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# A novel method to solve supplier selection problem: Hybrid algorithm of genetic algorithm and ant colony optimization

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## Highlights

- A novel hybrid algorithm of GA and ACO is proposed.
- In hybrid algorithm, GA and ACO are improved separately to enhance its efficiency and effectiveness.
- It is an innovative and pilot research to leverage hybrid algorithm of GA and ACO to settle the supplier selection problem.

## Abstract

Nowadays, with the development of information technology and economic globalization, supplier selection problem gets more and more attraction. The recent literature shows huge interest in hybrid artificial intelligence (AI)-based models for solving supplier selection problem. In this paper, to solve a multi-criteria supplier selection problem, based on genetic algorithm (GA) and ant colony optimization (ACO), hybrid algorithm of GA and ACO is developed. It combines merits of GA with great global converging rate and ACO with parallelism and effective feedback. A numerical experiment was conducted to optimize parameters and to analyze and compare the performance of the original and hybrid algorithms. Results demonstrate the quality and efficiency improvement of new integrated algorithm, verifying its feasibility and effectiveness. It is an innovative pilot research to leverage hybrid AI-based algorithm of GA and ACO to settle the supplier selection problem, which not only makes a clear methodological contribution for optimization algorithm research, but also can be served as a decision tool and provide management reference for companies.



*Keywords:* Supplier selection; Hybrid algorithm; Genetic algorithm; Ant colony optimization

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## 1. Introduction

Since 1990s, along with the background of economic globalization, advances of information technology and personalization of customer needs, the idea of "Supply Chain Management" (SCM) has received much attention in academics and business. Supplier evaluation plays an important role in a successful SCM. Therefore, evaluation and selection of the right suppliers have become a primary decision for manufacturing business activities [11]. As defined by Council of Supply Chain Management Professionals, SCM is employed to manufacture and provide end-products, including all efforts from suppliers' suppliers to customers' customers, which covers strategic management, partnership, logistics, best practice, organizational behavior and so on [6]. Selecting the right suppliers has significant influences on the supply chain performance, not only increasing customer satisfaction but also improving product and service quality. Walmart, as the largest chain retailer in the world, has struggled to select and manage its suppliers until building Walmart Global Sourcing (WMGS). Before WMGS, due to relying mainly on importers as its suppliers who gained most parts of the profits, Walmart lost its cost competitive advantage. WMGS allows Walmart run purchasing in its own right and helps maintain low purchasing cost and high product quality. Disqualified or inappropriate suppliers can also cause non-economic damage, such as reputation and trust damage. Sanlu Milk Powder Accident in China has induced consumers' extreme distrust in domestic milk powder brands until now, whose influence is irreversible. As Jain et al. [19] stated, to fulfill business growth, corporations must stress the establishment of an effective supply chain with trading partners, and concern their consumers simultaneously. They also pointed out more efforts should be made to enhance relationship between companies with their supply chain partners. Hence, supplier selection process has become a critical step in supply chain design and an important aspect in production research. Therefore, it makes a contribution to both knowledge and methodologies that trying some new approaches to solve supplier selection problem efficiently.

Tsai et al. [42] reported that the selection of appropriate supply partners can significantly improve a firm's competitive advantages, and further influence qualities and prices of the final products offered to customers. As a multi-criteria decision-making problem (MCDM), supplier selection problem with multiple criteria is a very complicated decision process. Thus, various techniques and methods have been proposed and applied in evaluating and selecting the right suppliers. Based on used decision-making techniques, Chai et al. [5] categorized methodologies served to select suppliers into three main groups, (1) Multi-criteria Decision-making (MCDM) Techniques such as Analytic Hierarchy Process (AHP), Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS), and Analytic Network Process (ANP), (2) Mathematical Programming (MP) models such as Linear Programming (LP), Data Envelopment Analysis (DEA) and Multi-objective Programming (MOP), and (3) Artificial Intelligence (AI) approaches such as Genetic Algorithm, Grey System Theory (GST), and Artificial Neural Network (ANN). Supplier selection problem could become increasingly complex with its increasing problem scale, so some integrated models have been proposed and applied in supplier selection problem such as integrated DEA and ANN, integrated GA and ACO. Providing a novel insight and powerful computation ability, most hybrid algorithms have been extensively explored in recent decades and successfully used to select suppliers.

Inspired by using hybrid GA and ACO for partner selection problem in virtual enterprise [51,52], in this paper, we demonstrate a hybrid meta-heuristic algorithm of GA and ACO to resolve supplier selection problem. Specifically, according to the characteristics of supplier selection problem, we develop a multi-criteria supplier selection model. Hybrid algorithm of GA and ACO is developed and improved to solve proposed model. Xiong et al. [49] have reported that GA algorithm has a fast converging rate in the earlier searching process, but as the search continues, its efficiency will apparently reduce. On the other hand, because of lacking initial pheromone information, ACO has a slow speed at the beginning of searching stage. With the availability and accumulation of pheromones, ACO will obviously speed up at the later stage. By fusing these two algorithms, we can utilize the advantages of GA with high initial speed-up convergence and the merits of ACO with parallelism and effective feedback. Regarding the hybrid algorithm, the solutions produced by GA will be used to allocate the initial pheromones for ACO, the key idea of our hybrid algorithm. With numerical experiment, we observed that the hybrid algorithm performed better in respect of converging speed and efficiency than that of traditional GA and ACO. Using hybrid GA and ACO algorithm to settle supplier selection problem is innovative, which can extend the method framework of supplier selection and may help to shed new light on contemporary problems faced in research arenas of supplier selection. More importantly, it can offer a practical guidance and management reference for companies to select their suppliers more effectively.

The organization of the reminder in this paper is described as followed: Section 2 primarily reviews the literatures about technique and evaluation criteria for supplier selection problem. Section 3 describes the problem of supplier selection and presents the supplier selection model including the objective functions and constraints. Section 4 introduces the genetic algorithm and ant colony algorithm, and lays great emphases on the key points of hybrid algorithm. Section 5 elaborates the processes of hybrid algorithm to solve supplier selection problem. In Section 6, a numerical experiment is designed to optimize parameters and evaluate performance of the new hybrid algorithm. Finally, we come to the conclusions and future research in the last section.

## 2. Literature review

Nowadays, the issue of supplier selection has become a popular problem, being extensively studied in recent years. After reviewing 123 articles about supplier selection problem published from 2008–2012, based on decision-making techniques Chai et al. [5] classified methodologies employed to select suppliers into three, MCDM techniques, MP models, and AI approaches. Statistics among these articles show that the usage of MCDM accounts for 44.4%, MP 35.1% and AI 20.5%. Based on their categorization, we reviewed literatures including the top three used techniques in recent years, and displayed their supplier evaluation criteria. The summarization of reviewed literatures is shown in Table 1.

As Table 1 shows, MCDM and MP methodologies are primary techniques employed to solve supplier selection problem in recent years. However, for intelligence optimization algorithms, as indicated by statistical analysis, its usage is a little less (20.5%), especially using intelligent algorithm GA, ACO or their hybrid, despite the outstanding optimization capability of these heuristic algorithms. To narrow this gap, in this paper, AI approaches are utilized to solve proposed supplier selection model. In fact, intelligent optimization methods GA and ACO are promising because they are capable to significantly increase the possibility of finding high-quality solutions for some complex combinatorial optimization problems. For example, regarding supplier selection problem as a grouping problem, Mutingi and Mbohwa [30] presented a fuzzy multi-criterion grouping genetic algorithm by using adaptive crossover, mutation and adaptive two-point inversion to improve GA. Paydar and Saidi-Mehrabad [33] proposed to perform GA and VNS (Variable neighborhood search) consecutively to improve the local search capability of GA. Specifically, in each population VNS serves as a subset of the population to search for better solutions among individuals' neighborhood. Tsai et al. [42] reported an attribute-based ant colony system (AACS) to examine the critical factors and their weights based on which to score suppliers for finding the most suitable ones. Abdollahzadeh and Atashgar [1] proposed a multi-objective ant colony optimization (MOACO) algorithm by using redundancy level pheromone matrices and maintenance thresholds pheromone matrices to handle uncertainty in supplier selection. Hfeda et al. [16] applied hybrid meta-heuristic approach of GA and ACO to obtain a possible optimal solution (more efficient delivery route with fewer iterations) for a milk-run delivery issue in lean supplier chain management.

Furthermore, the hybrid evolutionary algorithm of GA and ACO has also shown substantial potential to solve many complex problems, such as logistics distribution route optimization, 0–1 knapsack problem and QoS (Quality of service), optimization of cloud database route scheduling, virtual enterprise partner selection problem and some NP-complete problem including the satisfaction problem (SAT), the tripartite matching problem, and the traveling-salesman problem (TSP) [8,51,52,56,57,59]. Therefore, in this paper, a hybrid algorithm of GA and ACO is proposed to solve supplier selection problem. It helps to select proper suppliers more efficiently under a dynamic and competitive business environment and contributes to the methodology development of supplier selection problem. According to existing research of hybrid algorithm of GA and ACO, fusing approaches can be roughly divided into three categories. The first is using the solutions generated by GA to initiate the pheromone of ACO, subsequently ACO is utilized to find the best solution [16,51,52,56,57,59]. The second is adding genetic operation into the process of ACO to increase its solution diversity [56]. The last is the combination of both [8]. The primary idea to fuse GA and ACO in this paper is the first one.

## 3. Problem modeling and analysis

As a multi-goal combinational optimization problem, optimized objective of supplier selection is to select the right suppliers for each component without resource conflicts and to reach the target of lowest cost and best profit simultaneously. The mathematical model proposed in this paper is developed based on the following assumptions:

- Single-purchaser, multi-product, multi-supplier condition and budget constraints are assumed.
- Multi-criteria and multi-objective restrictions are utilized to evaluate potential suppliers.

**Table 1**
The summarization of reviewed literatures regarding to MCDM, MP and AI.

| Approach | | Literature | Core Tech | Supplier evaluation criteria |
|---|---|---|---|---|
| MCDM | AHP | Fashoto et al. 2016 [12] | AHP, NN | Quality; Service; Cost; Delivery; Risk |
| | | Buyukozkan, Gocer, 2017 [4] | Fuzzy AHP | Product quality; Delivery compliance; Quality; Cost |
| | | Jovanovic, Delibasic, 2014 [20] | Fuzzy AHP, QFD | Delivery conditions; Management systems; Warranties |
| | ANP | Sarkar et al.2017 [39] | ANP, FVIKOR, DEMATEL | Quality; Delivery; Risk; Cost; Service; Environmental collaboration |
| | | Dargi et al. 2014 [7] | Fuzzy ANP | Quality; Price; Production Capacity; Technical Capacity & Facility; Service & Delivery; Reputation; Geographical Location |
| | | Zhang et al. 2014 [54] | ANP, Evidence Theory | Business Improvement; Extent of Fitness; Quality; Service; Risk |
| | | Zhang et al. 2015 [55] | Fuzzy ANP | Cost; Quality; Service Performance; Supplier's Profile; Risk |
| | | Gupta et al. 2015 [14] | ANP | Cost; Quality; Long Term Relationship |
| | TOPSIS | Pramanik et al.2016 [35] | TOPSIS, AHP, QFD | Quality; Delivery; Reliability; Processing time; Profit margin |
| | | Liu et al.2014 [26] | TOPSIS | Quality; Parts Price; Delivery time; Geographical Location; Scientific Payoffs; Registered Capital; Channel Dependency; Batch Flexible; Production capacity |
| | | Rouyendegh, Saputro, 2014 [38] | Fuzzy, TOPSIS, MCGP | Supply Capacity; Production Capacity; On Time Delivery; Production technology; Price; Quality |
| | | Lima-Junior,Carpinetti, 2016 [23] | Fuzzy, TOPSIS, SCOR | Cost; Delivery Performance |
| MP | DEA | Azadi et al. 2014 [2] | DEA | Total Cost of Shipment; Price; Numbers of Shipment Per Month; Eco-design Cost; Cost of Work Safety and Labor Health |
| | | Karsak, Dursun, 2014 [21] | DEA, QFD | Product Volume; Delivery; Payment Method; Supply Variety; Reliability; Experience in the Sector; Earlier Business Relationship; Management; Geographical Location |
| | | Dotoli et al. 2015 [10] | DEA | Price; Lead Time; Distance |
| | LP | Lin et al. 2011 [24] | LP, ANP, LP, TOPSIS | Quality Defect; Delivery Delayed Rate; Capacity; Unit Price |
| | | Toloo, 2016 [41] | DEA | Cost Efficiency |
| | MOP | Yucel, Guneri, 2011 [53] | Fuzzy MOLP | Net Price; Quality; On-time Delivery |
| | | Nazari-Shirkouhi et al. 2013 [31] | MOLP | Purchasing and Ordering Costs; Capacity; Flexibility etc. |
| AI | GA | Paydar,Saidi-Mehrabad 2017 [33] | GA | Cost (material handling, machines, inventory, production, procurement ) |
| | | Mutingi, Mbohwa, 2017 [30] | FGGA | Price; Lead time; Quality |
| | | Fallahpour et al. 2015 [11] | GA, DEA | Quality of Material; Service; Cost; Delivery; Resource consumption; Pollution Control |
| | | Hfeda et al. 2017 [16] | GA, ACO | Quality; cost; delivery capacity and flexibility; innovation and development capacity |
| | GST | Hashemi et al. 2015 [15] | GRA, ANP | Cost; Quality; Technology; Resource consumption; Pollution Production; Management commitment |
| | | Rajesh,Ravi, 2015 [36] | GRA | Quality; Cost; Flexibility; Vulnerability; Collaboration; Risk awareness; Supply Chain Continuity Management; Technological Capability; R & D; Safety; Concern for Environment |
| | ANN | Azadnia et al. 2012 [3] | ANN | Economic: Cost; Quality; Time; Social: Occupational Health and safety Management System; Rights of Stakeholders; Environmental: Pollution etc. |
| | | Wu, 2009 [47] | ANN, DEA | Quality; Cost; Delivery; Design and Development Capability etc. |

Note: Grey Relational Analysis (GRA).

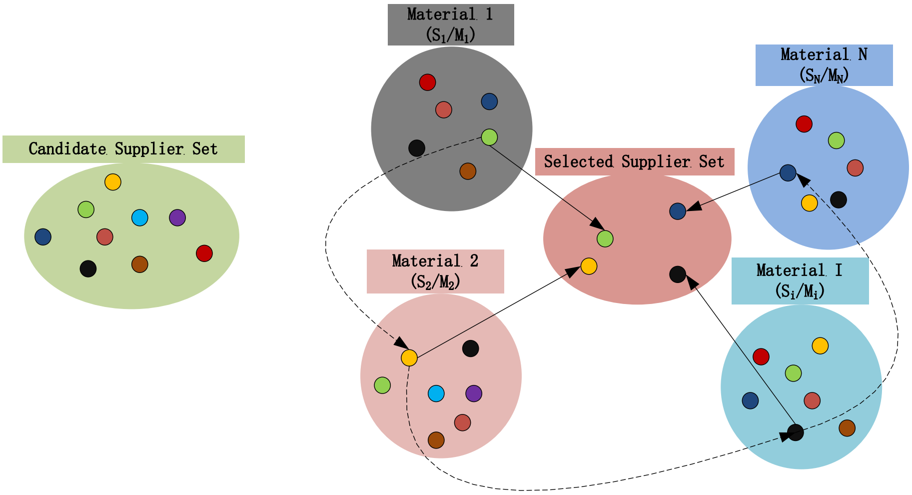


**Fig. 1.** Model of supplier selection.

- Each material is offered by a limited number of suppliers.
- All suppliers are grouped into $N$ categories according to the materials and component they can provide, and only one supplier can be selected from each category at a time.

Fig. 1 demonstrates the supplier selection model presented in this paper. There are $N$ kinds of raw materials needed to be purchased and totally $J$ numbers of qualified suppliers to be selected. These potential suppliers are classified into $N$ categories according to materials they can provide, written as $S_i$ $(i = 1, 2, \ldots, N)$, and for each material, there are $M_i$ $(i = 1, 2, \ldots, N)$ eligible suppliers, namely $M_i$ is the size of $S_i$. Noting that each $M_i$ may be different and the total number of suppliers is $J$. The task is to select one supplier for each material to achieve the optimal objective.

Although there are many factors affecting the supplier selection process, price, delivery and quality are most frequently used in various studies [35], which can also be indicated from Table 1. In essence, except the least cost, due date and delivery time, other crucial factors should also be incorporated in the decision-making process [32]. As Liu et al. [25] stated, at supplier evaluation and selection stage, price factors, quality factors, cultural compatibility, financial status, technical research and development strength etc. should be taken into full consideration. In this paper, considering the previous research and current context that innovation is especially emphasized in enterprise development strategy, quality ($Q$), cost ($C$), delivery capability and flexibility ($T$), innovation and development capability ($D$) are categorized and considered to evaluate the potential suppliers. Moreover, considering their different properties and influential factors, the four main criteria are assessed and analyzed by their corresponding sub-criteria as shown in Fig. 2 (depict referring to [32]), where a rounded rectangle represents a main criterion and a hexagon refers to its sub-criterion.

The objective of selecting proper suppliers is to maximize quality, delivery capability and flexibility, innovation and development capability, and to minimize cost, namely {max $Q$, max $T$, max $D$, min $C$}, denoted as max $\{Q, T, D, -C\}$. Specifically, a company needs $N$ kinds of materials provided by $J$ qualified suppliers, and for the $i$th material, it has $M_i$ potential suppliers. For candidate $j$, its four index values of quality ($Q$), delivery capability and flexibility ($T$), innovation and development capability ($D$) and cost ($C$) for the $i$th material are written as $q_{ij}$, $t_{ij}$, $d_{ij}$, $c_{ij}$. These potential suppliers need to satisfy the following functions:

Objective functions:

$$\max \mathrm{Q} = \sum_{i=1}^{N} \sum_{j=1}^{M_i} q_{ij} \beta_i^j \tag{1}$$

$$\max D = \sum_{i=1}^{N} \sum_{j=1}^{M_i} d_{ij} \beta_i^j \tag{2}$$

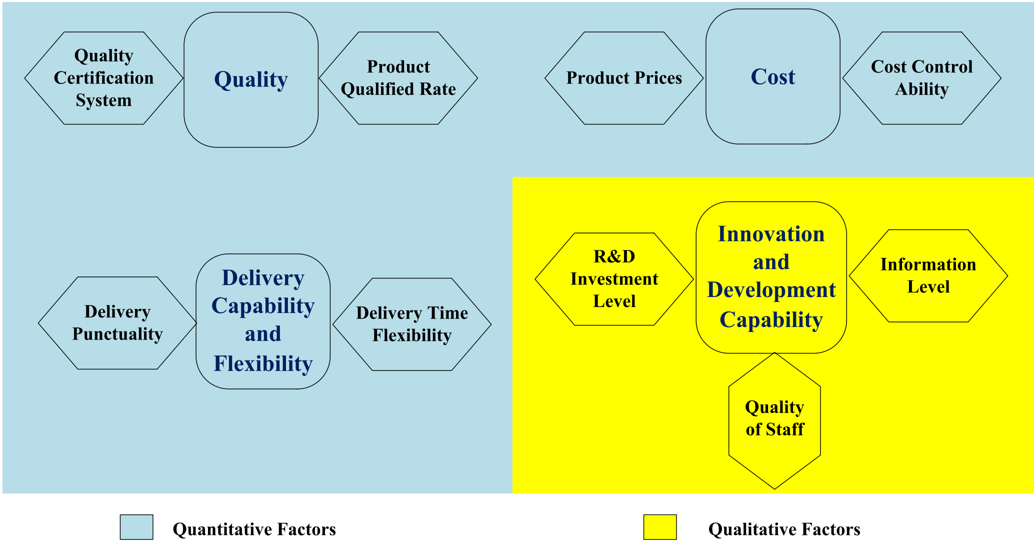


**Fig. 2.** Main criteria and their sub-criteria.

$$\max C = \sum_{i=1}^{N}\sum_{j=1}^{M_i}(-c_{ij})\beta_i^j \tag{3}$$

$$\max T = \sum_{i=1}^{N}\sum_{j=1}^{M_i} t_{ij}\beta_i^j \tag{4}$$

Constraints:

$$\sum_{i=1}^{N}\sum_{j=1}^{M_i} c_{ij}\beta_i^j \le Budget \tag{5}$$

$$\sum_{j=1}^{M_i}\beta_i^j = 1,\ i = 1, 2, \ldots, N \tag{6}$$

$$\sum_{i=1}^{N}\sum_{j=1}^{M_i}\beta_i^j = N \tag{7}$$

$$\beta_i^j = \begin{cases} 1, & \text{if choose supplier } j \text{ for } i\text{th material} \\ 0, & \text{otherwise} \end{cases} \tag{8}$$

For Eq. (1), $Q$ represents the quality level of a supplier, and according to the sub-criteria in Fig. 2, it is obtained from evaluating product qualified rate and quality certification system. For Eq. (2), $D$ shows innovation and development capability of a supplier, obtained from assessing the sub-criteria: information level, R&D investment level and quality of staff. For Eq. (3), $C$ demonstrates the cost level of a supplier, assessed from sub-criteria: product prices and cost control ability, integrally reflected by purchase cost. For Eq. (4), $T$ expresses the delivery capability and flexibility, acquired from appraising sub-criteria: delivery punctuality and time flexibility. Constraint Eq. (5) regulates the total cost is less than overall budget. Constraint Eq. (6) guarantees each material is offered only by one supplier. Constraint Eq. (7) makes sure that each material has its own supplier. Constraint Eq. (8) is a variable constraint.

Obviously, supplier selection problem is a combinatorial explosion problem with the increase of $J$. It is hard to select suppliers to meet all requirements. Therefore, it is necessary to transform the problem into a single objective decision-making issue. TOPSIS is a very effective method in the multi-objective decision analysis. Its core idea is that first build a matrix based on standardization data for identifying the best and worst targets. Then calculate the distance between each evaluation option and positive/ negative ideal solution. Thereafter score them by ranking their closeness to the ideal solutions, based on which to obtain assessment results [26]. Considering the multi-objective and multi-attribute characteristics of supplier selection problem proposed in this paper, referring to TOPSIS, for $i$th material, evaluation goal of its $j$th supplier can be written as Eq. (9). For the four main indexes cost ($C$), quality ($Q$), delivery capability and flexibility ($T$), and innovation and development capability ($D$), assuming that their positive ideal value and negative ideal value are ($C^+$, $Q^+$, $T^+$, $D^+$) and ($C^-$, $Q^-$, $T^-$, $D^-$) respectively. The specific formulations based on the idea of TOPSIS are displayed as Eqs. (10) and (11). Here $f_{ij}$ is the evaluation goal of $j$th supplier for $i$th material, $d^+$ and $d^-$ are the distance between each index value and positive/negative ideal value, and $w_q^i$, $w_d^i$, $w_c^i$, $w_t^i$ denote the weight of index $Q$, $D$, $C$, $T$ for $i$th material.

There are many approaches to set the weight of indexes, such as AHP, TOPSIS, factor analysis method and so on, most of which are subjective evaluations by experts. In this paper, referring to Liu et al. [26], an objective weight vector method shown as Eq. (12) is introduced. It utilizes the idea of TOPSIS and successfully avoids the influence of subjective factors, where $k$ is the number of evaluation indexes ($k = 1, 2, 3, 4$), $y_{kj}$ is the $k$th index value of the $j$th supplier, and $y_k^*$ is the ideal value of the $k$th index.

$$f_{ij} = \frac{d_{ij}^-}{d_{ij}^+ + d_{ij}^-} \tag{9}$$

$$d_{ij}^+ = w_c^i \frac{|c_{ij} - C^+|}{C^+ + C^-} + w_q^i \frac{|q_{ij} - Q^+|}{Q^+ + Q^-} + w_t^i \frac{|t_{ij} - T^+|}{T^+ + T^-} + w_d^i \frac{|d_{ij} - D^+|}{D^+ + D^-} \tag{10}$$

$$d_{ij}^- = w_c^i \frac{|c_{ij} - C^-|}{C^+ + C^-} + w_q^i \frac{|q_{ij} - Q^-|}{Q^+ + Q^-} + w_t^i \frac{|t_{ij} - T^-|}{T^+ + T^-} + w_d^i \frac{|d_{ij} - D^-|}{D^+ + D^-} \tag{11}$$

$$w_k = [\sum_{k=1}^{4} \frac{1}{\sum_{j=1}^{Mi}(y_{kj} - y_k^*)^2} \sum_{j=1}^{Mi}(y_{kj} - y_k^*)^2]^{-1} \; (i = 1, 2, \ldots, n) \tag{12}$$

With TOPSIS method we can get a standardization matrix of qualified suppliers' evaluation goal value. The objective function for supplier selection problem is described as Eq. (13), finding the maximum sum of all selected suppliers' evaluation goal values. Based on TOPSIS, we have converted a multi-objective combination optimization problem into a single one.

$$maxf = \sum_{i=1}^{N} f_{ij}, \; j = 1, \ldots, M_i \tag{13}$$

## 4. Ideas of fusing the genetic algorithm and ant colony optimization

### 4.1. Background of GA and ACO

Inspired by Darwin's evolution theory and Mondel's heredity theory, Genetic Algorithm, as a bionic optimization algorithm, was first proposed by Holland [17]. It imitates the evolution of biotic population in the nature, and attempts to find the optimum for some complex problems by the evolutions of defined "chromosomes" (a population of solutions) from generation to generation. When adopting GA, the problem will be coded as binary codes, and the searching processes of optimal solution are conducted based on operators of copy, crossover and mutation, in accordance with the principle of "Survival of the Fittest". As a global optimization method, GA has advantages of self-organization, self-adaption and good global search ability. However, it does not have a good feedback mechanism, and thus a large number of redundant iterations will be generated, resulting in a low efficiency [34].

On the other hand, inspired by foraging behavior of ants in the nature, Ant Colony Optimization, as a kind of simulative evolutionary algorithm, was first proposed by Dorigo and Gambardella [9]. During the foraging process, when there is a fork never encountered before in the road, the ant will choose one path according to a certain random probability, and release some pheromones for other ants to make decision. The more pheromones a path accumulated, the more possibly other ants will use this path. Therefore, pheromone trail on such a path will accumulate faster and help attract more ants to follow (called positive feedback) [42]. Based on this nature process, without any prior knowledge, ant colonies find the optimal solution through exchanges of information between individuals and mutual cooperation. As a swarm intelligence optimal algorithm, ACO has merits of parallel computation, self-learning and effective information feedback. But at initial searching stage where there is less or no available information, the speed of convergence is slow.

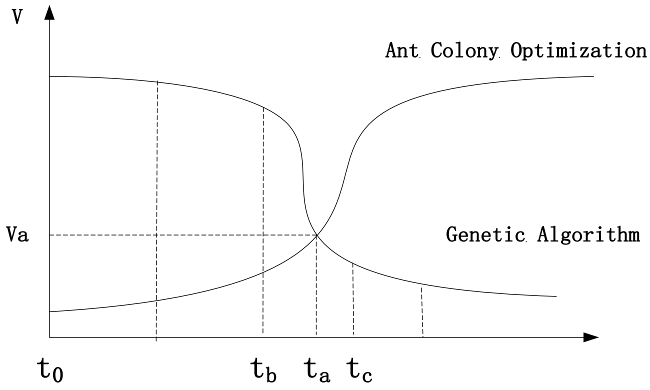


**Fig. 3.** Difference of speed curve of GA and ACO.

### 4.2. The idea of fusing GA and ACO

In literatures, the key idea of various hybrid algorithms is to integrate the population diversity and global searching ability of GA into feedback mechanism of ACO for improving accuracy and efficiency of hybrid algorithm. In Zhang and Wu's work [58], the hybrid algorithm has two procedures: (1) approximate the global maximum by GA, and (2) search the optimal solution using ACO with GA operators. Two fusion ideas were proposed in Xiao and Tan's study [48]: the first one is that GA was used to search a rough solution, which was applied as initial information of ACO, and then ACO began its searching process to find optimal solution. The second one is to add crossover operator into ACO in case of getting bogged down into local optimum, and therefore enhance the global searching ability of ACO. In Liu's research [25], GA was used to optimize the coefficient of pheromone, heuristic and pheromone volatilization in ACO. Specifically, she implemented the integration of GA and ACO by means of adopting GA for finding optimal parameters to improve the efficiency of ACO. Oppositely, Hfeda et al. [16] proposed a hybrid meta-heuristic approach of GA and ACO by applying ACO to create candidate solutions as the initial population for GA.

In this paper, the basic idea of dynamic integration of GA and ACO comes from Yao et al. [51,52] and Xiong et al. [49]: adopt GA to generate available solutions, based on which to update initial pheromones, and thereafter apply ACO to search until the optimum is reached. Xiong et al. [51] has presented the speed-time curve of GA and ACO as displayed in Fig. 3, where $t_a$ is the best fusing time. In order to make the fusion time be around $t_a$, they proposed a dynamic integration strategy where they set a minimum iteration $Ge_{min}$ ($t_b$ moment), a maximum iteration $Ge_{max}$ ($t_c$ moment) and a constant $Ge_{die}$ for GA. If the evolutionary rate is continuously less than a constant for $Ge_{die}$ generations, the hybrid algorithm will terminate GA iterations and step into the searching part of ACO. The process of hybrid algorithm of GA and ACO is shown as Fig. 4.

## 5. Supplier selection algorithm based on the fusion method

Genetic algorithm and ant colony optimization are promising intelligent heuristic algorithms, which have been broadly applied in the field of optimization. Based on their initial versions, there have been continuous improvements to advance the performance of GA and ACO. With constraints of service level and budget, Yang et al. [50] settled a stochastic-demand multi-product supplier selection problem by using GA, where the largest value of average expected profit and the smallest value of the standard deviation are reached via different combination of crossover and mutation rates. In order to improve the global search capability and convergence performance of GA, Wang et al. [46] proposed four kinds of improved genetic algorithms, including hierarchic genetic algorithm, simulated annealing genetic algorithm, simulated annealing hierarchic genetic algorithm and adaptable genetic algorithm, which overcome the defects of traditional GA by fusing it with simulated annealing algorithm and modifying its coding method. With another idea of fusing GA and ACO, Li et al. [22] added a heuristic factor of genetic information into the initial fixed heredity proportion to determine the transition probability of ACO, which aims to decrease the calculation during the path searching process and increase the convergence rate. Niu et al. [32] stated that as a typical greedy heuristic

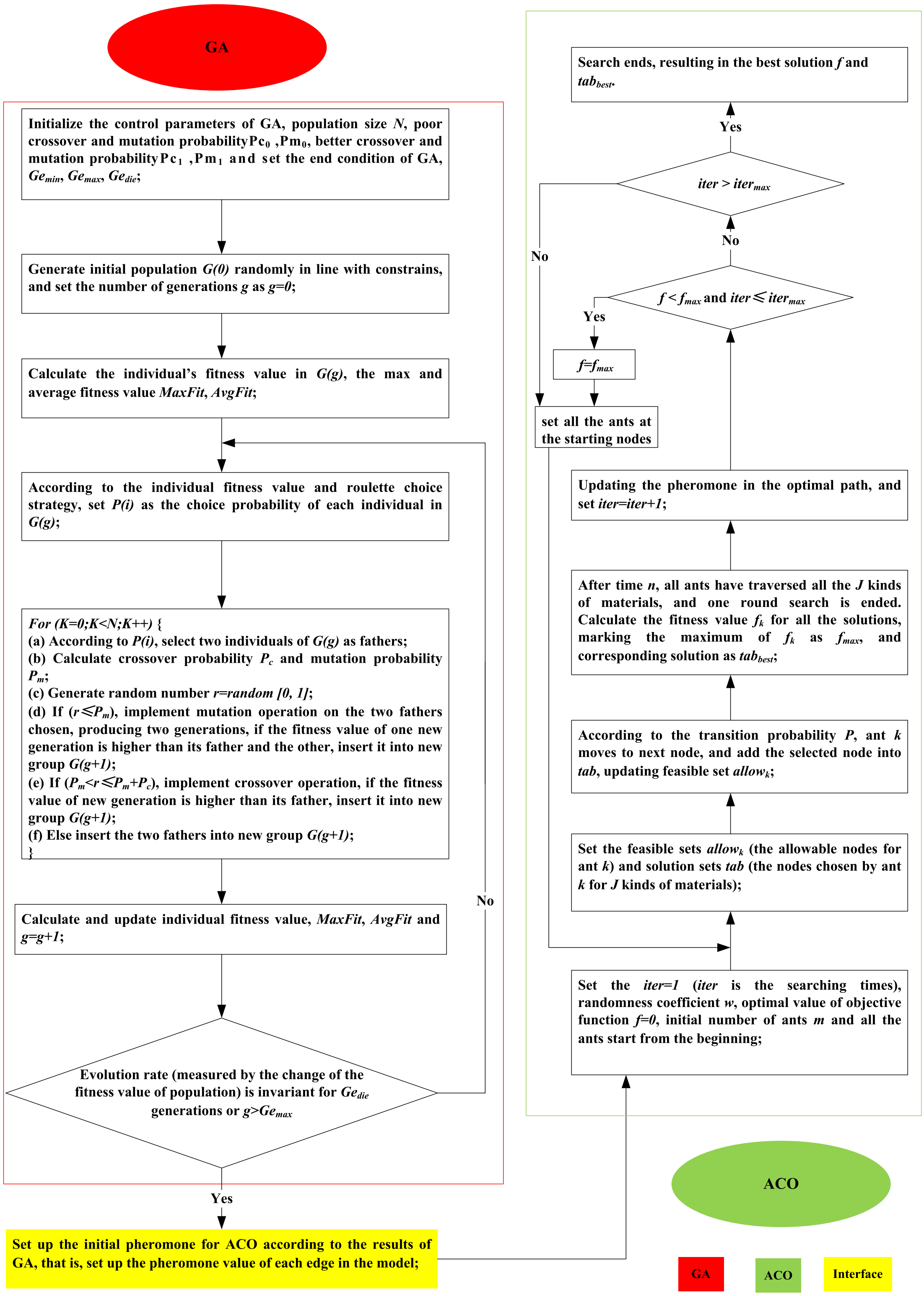


**Fig. 4.** Hybrid algorithm of GA and ACO.

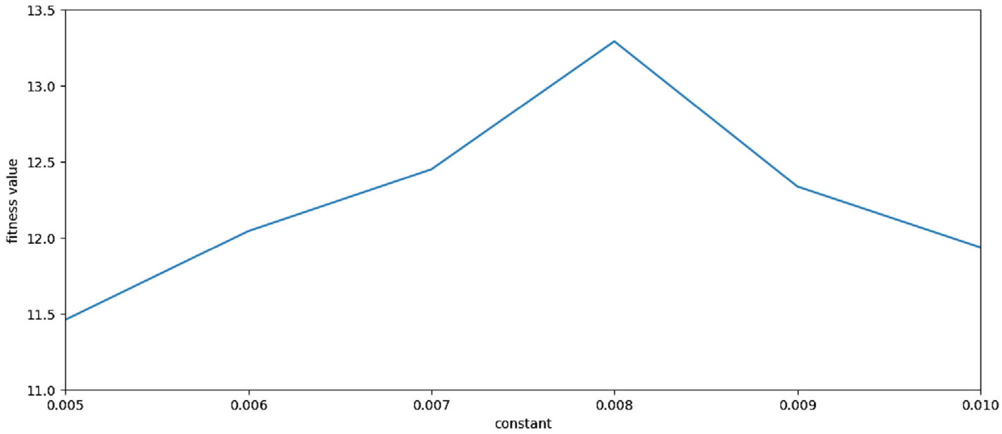


**Fig. 5.** Variation of optimal fitness value among different constants.

algorithm, ACO is prone to be trapped in local optima. They proposed a way to guide the search out of the local optima by adding the disturbance into the original probability. Moreover, a coefficient, representing the influence effects of average pheromone, was utilized to update pheromones and to decrease the effects of parameter $Q$. In this paper, we also make some improvements of traditional GA and ACO to enhance the performance of hybrid algorithm.

(1) *The explanation of fusing time of GA and ACO*

Referring to the idea of setting fusing time in Xiong's work [49], in this paper, we define evolutionary rate as the variation rate of optimal fitness values between two adjacent iterations. When the evolutionary rate is less than a certain constant more than 3 times, it is considered that the efficiency of GA part is low enough for the hybrid algorithm to turn into ACO part. In order to determine the constant, according to the value distribution of evolutionary rate, we compare the optimal fitness values among different constants from 0.005–0.01. Fig. 5 shows the average fitness value of 10 iterations under different constants, and obviously the 0.008 is the best suitable constant value.

(2) *Genetic algorithm with self-adaptive crossover and mutation probability*

For general GA, the crossover probability and mutation probability are constants. Although the algorithm has a high convergence rate at the beginning, its efficiency gradually declines for the lack of feedback information. Referring to Ma [27], a self-adaptive crossover and mutation probability are introduced in this paper. By adjusting crossover and mutation probability automatically, the enhanced GA avoids redundant iterations and low searching efficiency successfully at the later stage. The functions of self-adaptive crossover and mutation probability are shown as followed:

$$P_c = \begin{cases} P_{c_0} & f \le \overline{f} \\ P_{c_1}(\dfrac{P_{c_0}}{P_{c_1}})^{\left(\frac{f\max - f}{f\max - \overline{f}}\right)} & f > \overline{f} \end{cases} \tag{14}$$

$$P_m = \begin{cases} P_{m_0} & f' \le \overline{f} \\ P_{m_1}(\dfrac{P_{m_0}}{P_{m_1}})^{\left(\frac{f\max - f'}{f\max - \overline{f}}\right)} & f' > \overline{f} \end{cases} \tag{15}$$

where $Pc_0$, $Pm_0$ represent the poorer crossover and mutation probability, $Pc_1$ ($Pc_1 < Pc_0$), $Pm_1$ ($Pm_1 < Pm_0$) are the better ones, $f$ and $f'$ are the lower fitness value of individuals, $f_{max}$ and $\overline{f}$ are the best and average fitness value in the population.

(3) *Updating mechanism of the pheromone in ant colony optimization*

Pheromone updating is a critical process of ACO. Referring to Max–Min ACO [40], only pheromones of the optimal solution are updated after each iteration [46]. This idea simplifies the way of pheromone update compared with traditional ACO, which needs to update the pheromone of all solutions. For pheromone constant $Q$, it also affects the efficiency of ACO. In general, $Q$ has an artificial initial value and cannot be changed as the process is going, resulting that ACO is easy to fall into local optima. Therefore, the self-adaptive $Q$ is introduced in this paper, where $Q$ is not a constant but varies according to a step function. Based on this, the functions of pheromone updating are displayed as followed:

$$\tau_{S_{ij}}(t+n) = (1-\rho)\tau_{S_{ij}}(t) + \rho\Delta\tau_{S_{ij}}(t) \tag{16}$$

$$\Delta\tau_{S_{ij}}(t) = \sum_{k=1}^{m} \Delta\tau_{S_{ij}}^{k}(t) \tag{17}$$

$$\Delta\tau_{S_{ij}}^{k}(t) = \begin{cases} Q/F_{\max} & S_{ij} \in F_{\max} \\ 0 & \text{else} \end{cases} \tag{18}$$

$$Q = Q_0 * (1 - w * N_t/MaxN) \tag{19}$$

where $\rho \in [0, 1]$ is pheromone volatilization coefficient, $\triangle\tau_{\mathrm{Sij}}(t)$ is pheromone variation of the optimal solution, $\triangle\tau_{\mathrm{Sij}}^{\mathrm{k}}(t)$ is the pheromone left by each ant traversed nodes of the optimal solution. Eq. (19) is the step function for $Q$, where $Q_0$ is the initial value of $Q$, $w \in [0, 1]$ is adjustment coefficient, $N_t$ is the current iteration, and $MaxN$ is the maximum number of iteration.

(4) *Settings of transition probability in ant colony optimization*

Transition probability $P$ is the only determinant to decide which node will be chosen by ant $k$. Considering that ACO is prone to get bogged down in local optima, we refer to Niu's work [32] which introduces randomness in the transition probability. Specifically, at moment $t$ the transition probability $P$ of ant $k$ from node $v_i$ to node $v_j$ can be expressed as followed:

$$P_{\mathrm{S}_{ij}}^{k}(t) = \begin{cases} \dfrac{[\tau_{\mathrm{S}_{ij}}(t)]^{\alpha}[\eta_{\mathrm{S}_{ij}}(t)]^{b}}{\sum_{allowed}[\tau_{\mathrm{S}_{ij}}(t)]^{\alpha}[\eta_{\mathrm{S}_{ij}}(t)]^{b}} + \dfrac{s * U(0,1)}{M_i} & S_{ij} \in allowed \\ 0 & \text{else} \end{cases} \tag{20}$$

where *allowed* gives the available nodes for ant $k$. $\alpha$ and $b$ are coefficient of pheromone and heuristic respectively, $\tau_{\mathrm{Sij}}(t)$ is the pheromone value of a node. $\eta_{\mathrm{Sij}}(t)$ is the heuristic function (defined as the evaluation goal value of a node in this paper). $U(0, 1)$ is a uniformly distributed pseudo-random number between 0 and 1. $s$ is the randomness coefficient. $Mi$ is the total number of qualified suppliers for $i$th material.

## 6. Numerical experiments

To examine the viability and efficiency of the hybrid algorithm to resolve the supplier selection problem, we set a simulation case referring to extant literature. In our case, 20 kinds of materials are considered, and there exist 130 suppliers for continued selection. Each kind of material can only be provided by a limited number of suppliers, and the amount is bigger than zero but not more than 130. To ensure the rational efficiency of selection solutions, we will only choose one supplier for each distinct kind of material, and then, the maximum of 2 times will be allowed for one single supplier being selected. Due to its complexity, this is a large-scale problem, which cannot be solved by some other common algorithms. The attribute data of suppliers is randomly generated by computers. The input data are the same for all the algorithms, that is, the original GA and the enhanced GA, the original ACO and the enhanced ACO, the original hybrid algorithm and the enhanced hybrid algorithm. There are two different parts in our numerical experiment. The first part is about parameter optimization of the fuse algorithm and the second part is to test the performance of the original and enhanced algorithms with optimal parameters applied.

### 6.1. Parameters optimization

Owing to the lack of common criteria of parameters in ACO, the main purpose of this part of experiment is to obtain the optimal parameters of ACO, which include the number of ants *antNumber*, pheromone coefficient $a$, heuristic coefficient $b$, and pheromone volatilization coefficient $r$. The general method of parameters optimization is to try the feasible values at a fixed step length and search for the point contributing to the optimal objective value. The results are shown in the below pictures.

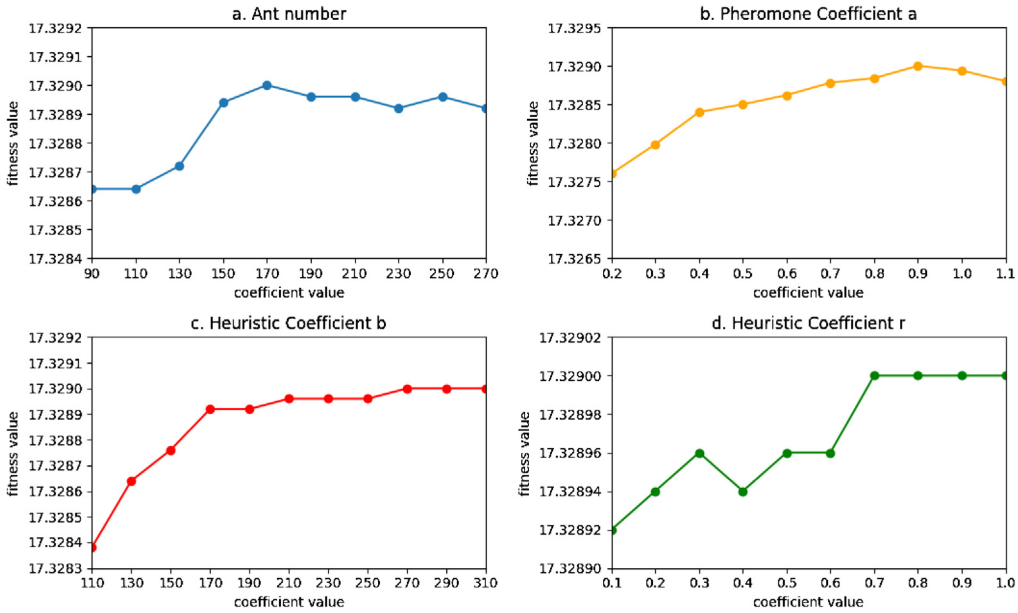


**Fig. 6.** Optimization of parameters of ACO.

To a great degree, the search efficiency of ACO for optimal solution is affected by the default number of ants. Generally, the search results will get better as ant number is increasing until exceeding some certain extent, that is, there exists a limitation. From Fig. 6a we can find that there is a critical point where ant number is 170. The ant number varies from 90 to 270 at a fixed step length of 20 and fitness value is representative of the average search result on ten test iterations. When ant number is below the critical point, the search efficiency is increasing basically. As the blue line moves to the critical point, the algorithm reaches its best, which proves a limitation exists indeed. Therefore, we set the default number of ants as 170 in our algorithm.

In ACO algorithm, both coefficient $a$ and coefficient $b$ are used to calculate the transition probability at which one supplier moves to another supplier of next node, while coefficient $r$ helps updating the pheromone concentration after every search. For coefficient $a$, the larger its value is, the bigger proportion of impact on transition probability pheromone value has. We can figure out from Fig. 6b that when its value is 0.9, the algorithm attains the best excellent result. For coefficient $b$, heuristic value has more influence on transition probability while $b$ is getting larger. From Fig. 6c we can discover that algorithm comes to its leading point while $b$ equals 270. Coefficient $r$ represents the decay ratio of pheromone strength against every search. On one hand, when the value of $r$ is too large, it will take more running time to reach the best search result; on the other hand, it will reduce diversity of algorithm solutions and tend to fall into local optimum trap if the value of $r$ is too small. Fig. 6d reveals that it is optimal for the search result when the value of $r$ is 0.7.

### 6.2. *Simulation results and analysis*

To simulate the case on computers, we implement the algorithms with object-oriented programming Java language and run them based on Java Development Kit 7. From obtained simulation results, we undertake detailed comparison between relevant algorithms. The specific comparison results are shown as followed.

(1) *Genetic algorithm*

Fig. 7 shows the search performance between original genetic algorithm and enhanced genetic algorithm. We observed two findings from the results. Firstly, the two result curves show a similar tendency pattern. The searched fitness value increases sharply at the initial stage, especially in the first several iterations. However, the searching efficiency has a quick decrease in the subsequent part. Obviously, the enhanced algorithm still sustains the original

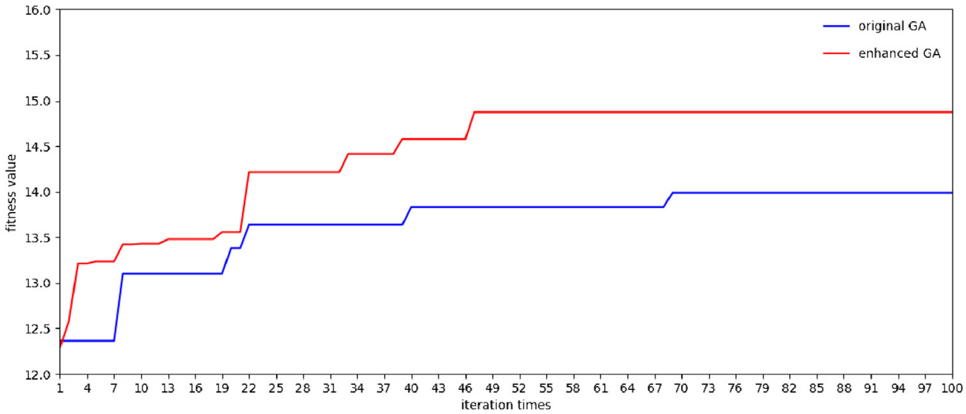


**Fig. 7.** Comparison between original GA and enhanced GA.

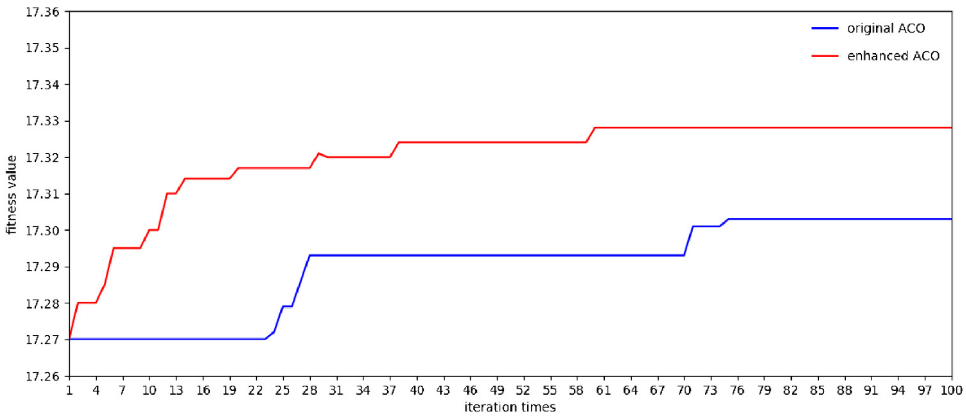


**Fig. 8.** Comparison between original ACO and enhanced ACO.

defect that after certain iterations, the gradually declined efficiency of GA contributes to redundant results. Secondly, after improvement in algorithm, the genetic algorithm reaches a better objective value near to 15. The mechanism of self-adaptive probability increases mutation and crossover chances of chromosome units who have poor performance. Thus the new generation will behave better in optimization search due to more outstanding units inherited from parent generation.

(2) *Ant colony optimization*

The difference of performance between the original ACO and the improved one is shown in Fig. 8. The blue curve, which represents the original ACO, has no significant improvement in fitness value until the 24th iteration for lacking of available feedback information. Moreover, the original ACO becomes stable at fitness value 17.303 after the 75th iteration, revealing a defect that the original algorithm tends to be trapped into local optima. The enhanced algorithm applies a disturbance mechanism to update transition probability for each route before next search and introduces a self-adaptive decay function of pheromone constant $Q$. The improvements effectively avoid this original flaw and increase diversity of selection solutions, which can be clearly seen from the red curve referring to enhanced ACO.

(3) *Hybrid Algorithm*

The comparison of performance among the enhance GA, ACO and hybrid algorithm is explained in this part. From Fig. 9a, which illustrates searching fitness value, the red and green curves represent ACO and hybrid algorithm respectively. The curve of GA is not involved for the fact that maximum fitness value, near to 15, of GA is largely smaller than that of the other two algorithms, varying at a more delicate level between 17.31 and 17.33. Owing to the

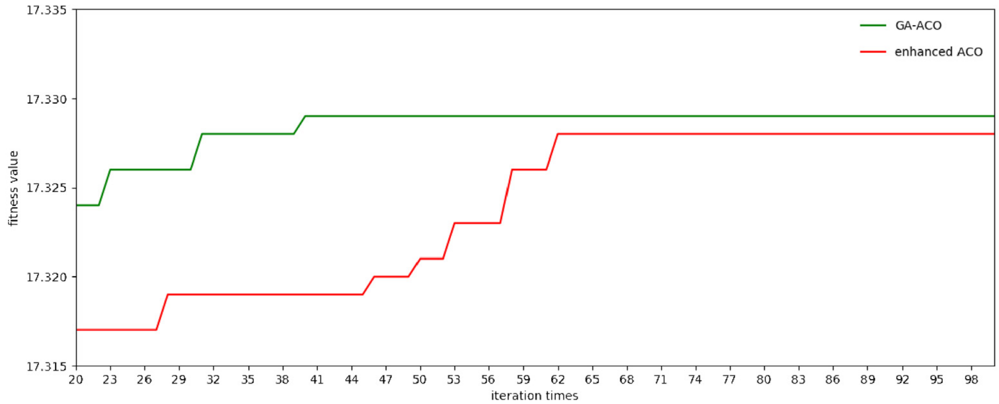


**Fig. 9.** Comparison among enhanced GA, ACO and hybrid algorithm.

flaw that GA generates redundant iterations, it is difficult to have excellent performance on large-scale problems. The curves shown in the picture depict the search process after the 20th iteration, which is the fusing time of GA and ACO in hybrid algorithm. For utilizing the optimal solutions generated by GA to update initial pheromone, the ACO part in hybrid algorithm performs better than pure ACO from the initial stage. The hybrid algorithm rapidly achieves stable optimal result 17.329 at the 41st iteration while ACO reaches 17.328 at the 63rd iteration. Hence, hybrid algorithm is more prominent for its lower time cost compared with ACO.

## 7. Conclusions and future research

In this paper, we describe a novel hybrid algorithm that employs Genetic Algorithm and Ant Colony Optimization to solve supplier selection problem. A multi-objective linear programming model for supplier selection is introduced along with considering the dependence of product quality, price, delivery capacity and innovation ability. It was simplified as a single one by applying for TOPSIS method. Hybrid algorithm of GA and ACO was used to solve the linear programming model for supplier selection problem. Each part of the hybrid algorithm is improved respectively and referring to Xiong et al. [49], the rational occasion to integrate two algorithms is carefully observed and designed. To test the feasibility and effectiveness of the new hybrid algorithm, a case simulation was designed and implemented, where GA, ACO and new hybrid algorithm were applied separately. Analysis of the results shows that new hybrid algorithm has a better time and optimal performance and can provide a decision tool for managers to adopt appropriate strategies in the purchase activities. The proposed model can serve as a decision making support system for practitioners to select suppliers in real cases. It helps shed a new light on the complex and significant supplier selection problem.

Honestly, there are some limitations, and some issues are worthy of further improvement and exploration. For example, under changeable marketing environment more and more uncertain or stochastic demands [13] have shown in supplier selection problem, other artificial intelligent methodologies, such as Particle Swarm optimization (PSO) [28,29,43–45] and Grey Wolf Optimizer (GWO) Algorithm [37], can be applied to handle these kinds of demands in future work. Also using hybrid algorithm of GA and ACO to solve supplier selection problems incorporating non-linear, fuzzy, uncertainty or stochastic demands is a valuable investigation direction. On the other hand, with the popularity of green supplier chain management, some environment related factors have been considered by researchers, like low-carbon [18]. How the hybrid algorithm of GA and ACO can function under green supplier chain management is another promising future research.

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## Conflict of interest

We report no conflicts of interest.

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