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ORIGINAL PAPER

Low-carbon supply chain resources allocation based on quantum chaos neural network algorithm and learning effect

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Abstract This paper focuses on designing a novel quantum chaos neural network algorithm for low-carbon supply chain resources allocation problem (LCSCRAP) which is an efficient extension of the resources allocation. Quantum chaos neural network algorithm based on cloud model (C-QCNNA) is put forward to solve the LCSCRAP with several conflicting and incommensurable multi-objectives. The results of simulation experiments have been obtained from the set of standard instances, and the C-QCNNA is confirmed to be very competitive after extensive experiments. The computational results have proved that the C-QCNNA is an efficient and it is effective for the LCSCRAP. This study can not only develop the C-QCNNA for the LCSCRAP, but also promote the C-QCNNA and cloud model theory themselves. Simultaneously, it has important theoretical and practical significance.

Keywords Low-carbon supply chain · Quantum chaos neural network algorithm · Learning effect · Cloud model

1 Introduction

The recent movement toward sustainability has provided the PSE community with an opportunity to investigate low-carbon supply chains. Alterations in the state of the environment which result from industrial manufacturing activities meanwhile caused a quantum leap for low-carbon supply chain management and business practices. Most efforts

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focus on developing sustainability analytical approach and integrating them with low-carbon supply chain designs. The continuous rise in environmental awareness has affected several aspects of the global economy including supply chain management. Traditional supply chain is designed and operated in a way that minimizes costs and increases profitability. However, this is not sufficient nowadays. It is of crucial importance to incorporate the target of emissions reduction in the supply chain. Thus, the current paper addresses a joint location-inventory problem and extends it to account for the reduction of carbon emissions. The original problem consists of one plant, multiple distribution centers and multiple retailers with products flowing from a plant to DCs and from there to retailers. In terms of the solution technique, it develops a genetic algorithm (GA) and justifies the choice of this heuristic approach by the fact that the resulting model is high in complexity and requires solving within reasonable time. Finally, it is validated that the accuracy of GA on small instances has been solved to optimality using GAMS (Diabat and Al-Salem 2015). Imposition of strict environmental protection acts and the imperative need of best possible allocation of resources have given birth to the concept of "low-carbon logistics." Environmental laws force the manufacturers to extend their existing supply chains to form a closed-loop supply chain (CLSC) through the setup of an efficient recovery system. To consider the environmental issues in the proposed CLSC network, the biobjective integer nonlinear programming problem is formulated to solve through an interactive multi-objective programming approach algorithm. A numerical experimentation of the proposed model to validate the applicability of the model is done with the help of data from a real-life case study (Garg et al. 2015). A two-stage stochastic programming model is presented and used to design and manage biodiesel supply chains. This is a mixed-integer linear program and an extension of the classical two-stage stochastic location–transportation model. The objective function and model constraints reflect the impact of different carbon regulatory policies such as carbon cap, carbon tax, carbon cap-and-trade and carbon offset mechanisms on supply chain decisions. The results from the computational analysis point to important observations about the impacts of carbon regulatory mechanisms as well as the uncertainties on the performance of biocrude supply chains by using Lagrangian relaxation and L-shaped solution methods (Marufuzzaman et al. 2014).

Globalized supply chains, volatile energy and material prices, increased carbon regulations and competitive marketing pressure for environmental sustainability are driving supply chain decision makers to reduce carbon emissions. Enterprises face the necessity and the challenge of implementing strategies to reduce their supply chain environmental impact in order to remain competitive. Therefore, the logistics network should be designed in a way that it could reduce both the cost and the carbon footprint across the supply chain. In this context, this research proposes a quantitative optimization model for integrated forward–reverse logistics with carbon-footprint considerations by integrating the carbon emission into a quantitative operational decision-making model with regard to facility layout decisions. To solve the quantitative model, this research implements a modified and efficient forest data structure to derive the optimal network configuration, minimizing both the cost and the total carbon footprint of the network. A comparative analysis shows the out performance of the proposed approach over the conventional genetic algorithm (GA) for large problem sizes (Choudhary et al. 2015). The product-related carbon emission abatement target (PCEAT) allocation problem is investigated in a decentralized make-to-order supply chain which is composed of a manufacturer and a retailer. The product-related carbon emissions here refer to the total emissions generated from the product manufacturing and retailing processes. It is found that if the leader is the allocator, the proportions of the PCEAT allocated to the two participators are determined by their marginal abatement costs. If the follower is the allocator, the PCEAT will be completely allocated to the leader. When the abatement limits of firms are taken into consideration, the firm constrained by the limit will undertake the portion of PCEAT up to its limit (Ren et al. 2015)· A tactical supply chain planning model is presented that can be used to investigate trade-offs between cost and environmental degradation including carbon emissions, energy consumption and waste generation. The proposed model also incorporates other aspects of real-world supply chains such as multiple transport lot sizing and flexible holding capacity of warehouses. A solution methodology and the Nested Integrated Cross-Entropy (NICE) method are developed to solve the proposed mixed-integer nonlinear mathematical model. The application of the model and solution method is investigated in an actual case problem. Analysis of the numerical results focuses on investigating the relationship between lean practices and green outcomes. Not all lean interventions at the tactical supply chain planning level result in green benefits, and a flexible supply chain is the greenest and most efficient alternative when compared to strictly lean and centralized situations (Fahimnia et al. 2015). Recently it is founded that manufacturing companies have been increasing overseas production in order to decrease local production cost and a global supply chain network is now being constructed not only in developed but also in emerging countries. Furthermore, in order to prevent global warming, a low-carbon supply chain has been required to reduce CO_2 emissions in materials production. The low-carbon supply chain should be constructed and evaluated by multi-criteria for the lead time, costs and CO_2 emissions. This study models a low-carbon supply chain network between Malaysia, China and Japan on a discrete event simulation, evaluates multi-criteria decisions for the lead times, costs and CO_2 emissions and analyzes the effect of the fluctuating lead time (Kawasaki et al. 2015).

Today, tracking the growing interest in closed-loop low-carbon supply chain shown by both practitioners and academia is easily possible. There are many factors which transform closed-loop low-carbon supply chain issues into a unique and vital subject in supply chain management. It is considered to cope with this problem by proposing a new and effective solution methodology by improving low-carbon supply chain network optimization processes through dealing with mathematical programming tools and finally presenting an appropriate methodology to solve various sizes of instances. Both design and planning decision variables are considered in the proposed network. Besides in order to have a reliable performance evaluation process, large-scale instances are regarded in computational analysis. Two popular meta-heuristic algorithms are considered to develop a new elevated hybrid algorithm. In small instances, the global optimum points of CPLEX for the proposed hybrid algorithm are compared to genetic algorithm and particle swarm optimization. The results of performances of the proposed meta-heuristics reveal the superiority of the proposed hybrid algorithm when compared to the GA and PSO (Soleimani and Kannan 2015). Modern enterprises of all sizes operate in global manufacturing networks and complex global supply chains. A multi-objective optimization model is presented that provides a rigorous method to optimize over all the three pillars of sustainability using a cradle-to-gate approach Because sustainability is now a major concern, global manufacturing enterprises must optimize the global supply chain over multi-objectives including sustainability. It is important for such enterprises to analyze the global supply chain across all the three pillars of sustainability (society, economy and environment) when making a distribution network decision (Bhinge et al. 2015). This paper aims to help decision makers, managers and practitioners to achieve economic growth, societal development and environmental protection by developing sustainable supply chain performance measures and proposes a partner selection and flow allocation decision-making model. An integrated method of structural equation modeling, fuzzy analytical hierarchy process and fuzzy multi-objective linear programming was applied to the proposed model. The results of the structural equation modeling analysis indicate that the survey respondents considered sustainable production performance to be of prime importance which thus indicates its significance in developing a sustainable supply chain for the apparel industry. Optimal results are obtained for two strategies—sustainability and cost saving when developing a sustainable supply chain. Using comparative performance, a decision maker can choose an appropriate strategy based on cost–benefit analysis of the presented trade-offs (Jakhar 2015).

An effective solution method is discussed for a two-layer, NP-hard sustainable supply chain distribution model. A DoE-guided MOGA-II optimizer-based solution method is proposed for locating a set of non-dominated solutions distributed along the Pareto frontier. The solution method allows decision makers to prioritize the realistic solutions while focusing on alternate transportation scenarios. The solution method has been implemented for the case of an Irish dairy processing industry's two-layer supply chain network. The solution method characterizes the Pareto solutions from disparate scenarios through numerical and statistical experimentations. A set of realistic routes from plants to consumers is derived and mapped which minimizes total CO_2 emissions and costs where it can be seen that the solution method outperforms existing solution methods (Validi et al. 2015). The environmental sustainability has become one of the major concerns of today's society and sparked tremendous amount of research. According to the related literature analysis, there is no specific study to design the low-carbon supply chain network based on consumers' green expectations. A set of scenarios is also studied to offer an insight on how the consumer determination level of greenness affects the low-carbon supply network. The findings of the study present a way to measure the relations between low-carbon supply chains and consumer behavior (Coskun et al. 2016). The aim of most supply chain optimization problems is to minimize the total cost of the supply chain. However, environmental protection is of concern to the low-carbon supply chain because its minimum effect on nature has been seriously considered as a solution to this concern. The modeling and solving of a supply chain design is developed for annual cost minimization while considering environmental effects. The cost elements of the low-carbon supply chain such as transportation, holding and backorder costs are considered. Considering the cost and environmental effects, a multi-objective optimization problem is proposed. A mimetic algorithm is utilized in combination with the Taguchi method to solve this complex model. The performance of the proposed solution method has been examined against the hybrid genetic Taguchi algorithm (GATA) on a set of numeric instances, and results indicate that the proposed method can effectively provide better results than previous solution procedures (Jamshidi et al. 2012).

In recent years consumers and legislation have been pushing companies to design the activities in such a way as to reduce negative environmental impacts more and more. It is therefore important to examine the optimization of total supply chain costs and environmental impacts together. However, the recycling of deteriorated items and the environmental impacts of deteriorating items are more significant than those of non-deteriorating ones. The objective of the paper is to develop a stochastic mathematical model and to propose a new replenishment policy in a centralized supply chain for deteriorating items. The best transportation vehicles producing various greenhouse gas (GHG) levels and inventory policy are determined by finding a balance between financial and environmental criteria. In this way, a linear mathematical model is developed and a numerical example is presented from the real world to demonstrate its applicability and effectiveness. Finally, more promising directions are suggested for future research (Sazvar et al. 2014). The goal of this research is to develop a novel multi-objective mathematical model in a low-carbon supply chain network consisting of manufacturers, distribution centers and dealers in an automotive manufacture case study. In addition to minimizing the costs and environmental impacts particularly the emission of CO_2, the model can determine the low-carbon economic production quantity using Just-In-Time logistics. Furthermore, multi-objective genetic algorithm is applied in order to minimize these conflicting objectives simultaneously. Finally, the performance of the proposed model is evaluated by comparing the obtained Pareto fronts from MOGA (Memari et al. 2015).

2 Quantum neural network algorithm based on cloud model

Quantum neural network algorithm is the combination of information science and quantum mechanics which is an interdisciplinary full of vitality. Quantum neural network algorithm is represented by quantum neural network owing to its high degree of parallelism. The exponential storage capacity as well as the heuristic acceleration for classical algorithms has become the cutting-edge research field of many international scholars. The quantum computing mechanism in the traditional neural network improves the nonlinear approximation capability of neural networks, convergence, stability and other properties of the algorithm which has a great advantage and bears a strong vitality. Therefore, the research on quantum neural network has important theoretical and practical significance.

Multi-layer quantum neural network that uses qubit neurons is considered as information processing unit. To improve learning performance, the multi-layer quantum neural network is provide for the supervised training instead of applying a back-propagation algorithm. Experimental results confirmed the effectiveness of the real-coded genetic algorithm in training a quantum neural network and proved the feasibility and robustness of the direct quantum neural network controller (Takahashi et al. 2014). A novel approach to adjusting the weightings of fuzzy neural networks using a real-coded chaotic quantum-inspired genetic algorithm (RCQGA) was proposed. Fuzzy neural networks are traditionally trained by using gradient-based methods which may fall into local minimum during the learning process. To overcome the problems encountered by the conventional learning methods, RCQGAs are adopted because of their capabilities of directed random search for global optimization. A real-coded chaotic quantum-inspired genetic algorithm (RCQGA) is proposed based on the chaotic and coherent Q-bits characters. Q-bit probability-guided real cross and chaos mutation is applied to the evolution and searching of real chromosomes. Simulation results have shown that faster convergence of the evolution process in searching for an optimal fuzzy neural network can be achieved. Examples of nonlinear functions approximated by using the fuzzy neural network via the RCQGA are demonstrated to illustrate the effectiveness of the proposed method (Zhao et al. 2009). A quantum BP neural networks model with learning algorithm is proposed. In this model, the input is described by quits and the output is given by the probability of the state in which $|1\rangle$ is observed. The phase rotation and the reversal rotation are performed by the universal quantum gates. Secondly, the quantum BP neural networks model was constructed in which the output layer and the hide layer are quantum neurons. With the application of the gradient descent algorithm, a learning algorithm of the model is proposed. It is shown that this model and algorithm are superior to the conventional BP networks in three aspects: convergence speed, convergence rate and robustness (Panchi and Shiyong 2008). Two optimization algorithms are used for comparison: response surface methodology (RSM) and radial basis function neural network coupling quantum-behaved particle swarm optimization algorithm (RBF-QPSO). It is indicated that both models provide similar quality predictions for the above three independent variables in terms of HA yield, but RBF model gives a slightly better fit to the measured data compared to RSM model. This work showed that the combination of RBF neural network with QPSO algorithm had good predictability and accuracy for bioprocess optimization and may be helpful to the other industrial bioprocesses optimization to improve productivity (Liu et al. 2009).

A fuzzy analysis model can make use of the study ability of neural network. Cloud model is a theory dealing with uncertainty reasoning between a linguistic term of a qualitative concept and its numerical representation. Cloud model is an effective tool in uncertain transforming between qualitative concepts and their quantitative expressions. Super entropy will be the fuzziness and randomness associated, it reflects on the cloud said cloud thickness, and hyper entropy is bigger. Two figures contrast can be seen, big super entropy diagram cloud droplets of discrete degree are big, and the entropy of small cloud droplets is relatively concentrated. The cloud model simulation results of the cloud droplets experiments phenomenon are shown as follows in Figs. 1 and 2.

Cloud model is also used two-order Gaussian distribution to produce cloud drops whose distribution displays high kurtosis and fat tail with power-law decay. Many phenomena have been found to share high kurtosis and fat tail in sociology and economics because of preferential attachment in evolution processes. We find that cloud model presents the new technique to represent the randomness and fuzziness of concepts and realize the indeterminacy transformation between qualitative concepts and quantitative instantiations.

Since advantages of fuzzy control and neural network are complementary, the result of their combination, called as fuzzy neural network (FNN), becomes primary researches in the domain of intelligence control nowadays. This paper proposes a new identification method based on cloud model and vector neural network (CMVNN). The new method that utilizes cloud model to realize the transformation from qualitative concepts to their quantitative interval expressions can make use of the improved vector neural network to come true the nonlinear mapping between the interval value input data and the interval

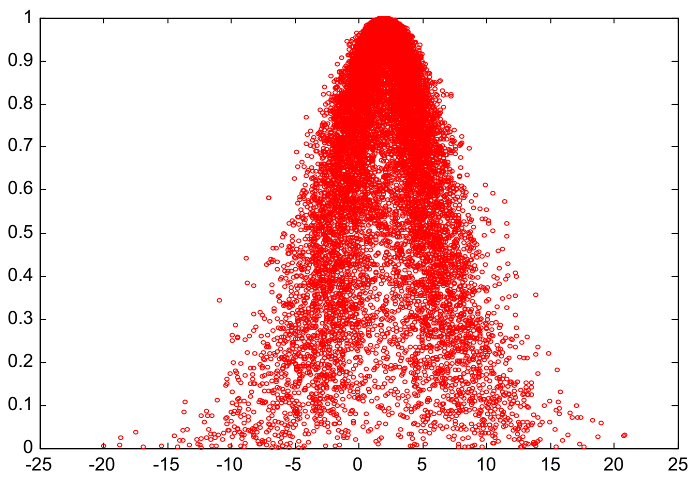

Fig. 1 He $=$ 1.58 simulation results of cloud model

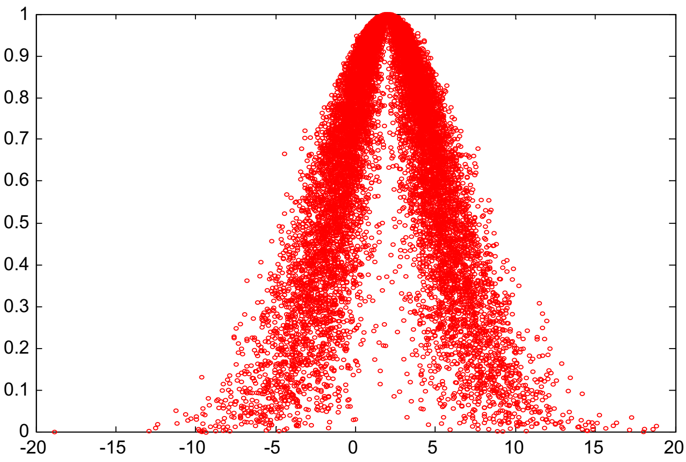

Fig. 2 He = 0.98 simulation results of cloud model

value output emitter types. Cloud model is an uncertain inference system based on linguistic rules. The number of linguistic rules is usually increased to improve the accuracy of identification. The high dimension of the input space will cause the curse of dimensionality. To solve this problem a wavelet network cloud model (WNCM) is proposed. A wavelet neural network is used to substitute the consequent part of the cloud model. The structure and learning algorithm of WNCM is designed. Simulation results and comparisons with other methods indicate that WNCM can approximate arbitrary nonlinear functions. The accuracy of identification is realized without increasing linguistic rules.

A fuzzy analysis model that makes use of the study ability of neural network and fuzzy information processing of cloud model is proposed in this paper. Cloud model is an effective tool for qualitative and quantitative transform, and a specific structure generator is formed by normal cloud model through expectation, entropy and hyper entropy. This particular structure makes the normal cloud model has more general applicability and straightforward completed conversion process between qualitative and quantitative. In a quantum process all transitions of the neurons must be designated by unitary operators. Hence, we have a less spectacular unitary transformation that simply performs a rotation of the state vector or the qubit in place of the firing of a neuron. The need for a phase change during flipping is needed for unitarily as can be seen easily when real coefficients are used for the qubit superposition. The control and target bits of the quantum can be shown by the following:

$$|c\rangle = a|0\rangle + b|1\rangle \quad \text{and} \quad |t\rangle = c|0\rangle + d|1\rangle \tag{1}$$

Then, normalization of the quantum state demands is shown by the following:

$$|a|^2 + |b|^2 = 1 \quad \text{and} \quad |c|^2 + |d|^2 = 1 \tag{2}$$

After the cNOT operation, we can get the following formula:

$$|c'\rangle = |c\rangle \quad and \quad |t'\rangle = (ac + bd)|0\rangle + (ad - bc)|1\rangle \tag{3}$$

Another interesting aspect of a quantum gated machine is as previously mentioned. It is potentially closer to biological systems than the present electronic machines because quantum gates acting on photon nodes may have connectivity with the nodes that is unattainable in electronic devices that have only one or two inputs and outputs. The operation should involve time too, and we can express as follows:

$$|t\rangle = U(t, t_0)|0\rangle \tag{4}$$

It indicates the transformation of a neuron from time t_0 to time t. For small time changes, it can be possible to describe as follows:

$$U(t + d_t, t) = U(t, t_0) + id_t H \tag{5}$$

$$d|t\rangle = id_t H|t\rangle \tag{6}$$

The performance depends on several factors such as choice of learning parameters, cost function and network topology. An important and commonly adopted strategy is that the initial weights are chosen to be small in magnitude in order to prevent premature saturation in the training procedure. Quantum machines developed some of the advantages of biological systems of information processing which a certain amount of indeterminism and the multiple connectivity nodes working with classical quantum gates. We have shown that a quantum neural network similar to the biological integrates and fire neuron network can be constructed with quantum elements which consisting of qubit nodes connected by quantum cNOT and quantum gates. The number of possible connectivity also makes quantum neural network gated systems more a kin to biosystems and the ability of biosystems to handle ill-posed information quantum algorithm in a more effective way. It can inspire the quantum neural network gated machines with their inherent probabilistic quantum algorithm. It may also achieve similar robustness in processing real-life situations with incomplete or confounded information.

Fuzzy clustering reduces the dependency on initialization. However, it constitutes a slow learning process. The proposed strategy aims to search for a trade-off among these two potentially different effects. The hybrid clusters are directly involved in the estimation process of the neural network's parameters. Specifically, the center elements of the basis functions coincide with cluster centers, while the respective widths are calculated by taking into account the topology of the hybrid clusters. To this end, the network's design becomes a fast and efficient procedure. We propose a novel fuzzy hybrid double chains quantum chaos neural network clustering algorithm based on cloud model (C-QCNNA) in vague sets (IVSs) which is more expressive than the other fuzzy sets. Cloud model integrates the fuzziness and randomness of concept representation and the uncertain transition between qualitative and quantitative. Converting quantitative attributes into Boolean attributes is the general way for mining quantitative association rules. Cloud model is applied to neural network improvement which avoids neural network trapping to local least value. This learning rate self-turning method is based on cloud model and input parameter domain partition. Finally, the C-QCNNA is simulated under complex nonlinear neural network classification circumstances. General cloud overcomes the shortcomings of unreasonable spatial division, and it has several non-equilibrium and non-symmetric forms. On the other hand, the heterogeneous characteristics of general multi-dimensional cloud model have great superiority in simulating complex phenomena.

Traditional method is not easy to understand the knowledge because it cannot reflect the actual data distribution or the partition is too sharp. Cloud model uses many concepts represented to fit the real distribution of data introduced. This cloud model can reflect the distribution of data in that domain while keeping the soft boundaries. Therefore, the discovered association rules are also easy to understand uncertainty reasoning. After the interval-cloud model is constructed, it is used to express the different importance between two factors in the interval index system and the experts' linguistic judgments are synthesized with the built floating cloud method. From the above research, we can assume a virtual floating cloud between two neighbor clouds such as $C_1 = (Ex_1, En_1, He_1)$ and $C_2 = (Ex_2, En_2, He_2)$. Accordingly, we can be also defined by the following equation:

$$Ex = w_1 Ex_1 + w_2 Ex_2 \tag{7}$$

$$En = \frac{En_1(Ex_2 - Ex) + En_2(Ex - Ex_1)}{Ex_2 - Ex_1} \tag{8}$$

$$He = \frac{He_1(Ex_2 - Ex) + He_2(Ex - Ex_1)}{Ex_2 - Ex_1} \tag{9}$$

If $C_i \in (c_1, c_k)$, $C = (Ex, En, He)$ can then be defined by the following equation:

$$Ex_i = \frac{Ex_i^1 * En_i^1 + Ex_i^2 * En_i^2 + \cdots + Ex_i^k * En_i^k}{En_i^1 + En_i^2 + \cdots + En_i^k} \tag{10}$$

$$En_i = En_i^1 + En_i^2 + \cdots + En_i^k \tag{11}$$

$$He_i = \frac{He_i^1 * En_i^1 + He_i^2 * En_i^2 + \cdots + He_i^k * En_i^k}{En_i^1 + En_i^2 + \cdots + En_i^k} \tag{12}$$

In this paper, the analytic hierarchy process is combined with floating cloud. $C_\mathrm{i} = (Ex_i, En_i, He_i) \in [C_\mathrm{i}, C_k]$ is interval number. We can conclude that the level of nodes in pan-concept-tree can be raised stage by stage through using multi-dimensional cloud synthetic cooperator mentioned above. It is worth emphasizing that we should employ the union of different scope when facing concepts in the same level with different direction.

$$T_i^{v_i} = \left\{ v_i \in T_k^{v_i - 1} : \|x_k - v_i\| \leq \frac{2 + (T_{k-1}^{v_i - 1} - 2)\theta}{\theta} * \frac{1}{\sum v_i \in T_k^{v_i - 1}\left(\frac{1}{\|x_k - x_0\|}\right)^2} \right\} \tag{13}$$

$$u_i^{v_i} = \frac{2 + (T_{k-1}^{v_i - 1} - 2)\theta}{2(1-\theta)} * \frac{1}{\sum v_i \in T_k^{v_i - 1}\left(\frac{1}{\|x_k - x_0\|}\right)^2} - \frac{\theta}{2(1-\theta)} \tag{14}$$

$$v_i = \frac{\sum_{i=1}^{n} \left[\theta u_i + (1-\theta) u_i^2\right] x_i}{\sum_{i=0}^{n} \left[\theta u_i + (1-\theta) u_i^2\right]} \tag{15}$$

Since those that were set equal to zero will not influence the final result, we used all the membership degrees. Hence, the vector x_i is assigned zero or positive membership degrees with respect to all clusters during the learning process. The sum of whose is unity fulfilling in this way the basic constraint.

Clustering algorithms are fundamental and important methods for data analysis which have been applied in a variety of fields such as data mining and pattern recognition. A multilayer perception artificial neural network which is a universal classifier is combined with the k-means clustering method to accurately detect skin. The experimental results show that the proposed method can achieve high accuracy with an F1-measure of 87.82 %

based on images from the ECU database (Hani K. Al-Mohair et al. 2015). Different from most existing clustering techniques, the proposed method is able to generate a dynamic two-dimensional topological graph which is used to explore both partitioned information and detailed data relationship in each cluster. The comparable experimental results demonstrate the superior performance of the proposed algorithm in learning robustness, efficiency, working with outliers and visualizing data relationships (Liu and Ban 2015). After reviewing the general principles of a biological network and a quantum one, we study a specific model network with qubits, i.e., quantum bits replacing classical neurons having deterministic states and also with quantum operators in place of the classical action potentials observed in biological contexts. With the choice of gates interconnecting the neural lattice, the state of the system behaves in ways reflecting both the strength of coupling between neurons and the initial conditions in biological systems. We are interested to find clustering algorithm depending on whether there is a threshold for emission from excited to ground state. Meantime, we also realized that the system shows either chaotic oscillations or coherent ones with periodicity that depends on the strength of coupling. The initial input also affects the subsequent dynamic behavior of clustering algorithm which indicates that it can serve as a dynamic memory system analogous to biological ones. The clustering results of the algorithm seem to suggest that such quantum networks may contain some advantageous features more efficiently than the other classical clustering algorithm. The C-QCNNA can be applied to the clustering algorithm. The comparisons of experimental results through numerical examples are shown in Figs. 3, 4 and 5.

It can be observed from the results that the C-QCNNA clustering algorithm is competitive with the other two approaches. The C-QCNNA utilizes the cloud model to realize the transformation from qualitative concepts to their quantitative interval expressions. The C-QCNNA based on CNOT gate and the characteristics of the imitation of CNOT gate is analyzed. A kind of quantum neural network based on CNOT gate is established with traditional neural network framework so that his network model is proved theoretically which has a good continuity, and it is used to calculate the network parameters. Finally, we strongly emphasize that the implementation of a gradient descent approach to fine-tune the neural network's parameters is still possible, but the resulting learning scheme will become a litter lower. Therefore, we do not use such kind of neural network learning mechanism. The C-QCNNA can automatically generate a dynamic two-dimensional topological graph which is used to explore both cluster information and detailed information of each cluster.

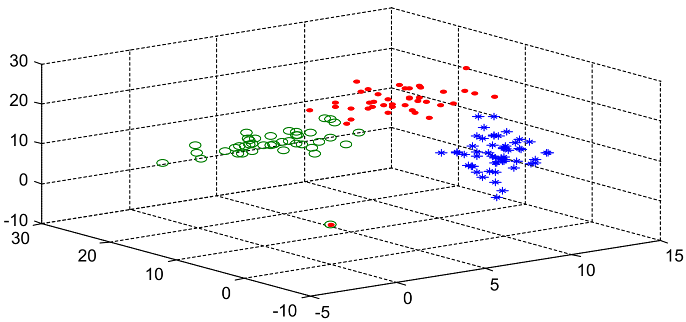

Fig. 3 Clustering results of the NNA

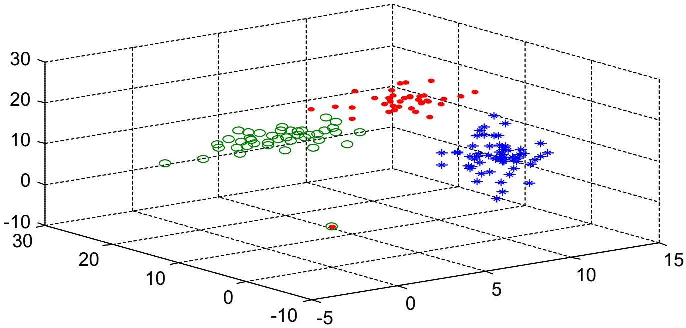

Fig. 4 Clustering results of the QCNNA

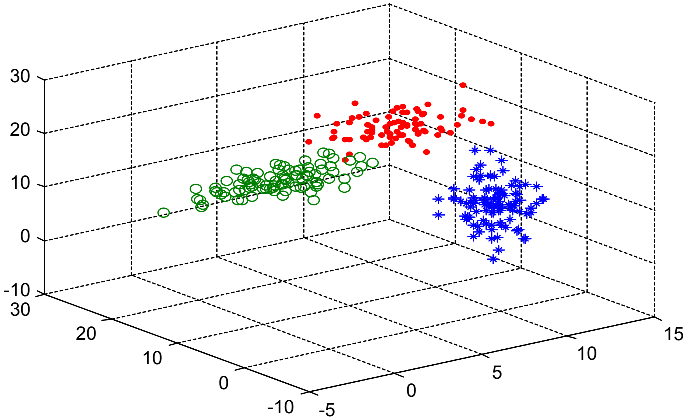

Fig. 5 Clustering results of the C-QCNNA

The experimental results of C-QCNNA have demonstrated the superior performance in learning robustness and efficiency.

3 Low-carbon supply chain resources allocation model based on learning effect

Designing integrated system of bioenergy production supply chain that simultaneously utilizes a set of bioresources together is a complicated task considered here. Moreover, the different concerns that decision makers should take into account, to overcome the trade-off anxieties of the socialists and investors, i.e., social, environmental and economical factors, were considered through the options of multi-criteria optimization. Two levels decision system were also considered for efficient planning and implementation of bioenergy production. The optimization model is presented and followed by a case study on designing a supply chain of nine bioresources at Iida city in the middle part of Japan (Ayoub et al. 2009). Closed-loop supply chain aims at integrating return products in the traditional supply chain processes. The return flows generate new uncertain elements, and optimization of inventory control in this context is a complex issue. Inventory policies have to generate good performances and be easy to implement in practice. A supply chain model based on simulation and multi-objective optimization is proposed to optimize control policies for multi-echelon supply chain with returned products. The method is tested on three inventory policies which correspond to different ways of making decision (Godichaud and Amodeo 2015). Stricter governmental regulations and rising public awareness of environmental issues are pressurizing firms to make their supply chains greener. Partner selection is a critical activity in constructing a low-carbon supply chain because the environmental performance of the whole supply chain is significantly affected by all its constituents. A model for green partner selection and supply chain construction is presented by combining analytic network process (ANP) and multi-objective programming (MOP) methodologies. The model offers a new way of solving the green partner selection and supply chain construction problem both effectively and efficiently as it enables decision makers to simultaneously minimize the negative environmental impact of the supply chain while maximizing its business performance. The applicability and practicability of the model is demonstrated in an illustration of its use in the Chinese electrical appliance and equipment manufacturing industry (Wu and Barnes 2016). The impacts of a carbon emission-sensitive demand on decisions relative to the design of forward supply chains are explored. The demand for the final product is an endogenous variable sensitive to carbon emissions per unit, and it is also assumed to increase with a decrease in the per unit carbon emissions of the product. The results augment the research to the fields of design of forward and greener supply chains by modeling and experimenting an endogenous demand sensitive to carbon emissions (Nouira et al. 2016).

We develop a novel multi-objective mathematical model in the low-carbon supply chain network consisting of manufacturers, distribution centers and dealers in an automotive manufacture case study. The aim of the model is to optimize total costs including production, holding, shipping and dealer shortages due to out of stock as well as minimizing carbon emission in the whole supply chain. Recently, learning effects in the low-carbon supply chain network problems have received growing attention. Recently, classic learning effect model has been applied into many fields. We propose a new low-carbon supply chain resources allocation with deteriorated learning model where the learning effect depends on the group resources allocation position and the deteriorated effect depends on the low-carbon supply chain resources allocation resource. The positive learning effect model of low-carbon supply chain resources allocation is shown as follows:

$$\begin{cases} R'_{[i][j]} = R^0_{[i][j]} * \left(\dfrac{R'_{[i][j-1]} * q^{-\eta}_{[i][j-1]}}{R_{[i][j-1]}} + \alpha\left(R^{[i]}_{[j-1][j]}\right) * \left(\dfrac{R_{[i][j-1]} - R'_{[i][j-1]} * q^{-\eta}_{[i][j-1]}}{R_{[i][j-1]}} \right) \right) \\ R' = R^0_{[i][j]} * \left(\alpha\left(R^{[i]}_{[j-1][j]}\right) + \left(1 - \alpha\left(R^{[i]}_{[j-1][j]}\right)\right) * \dfrac{R'_{[i][j-1]} * q^{-\eta}_{[i][j-1]}}{R_{[i][j-1]}} \right) \\ R'_{[i][j]} = R^0_{[i][j]} * \left(\alpha\left(R^{[i]}_{[j-1][j]}\right) + \left(1 - \alpha\left(R^{[i]}_{[j-1][j]}\right)\right) * \dfrac{R'_{[i][j-1]} * q_{[i][j-1]}}{R_{[i][j-1]}} \right) \end{cases} \quad (16)$$

where $\alpha\left(R^{[i]}_{[j-1][j]}\right)$ and $\alpha\left(R^{[G]}_{[i-1][i]}\right)$ are the coefficient of deteriorated learning effect. Meanwhile, $\left(1 - \alpha\left(R^{[i]}_{[j-1][j]}\right)\right)$ and $\left(1 - \alpha\left(R^{[G]}_{[i-1][i]}\right)\right)$ are the coefficient of positive learning effect in the low-carbon supply chain resources allocation.

In the paper, we propose a general learning model which considers the cost-based learning and the sum-of-cost-based learning effects at the same time. We present polynomial cost optimal solutions for some special cases of the problems of minimizing the total cost of in the low-carbon supply chain network. We propose a learning model of low-carbon supply chain resources allocation which is considered both the positive learning effects and the deteriorated learning effects. Simultaneously, we first show the sum-of-processing-resources-based learning effects model of low-carbon supply chain resources allocation in Formula (17).

$$OBJ = OBJ_1 + OBJ_2 + OBJ_3 + OBJ_4$$

$$st.$$

$$\begin{cases} OBJ_1 = \rho_1 W_1 * \sum_{i=1}^{I}\sum_{j=1}^{J}\left[\left(\sum_{k=1}^{K} C_{ijk}\right) * PC_{ijk}\right] \\ OBJ_2 = \rho_2 W_2 * \sum_{i=1}^{I}\sum_{j=1}^{J}\left[\left(\sum_{k=1}^{K} C_{ijk}\right) * WC_{ijk}\right] \\ OBJ_3 = \rho_3 W_3 * \sum_{i=1}^{I}\sum_{j=1}^{J}\left[\left(\sum_{k=1}^{K} C_{ijk}\right) * QC_{ijk}\right] \\ OBJ_4 = \rho_4 W_4 * \sum_{i=1}^{I}\sum_{j=1}^{J}\left[\left(\sum_{k=1}^{K} C_{ijk}\right) * RC_{ijk}\right] \end{cases} \tag{17}$$

where OBJ_1 is production cost and it seeks to minimize the production cost when product s is produced by producer j. OBJ_2 is the cost of component disposal, and it seeks to minimize the component disposal cost during the whole manufacturing processes which include solid waste treatment cost, chemical waste treatment cost and air emission treatment cost. OBJ_3 is quality cluster with the products quality level and the customer service level. OBJ_4 is resource consumption cluster within the resource consumption cluster, and it seeks to minimize the energy consumption and the non-renewable resources consumption. The learning effects model contains the transportation process from producers to distributors and from distributors to customer zones. The model can efficiently offer a new way of solving the low-carbon supply chain network construction problem, and it minimizes the negative environmental impact of the low-carbon supply chain network while maximizing its business performance.

4 Numerical example

The proposed C-QCNNA clustering algorithm is able to find a stochastic frontier based on a set of input and output observational data of neural network structures and does not require explicit assumptions about the function structure of the stochastic frontier. Recently, it has been found that there is chaos in the brain and chaos theory can be used to understand some irregular activities in the brain. Therefore, the chaotic dynamics provides a new opportunity for the study of neural networks. Because of the characteristics of the artificial neural network with chaotic characteristics, a wide range of research is obtained which is different from the conventional neural network with gradient descent property. The complex dynamics of chaotic neural network is a kind of technology which can be widely used in information processing and optimization calculation. We interestingly find that the C-QCNNA shows different performance with the different parameters of chaos in Figs. 6 and 7.

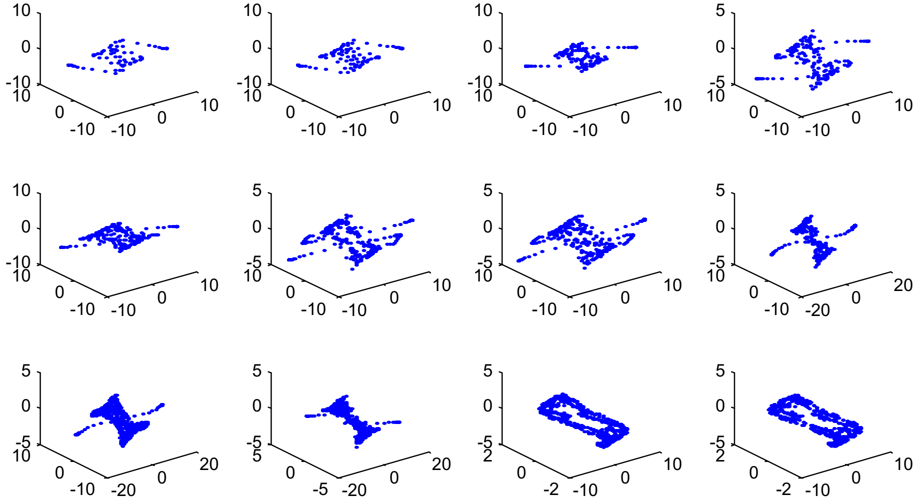

Fig. 6 Simulation results with chaos when mse = 4.0938e−007

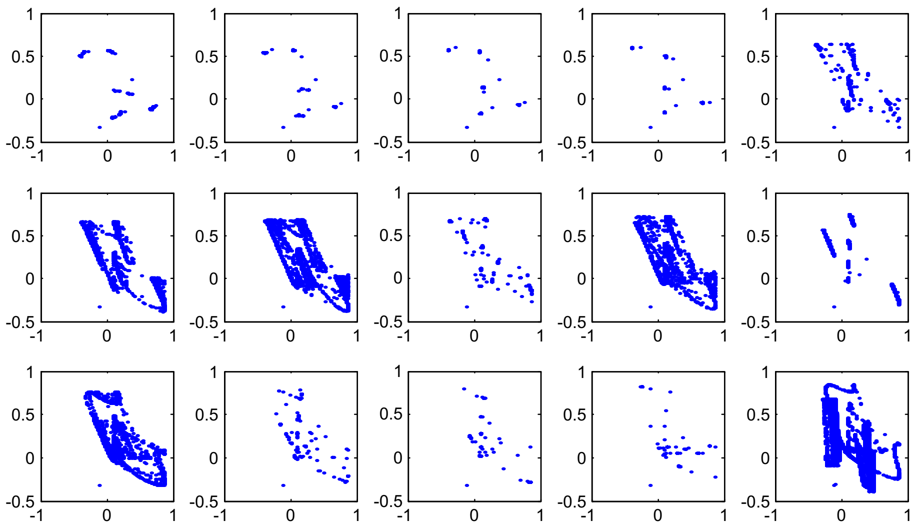

Fig. 7 Simulation results with chaos when mse = 2.2356e−004

To enhance the performance of classical neural networks, the C-QCNNA based on the controlled-Hadamard gates is proposed. In the proposed algorithm, the samples are linearly transformed to quantum bit phase and the qubits are rotated about three coordinate axes, respectively. The results of experiments show that the C-QCNNA is superior to the classical algorithm in approximation ability, generalization ability and robust performance. We have successfully obtained several interesting results from applications and plants divided into clusters by means of the C-QCNNA clustering algorithm. The results of the C-QCNNA for each of the clusters are summarized in Table 1.

Table 1 Calculating efficiency of the C-QCNNA clustering algorithm

DMU	P_R	P_S	P_C	W_i	E_i	E'_i
Cluster 1						
Shazand	7,438,002.00	7,164,642.95	7,164,643.00	0.19	273,359.10	1,438,981.00
Rajaei	6,342,203.00	5,701,384.45	5,701,384.00	0.14	640,818.50	4,428,499.00
Mofatteh	5,134,547.00	5,378,608.18	5,378,608.00	0.15	−244,061.00	−1,804,718.00
Esfahan	5,621,431.00	5,310,960.15	5,310,960.00	0.13	310,470.80	2,329,583.00
Tabriz	4,341,330.00	4,617,026.05	4,617,026.00	0.11	−275,696.00	−2,427,296.00
Bistoon	4,210,280.00	4,249,969.05	4,249,969.00	0.10	−39,689.00	−383,560.00
Toos	3,831,065.00	3,858,784.95	3,858,785.00	0.09	−27,720.00	−298,283.00
Montazerghaem	3,297,100.00	3,628,549.65	3,628,550.00	0.10	−331,450.00	−3,817,118.00
Cluster 2						
Montazeri	11,137,177.00	9,370,519.03	9,370,519.00	0.23	1,766,658.00	7,541,517.00
Ramin	10,861,867.00	9,195,861.73	9,195,862.00	0.23	1,666,005.00	7,286,631.00
Salimi	11,310,817.00	8,177,297.45	8,177,297.00	0.20	3,133,520.00	15,901,986.00
Bandarabbas	7,196,540.00	7,340,823.65	7,340,824.00	0.17	−144,284.00	−836,275.00
Shazand	7,438,002.00	7,164,642.95	7,164,643.00	0.17	273,359.10	1,631,797.00
Cluster 3						
Besat	1,500,253.00	2,053,443.70	2,053,444.00	0.22	−553,191.00	−2,695,686.00
Iranshah	1,492,847.00	2,043,592.05	2,043,592.00	0.20	−550,745.00	−2,699,867.00
Beheshti	1,435,991.00	1,757,228.32	1,757,228.00	0.17	−321,237.00	−1,893,718.00
Madhaj	922,587.00	1,685,681.95	1,685,682.00	0.16	−763,095.00	−305,645.00
Mashhad	665,887.00	1,245,295.40	1,245,295.00	0.11	−579,408.00	−5,103,347.00
Zarand	341,402.00	891,289.55	891,289.50	0.09	−549,888.00	−7,027,011.00
Firoozi	212,403.00	782,995.75	782,995.80	0.07	−570,593.00	−8,394,023.00

The C-QCNNA clustering algorithm is proposed to measure and rank the decision-making unit's (DMUs) efficiency because of nonlinearity of the fuzzy neural networks based on cloud model in addition to its universal approximations of functions and its derivates which makes them highly accurate. At the same time, we also interestingly find that the results of the C-QCNNA clustering algorithm performance by three functions are as following in Fig. 8.

The simulation results of the numerical examples show that the clustering effectiveness of the C-QCNNA algorithm if fast convergence and improved the accuracy of the QCNN clustering algorithm. A fuzzy analysis model that makes use of the study ability of neural network and fuzzy information processing of cloud model is proposed. The results show that the model achieves a high hit rate and low false alarm rate. The quantum hybrid algorithm is used to optimize, and thresholds of the quantum neural network model are used to initialize the C-QCNNA. Simulation experiments on the improved quantum neural network model and the existing models are operated, respectively. The validity and feasibility of forecast performances are proved by the results in Figs. 9, 10, 11 and 12.

The numerical results show that the performance of the C-QCNNA significantly outperforms other algorithms. At length, we study the low-carbon supply chain resources allocation of the 500 database with different learning factors (ρ) based on the learning

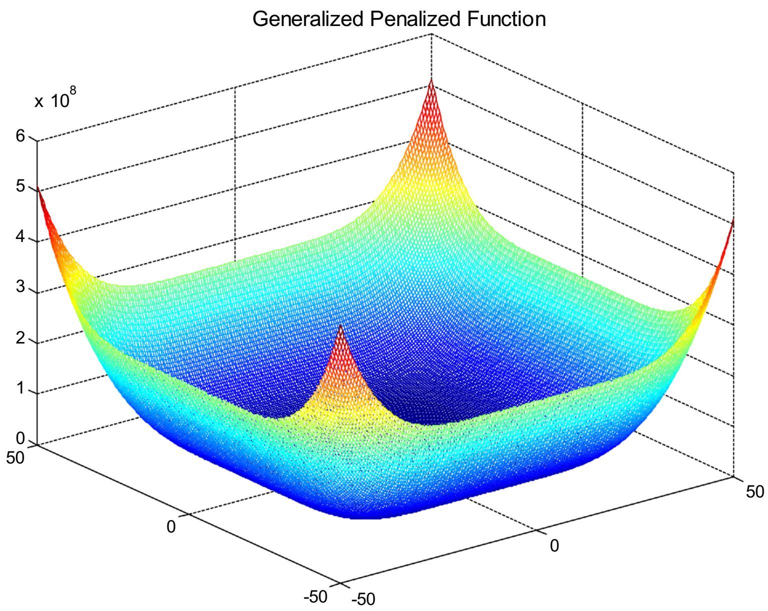

Fig. 8 The performance of penalized by the C-QCNNA

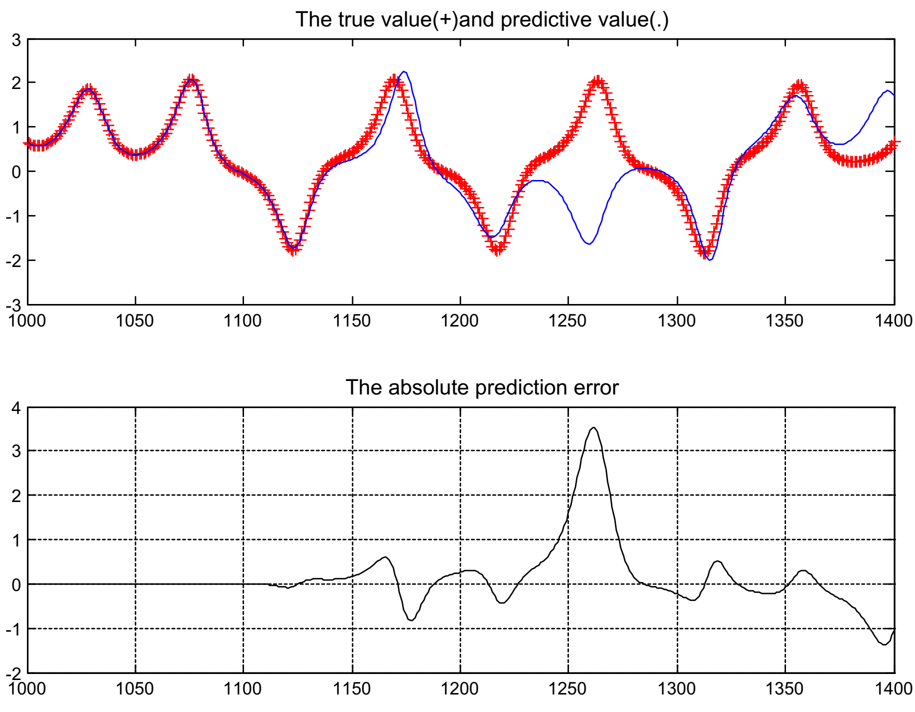

Fig. 9 The forecast performances of the QCNNA

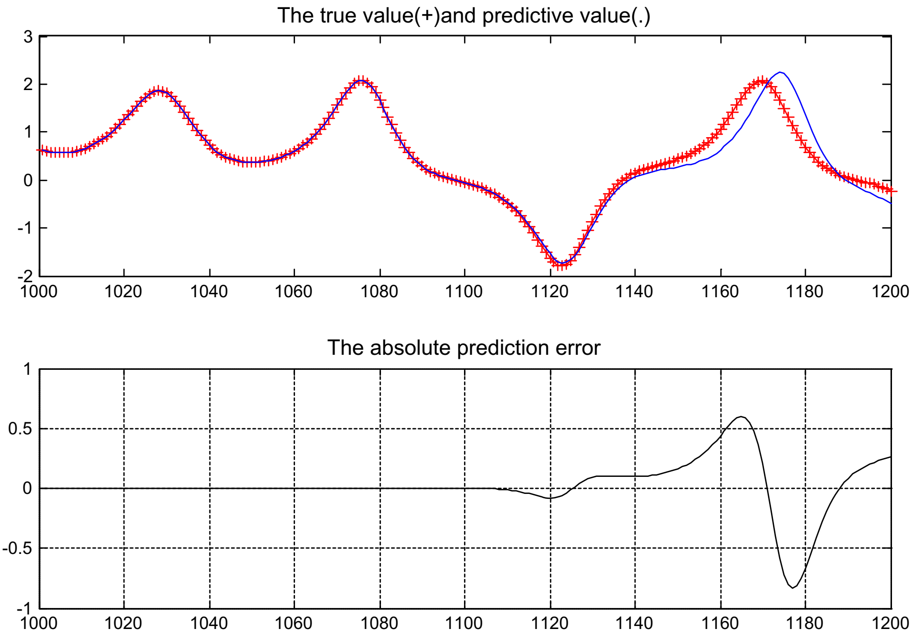

Fig. 10 The forecast performances of the C-QCNNA

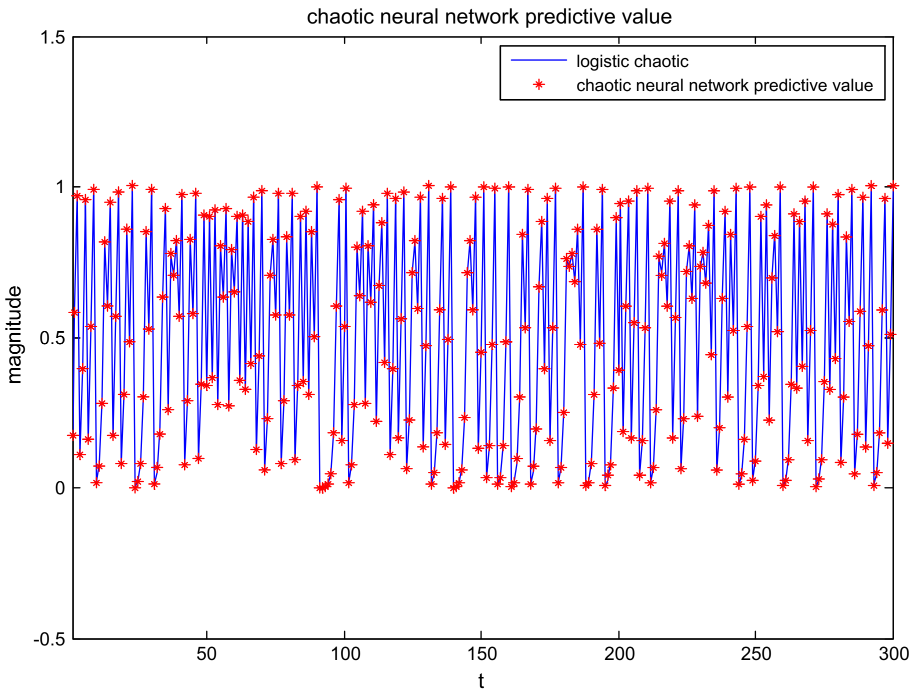

Fig. 11 The forecast value of the C-QCNNA

effect of the low-carbon supply chain resources allocation experimental results shown in Figs. 13, 14 and 15.

Through the simulation analysis of different learning factors, we can find the efficiency and configuration of low-carbon supply chain resources allocation. Therefore, we can improve the learning efficiency of flexible resource. So we should pay more attention to improve the learning effect of low-carbon supply chain resources allocation.

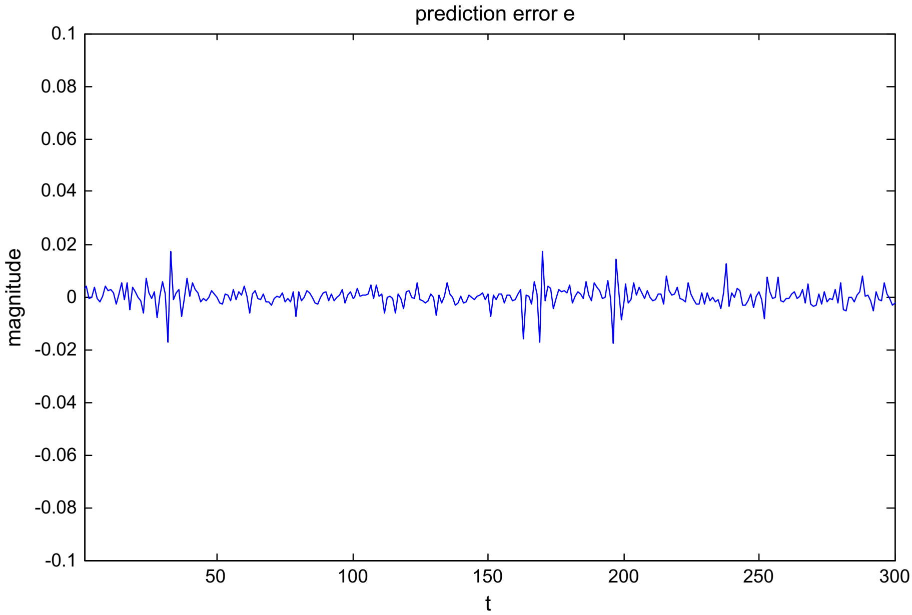

Fig. 12 The forecast error of the C-QCNNA

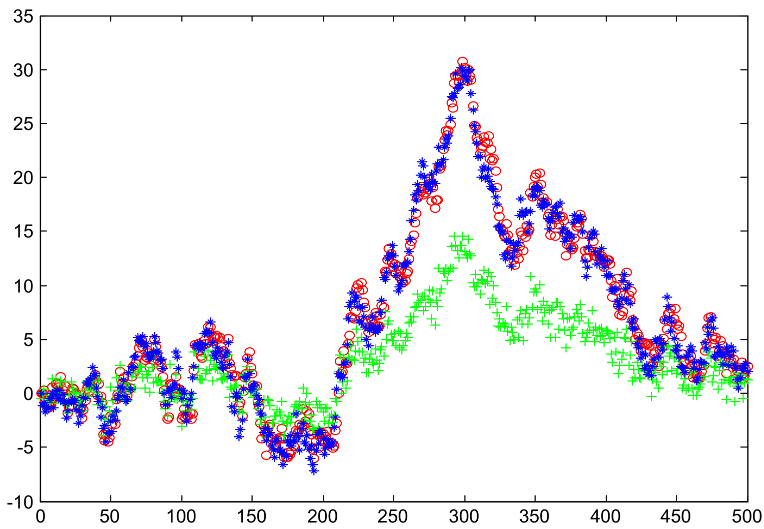

Fig. 13 The result of low-carbon supply chain resources allocation when $\rho = 0.4500$

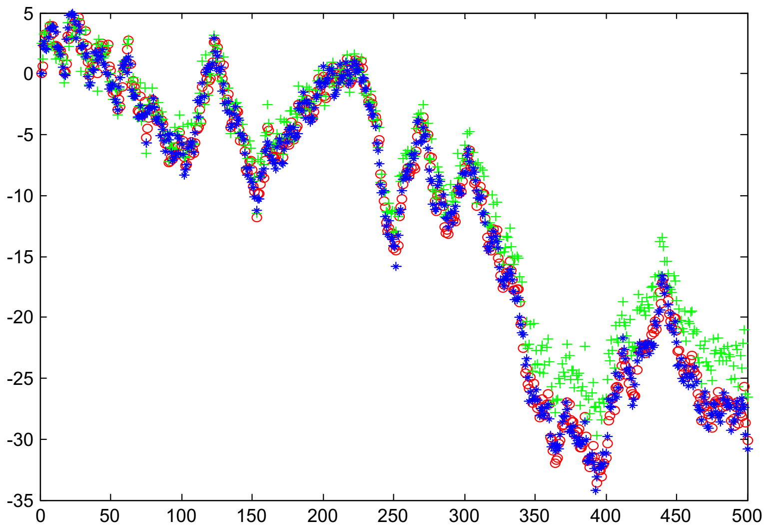

Fig. 14 The result of low-carbon supply chain resources allocation when $\rho = 0.8500$

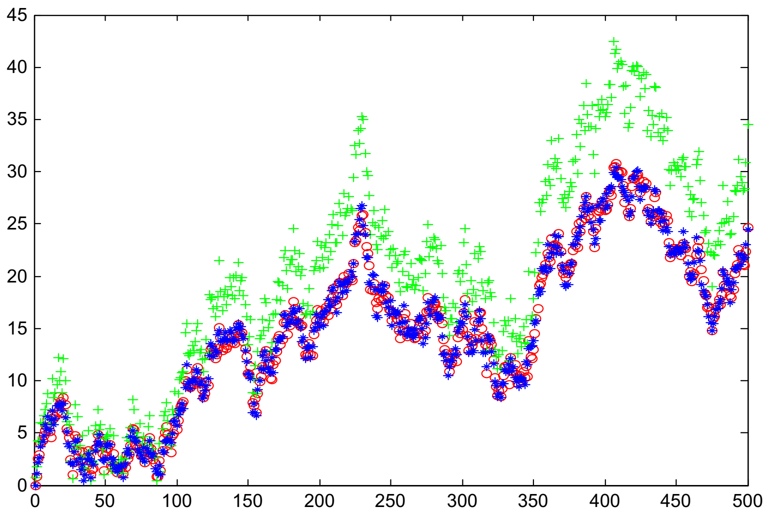

Fig. 15 The result of low-carbon supply chain resources allocation when $\rho = 1.3500$

5 Conclusion

According to these studies, there are many different kinds of clustering algorithms which can be applied. We have developed effectively the hybrid C-QCNNA clustering algorithm concerning the way we determine the structure of the hybrid clustering algorithm in the multidimensional feature space. To accomplish this task, we use a transition strategy from cloud model where each training vector is assigned to the C-QCNNA clustering algorithm with different degrees of participation to crisp mode where each training vector is assigned to only one cluster. Efficiency frontier analysis through the C-QCNNA clustering algorithm has been an important approach for evaluation. However, the assumptions made for each of these methods are restrictive. Each of the other clustering algorithms has its strength as well as major limitations. This study proposes a nonparametric efficiency frontier analysis method based on the C-QCNNA clustering algorithm for measuring efficiency as a complementary tool. The main advantages of the C-QCNNA are the linkage between data topology preservation and class's representation by using the cluster posterior probabilities of classes. In addition to the extension of the application domain, we can investigate the combinatorial clustering algorithms to improve its solution quality of the C-QCNNA clustering algorithm.

In order to solve the low-carbon supply chain resources allocation problem (LCSCRAP), we develop a novel hybrid quantum chaos neural network algorithm based on cloud model (C-QCNNA). In the meantime, the simulation results show that the algorithm can be very competitive in terms of LCSCRAP. Compared with average deviations and percentages of optimal solution, the C-QCNNA outperforms the other algorithms. Simultaneously, we have not only evaluated the performance of the algorithm but also analyzed the reasons. And these designed mechanisms of the algorithm have been verified through the simulation experiments. Finally, the effectiveness of the C-QCNNA is verified by the simulations. Based on the developed analysis, the LCSCRAP with the algorithm is considered in the utility function employed to realize optimization. The elements of the low-carbon supply chain resources allocation are multi-objective optimization model which has been adapted to include the objective costs. Consequently, improving the algorithm and the efficiency for the LCSCRAP is our future research topic. Moreover, improving the processing-resource-based learning effects model of low-carbon supply chain resources allocation optimization and integrating the future developments for trends in energy prices are also our interesting future works. It is of great interest to identify the optimized network alternatives for costs and environmental sustainability separately and to discuss the advantages and disadvantages for the low-carbon supply chain resources allocation. We will extend the developed approach to account with other important supply chain aspects such as the social objective aiming at establishing sustainable supply chains. Simultaneously, we will also apply the hybrid intelligent algorithm to solve the multi-objective optimization problem for low-carbon supply chain resource allocation.

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