



Fast artificial bee colony algorithm with complex network and naive bayes classifier for supply chain network management

Jianhua Jiang¹ · Di Wu¹ · Yujun Chen¹ · Dianjia Yu¹ · Limin Wang¹ · Keqin Li²

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Abstract

In supply chain network (SCN) management, multi-objective Pareto optimization means the network can meet the demand for both minimal cost and minimal lead-time in SCN. Due to the compromise between cost and lead-time, it is a non-trivial issue to search for multi-objective Pareto optimal solutions (POS) in SCN. Furthermore, with the wide application of the internet, an increasing number of SCN applications have been based on the internet. As a result, the complexity of SCN increases exponentially with the number of suppliers increasing. It is really a big challenge to find the global multi-objective POS within a limited time in SCN management. In order to solve this problem, first, this paper proposes an artificial bee colony (ABC) optimization algorithm with two improvements: (1) a novel solution framework designed to extend the application field of the SCN based on complex network; (2) the acceleration of search speed by adopting naive Bayes classifier. Second, the paper provides a case example of optimizing a three-echelon SCN with the objective of minimizing both cost and lead-time. After the simulation with this example, it turns out that the enhanced ABC algorithm can satisfy the requirements of: (1) finding the global multi-objective POS; (2) improving the speed of finding optimal solutions in SCN management.

Keywords Artificial bee colony · Complex network · Multi-objective optimization · Pareto optimal solutions · Three-echelon supply chain

1 Introduction

Nowadays, with the drastic change of business environment, corporations are required to evaluate and configure their supply chain management (SCN) to provide customers with high-quality products/services at the lowest possible cost and within the shortest possible lead-time (Gou et al. 2017; Pishvaei et al. 2011) to support their sustainable development (Kleindorfer et al. 2005; Linton et al. 2007). The supply chain of manufacturing, processing and delivering resources is typically a large complex network (Aslam and Ng 2010; Tan

2001; Zhou et al. 2017), its operation management requiring optimization based on complex network. Suppliers are growing exponentially because of the wide application of e-commerce systems, which makes the supply chain network ever more complex and difficult to be optimized. Therefore, multi-objective Pareto optimization in complex SCN is one of the fundamental functions in e-commerce operation management.

The optimization in SCN management refers to discovering the best flow patterns (i.e. choices of resources) for a family of products (Goetschalckx et al. 2002). The flow pattern in SCN management involves selections through which materials (raw materials, partially processed, and finished products) and information (demand data, due date, delivery, assembly cost and lead-time) are allocated in order to satisfy its multi-objective functions (Corner and Buchanan 1995; Ke et al. 2017; Li et al. 2017; Nasiri et al. 2010; Nemati and Alavidoost 2018; Schtz et al. 2009; Zhang et al. 2016).

In order to determine an efficient flow pattern for every product in a family, it requires: (1) the selection of a supplier (or suppliers) for every component used in the product portfolio, (2) the selection of a manufacturing plant (or plants) for

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✉ Jianhua Jiang
jjh@jlufe.edu.cn; jianhuajiang@yahoo.com

✉ Keqin Li
lik@newpaltz.edu

¹ School of Management Science and Information Engineering, Jilin University of Finance and Economics, Jinyue 3699, Changchun 130117, China

² Department of Computer Science, State University of New York, New Paltz, NY 12561, USA

every sub or final component assembly, and (3) the selection of transport options to deliver every product to customers (Moncayo-Martnez and Zhang 2011). In a typical case of SCN, there often exist many suppliers for the same raw materials or components, as well as multiple manufactures to conduct the sub or final assembly, and also a number of distributors to deliver products to customers. Different resource selections in the flow pattern will generate different costs and lead-times, thus it is necessary to design a multi-objective optimization model to get the global optimal solution of this combinatorial selection to reach an optimized balance between total cost and lead-time for SCN management. This is not an easy task due to high complexity, which requires simultaneous optimization of cost and lead-time, both often contradicting with each other. Moreover, it involves multiple products in different hierarchy sharing common components and subassemblies, and the existence of a large number of resource options across the supply chain (Goetschalckx et al. 2002). However, aggregating all these objectives through weighted sum can transform the multi-objective problem into a single one. Every objective is multiplied by a weighted factor, and the sum of the weighted object is the objective function (Moncayo-Martnez and Zhang 2011; Kamali et al. 2011; Wang et al. 2011; Yuce et al. 2013, 2014, 2015). This alternative method is a collection of different criteria under certainty, which helps decision-makers to find the trade-off proposals and Pareto optimal solutions.

Existing literatures have proposed various models to solve the multi-objective optimization for SCN design. For instance, (Shaw et al. 2012) proposed an integrated approach for selecting appropriate suppliers in SCN through fuzzy-AHP and fuzzy multi-objective linear programming, which neglected the importance of complex network structure. Shen et al. (2013) proposed a fuzzy multi-criteria approach for green suppliers evaluation. Moncayo-Martnez and Zhang (2013) proposed an approach based on ant colony optimization (ACO) to minimize the total supply chain cost and the products lead-time simultaneously to ensure delivery of products without delay. Mastrocinque et al. (2013) adopted the artificial bee colony (ABC) algorithm to deal with the multi-objective supply chain model to find the optimum configuration in a given SCN situation that could minimize the total cost and the total lead-time. Hence, the nature-inspired optimization algorithms for SCN management is a hot topic. However, these algorithms neglected the influence of exponential growth in suppliers to the convergence speed of seeking multi-objective Pareto solutions.

The majority of studies on SCN have considered only one product and one manufacturing plant (Shu et al. 2016). But, in reality, most enterprises involve more than one product and multiple manufacturing plants in different regions. Hence, our study is fit to be a solution for complex SCN with multiple products and manufacturing plants, in which both the cost and

the lead-time are considered as the objective functions, and are optimized in a three-echelon supply chain management. With the wide application of internet-based e-commerce platform, suppliers are increasing exponentially. Therefore, it is significant to find global multi-objective POS in a three-echelon SCN to support multiple products and manufacturing plants under such requirement of the age.

To solve these problems, the complex network structure is for the first time taken into consideration as the basic solution framework with the ABC algorithm. We proposed a novel ABC algorithm based on complex network (ABC-CN) to find POS in a three-echelon SCN. Now, to satisfy the need of increasing suppliers in e-commerce platforms, we propose a new ABC algorithm based on complex network and naive Bayes classifier (ABC-CN-NBC), improving its capability of accelerating the convergence speed of seeking global POS. The major contributions of this paper can be highlighted as follows:

- Solutions are modelled in complex network structures to simulate the contemporary nature of SCN;
- The proposed ABC-CN and ABC-CN-NBC have the capability of discovering global POS in a complex three-echelon SCN;
- The speed of seeking global POS is further accelerated to satisfy the need from the wide application of e-commerce.

The organization of this paper is as follows: materials and methods are depicted in Sect. 2; the optimized results of the test example are given in Sect. 3; the simulated results are analysed in Sect. 4; and the final conclusion is drawn in the last section.

2 Materials and methods

2.1 Problem representation

The previous researches on SCN have mostly considered only one product and one manufacturing plant, as Shukla et al. (2013) did. Nowadays, multiple products and manufacturing plants are explored, as is shown from Shu et al. (2016). Three-echelon model has been adopted by many researchers (Shu et al. 2016; Shukla et al. 2013; Pasandideh et al. 2015; Seifert et al. 2012), which can construct a more complexed network. To demonstrate the advantage of the proposed optimization algorithm, three-echelon model with multiple products is designed in this paper: wheel loader (WHL), track loader (TRL), track-type tractor (TTT), and manufacturing plants (main assembly in node a_{17} , subassembly in node a_{20} , common subassembly in node a_{12} etc.) as shown in Fig. 1. In this

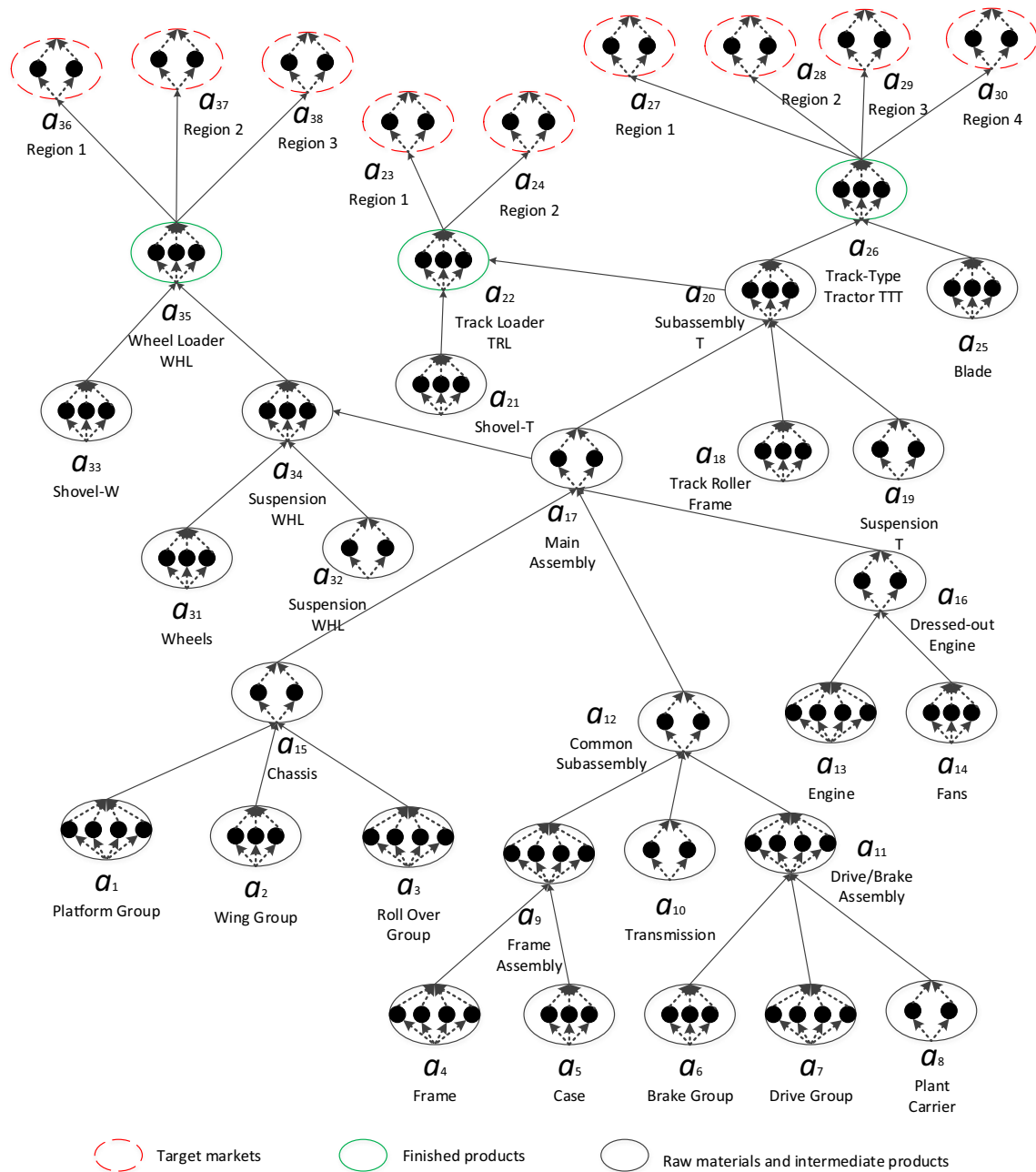


Fig. 1 This is a Bulldozer SCN topology, different nodes show different assembling processes: (a) The black nodes represent the processing of raw materials or intermediate materials. (b) The green nodes depict the final assembly of products. (c) The red nodes represent the deliv-

ery of products to target markets. Arrow lines among nodes indicate their supply relationship, and dotted lines in each node represent their choices

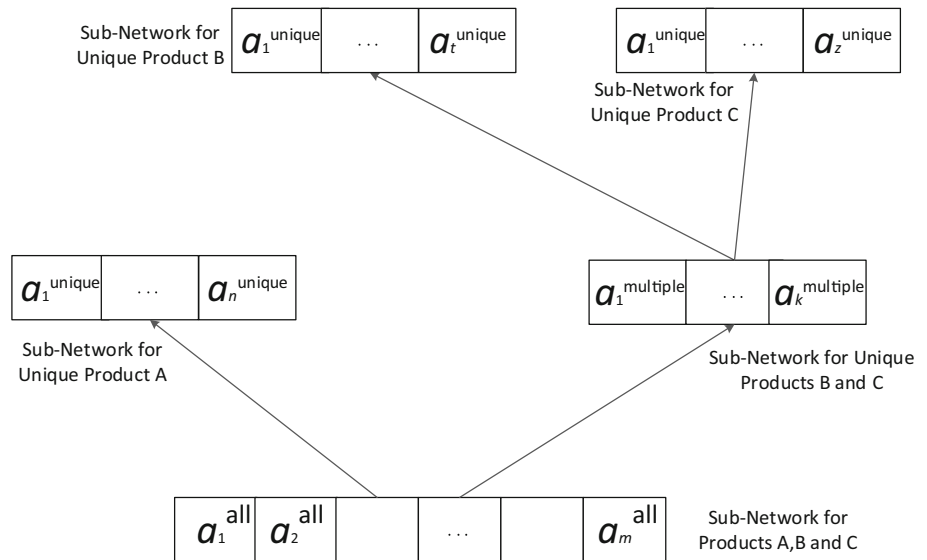
SCN, every blackspot with its connected line in each node represents a choice with its cost and lead-time.

The three-echelon SCN can be modelled as a complex network with a set of individual nodes represented by $\{a_1, a_2, a_3, \dots, a_i, \dots, a_n\}$, with each node containing all possible blackspots as its links which can be marked by $a_{ij}(j = 0, 1, 2, \dots, N_i)$, and N_i is the number of

blackspots available to a node a_i . At the same time, we use two objectives of cost and lead-time to represent the degree of satisfaction of enterprises and customers, and the following formulas are introduced to describe this matter:

$$Z = \omega_1 \times PC + \omega_2 \times LT \tag{1}$$

Fig. 2 Different types of sub-networks for a complex network



Equation 1 shows the main objective function, where PC is the total cost and LT is the total lead-time. ω_1 and ω_2 are the weights to balance importance between total cost and total lead-time, and $\omega_1 + \omega_2 = 1$.

$$PC_i = \mu_i \sum_{j=1}^{N_i} C_{ij} \times y_{ij} \tag{2}$$

$$PC = \xi \sum_{i=1}^N PC_i \tag{3}$$

Equations 2 and 3 show the summation of cost. ξ is the interest per month or per week at a_i , μ_i denotes the average demand of products per unit time. The cost of each link in a_{ij} is represented by C_{ij} . If a_{ij} is selected, y_{ij} equals to 1, or 0 otherwise.

$$LT_i = \sum_{j=1}^{N_i} T_{ij} \times y_{ij} + \max_{\alpha_k \in S_i} LT_k \tag{4}$$

where T_{ij} is the processing lead-time of the j th resource option in node a_i , S_i is the set of blackspots denoting input to node a_i , a_k is the activity chosen from S_i and LT_k is the cumulative lead-time of node a_k .

$$LT = \sum_{i=1}^N LT_i \tag{5}$$

where LT_i is the total lead-time of node a_i , and LT represents the total lead-time of the SCN.

$$y_{ij} = \begin{cases} 1, & \text{if } j \text{ s selected} \\ 0, & \text{otherwise} \end{cases}, \quad \forall i \in N, j \in N_i \tag{6}$$

$$\sum_{j=1}^{N_i} y_{ij} = 1 \tag{7}$$

For any $a_i (i = 1, 2 \dots N)$, Eqs. 6 and 7 aim to ensure that only one option (blackspot) can be selected.

$$\sum_{i=1}^N T_{ij} + \max_{\alpha_k \in S_i} LT_k - LT_i = 0 \tag{8}$$

Equation 8 validates its relationships of lead-time among nodes.

2.2 Expressed solutions

Optimization of a complex supply chain network refers to a combinatorial optimization issue. Many sub-networks can be extracted from a complex SCN. In the proposed algorithms of ABC-CN and ABC-CN-NBC, a set of feasible solutions, named as “solution vector”, is defined. The solution vector is structured as fragments of supply chain network. As a complex supply chain network in this paper, the major hypothesis includes: (1) multiple products in multiple assembling centres; (2) multiple objective optimization; (3) one-way production flow. For instance, a three products supply chain illustrated in Fig. 2, there will be different sub-networks for a complex network, includes: (1) sub-network for all products A, B and C; (2) sub-network for unique product A, B or C; (3) sub-network for product AUB, AUC, or BUC.

In the Bulldozer SCN topology illustrated in Fig. 1, nodes a_{35} , a_{22} and a_{26} are three final assembling nodes for products WHL, TRL and TTT, respectively, and these three products are assembled by a range of common supply nodes, e.g. $\{a_1, a_2, a_3, \dots, a_{16}, a_{17}\}$. Hence, it is the first type of sub-network for all products, such as the fragment from node a_1 to a_{17} . Sub-network for two products is the second type, such as the fragment nodes for both TRL and TTT for nodes a_{18} to a_{20} . The sub-network for a unique product is the third type,

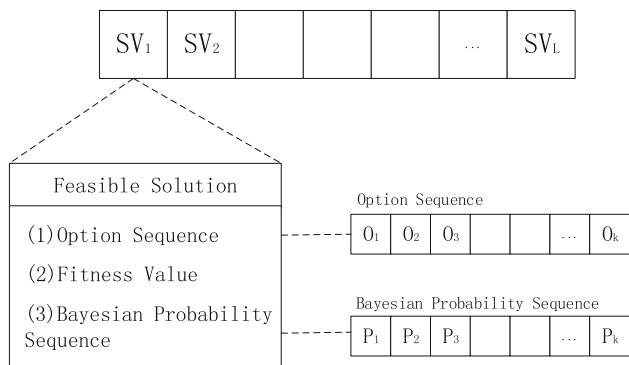


Fig. 3 Feasible Solution for sub-networks of a SCN

and its fragment can range from node a_{31} to a_{38} , fragment from node a_{21} to a_{24} , and fragment from node a_{25} to a_{30} . For a more universal complex network-oriented solutions, it can be modelled as Fig. 2.

Every sub-network in Fig. 2 can be modelled as feasible solutions as Fig. 3. In Fig. 3, $\{SV_1, SV_2, \dots, SV_L\}$ represents all possible solution vectors (SV) for the solution space of the SCN optimization problem, $SV_i (i \in L)$ indicates the i_{th} iteration of the maximal iteration of L . For any solution vector SV_i , it has three parts, such as option sequence, fitness value and Bayesian probability sequence. Option sequence of $\{O_1, O_2, \dots, O_k\}$ is the selection sequence formed by its selection of each node a_i in a sub-network, and Bayesian probability sequence of $\{P_1, P_2, \dots, P_k\}$ is the probability sequence with its initial probability of equal chance for each selection.

Based on the nature of SCN, the cost and lead-time should be computed from its topology. When calculating the cost of a product, it can be considered as a combinatorial optimization issue (Moncayo-Martnez and Zhang 2011). The complex network topology should be taken into consideration when the lead-time of a node is computed, since it is influenced by its sub-nodes directly.

In Fig. 1, each node refers to an activity, each blackspot in a node indicates an available option of a certain activity and each arrow line refers to the mutual relations between two nodes. The ABC algorithm is fit for solving the combinatorial optimization issue (Moncayo-Martnez and Zhang 2011; Bolaji et al. 2013; Zhang et al. 2017, 2016). Hence, it is the most crucial to design a good solution expressed based on complex networks for the ABC algorithm.

As a combinatorial issue, solutions in the ABC algorithm can be expressed as $A_i = (a_1, a_2, a_3, \dots, a_n)^T$. The combination of different nodes forms the distribution routing in a SCN of its corresponding products. At the same time, node $a_i = (a_{i1}, a_{i2}, a_{i3}, a_{i4}, a_{i5})^T$ is also a five-dimensional vector including the sequence number of nodes, options of blackspots, lead-times of blackspots, costs of blackspots and chosen probabilities of blackspots.

2.3 Methods

In this paper, to solve these problems mentioned in Sect. 2.1 with solutions expressed in Sect. 2.2, basic ABC algorithm (ABC), proposed ABC algorithm based on complex network (ABC-CN), and the enhanced ABC algorithm based on complex network and naive Bayes classifier (ABC-CN-NBC) are adopted to evaluate their capability and feasibility.

2.3.1 Basic ABC algorithm

The basic ABC algorithm is a novel optimization approach in 2006 by Karaboga, which mimicks the behaviour of bees in collecting honey (Pham et al. 2006). Karaboga et al. (2014) have shown that ABC has been widely applied in feature selection (Schiezaro and Pedrini 2013), real-parameter optimization (Akay and Karaboga 2012), job scheduling (Banharnsakun et al. 2012), travelling salesman issues (Yang and Pei 2013), and combinatorial problems (Bolaji et al. 2013). In previous work, it is proved that the ABC algorithm has better performance in handling optimization for continuous problems than other classical optimization algorithms, such as stochastic simulated annealing, genetic algorithm, ant colony optimization (Ebubekir 2010), etc. Various UCI data sets have been used to demonstrate the effectiveness of ABC compared with ant colony optimization, particle swarm optimization, and bat algorithm (Schiezaro and Pedrini 2013). Sharma and Bhambu (2016) have found its advantages in 35 objective functions. Bolaji et al. (2013) have drawn a conclusion that it is a potential advantage for this to be easily hybridized with different metaheuristic algorithms and data structures. Therefore, we adopt ABC algorithm as the fundamental approach of our proposed algorithms.

2.3.2 ABC algorithm based on complex network

The research on complex networks begins with the effort of defining new concepts and measures to characterize the topology of real networks (Boccaletti et al. 2006). *Out degree*, *Uni-assembly node*, *Multi-assembly node* and *Final-assembly node* are defined in Definitions 1, 2, 3 and 4. Based on these definitions, different types of nodes can be detected with its *OutDegree*(a_i) value and relationships. Sub-networks can be detected and extracted from the SCN with the procedure expressed in the Step 1 in the proposed Algorithms 1 and 2.

Definition 1 Out degree of node a_i . *OutDegree*(a_i) equals the number of arrow lines that start from node a_i to other nodes.

Definition 2 Uni-assembly node. The node a_i belongs to a uni-assembly node when its *OutDegree*(a_i) = 1.

Definition 3 Multi-assembly node. The node a_i belongs to a multi-assembly node when its $OutDegree(a_i) = k$ to support assembling k products, $k \neq 1$.

Definition 4 Final-assembly node. The node a_i belongs to a final-assembly node when its child nodes are all delivering nodes.

The ABC algorithm can carry on parallel processing via sub-network decomposition. Employed bees and scout bees cooperate to detect, evaluate, and identify best solution obtained so far with greedy principle to filter the generated solutions. After exceeding certain limited iterations, a new solution will be generated to avoid falling into a local optimal solution. The parallel computing model and greedy principle in the proposed ABC-CN will accelerate the convergence speed of seeking global POS in a SCN. The detailed procedure is depicted in the Step 2 of Algorithm 1.

Algorithm 1 ABC algorithm based on complex network (ABC-CN)

Input: 5-dimensional vector in Table 1 and 2, including their number of groups, sequence number of nodes, lead-times, costs and chosen probabilities of blackspots, $ABCOpts.Limit = 50$.

Step 1: Extract sub-networks from a SCN

- 1.1 Calculate $OutDegree(a_i)$ for each node a_i based on Definition 1;
- 1.2 Classify node types based on Definition 2, 3 and 4;
- 1.3 Extract sub-networks based on these three type of nodes as Fig. 2;
- 1.4 Form the solution vector of Sub-Network as Fig. 3.

Step 2: Search the global POS using the ABC algorithm

for Each sub-network in a SCN **do**

while $Cycle \neq MaxCycles$ **do**

STEP 2.1: Send employed bees to find a nectar

 2.1.1. Generate initial solutions in a random way;

 2.1.2. Evaluate the value of the objective function based on Eq.

1;

 2.1.3. Calculate the fitness value based on $Z(SV_{t+1}) - Z(SV_t)$.

STEP 2.2: Send scout bees to search neighbourhoods of the nectar

 2.2.1. Generate a new nectar in the neighbourhood;

 2.2.2. Evaluate the value of the objective function based on Eq.

1;

 2.2.3. Calculate the fitness value based on $Z(SV_{t+1}) - Z(SV_t)$;

 2.2.4. Select the optimal solution based on greedy principle

$\max(|Z(SV_{t+1}) - Z(SV_t)|)$;

 2.2.5. Record the best solution obtained so far.

STEP 2.3: Jump out from local optimums

if $\max(Bas) > ABCOpts.Limit$ **then**

 2.3.1. Generate a new solution to replace the original solution;

 2.3.2. Evaluate the value of the objective function based on

Eq. 1;

 2.3.3. Calculate the fitness value based on $Z(SV_{t+1}) - Z(SV_t)$.

$Cycle = Cycle + 1$.

Record the global optimal solution with $GlobalParams$;

Calculate the value of $GlobalBestCost$ and $GlobalBestLeadtime$.

return $GlobalParams, GlobalBestCost, GlobalBestLeadtime$

2.3.3 ABC algorithm based on complex network and naive Bayes classifier

In Algorithm 1 mentioned in Sect. 2.3.2, it is a good solution to solve the problem with a complex network. However, it still needs to be accelerated as the number of suppliers increases. The chosen probabilities of blackspots in each node is equal in the basic ABC Algorithm 1. The ABC algorithm generates solutions randomly, which will increase the cost of seeking the global POS. Henceforth, it is necessary to search for a solution with metaheuristics.

The naive Bayes classifier is one of top 10 algorithms in data mining (Wu et al. 2007). It is useful for extracting classification rules based on its Bayes probability. In order to accelerate the speed of the proposed Algorithm 1, the principle of the naive Bayes classifier is adopted as illustrated in Algorithm 2 (ABC-CN-NBC).

3 Results

In order to evaluate the proposed two novel algorithms effectively, a test example is used and the following situations are put forward:

- A total of three products has to be made in the production of Bulldozer SCN, [Wheel Loader (WHL), Track Loader (TRL) and Track-Type Tractor (TTT)]. This SCN covers the whole process from raw materials to manufacturers and distributors.
- Each product can be assembled with a flow pattern that requires the selection of a supplier (or suppliers) for every component used by the product mix.
- Each node has a number of selective options, in which each one of them represents a single decision that has its own cost and lead-time for assembling this product.
- All the experimental data are under ideal conditions with high stability. There are no other external influencing factors, such as the shortage of raw materials, bad weather under uncertainty.

The network topology which represents the Bulldozer SCN is depicted in Fig. 1. In Fig. 1, the entire SCN has a total of 38 nodes, with a varying number of 2 to 4 blackspots (choices) in each node. Each assembly node can represent an enterprise. Among these nodes, a_{22} , a_{26} and a_{35} are *Final-assembly nodes* for assembling the final products, a_{17} and a_{20} are *Multi-assembly nodes*, and most other nodes are *Uni-assembly nodes*. After extracting sub-networks from Fig. 1, the set of $\{a_1, a_2, a_3, \dots, a_{16}, a_{17}\}$ can be formed as a sub-network to provide public intermediate products of product WHL, TRL and TTT. Nodes of a_{18} , a_{19} and a_{20} can be formed as another sub-network to serve the two products

Algorithm 2 ABC algorithm based on complex network and naive Bayes classifier (ABC-CN-NBC)

Input: 5-dimensional vector in Table 1 and 2, including their number of groups, sequence number of nodes, lead-times, costs and chosen probabilities of blackspots, $ABC\ Opts.Limit = 50$.

Step 1: Extract sub-networks from a SCN

- 1.1 Calculate $OutDegree(a_i)$ for each node a_i based on Definition 1;
- 1.2 Classify node types based on Definition 2, 3 and 4;
- 1.3 Extract sub-networks based on these three type of nodes as Fig. 2;
- 1.4 Form the solution vector of sub-network as Fig. 3.

Step 2: Search the global POS using the ABC algorithm

for Each sub-network in a SCN **do**

while $Cycle \neq MaxCycles$ **do**

STEP 2.1: Send employed bees to find a nectar

 2.1.1. Generate initial solutions in a random way according to a certain probability;

 2.1.2. Evaluate the value of the objective function based on Eq. 1;

 2.1.3. Calculate the fitness value based on $Z(SV_{t+1}) - Z(SV_t)$.

STEP 2.2: Sent scout bees to search neighbourhoods of nectar

 2.2.1. Generate a new nectar in its neighbourhoods;

 2.2.2. Evaluate the value of the objective function based on Eq. 1;

 2.2.3. Calculate the fitness value based on $Z(SV_{t+1}) - Z(SV_t)$;

 2.2.4. Select the optimal solution based on greedy principle

$max(|Z(SV_{t+1}) - Z(SV_t)|)$;

 2.2.5. Record the best solution obtained so far.

STEP 2.3: Update probability with naive Bayes classifier

if $mod(size(BayesParams, 1), 50) = 0$ **then**

 2.3.1. Calculate the conditional probability of each choice(j) in a node(a_{ij}) based on $P(a_{ij})/P(a_i)$;

 2.3.2. Label the classification based on the fitness value based on $Z(SV_{t+1}) - Z(SV_t)$;

 2.3.3. Update the probability of each choice with the naive Bayes classifier.

STEP 2.4: Jump out from a local optimum

if $max(Bas) > ABC\ Opts.Limit$ **then**

 2.4.1. Generate a new solution to replace the original solution;

 2.4.2. Evaluate the value of the objective function based on Eq. 1;

 2.4.3. Calculate the fitness value based on $Z(SV_{t+1}) - Z(SV_t)$.

$Cycle = Cycle + 1$.

Record the global best solution with $GlobalParams$;

Calculate the value of $GlobalBestCost$ and $GlobalBestLeadtime$.

return $GlobalParams, GlobalBestCost, GlobalBestLeadtime$

of TRL and TTT. The set of $\{a_{25}, a_{26}, a_{27}, a_{28}, a_{29}, a_{30}\}$ can be formed as a sub network for serving only one product of TTT. The set of $\{a_{21}, a_{22}, a_{23}, a_{24}\}$ can be aggregated as a sub-network for serving the TRL product, and the set of $\{a_{31}, a_{32}, a_{33}, a_{34}, a_{35}, a_{36}, a_{37}, a_{38}\}$ can be clustered as a sub-network for the WHL product.

In Table 1, we list 30 nodes of raw materials or intermediate products. Every node has 2 to 5 options, and each option has a different cost C_{ij} (in \$) and lead-time T_{ij} (in days) required.

Table 1 Data for solving the Bulldozer SCN

$N(a_i)$	$SN(i)$	$OP(j)$	$LT(T_{ij})$	$C(C_{ij})$	$ICP(P_j)$
Platform group	1	1	11	575	1/4
		2	0	690	1/4
		3	5	592	1/4
		4	3	630	1/4
Wing group	2	1	4	575	1/3
		2	9	897	1/3
		3	0	912	1/3
Roll over group	3	1	7	4459	1/4
		2	3	1161	1/4
		3	0	1167	1/4
Frame	4	1	17	609	1/4
		2	10	618	1/4
		3	19	605	1/4
		4	0	622	1/4
Case	5	1	12	2241	1/3
		2	7	2263	1/3
		3	15	2200	1/3
Brake group	6	1	11	575	1/3
		2	11	575	1/3
Drive group	7	1	8	1553	1/4
		2	3	1571	1/4
		3	9	1550	1/4
Plant carrier	8	1	9	1563	1/4
		2	1	157	1/2
		3	19	605	1/4
Frame assembly	9	1	5	620	1/4
		2	12	612	1/4
		3	19	605	1/4
Transmission	10	1	15	7450	1/2
		2	10	7618	1/2
		3	9	1550	1/4
Drive/brake assembly	11	1	4	1551	1/4
		2	0	1571	1/4
		3	9	1550	1/4
Common assembly	12	1	5	8000	1/2
		2	2	8070	1/2
		3	0	4804	1/5
Engine	13	1	6	4596	1/5
		2	3	4763	1/5
		3	0	4804	1/5
Fans	14	1	12	650	1/3
		2	0	662	1/3
		3	8	659	1/3

Table 1 continued

$N(a_i)$	SN(i)	OP(j)	LT(T_{ij})	$C(C_{ij})$	ICP(P_j)
Chassis	15	1	7	4320	1/2
		2	2	4395	1/2
Dressed-out engine	16	1	10	4100	1/2
		2	3	4175	1/2
Main assembly	17	1	8	12000	1/2
		2	2	12150	1/2
Track roller frame	18	1	6	3005	1/3
		2	10	3000	1/3
		3	2	3045	1/3
Suspension T	19	1	7	3600	1/2
		2	2	3675	1/2
Subassembly T	20	1	4	8000	1/3
		2	1	8300	1/3
		3	3	8150	1/3
Shovel-T	21	1	35	90	1/3
		2	20	95	1/3
		3	18	93	1/3
Track Loader-TRL	22	1	6	725	1/3
		2	2	732	1/3
		3	5	730	1/3
Blade	25	1	35	90	1/3
		2	20	95	1/3
		3	18	93	1/3
track-type tractor-TTT	26	1	6	725	1/3
		2	2	732	1/3
		3	5	730	1/3
Wheels	31	1	6	725	1/3
		2	2	732	1/3
		3	4	730	1/3
Suspensions WHL	32	1	7	3600	1/2
		2	2	3675	1/2
Shovel-W	33	1	35	90	1/3
		2	20	95	1/3
		3	18	93	1/3
Subassembly WHL	34	1	4	8000	1/3
		2	1	8300	1/3
		3	3	8150	1/3
Wheel Loader-WHL	35	1	6	725	1/3
		2	2	732	1/3
		3	5	730	1/3

Table 2 is the set of target markets for the three final products, and each delivery node has 2 options with parameters of lead-time T_{ij} (in days) and delivery cost C_{ij} (in \$). In the following Tables 1 and 2, $N(a_i)$ represents a node, SN(i) is sequence number, OP(j) means options in each node, LT(T_{ij}) is the lead-time of each option, $C(C_{ij})$ represents

Table 2 Data for target markets

$N(a_i)$	SN(i)	OP(j)	LT(T_{ij})	$C(C_{ij})$	ICP(P_j)
R1-TRL	23	1	20	300	1/2
		2	10	7000	1/2
R2-TRL	24	1	1	500	1/2
		2	8	1000	1/2
R1-TTT	27	1	10	1200	1/2
		2	1	2000	1/2
R2-TTT	28	1	20	3000	1/2
		2	10	7000	1/2
R3-TTT	29	1	15	1500	1/2
		2	2	3000	1/2
R4-TTT	30	1	1	500	1/2
		2	8	0	1/2
R1-WHL	36	1	10	1200	1/2
		2	1	2000	1/2
R2-WHL	37	1	15	1500	1/2
		2	2	3000	1/2
R3-WHL	38	1	1	500	1/2
		2	8	1000	1/2

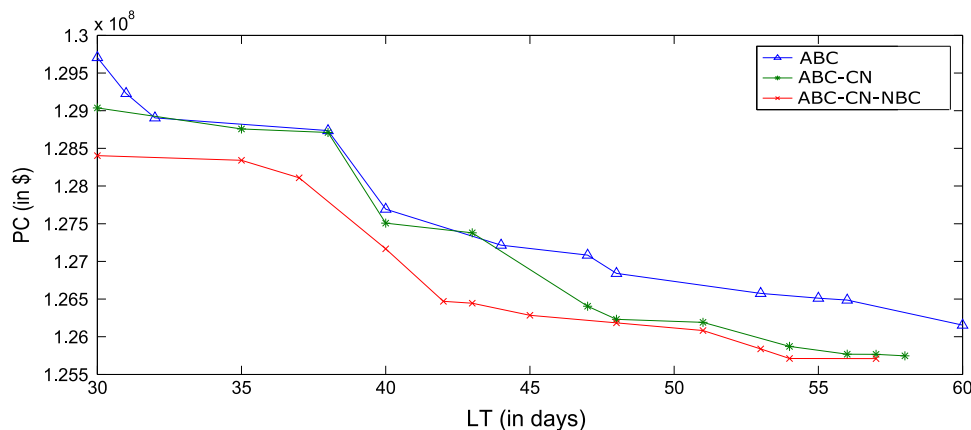
the cost of each option, and ICP(P_j) is initial chosen probability for each option.

3.1 The capability of searching global optimal solution with different methods

In order to measure the global optimization effect of the proposed algorithms, we, respectively, draw the Pareto front line chart of the basic ABC, the proposed ABC-CN and ABC-CN-NBC algorithms, as shown in Fig. 4. In Fig. 4, we can clearly observe the Pareto frontal value of three different methods in the same data set optimization where the abscissa is the total lead-time (LT), and the ordinate is the total cost of the business (PC). And with the increase in LT, PC shows a gradual downward trend. Moreover, it is obvious that the curve of Pareto fronts obtained by the ABC-CN algorithm is lower than that of the basic ABC algorithm, which proves that the proposed ABC-CN algorithm has a stronger advantage than ABC in finding the global optimal solution. The curve of Pareto peak obtained by ABC-CN-NBC algorithm is lower than that of the ABC-CN algorithm, which proves that the ABC-CN-NBC algorithm has a better advantage than the ABC-CN algorithm in finding the global optimal solution. Therefore, in the same data set, the ABC-CN-NBC algorithm has a better global optimum than the ABC algorithm, and it has a stronger global search capability.

To facilitate the observation and comparison of the search results of the proposed algorithms, we list the results of 9 different weights of PC and LT. In Tables 3 and 4,

Fig. 4 Pareto fronts



we can see the different results based on these two proposed approaches. Each approach takes into account the different weights of cost and lead-time. Each weight corresponds to a different solution. Table 3 shows the results of using the proposed ABC-CN. When the weight ranges from $\omega_1 = 0.1$ to $\omega_1 = 0.9$, the PC (in \$) is obtained for 129,445,800, 129,042,720, 128,847,720, 127,200,600, 127,253,100, 126,444,600, 125,924,448, 125,809,512 and 125,830,608, and the LT (in days) is 30, 35, 42, 40, 43, 54, 57, 30 and 54, respectively. Table 4 gives the results of using the proposed ABC-CN-NBC. When the weight of the PC (in \$) ranges from $\omega_1 = 0.1$ to $\omega_1 = 0.9$, the PC (in \$) is obtained for 129,130,020, 129,025,980, 128,411,820, 127,350,300, 126,512,292, 126,038,328, 125,816,928, 125,764,500 and 125,715,660, and LT (in days) is 30, 30, 40, 40, 49, 51, 52, 57 and 61, respectively.

Mastrocinque et al. (2013) use the basic ABC algorithm to solve the same problem (Mastrocinque et al. 2013). Using the same raw data, when the weight of the PC (in \$) changes from $\omega_1 = 0.1$ to $\omega_1 = 0.9$, PC (in \$) are obtained from 129,652,620, 129,051,300, 128,485,608, 128,332,908, 127,023,480, 126,821,568, 126,500,100, 126,421,236 and 126,572,640, and the LT (in days) are 30, 31, 34, 36, 46, 54, 58, 70 and 60, respectively. In Fig. 5, we adopt three algorithms for global optimal solutions under different weights of PC (in \$). Figure 5a is a line graph of global optimal solutions for PC (in \$) with the changing weight of PC (in \$). Each point on the line is the global optimal solutions when the weight of PC (in \$) changes from $\omega_1 = 0.1$ to $\omega_1 = 0.9$. When the weight of the objective function of PC (in \$) is increasing, the global optimal solutions have a tendency to decrease. Figure 5b is a line graph of global optimal solutions for LT (in days) with the varying weight of PC (in \$). When the weight of the PC (in \$) objective function is increasing, the weight of LT (in days) in the objective function decreases, and the global optimal solutions value is gradually increased.

Through Fig. 5, both ABC-CN and ABC-CN-NBC have achieved better optimal solutions, while the ABC-CN-NBC

has better global POS compared with ABC-CN. The results show that our proposed algorithms have achieved a better feasibility and efficiency.

3.2 The convergence speed of searching global POS with different algorithms

In order to test the efficiency of our proposed algorithms, we test the convergence speed of finding global POS with the metric of *minimal iterations*(δ), defined in Definition 5, with different weights of ω_1 and ω_2 . Figure 6 illustrates the capability of searching global POS with Boxplot graph. The ABC-CN with the red Boxplot can reduce the number of minimal iterations to search the global POS in the Bulldozer SCN. Moreover, the ABC-CN-NBC has good performance with its heuristic optimization of the naive Bayes classifier.

Definition 5 (*Minimal iterations δ*) It refers to minimal number of iterations when their fitness values have micro change.

Figure 7b is the value of *GlobalMins* for WHL product obtained by ABC-CN under different weights of PC. When the value of *GlobalMins* becomes unchangeable, it indicates that the global optimal solution is obtained. From $\omega_1 = 0.1, \omega_2 = 0.9$ to $\omega_1 = 0.9, \omega_2 = 0.1$, the iterations of the global optimal solution are 169, 58, 147, 143, 179, 89, 116, 139 and 284. Figure 7c is the value of *GlobalMins* for WHL product obtained by ABC-CN-NBC under different weights of PC (in \$). When the value of *GlobalMins* becomes unchangeable, it indicates that the global optimal solution is obtained. From $\omega_1 = 0.1, \omega_2 = 0.9$ to $\omega_1 = 0.9, \omega_2 = 0.1$, the iterations of the optimal solution are 180, 145, 122, 107, 251, 157, 74, 109 and 52. The results show that our proposed ABC-CN and ABC-CN-NBC algorithms with its better capability that can accelerate the convergence speed of searching better global multi-objective POS.

Table 3 The global best solution obtained based on the proposed ABC-CN

node(a_i)	z^* index	option (j)	option (j)	option (j)	option (j)	option (j)	option (j)	option (j)	option (j)	option (j)	option (j)
Platform group	1	2	4	1	4	2	1	3	1	1	1
Wing group	2	1	1	2	3	1	3	2	2	2	3
Roll over group	3	4	2	3	3	2	4	2	2	2	2
Frame	4	2	2	2	4	4	4	2	3	3	4
Case	5	2	2	2	1	2	3	3	3	3	3
Brake group	6	3	3	1	1	3	2	3	2	2	1
Drive group	7	3	2	2	3	2	4	2	4	3	3
Plant carrier	8	2	2	2	1	2	2	2	2	1	1
Frame assembly	9	4	4	4	4	4	4	4	4	1	1
Transmission	10	2	2	2	1	2	1	1	1	1	1
Drive/brake assembly	11	2	1	1	1	2	3	2	4	3	3
Common assembly	12	2	2	2	2	2	2	1	2	1	1
Engine	13	1	5	1	1	5	5	5	5	5	5
Fans	14	3	3	1	2	1	3	3	1	1	1
Chassis	15	1	1	2	1	1	1	2	1	1	1
Dressed-out engine	16	2	2	2	2	2	1	1	1	1	2
Main assembly	17	2	2	2	2	2	2	1	1	1	1
Track roller frame	18	2	2	2	2	1	2	2	1	1	1
Suspension T	19	1	1	1	1	1	1	1	1	1	1
Subassembly T	20	2	2	2	2	2	2	1	1	1	1

Table 3 continued

node(a_i)	z^* index	option (j)	option (j)	option (j)	option (j)	option (j)	option (j)	option (j)	option (j)	option (j)	option (j)	option (j)	option (j)
Shovel-T	21	3	3	3	3	3	3	3	3	3	3	3	3
Track Loader-TRL	22	2	2	2	2	2	2	2	2	2	2	2	2
Blade	25	2	2	2	2	2	2	2	2	2	2	2	2
Track-type tractor-TTT	26	1	1	1	1	1	1	1	1	1	1	1	1
Wheels	31	3	3	3	3	3	3	3	3	3	3	3	3
Suspensions WHL	32	2	2	2	2	2	2	2	2	2	2	2	2
Shovel-W	33	1	1	1	1	1	1	1	1	1	1	1	1
Subassembly WHL	34	2	2	2	2	2	2	2	2	2	2	2	2
Wheel Loader-WHL	35	2	2	2	2	2	2	2	2	2	2	2	2
R1-TRL	23	2	2	2	2	2	2	2	2	2	2	2	2
R2-TRL	24	1	3	1	3	1	3	1	3	1	3	1	3
R1-TTT	27	2	1	2	1	2	1	2	1	2	1	2	1
R2-TTT	28	3	2	2	3	2	3	2	3	2	3	2	3
R3-TTT	29	2	3	1	1	1	1	1	1	1	1	1	1
R4-TTT	30	2	2	2	2	2	2	2	2	2	2	2	2
R1-WHL	36	2	2	2	2	2	2	2	2	2	2	2	2
R2-WHL	37	2	2	2	2	2	2	2	2	2	2	2	2
R3-WHL	38	1	1	1	1	1	1	1	1	1	1	1	1
ω_1		0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	0.9	0.9	0.9
ω_2		0.9	0.8	0.7	0.6	0.5	0.4	0.3	0.2	0.1	0.1	0.1	0.1
PC (in \$)		129,445,800	129,042,720	128,847,720	127,200,600	127,253,100	126,444,600	125,924,448	125,809,512	125,830,608			
LT (in days)		30	30	35	42	40	43	54	57	54			

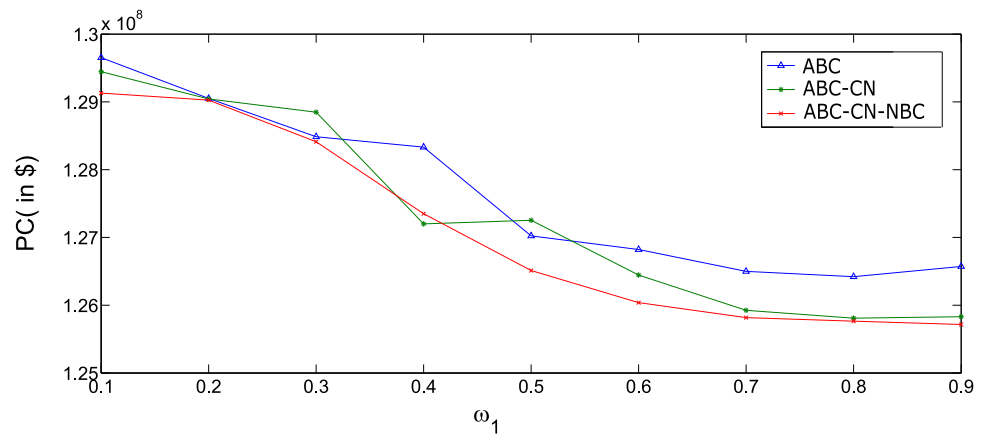
Table 4 The global best solution obtained based on the proposed ABC-CN-NBC

node(a_i)	z_i^* index	option (J)	option (J)	option (J)	option (J)	option (J)	option (J)	option (J)	option (J)	option (J)
Platform group	1	4	4	3	3	3	1	1	1	3
Wing group	2	3	3	1	3	3	1	2	2	2
Roll over group	3	2	2	4	4	4	2	3	3	3
Frame	4	2	2	4	4	4	2	4	2	4
Case	5	2	2	2	2	2	3	3	3	3
Brake group	6	2	3	3	2	2	1	2	1	1
Drive group	7	4	2	2	1	2	2	3	3	3
Plant carrier	8	2	2	2	2	2	2	1	2	2
Frame assembly	9	4	4	4	4	4	4	4	4	4
Transmission	10	2	2	2	2	2	1	1	1	1
Drive/brake assembly	11	2	4	4	2	2	1	4	1	4
Common assembly	12	2	2	2	2	2	2	2	2	1
Engine	13	5	5	5	1	5	5	5	5	5
Fans	14	2	3	1	3	3	3	1	1	2
Chassis	15	1	1	2	2	1	1	1	1	1
Dressed-out engine	16	2	2	2	2	2	1	1	1	1
Main assembly	17	2	2	2	2	2	1	1	1	1
Track roller frame	18	2	2	1	2	2	2	2	1	2
Suspension T	19	1	1	1	1	1	1	1	1	1
Subassembly T	20	2	2	2	2	2	2	1	1	1
Shovel-T	21	3	3	3	3	3	3	2	1	1

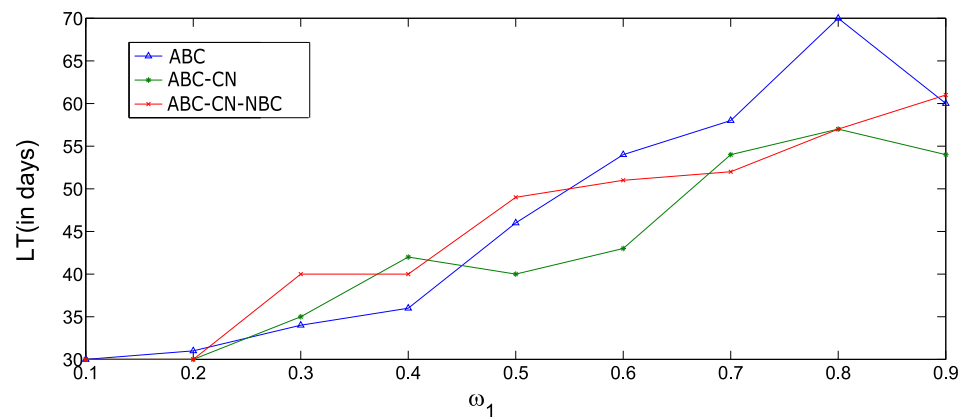
Table 4 continued

node(a_i)	z^* index	option (j)	option (j)	option (j)	option (j)	option (j)	option (j)	option (j)	option (j)	option (j)
Track Loader-TRL	22	2	2	2	2	2	2	2	2	1
Blade	23	2	2	1	1	1	1	1	1	1
Track-type tractor-TTT	24	1	1	1	1	1	1	1	1	1
Wheels	25	3	3	3	3	3	3	3	3	2
Suspensions WHL	26	2	2	2	2	2	2	2	2	1
Shovel-W	27	1	1	1	1	1	1	1	1	1
Subassembly WHL	28	2	2	2	2	2	2	2	2	1
Wheel Loader-WHL	29	2	2	2	2	2	2	2	2	1
R1-TRL	30	2	1	2	2	2	2	2	2	2
R2-TRL	31	2	3	2	1	1	2	2	3	1
R1-TTT	32	2	1	1	1	1	1	1	1	1
R2-TTT	33	3	3	3	3	3	3	3	3	3
R3-TTT	34	3	1	2	1	1	1	1	1	1
R4-TTT	35	2	1	2	2	2	2	2	2	1
R1-WHL	36	2	2	2	1	2	1	1	1	1
R2-WHL	37	2	2	2	1	2	1	1	1	1
R3-WHL	38	1	1	1	1	1	1	1	1	1
ω_1		0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
ω_2		0.9	0.8	0.7	0.6	0.5	0.4	0.3	0.2	0.1
PC (in \$)		129,130,020	129,025,980	128,411,820	127,350,300	126,512,292	126,038,328	125,816,928	125,764,500	125,715,660
LT (in days)		30	30	40	40	49	51	52	57	61

Fig. 5 Global optimal solutions with ABC, ABC-CN and ABC-CN-NBC



(a) Global optimal solutions of PC (in \$) with different ω_1



(b) Global optimal solutions of LT (in days) with different ω_1

4 Discussion

As mentioned in Sect. 3 of experimental results, we fully take into account the real situation (a three-echelon SCN supports assembling multiple products and multiple manufacturing centres). The experimental results show that the proposed two algorithms have achieved a faster convergence speed of finding better global POS when compared with the basic ABC algorithm.

Complex network-oriented solution can improve the capability of finding global POS for multi-objective optimization in a SCN. As explained in Sect. 2.3.2, the objective of cost is a combinatorial issue, while the objective of lead-time should be computed based on the assembling flow in the SCN. Therefore, it will be not effective when it is simply regarded as an optimization of combinatorial issue with these two objectives of cost and lead-time. In Sect. 2.3.2, we have defined different types of nodes to extract sub-networks from a SCN. Finding global POS from sub-networks is more efficient as illustrated in Fig. 5. The results are much effective with the use of the principle of *divide and conquer* (DC). The DC technique is

the basis of efficient algorithms for all kinds of problems, such as sorting, multiplying large numbers, finding closest pair of points, and many others.

The complexity of solutions can be decreased efficiently when extracting sub-networks from a complex SCN. In Fig. 1, the Bulldozer SCN is composed of 38 nodes and 105 options for a total possible solutions of 1.284×10^{16} from Eq. 9. That is to say, it is really a non-trivial problem. Hence, the DC technique should be adopted to decrease its complexity.

$$\prod_{i=1}^{38} a_i = 1.284 \times 10^{16} \quad (9)$$

Naive Bayes classifier can accelerate the convergence speed based on information of classification. Metaheuristics is an efficient approach to an optimization problem. As depicted in Eq. 9, the set of solutions is too large to be completely sampled. Bayesian theory is to estimate subjective probability for partial unknowns under incomplete information, and then to use Bayesian formula to update

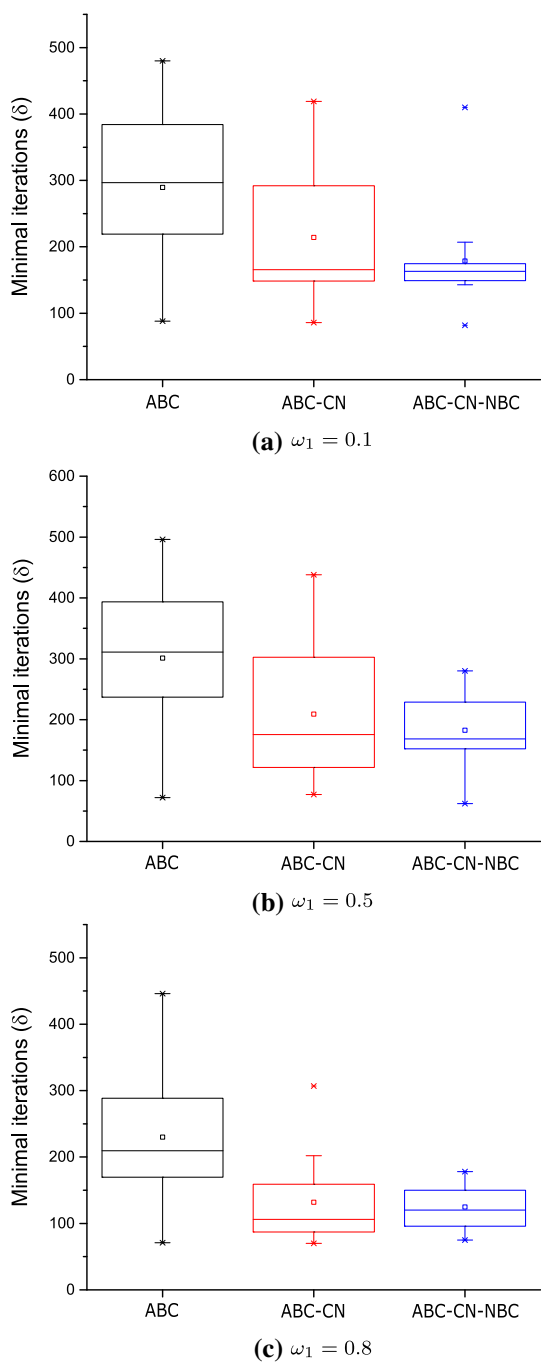


Fig. 6 Minimal iterations (δ) with ABC, ABC-CN and ABC-CN-NBC. The convergence speed of searching global POS is accelerated with ABC-CN and ABC-CN-NBC in Fig. 6a-c obviously

the probability of occurrence. Finally, the optimal decision is made by using expected value and updated probability. However, the traditional ABC does not update its probability of each option in a node, and the probability of an option to be selected is generated randomly. In this way, the previous result will not have an active effect on the next solution which results in a certain amount of waste of resources.

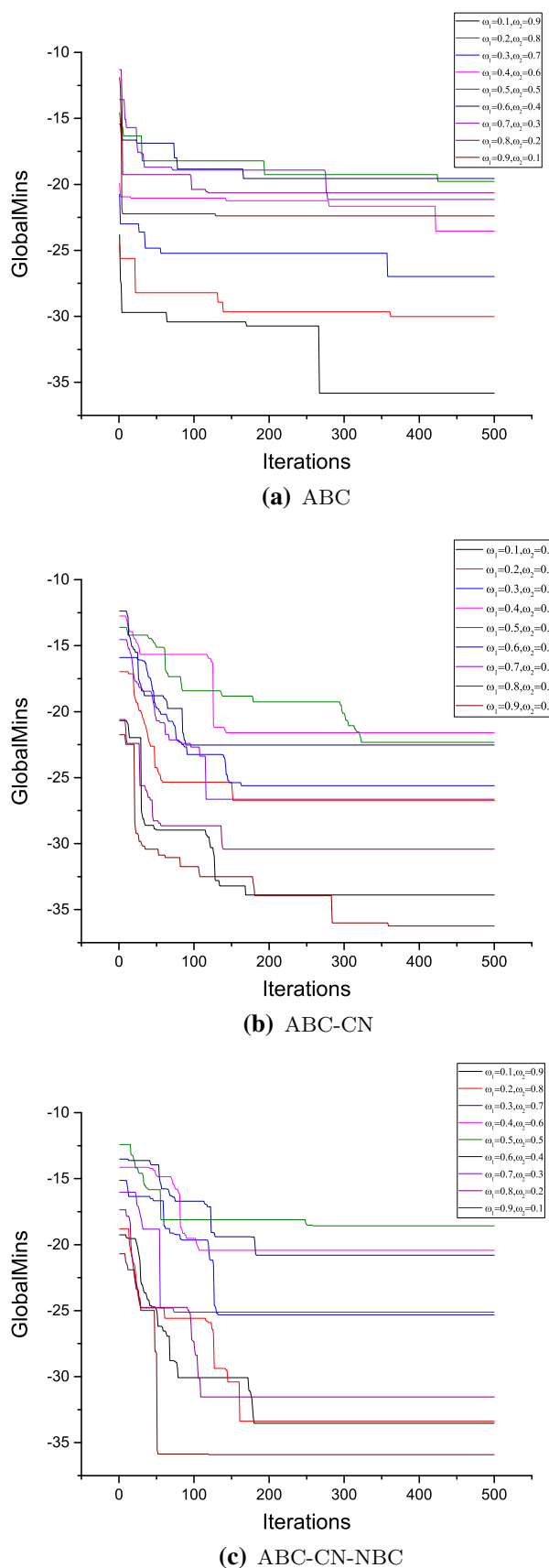


Fig. 7 Global min(Z) value

5 Conclusions

Optimization of three-echelon SCN with multiple products and multiple manufacture centres is really a challenge to get multi-objective Pareto solutions. To solve this problem, this paper proposes a novel ABC algorithm with complex network to satisfy the optimization requirement of SCN structure. After exemplifying with a real Bulldozer SCN, our proposed ABC-CN can find better global POS than the traditional ABC.

In addition, with the increase of suppliers in a SCN, the optimization method should be accelerated to support a more complex SCN. This paper adopts naive Bayes classifier to update the selection probability of options in each node. The proposed ABC algorithm with complex network and naive Bayes classifier (ABC-CN-NBC) can get the multi-objective Pareto optimal solutions within a limited time.

We hope that the proposed algorithm of ABC-CN-NBC is a small step to solve the complex three-echelon SCN optimization issue. It will help logistics managers in making operation management decision for their suppliers. For engineers, this paper proposes an interesting approach to find a global bi-objective optima in SCN problems. Based on the guidance from naive Bayes classifier, the convergence speed can be accelerated in limited time.

The limitations and disadvantages of this paper can be summarized as: only two objective functions are considered in the three-echelon SCN management problems, and only naive Bayes classifier is adopted to give guidance. In the future, we recommend the following research directions: (1) more heuristic approaches should be proposed to solve three-echelon SCN management issue; (2) other optimization objectives should be investigated; (3) inventory problems in a complex SCN should be considered to validate its extension capability.

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Compliance with ethical standards

Conflict of interest All authors declare that they have no conflict of interest.

Ethical approval This article does not contain any studies with human participants or animals performed by any of the authors.

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