural Networks (QNN) is proposed here (Xie *et al*., 2004; Lv and Yu, 2007)

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QNN BASED EVALUATION MODEL

As a blended intelligent optimization algorithm, QNN combines quantum computing with Artificial Neural Network (ANN) to improve the structure and properties of traditional ANN. Current theoretical analysis and application research have proved that QNN has obvious advantage in learning speed, network structure and network performance compared with ANN. Moreover, QNN has been applied preliminarily in many fields such as pattern recognition, entanglement calculations, approximation of function, etc. (Lv, 2006; Wu and Peng, 2007). In the process of designing BRT evaluation model, it is the principle aim to promote the quick access to the accurate and abundant data of performance evaluation. It is demand that the established neural network model contribute to acquiring operation status of BRT in the current environment just in time. That means, neural network model should have characteristic of speediness, accurateness and high efficiency. With QNN, it becomes possible.

Structure of evaluation model: BRT is a complex, multi-factor, multi-level system involving various traffic factors such as people, vehicles, roads, environment, etc. The purpose of BRT construction is to improve the situation of urban traffic congestion and direct the development of urban traffic to TOD (Transit Oriented Development) mode (Elizabeth, 2002). The deployment of BRT has brought many benefits in our society, environment, city development, passengers and operation enterprises. Accordingly, for the evaluation of BRT, the interests of all parties should been taken into account. On this basis, a QNN model for such a complex system is proposed which is inspired by the cosmological perspectives in quantum theory and composed of many similar quantum neuron models by linear superposition (Li *et al*., 2004). The network model includes 5 subsidiary quantum neuron networks. Each subnet is made up of three layers: input layer, hidden layer and output layer, just as shown in Fig. 1.

In the previous evaluation model of BRT based on neural network, input vectors are just all the evaluation indexes of BRT (Mao, 2009). As shown in Fig. 1, in the evaluation model based on QNN, the input vectors of each subnet from No.1 to No.4 separately include society and environmental benefit index, city strategic development index, technology performance index, passenger satisfaction index, corporate image and benefit index. The outputs are corresponding to four aspects of the evaluation value. Then, processing these outputs as the input vectors of No. 5 subnet, the final result of comprehensive evaluation for BRT could be generated. Considering that the qualitative index is difficult to be described by the precise and quantitative value, fuzzy mathematics is employed to describe the qualitative index. From the practical point of view, it is suggested to use membership grade (A--excellent, B--good, C--average, D--barely passed, E--failed) in the evaluation model, in which the network node contains the percentage of index comment in each layer.

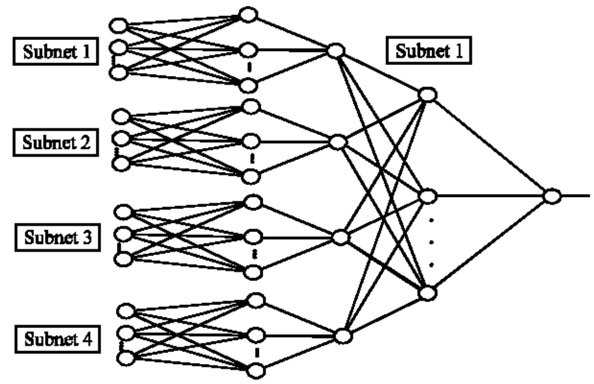

Fig. 1: Structure of evaluation model based on QNN

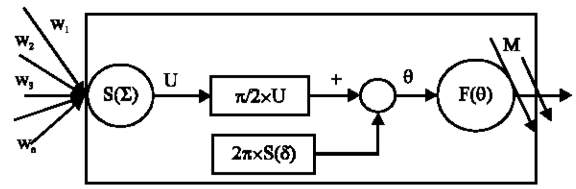

Fig. 2: Model of quantum neural unit

Training arithmetic of QNN: During the process of network learning and training, as the input vectors may be different, the network need be trained by corresponding component separately. During testing, incoming message of each input pattern is handled by corresponding network component too. Network adjustment is restricted to network component of a certain input pattern. Quantum neuron model is adopted by subnet. The topological structure is as shown in Fig. 2.

W_1, W_2,$\cdots W_n$ indicates the probability of adjacent neurons expressing activated state. $S(\Sigma)$ is the sum of probability values and weights by simple addition. $S(\bullet)$ is sigmoidal function, converting the collected comprehensive information into scope [0,1]. It's the initial stage of controlling quantum bit phase. $2\pi\times U$ means the phase for controlling quantum bit. $2\pi\times S(\delta)$ means the phase for internal state of neuron. δ is the adjustable parameter of phase. $F(\theta)$ indicates the changed neuron state base on controlling quantum bit with complex formulation. M indicates observation, as the output information of neuron by expressing the probability of neuronal activation state.

Quantum neural network is a three layer feed-forward network. The neuron activation function in output layer adopts the linear function. The hidden layer utilizes quantum neuron. The formulae of information processing are just as shown below:

$$U_j^{(p)} = S\left(\sum_{i=1}^{n} x_j^{(p)} w_{ij} - \theta_j\right) \tag{1}$$

$$V_j^{(p)} = F\left(\frac{\pi}{2} U_j^{(p)} - 2\pi S(\delta_j)\right) \tag{2}$$

$$y_j^{(p)} = \mathrm{Im}^2\left(V_j^{(p)}\right) \tag{3}$$

$$O_k^{(p)} = \sum_{j=1}^{m} y_j^{(p)} w_{jk} - \theta_k \tag{4}$$

where, $x_i^{(p)}$ is the i-th input of the p-th sample. n is the number of input neurons. w_0 is the weight from the i-th neuron of input layer to the j-th neuron of hidden layer. θ_j is the threshold of the j-th neuron in hidden layer. $S(\bullet)$ is sigmoidal function. $0.5\,\pi U_j^{(p)}$ is the controlling quantum bit phase of the j-th neuron in hidden layer of p-th sample. $2\pi S(\delta_j)$ is the quantum bit phase of the corresponding neuron. $V_j^{(p)}$ is the status of the j-th neuron in hidden layer of p-th sample. $y_j^{(p)}$ is output value of the j-th neuron in hidden layer of p-th sample. θ_k is the threshold of the k-th neuron in output layer. w_{jk} is the weight from the j-th neuron of hidden layer to the k-th neuron of output layer. $O_k^{(p)}$ is output of the k-th neuron in output layer of p-th sample. m is the number of hidden neurons.

The target function of network training with gradient descent method is shown as below:

$$J = \frac{1}{2}\sum_{p=1}^{P}\sum_{k=1}^{l}\left(d_k^{(p)} - O_k^{(p)}\right)^2 \tag{5}$$

where, $d_k^{(p)}$ is the ideal network output. p is the number of pattern samples. L is the number of network output neurons.

Formulae of parameter adjustment for weight and phase shift are shown as follows:

$$\begin{aligned} \Delta w_{jk} &= \eta_w \sum_{p=1}^{P}\left(d_k^{(p)} - O_k^{(p)}\right) \bullet y_j^{(p)} \\ \Delta \delta_j &= -\eta_\delta \sum_{p=1}^{P}\sum_{k=1}^{l}\left(d_k^{(p)} - O_k^{(p)}\right) w_{jk}\, \mathrm{Im}\left(V_j^{(p)}\right) \end{aligned} \tag{6}$$

$$\mathrm{Im}(V_j^{(p)} \bullet i) S(\delta_j)\left(1 - S(\delta_j)\right) \tag{7}$$

$$\Delta w_{ij} = \eta_w \sum_{p=1}^{P}\sum_{k=1}^{l}\left(d_k^{(p)} - O_k^{(p)}\right) w_{jk} U_j^{(p)}\left(1 - U_j^{(p)}\right) x_j^{(p)}\, \mathrm{Im}\left(V_j^{(p)}\right) \mathrm{Im}(V_j^{(p)} \bullet i) \tag{8}$$

Here, η_w is learning rate, η_δ is regulation of phase shift. θ_k is regarded as the weight for adding a neuron of hidden layer with output equaling to 1 and the k-th neuron in output layer. So, θ_k could be updated with w_{jk} by similar update mode.

CASE STUDY IN HANGZHOU CITY

The demanded experiment data and the evaluation indexes are derived from survey information. By consulting professional scholars, experts, researchers engaged in studying of BRT, staff with rich practical experience in the departments such as urban construction, planning, public security, public transit agency, etc. and public traffic participants, the performance evaluation index of Hangzhou BRT system have been defined. In order to eliminate the effect caused by different quantities and dimensions, the raw data need to be standardized. The data standardizing helps to accelerate the training speed of neural network. The below Table 1 shows the standardized results of 12 evaluation indexes.

Table 1: Part of the Standardized data (A--excellent, B--good, C--average, D--barely passed, E--failed)

Index	A	B	C	D	E	Index	A	B	C	D	E
C1	0.07	0.24	0.46	0.21	0.02	C1	0.14	0.62	0.23	0.02	0.00
C2	0.04	0.25	0.53	0.17	0.01	C2	0.33	0.45	0.19	0.03	0.01
C3	0.14	0.32	0.24	0.21	0.09	C3	0.23	0.62	0.14	0.02	0.00
C4	0.08	0.23	0.32	0.33	0.04	C4	0.35	0.42	0.13	0.08	0.02
C5	0.19	0.42	0.36	0.03	0.00	C5	0.35	0.31	0.23	0.09	0.03
C6	0.05	0.32	0.35	0.24	0.04	C6	0.16	0.29	0.37	0.12	0.06
C7	0.04	0.25	0.53	0.17	0.01	C7	0.19	0.65	0.12	0.04	0.00
C8	0.35	0.04	0.30	0.31	0.00	C8	0.21	0.55	0.24	0.00	0.00
C9	0.08	0.23	0.32	0.33	0.04	C9	0.13	0.42	0.34	0.09	0.02
C10	0.16	0.12	0.34	0.26	0.12	C10	0.23	0.37	0.32	0.04	0.04
C11	0.07	0.24	0.46	0.21	0.02	C11	0.18	0.42	0.24	0.15	0.01
C12	0.16	0.12	0.34	0.26	0.12	C12	0.23	0.37	0.32	0.04	0.04

C1: Public transit ratio C2: BRT transit capacity C3: Average travel time C4: Road resource occupying index C5: Pollution coefficient C6: Coordination with other public transit modal C7: Influence on urban landscape C8: BRT route density C9: Percentage of dedicated BRT lane C10: Coverage range of BRT stations C11: Average distance between two adjacent BRT stations C12: Intelligent system factor for BRT stations

All of these constructed subnets belong to three layer feed-forward network just as shown in Table 2. The number of input nodes is the same with the number of indexes in each sub-rule layer. The number of output nodes is 1. About the number of nodes in hidden layer, it is a complex problem how to select the values depending on experience of designer and multiple experiments. In this study the number of nodes in hidden layer is determined according to the formula below and multiple experiments. Once the evaluation error of network is the minimum value, the number of neurons in middle layer could be considered as the best value.

Now, the model can be established based on BP network, Qubit NN network (Kouda *et al*., 2005) and Quantum neural networks respectively. The selected parameters of training are determined, in which the maximum number of training is 10000, the target error is 10-4, the learning rate is 0.01. The final simulation result is listed in Table 3 and 4.

Table 3 shows error comparison of synthesis evaluation results for three kinds of neural networks. It can be seen that the time required for simulation training of BRT evaluation model based on QNN is far less than traditional BP neural network with the same target deviation. Moreover,

Table 2: Connection parameters of neural network(NN)

NN	Input nodes	Hidden node	Output node
BP	31	7	1
Qubit NN	31	7	1
Subnet1	12	14	1
Subnet2	9	10	1
Subnet3	6	8	1
Subnet4	4	7	1
Subnet5	4	8	1

*BP: Back Propagation

both of its relative error and maximum relative error are very small, its generalization performance is best. Therefore, the evaluation model based on QNN could not only improve the learning efficiency greatly but also meet the precision requirements of BRT evaluation fully.

Table 4 shows the percentage of 5 indexes (the social environment and city developing, the technical performance, the passenger satisfaction, the corporate image and benefit, the synthesis evaluation) in comments and the relative errors of evaluation results. To meet the requirement of intuitive and comparability, the evaluation results have been translated into centesimal system according to the contribution value of different evaluation grade.

The evaluation based on BP or Qubit NN models could merely obtain the synthesis evaluation. Comparing with it from table 4, the proposed model based on QNN is evident to be able to get not only the synthesis evaluation score but also various scores concerning the society environment and city development, the technical performance, the passenger satisfaction, corporate image and benefit. The evaluation information of BRT in different implementation phases could be analyzed comparatively. As for elements of BRT system benefits, the analysis not only provides an accurate evaluation and location in whole BRT system, but also help operator understand the situation of BRT in all aspects detailedly and comprehensively to find the advantages and disadvantages, then finally provide a good guidance to improve the future new BRT project. Furthermore, as for the whole BRT system, the accurate evaluation of BRT benefit helps to increase work efficiency of BRT system and then improve the quality of operation service.

Table 3: Comparative table of simulation results based on three modes of neural network (NN)

NN mode	Test deviation	Max deviation	Training time (sec)
BP	9.9990e-005	0.0156	34.750
Qubit NN	5.7370e-005	0.0014	0.218
QNN	6.2061e-007	0.0009	0.000

Table 4: Relative error in table of simulation results of BRT synthesis evaluation using the model based on QNN

	Society environment city developing			System technical performance			Passengers' satisfaction			Corporate image and benefit			Synthesis evaluation of BRT		
Grade	Output value	Expect value	Error	Output value	Expect value	Error	Output value	Expect value	Error	Output value	Expect value	Error	Output value	Expect value	Error
A	0.1197	0.1191	0.0053	0.0762	0.0756	0.0086	0.0762	0.0756	0.0086	0.0758	0.0772	-0.0183	0.1198	0.1202	-0.0037
B	0.2060	0.2058	0.0011	0.2721	0.2717	0.0016	0.2721	0.2717	0.0016	0.3079	0.3074	0.0015	0.2373	0.2379	-0.0026
C	0.3697	0.3706	-0.0024	0.3931	0.3927	0.0010	0.3931	0.3927	0.0010	0.4654	0.4665	-0.0023	0.3790	0.3797	-0.0019
D	0.2452	0.2466	-0.0057	0.2255	0.2269	-0.0062	0.2255	0.2269	-0.0062	0.1702	0.1694	0.0048	0.2260	0.2246	0.0063
E	0.0591	0.0577	0.0239	0.0364	0.0367	-0.0072	0.0364	0.0367	-0.0072	0.0026	0.0027	0.0370	0.0375	0.0377	-0.0044
Score	70.8045	70.8004	0.0001	71.5014	71.4748	0.0004	71.5014	71.4748	0.0004	74.4232	74.4975	-0.0010	71.7260	71.7830	-0.0008

CONCLUSION

By analyzing the characteristics of existing evaluation models, an evaluation model of BRT based on QNN is proposed to overcome the shortcomings of previous evaluation model based on BP neural network. On the basis of established evaluation index system of BRT, the new model is applied to BRT for synthesis evaluation. The experiment result shows that QNN has strong ability in function fitting with fast training speed. Thus, the evaluation model is a scientific, simple and accurate model suitable for evaluation studies of other kinds of transportation system or other similar issues. Especially, in the case that there are a large number of factors in evaluation scheme and these factors have their own pros and cons, the evaluation model has more widespread application prospect. In practice, the samples may possess much more indexes and perhaps there is various correlation among them, to cope with this issue, the principal component analysis or factor analysis of indexes are required in the data preprocessing stage by which the number of input nodes of the network could be reduced and the whole network structure could be simplified.

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