ISSN 1330-3651 (Print), ISSN 1848-6339 (Online)

https://doi.org/10.17559/TV-20220723180901

Original scientific paper

Pareto Optimality of Centralized Procurement Based on Genetic Algorithm

Fengxia DING, Shifeng LIU*, Xuewei LI

Abstract: In the process of purchasing materials, small enterprises are often unable to meet the minimum availability of suppliers in the process of purchasing due to the lack of economic strength and storage capacity of goods. Therefore, they will encounter difficulties in the process of purchasing.To solve this problem, the group-led centralized procurement strategy for small enterprises has become a new craze. In this paper, we transform the problem of centralized procurement lot into a multi-objective optimization problem by establishing a multi-objective optimization model with cost, quality and logistics as sub-objectives, and use genetic algorithms to solve the multi-objective optimization problem in order to achieve Pareto optimality among each purchaser and supplier. Finally, an example of procurement by the China Energy Investment Corporation is used to verify that the multi-objective optimization model for the collection of lots constructed in this paper can effectively promote the cooperation between purchasers and suppliers, and stimulate the competitive vitality of enterprises in the market.

Keywords: centralized procurement; genetic algorithm; multi-objective optimization; Pareto optimal

1 INTRODUCTION

As global competition intensifies, the social economy has entered an era where differentiation and high value-added services are emphasized. Then, Professor Hososawa of Waseda University in Japan first proposed the idea of material management as a "third source of profit" in 1970, arguing that there was an "iceberg benefit" to material management costs: the material management costs shown in the financial statements were only the tip of the iceberg. The material management costs shown in the financial statements are only the tip of the iceberg, but those that are consumed internally, hidden beneath the surface and unknown to the managers are the main body of the huge iceberg. Therefore, strengthening material management is a new way for enterprises to obtain profits in the new era. By studying material purchasing management, the efficiency of material purchasing can be improved and the direct and indirect costs of purchasing can be reduced. As an important part of supply chain management, procurement management not only fundamentally affects the operating costs of enterprises, but also is an important part of the core competitiveness. Cebiand Otay introduced procurement management as a strategic component to enhance the performance and flexibility of the entire enterprise supply chain [1]. Then, procurement management has become a research hotspot for many scholars and practitioners [2-4]. Proper procurement practices have the efficacy of ensuring product quality, improving procurement efficiency, reducing inventory levels, controlling overall procurement costs, and preventing delivery delays, all of which contribute to the competitiveness of a company [5-9]. Efficient procurement activities have a significant positive catalytic effect on business performance. Therefore, companies have taken many measures to improve procurement management to maximise profitability, such as supplier evaluation and selection [10, 11], material inventory management [12], and procurement contract development [13].

With the intensification of competitive pressure in the industry, enterprises often face great challenges in the process of procurement, especially those with small procurement lots and unable to form a scale. Economic scale indicates the strength of supply chain control, and smaller companies often lack sufficient judgment in the procurement process, which may lead to an upstream supplier-dominated procurement environment [14]. In addition, the desire to reduce operating costs and eliminate inventory risk can lead to low inventory capacity, making it difficult to purchase critical materials in large quantities and resulting in higher procurement costs [15]. However, suppliers set minimum order quantities to ensure their own economic efficiency, which lead to the actual demand of SMEs (Small and Medium Enterprises) not meeting the minimum order quantities of suppliers. In order to ensure their own interests, when suppliers choose purchase orders, they often choose to establish cooperative relationships with companies with larger orders. Enterprises with small and unstable purchasing sizes are not the best choice for suppliers. In order to solve this realistic problem, SASAC (State-owned Assets Supervision and Administration Commission of the State Council) has proposed to require central enterprises to integrate the needs of the whole group, to form a synergy through centralized procurement. Then, through centralized and unified negotiation, subcontracting and other flexible procurement methods, the procurement efficiency can be improved and business operation costs can be saved. In addition, the development of e-commerce, the widespread use of intelligent mobile terminals and the continuous improvement of the third-party logistics industry have contributed to the fact that the technology and logistics of joint procurement can meet the requirements of centralized procurement operations [16].

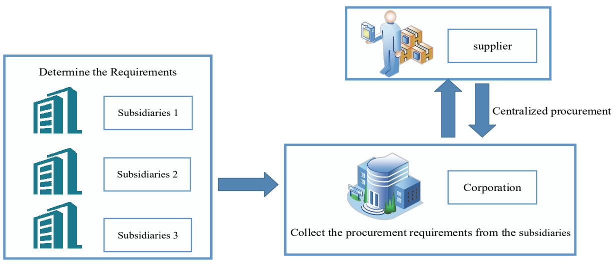

Figure 1 The structure of centralized procurement

Therefore, it is an inevitable trend in the current economic environment for large group enterprises to carry out centralized procurement jointly with their subordinate units. The structure of centralized procurement is as follows in Fig. 1.

Then, we introduce a multi-objective optimization model for centralized procurement and propose a novel method to solve the proposed model. In section 2, we conduct a literature review of the centralized procurement model and the multi-objective optimization problems. In section 3, we introduce the Pareto-optimal model for the centralized procurement which includes the proposed framework of the centralized procurement model, the establishment of a multi-objective optimization model and the use of a NSGA-II to solve the model in order to obtain the results between each purchaser and supplier by finding the Pareto-optimal boundary time. Section 4 verifies the reliability of the model using a case study of procurement by the China Energy Investment Corporation. The main contributions of this study are summarized in the section 5.

2 LITERATURE REVIEW

2.1 The Centralized Procurement Model

Centralized procurement strategy is a horizontal cooperation between different units within a large group of companies with common procurement needs, coordinated by a centralized procurement management body at group level, and carried out by a unified centralized procurement execution agent. The centralized procurement strategy reduces procurement costs and improves economic efficiency by integrating the procurement needs of each unit. Then a suitable and applicable procurement method must be found to determine the total volume of purchases and the distribution of orders between units. The key issue in the centralized procurement is to weigh up the interests of each purchaser and supplier, so as to achieving Pareto optimality [17, 18].

Purchasing quantities, purchasing costs are the important part of the centralized procurement. For companies, limiting storage capacity is the most effective way to reduce the operating costs of purchasing units [19]. In addition, quantity discounts is a classic part of the actual purchasing problem [20], so centralized procurement models need to consider both quantitative and qualitative criteria in the discount constraint. In addition, transportation distances are also a real-world factor in the procurement problem. Based on this analysis, we consider multiple realistic factors such as minimum order quantity, inventory constraints, quantity discounts, and transportation distances to construct a practical multi-objective optimization model for procurement in the centralized procurement process.

2.2 Multi-Objective Optimization Problems

Multi-objective optimization problems have their complexity in solving, so many studies have transformed them into a single-objective optimization problem. Jiang et al. transformed the simple summation of the buyer and seller utility functions into a single-objective problem and adopted an artificial immunity algorithm to solve the optimal solution [21]. In contrast to the simple summation of objective functions, Gao et al. added weight coefficients to each objective function and then used an artificial bee colony algorithm to solve the multi-objective optimization problem [22].

However, there are several drawbacks in converting a multi-objective problem into a single-objective problem: (1) the sub objective functions are simply summed or produced to obtain a single-objective optimization function, which does not take each sub objective into account in the final solution process; (2) the optimal result of single-objective optimization does not guarantee a win-win situation because it is a zero-sum game for each sub-objective; (3) the result obtained by single-objective optimization can only guarantee that a single objective function is optimal, not necessarily Pareto optimal. In summary, converting a multi-objective problem into a single-objective problem will lose the significance of the multi-objective problem.

Therefore, the best way to solve the multi-objective optimization problem is to retain its essence as a multi-objective optimization model. There are two current methods for solving Pareto bounds: the exhaustive method and the algorithmic solution. The exhaustive method refers to listing all possible negotiation solutions to determine the Pareto optimal solution and its Pareto boundary, but this method is theoretically feasible but difficult to implement in the actual solution process. Algorithmic solution refers to solving the Pareto bound of a multi-objective optimization model using a number of algorithms, such as vector evaluation genetic algorithm [23] (VEGA), multi-objective genetic algorithm [24] (NPGA), non-dominated ranking genetic algorithm [25] (NSGA), etc.

Erickson et al. applied the NPGA algorithm to solve the groundwater quality management problem of pump-and-treat remediation to achieve minimizing remediation design costs and maximizing the quality of contaminants remaining at the end of the remediation period [25]. Based on NSGA, an improved non-dominated ranking genetic algorithm with elite strategy (NSGA-II) was also proposed [26]. Song et al [27] used the NSGA-II algorithm to solve multi-objective land allocation problem. Compared with NSGA, NSGA-II is widely used by scholars to solve multi-objective optimization problems due to its faster computing speed and better robustness [28-30]. Zhang et al. applied NSGA-II to obtain Pareto-optimal solution of the multi-objective optimization technique for the bistable laminates and the presentation of a trade-off relation between the mechanical performances and configurations of bistable laminates has been established [31]. In order to solve the problem of SO_2 and NO_X standardized discharge, NSGA-II was applied to obtain the Pareto optimization curve to explore the trade-offs between economic and environmental goals [32].

3 PARETO OPTIMAL MODEL FOR CENTRALIZED PROCUREMENT

This section introduces the main framework of the centralized procurement model. Then, we focus on the main part of the model construction process, the establishment of the multi-objective optimization model and the solution of the algorithm.

3.1 The Framework of Centralized Procurement Model

In this part, we propose a framework of centralized procurement model to aggregate the requirements of units within a group into a larger purchase order. Then, it can obtain the volume discounts from suppliers and reduce the total procurement cost of the entire group. The framework of centralized procurement model is constructed as shown in Fig. 2. First, aggregate the dispersed order requirements of each unit to obtain the overall purchasing quantities. Second, the objectives in the model then include three components of purchasing cost, material quality and delivery delays, which are used in a comprehensive assessment of centralized purchasing activities. At the same time, strong suppliers often set minimum order quantities in order to ensure profitability. However, based on competitive market pressures, units tend to reduce their operating costs. One of the most common ways of doing this is to reduce storage capacity. Therefore, this paper considers three constraints in the model, including the supplier's minimum order quantity setting, inventory constraints and purchasing demand constraints [33]. Finally, an improved genetic algorithm is proposed to find the optimal purchasing volume and allocation scheme.

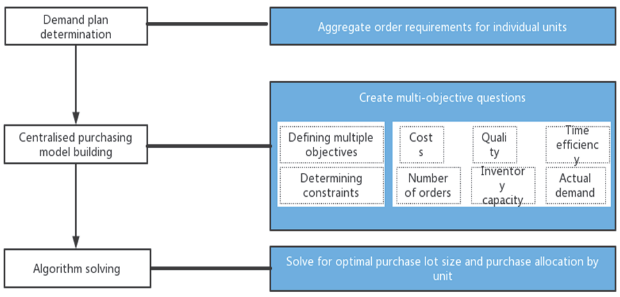

Figure 2 Centralized procurement batch model framework

3.2 The Model Design of Multi-Objective Optimization

In this subsection, we construct the multi-objective procurement optimization model of centralized procurement that breaks the limitations of single-objective models: (1) In the constructed multi-objective model for centralized procurement, cost, quality and logistics are used as sub-objectives to achieve a combination of three dimensions of objectives and sub-objectives: lower procurement cost, higher material quality and less delivery delay. (2) This model covers multiple objective constraints provided by suppliers and purchasing units, such as minimum order quantities, inventory capacity and discount levels. By constructing this model to better ensure the 5R (Right quality, Right time, Right cost, Right quantity and Right place), objectives of centralized procurement are used to minimize procurement costs while ensuring high quality supply.

The model constructed is based on the following assumptions: (1) Assume that each unit has conducted a comprehensive analysis of its centralized procurement material requirements and centralized its procurement plans; (2) Assume that suppliers are able to meet all the key materials required for centralized procurement and that there are no supply shortages in their production chains; (3) Assume that the actual order quantities for group procurement are usually minimum lot multiples. In the process of constructing the model, in addition to the integrated procurement cost target, this paper retains the material quality target and the delivery target by calculating the non-conformance rate and the number of delivery delays respectively. The specific construction process is as follows, and the meaning represented by each variable is detailed in Tab. 1.

Table 1 The description of the variable in the target function

Symbols	Description
i	The set of materials, $i = \{1, 2, ..., I\}$.
n	The set of units, $n = \{1, 2, ..., N\}$.
l	Range of quantity discounts, $l = \{1, 2, ..., L\}$.
Q_{in}	Quantity of material I purchased by the nth unit.
q_{in}	Actual demand for material i *in the* nth unit.
p_i	Price of material i.
x_l	1 if the subordinate unit receives a quantity discount, 0 otherwise.
y_l	Quantity Discount Level.
g_n	Transport distances between suppliers and material requirement units.
h	Unit transport costs.
H_{in}	nth unit to material i inventory cost.
F_{in}	Maximum inventory capacity of the nth unit for material i.
m_i	Defect rate of material i.
t_i	Delays in material delivery.
G	Minimum order quantity set by the supplier.

First, the overall objective function of the pooled procurement model is determined and expressed as follows:

$$\begin{aligned}&\mathrm{Min}Z=\sum_{i=1}^{I}\sum_{n=1}^{N}\left(Q_{in}\,p_i-x_l y_l Q_{in}\,p_i\right)+\sum_{i=1}^{I}\sum_{n=1}^{N}Q_{in}g_n h+\\&+\sum_{i=1}^{I}\sum_{n=1}^{N}\left(Q_{in}-q_{in}\right)H_{in}+\sum_{i=1}^{I}\sum_{n=1}^{N}Q_{in}m_i+\sum_{i=1}^{I}\sum_{n=1}^{N}Q_{in}t_i\end{aligned}\tag{1}$$

Secondly, the cost objective is to present an empirical and technical framework for purchasing decisions, including material purchase costs, transportation costs and inventory costs. Next, the procurement cost objective function of the pooled purchasing model is determined, consisting mainly of material purchase costs, transportation costs and inventory costs, which can be described as:

$$\begin{aligned}&\mathrm{Min}Z_1=\sum_{i=1}^{I}\sum_{n=1}^{N}\left(Q_{in}\,p_i-x_l y_l\,Q_{in}p_i\right)+\\&++\sum_{i=1}^{I}\sum_{n=1}^{N}Q_{in}g_n h+\sum_{i=1}^{I}\sum_{n=1}^{N}\left(Q_{in}-q_{in}\right)H_{in}\end{aligned}\tag{2}$$

Subsequently, the quality of purchased materials is of paramount importance to the production process, as substandard materials not only affect productivity but can also lead to safety incidents. Then, the quality objectives of purchased materials should be considered as important objectives to be achieved in procurement activities. Instead, it is expressed in terms of purchased materials. Therefore this model takes into account the quality objectives of the purchased goods and selects the substandard rate of the purchased materials to represent its quality objectives, and its specific objective function is set as:

$$\mathrm{Min}Z_2 = \sum_{i=1}^{I}\sum_{n=1}^{N} Q_{in} m_i \tag{3}$$

In addition, the on-time delivery of materials has a significant impact on business operations and generation, meaning that throughout the supply chain, in order to produce and deliver the final product on time, purchased materials also need to be delivered to the production site on time. Therefore, the model takes into account the delivery targets in the procurement process and uses the late delivery rate of materials to represent:

$$\mathrm{Min}Z_3 = \sum_{i=1}^{I}\sum_{n=1}^{N} Q_{in} t_i \tag{4}$$

This model takes into account the minimum order quantity constraint, the inventory capacity constraint and the purchasing demand constraint, as companies have limited purchasing size and inventory capacity. For suppliers, they will specify a minimum order quantity to ensure their own profitability, so the total number of purchases from each unit should make up a centralized purchasing lot larger than the minimum order quantity. For companies, inventory capacity is often limited due to cost and profitability considerations, so the quantity of material purchased is subject to inventory capacity constraints and is below the maximum inventory capacity. At the same time, in order to ensure the normal production operation of the enterprise, the quantity of materials purchased should be greater than the actual demand. The specific constraints for each are as follows.

Minimum order quantity constraint:

$$\sum_{i=1}^{I}\sum_{n=1}^{N} Q_{in} > G \tag{5}$$

Stock capacity constraints:

$$Q_{in} < F_{in},\ \forall i \in \{1, 2, ..., I\},\ \forall n \in \{1, 2, ..., N\} \tag{6}$$

Demand constraints:

$$Q_{in} > q_{in},\ \forall i \in \{1, 2, ..., I\},\ \forall n \in \{1, 2, ..., N\} \tag{7}$$

In summary, the multi-objective optimization model of centralized procurement is summarized as follows:

$$\mathrm{Min}Z = \sum_{i=1}^{I}\sum_{n=1}^{N}\left(Q_{in}\ p_i - x_l y_l\ Q_{in} p_i\right) + \sum_{i=1}^{I}\sum_{n=1}^{N} Q_{in} g_n h + \\ +\sum_{i=1}^{I}\sum_{n=1}^{N}\left(Q_{in} - q_{in}\right) H_{in} + \sum_{i=1}^{I}\sum_{n=1}^{N} Q_{in} m_i + \sum_{i=1}^{I}\sum_{n=1}^{N} Q_{in} t_i$$

$$\mathrm{Min}Z_1 = \sum_{i=1}^{I}\sum_{n=1}^{N}\left(Q_{in}\ p_i - x_l y_l Q_{in}\ p_i\right) + \sum_{i=1}^{I}\sum_{n=1}^{N} Q_{in} g_n h + \\ +\sum_{i=1}^{I}\sum_{n=1}^{N}\left(Q_{in} - q_{in}\right) H_{in}$$

$$\mathrm{Min}Z_2 = \sum_{i=1}^{I}\sum_{n=1}^{N} Q_{in} m_i$$

$$\mathrm{Min}Z_3 = \sum_{i=1}^{I}\sum_{n=1}^{N} Q_{in} t_i$$

$$\text{s.}t.\ \begin{cases} \sum_{i=1}^{I}\sum_{n=1}^{N} Q_{in} > G \\ Q_{in} > q_{in},\ \forall i \in \{1, 2, ..., I\},\ \forall n \in \{1, 2, ..., N\} \\ Q_{in} < F_{in},\ \forall i \in \{1, 2, ..., I\},\ \forall n \in \{1, 2, ..., N\} \\ 0 \le i \le I \\ 0 \le n \le N \\ 0 \le l \le L \\ x_i = \begin{cases} 1, \text{ satifsy discount} \\ 0, \text{ no discount} \end{cases} \end{cases}$$

3.3 Solving Pareto Optimal Bounds Based On Genetic Algorithm

Numerous scholars have often chosen to design procurement models for multi-objective problems in the form of penalty cost parameters to reflect the quality and delivery time of key materials, which in turn can transform the multi-objective model into a single-objective problem. As artificially set parameters are subject to greater subjective evaluation, the accuracy of the calculation results cannot be guaranteed in the process of weighting. Therefore, this paper chooses to retain the nature of the procurement model when solving its multi-objective problem. If the multi-objective function is to be optimal at the same time, a Pareto optimal set needs to be found. The Pareto optimal set can be reached at the Pareto boundary by plotting it in the solution space. At present, the mainstream solution algorithm is genetic algorithm, of which NSGA-II is the most representative. NSGA-II algorithm is proposed by Deb et al. on the basis of NSGA [26], which is more superior to NSGA algorithm. Compared with the NSGA algorithm, the NSGA-II algorithm uses a fast non-dominated sorting algorithm and introduces an elite strategy, which makes its computational complexity greatly reduced while improving the speed and robustness. Therefore, the NSGA-II algorithm [34] will be used to solve the multi-objective optimization model of the collection lot constructed in this paper and to find the Pareto optimum of the centralized procurement.

Following the previous definition of variables, the next section describes how to solve the constructed multi-objective model using the NSGA-II algorithm and obtain the Pareto optimum.

3.3.1 Chromosome Coding

Chromosome coding is an important component of genetic algorithms. Considering the characteristics of the set-pick batch model, the chromosome coding is decimal coding. The one-dimensional vector consists of two main parts: the decision area and the target area. The decision region represents the value of the decision variable, i.e. the quantity of a material purchased by each unit, represented by gene Q_{in}, which represents the quantity of material i purchased by enterprise n. The genes in the target region are represented by the genes Z_1, Z_2 and Z_3, which represent the three-dimensional values of the objective function, i.e. procurement cost, material quality and procurement timeliness. Thus, the chromosomes are coded as.

$$\begin{aligned}\beta_1 = [&Q_{11}, Q_{12}, ..., Q_{1n}, Q_{21}, Q_{22}, ..., Q_{2n}, \\ &, ..., Q_{i1}, Q_{i2}, ..., Q_{in}, Z_1, Z_2, Z_3]\end{aligned} \tag{8}$$

3.3.2 Crossover Operation

A uniform crossover operator is introduced during the crossover operation, with the same crossover frequency between crossover points, to ensure the stability and diversity of individuals, as follows.

Step 1.Random selection of any individual P_c and in the breeding population with crossover probability β_1 and β_2.

Step 2. Choose m intersection points $\delta_m \left(1 \le m \le i \times n - 1\right)$ at random among individuals β_1 and β_2; then, the individuals are divided into $m + 1$ parts in the interval $(0, m)$ denoted by F; the starting point is set to δ_0.

Step 3. Swap the genes of individuals (δ_{F}, $\delta_{\mathrm{F+1}}$) and in the individual β_1 and β_2 to obtain a new individual ψ_1 and ψ_2. The crossover operation is complete.

3.3.3 Variation Operations

During the mutation operation, the adaptive mutation operator is defined as:

$$P_m = P_0 \times \left(1 - t/G_{\max}\right) \tag{9}$$

where is P_m the probability of adaptive mutation, P_0 is the pre-set value of mutation probability, t is the current evolutionary generation and $G_{\max}$ is the maximum number of iterations.

From Eq. (9), it is revealed that when evolution starts with a small value of t, the mutation probability of an individual is relatively large, which helps the algorithm to perform a better global search. As the number of iterations t increases, the probability of variation for each individual decreases, meaning that the target satisfaction for each individual is essentially the same in general. Therefore, as the probability of variation is gradually adjusted to smaller values, the algorithm is able to discover and find better individuals through better global search capabilities.

3.3.4 Selection Operation

In order to ensure the diversity of the population and to prevent the generation of locally optimal solutions, the algorithm introduces a congestion comparison operator and an elite strategy for the selection operation, which are described as follows.

(1) Crowding distance as well as the crowding comparison operator. The crowding distance i_d is calculated by the crowding comparison operator, which indicates the distance between an individual and other individuals in the same population; the longer the crowding distance, the better the population diversity. After calculating the non-dominance ranking and the crowding distance, the individuals of the population all acquire two attributes, non-dominance ranking i_{rank} and crowding distance i_d, two attributes that distinguish between dominance and non-dominance of any two individuals in the population. Therefore, define the congestion comparison operators i_d and j_d, when individual i is better than individual j denoted as $i > j$, satisfying when and only when $i_{rank} < j_{rank}$ or $i_{rank} = j_{rank}$, $i_d > j_d$.

(2) Elite strategy. The elite strategy refers to the process of combining the best individuals from the parent population with the new generation of individuals produced by genetic manipulation, which in turn produces the next generation of the population. This helps to maintain the best individuals from the parent generation into the next generation and allows the best individuals to be retained by stratifying the individuals in the population, thereby improving the population.

3.3.5 Implementation of the Genetic Algorithm

First, a random parent population (chromosome population) $\beta = \{\beta_1, \beta_2, ..., \beta_N\}$ is systematically created and subjected to non-dominated sorting. Then after recombination and crossover operations, a child population of size N is created β_1. Next, the parent population is merged with the offspring population and a fast non-dominance sort is performed, while the crowding degree of each individual is calculated, and then the appropriate individuals are selected to form a new parent population β_{t+1} based on the non-dominance relationship and individual crowding degree. Finally, a new offspring population C_{t+1} is generated through genetic operations such as selection, crossover and mutation. The cycle continues in turn until the maximum number of evolutionary iterations is reached.

4 INSTANCE VERIFICATION

China Energy Investment Corporation is a central backbone energy enterprise with a full industrial chain of coal, power, transportation and chemical businesses. Now its branches need to centralize the procurement of a new batch of key components and materials W for the railway transportation process. Due to the national policy each branch chooses to aggregate the procurement requirements to China Energy Investment Corporation for unified manner. As the China Energy Investment Corporation has a fixed supplier of components, there is no need to select a supplier. The data related to the procurement process of each branch was investigated, such as the quantity, transport distance, transport cost, inventory cost and other basic parameters purchased by each branch, and the details are summarized and presented in Tab. 2.

Table 2 Basic parameters of sub-company

Production materials D_1					
	Subsidiaries M_1	Subsidiaries M_2	Subsidiaries M_3	Subsidiaries M_4	Subsidiaries M_5
q（Actual demand/10000 units）	12	9	15	21	13
g（Transport distance/kilometer）	6	4	12	9	11
h（Unit transport cost/thousand dollars per kilometer）	0.3	0.3	0.3	0.3	0.3
H（Inventory cost/thousand dollars）	2	3	3	2	3
F（Maximum stock capacity/million units）	15	10	20	25	15
Production materials D_2					
	Subsidiaries M_1	Subsidiaries M_2	Subsidiaries M_3	Subsidiaries M_4	Subsidiaries M_5
q（Actual demand/10000 units）	8	10	17	13	14
g（Transport distance/kilometre）	6	4	12	9	11
h（Unit transport cost/thousand dollars per kilometre）	0.3	0.3	0.3	0.3	0.3
H（Inventory cost/thousand dollars）	2	4	4	3	3
F（Maximum stock capacity/million units）	15	10	20	25	15
Production materials D_3					
	Subsidiaries M_1	Subsidiaries M_2	Subsidiaries M_3	Subsidiaries M_4	Subsidiaries M_5
q（Actual demand/10000 units）	10	11	14	17	16
g（Transport distance/kilometre）	6	4	12	9	11
h（Unit transport cost/thousand dollars per kilometre）	0.3	0.3	0.3	0.3	0.3
H（Inventory cost/thousand dollars）	3	4	4	3	4
F（Maximum stock capacity/million units）	15	15	20	20	20

The process of pooling requires the participation of both the purchaser and the supplier, so the relevant parameters for each production material provided by the supplier are also summarized, such as the purchase price set by the supplier and the purchase quantity discount, etc. The specific relevant parameters are summarized in Tab. 3.

Table3 The basic information of materials supported by supplier

	Materials W_1	Materials W_2	Materials W_3
p / Price/yuan	3	6	2
m / Material Defect Rate	0.10	0.15	0.10
t / Material Delivery Delay	0.05	0.10	0.05

In the process of purchasing, the supplier will provide different price concessions according to different purchase quantities in order to promote cooperation with the purchaser. The supplier provides a detailed price concession for the China Energy Investment Corporation, denoted by y, and its specific expression of the concession is shown in Eq. (9). Secondly, the transportation cost between the purchaser and the supplier is a constant, which is set to 0.5 thousand dollars/kilometer in this paper and expressed as $h = 0.5$; the minimum order quantity provided by the purchaser is also a constant, which is set to 2.1 million units in this paper and expressed as $G = 210$.

$$y = \begin{cases} 0, \textit{purchase quantitie} \le 50000 \\ 0.2, \ 50000 < \textit{purchase quantities} \le 100000 \\ 0.3, \textit{purchase quantities} > 100000 \end{cases}$$

4.1 Model Initialization

According to the basic parameters in Tab. 1 and Tab. 2, a specific multi-objective optimization model can be obtained, and the final multi-objective optimization model has been omitted to save space. The NSGA-II algorithm is used to solve the multi-objective optimization model, setting the population size to 150 and the maximum number of evolutionary generations to 100. The Pareto set with the values of the sub-objective functions is shown in Fig. 3.

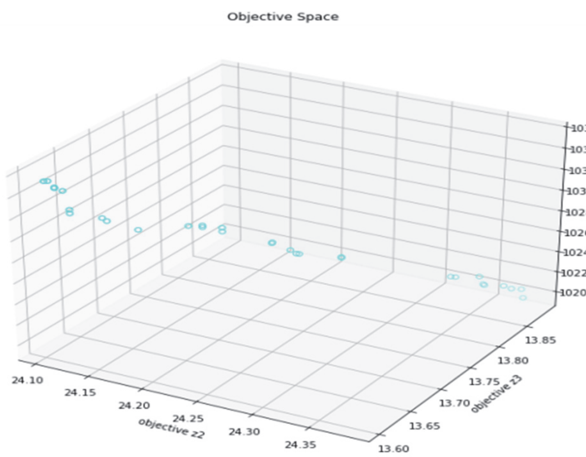

Figure 3 The objective values of the Pareto set

4.2 Model Optimization

Fig. 2 shows that the upper and lower limits of the targets z_1, z_2 and z_3 are very different. In the process of solving the model, there will be errors in the subsequent calculations due to the large gap between the upper and lower bounds of the different target values. If a certain objective value is large, it will dominate the subsequent congestion distance calculation process. In this paper a large objective value of z_1 will have a negative impact on the subsequent distance calculation in the target space, therefore, the objectives at different scales are treated in this paper. By looking at the upper and lower limit values of each objective function, the specific output is shown in Tab. 4. Next, normalise them using the so-called ideal and minimum points.

Table 4 The lower and upper bounds of the objectives

	Upper limit value	Lower limit value
Target function Z	10235.420	10390.760
Target function z_1	10197.156	10353.051
Target function z_2	24.104	24.383
Target function z_3	13.604	13.882

Furthermore, in the context of multi-objective optimization, a simple method for selecting a solution from a solution set is the pseudo-weight vector approach proposed by Deb [35]. Separately, the pseudo-weight w_i of the ith objective function can be calculated by the following equation.

$$w_i = \frac{\left(f_i^{\max} - f_i(x)\right) / \left(f_i^{\max} - f_i^{\min}\right)}{\sum_{k=1}^{K} \left(f_k^{\max} - f_k(x)\right) / \left(f_k^{\max} - f_k^{\min}\right)} \tag{10}$$

Eq. (10) calculates the normalized distance of the worst-case solution with respect to each objective i. It is worth noting that for non-convex Pareto fronts, the pseudo-weights do not correspond to the results of optimization using weighted sums. However, for convex Pareto fronts, the pseudo-weights represent positions in the target space.

After 13 iterations through the optimized model, the Pareto optimal set is obtained, which indicates that each purchaser and supplier reaches a purchasing agreement at this point. It is worth noting that the Pareto-based multi-objective problem generates a Pareto set that includes non-dominated solutions that do not improve one objective without degrading the others, and the specific quantities purchased by each purchaser for each material are presented in Tab. 5. Under this procurement solution, the total objective for this pooling process is 10263.94, the procurement cost is $10225.77 thousand, the quality of the material is 24.34 and the material delivered on time is 13.84.

Table 5 The solved Pareto Optimal Solution

	Subsidiaries M_1	Subsidiaries M_2	Subsidiaries M_3	Subsidiaries M_4	Subsidiaries M_5
Materials W_1	14.74	9.29	15.40	21.10	13.76
Materials W_2	12.62	10.00	17.07	13.00	14.05
Materials W_3	10.48	11.22	14.08	17.17	16.00

4.3 Model Analysis

Hypervolume is a well-known performance metric for multi-objective problems. The Hypervolume metric was first proposed by Zitzler et al [36] and represents the volume of the hypercube enclosed by the individuals in the solution set and the reference points in the objective space. As the dimensionality increases, the Hypervolume becomes computationally intensive, Fleischer proposed that the set is Pareto optimal when the Hypervolume metric of the set is maximized [37, 38]. In Fig. 4, it visualizes the Hypervolume calculation of this model in this case, where the Hypervolume values converge over the course of the iterations.

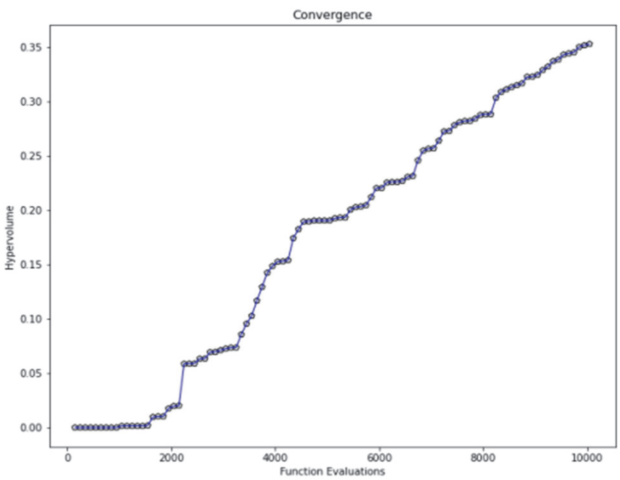

Figure 4 The results of the proposed model under case

Furthermore, when the Pareto solution of a multi-objective optimization model is unknown, the operational metrics of the algorithm become a new method of analysis. The run metric shows the difference in the objective space from one generation to another and uses the survival of the algorithm to visualize improvements. The metric is also used to determine the termination of a multi-objective optimization algorithm if no default termination criterion is defined. For example, Fig. 5 shows a significant improvement of the algorithm from generation 6 to generation 7.

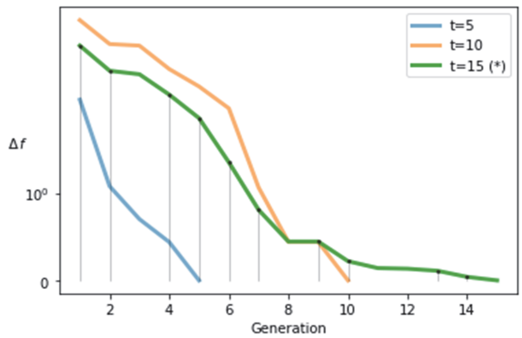

Figure 5 The running metric of the generation

5 CONCLUSION

This paper focus is on the problem of centralized procurement by large enterprises and various small enterprises. The main contributions of this paper are divided into three parts. Firstly, a multi-objective optimization model of centralized procurement is proposed, which contains the procurement cost, procurement quality and procurement logistics efficiency as sub-objectives. In the process of building the multi-objective optimization model, the capacity limits of the stored materials of each purchaser and the purchasing quantity limits of the suppliers are introduced into it. In addition, the quantitative and qualitative criteria of the discount constraints in the procurement process and the minimum order lot size are also taken into account. Secondly, the NSGA-II genetic algorithm is used to solve the problem and obtain the Pareto solution to achieve the optimal procurement solution among the buyers and suppliers. Thirdly, the effectiveness and practicability are illustrated by a numerical example of the China Energy Investment Corporation. From a research point of view, the model proposed in this paper transforms the centralized procurement problem jointly carried out by the group enterprise and its subordinate units into a multi-objective optimization problem. From a practical point of view, the construction of this model helps to provide a decision-making method for enterprises to carry out bulk procurement of continuously consumable materials, reduce transaction costs and maximize procurement efficiency.

Acknowledgements

This study is supported by the Contract for Science and Technology Research and Development Plan of China National Railway Corporation(Grant No:N2021S017). We thank for the supports from all reviewers and editors.

6 REFERENCES

[1] Çebi, F. & Otay, İ. (2016). A two-stage fuzzy approach for supplier evaluation and order allocation problem with quantity discounts and lead time. *Information Sciences*, *339*, 143-157. https://doi.org/10.1016/j.ins.2015.12.032

[2] Lo, H. W., Liou, J. J. H., Wang, H. S., & Tsai, Y. S. (2018). An integrated model for solving problems in green supplier selection and order allocation. *Journal of Cleaner Production*, *190*, 339-352. https://doi.org/10.1016/j.jclepro.2018.04.105

[3] Laosirihongthong, T., Samaranayake, P., & Nagalingam, S. (2019). A holistic approach to supplier evaluation and order allocation towards sustainable procurement. *Benchmarking: An International Journal*, *26*(8), 2543-2573. https://doi.org/10.1108/BIJ-11-2018-0360

[4] Gören, H. G. (2018). A decision framework for sustainable supplier selection and order allocation with lost sales. *Journal of Cleaner Production*, 183, 1156-1169. https://doi.org/10.1016/j.jclepro.2018.02.211

[5] Ghadimi, P., Toosi, F. G., & Heavey, C. (2018). A multi-agent systems approach for sustainable supplier selection and order allocation in a partnership supply chain. *European Journal of Operational Research*, *269*(1), 286-301. https://doi.org/10.1016/j.ejor.2017.07.014

[6] Hosseini, S., Ivanov, D., & Dolgui, A. (2019). Review of quantitative methods for supply chain resilience analysis. *Transportation Research Part E: Logistics and Transportation Review*, *125*, 285-307. https://doi.org/10.1016/j.tre.2019.03.001

[7] Pan, S. Y., Du, M. A., Huang, I. T., Liu, I. H., & Chang, E. E. (2015). Strategies on implementation of waste-to-energy (WTE) supply chain for circular economy system: a review. *Journal of Cleaner Production*, *108*, 409-421. https://doi.org/10.1016/j.jclepro.2015.06.124

[8] Pazhani, S., Ventura, J. A., & Mendoza, A. (2016). A serial inventory system with supplier selection and order quantity allocation considering transportation costs. *Applied Mathematical Modelling*, *40*(1), 612-634. https://doi.org/10.1016/j.apm.2015.06.008

[9] Thomas, V. A. & Mahanty, B. (2020). Assessment of emergency sourcing strategy of a supply chain through dynamic simulation approach. *Journal of Industrial and Production Engineering*, *37*(1), 56-69. https://doi.org/10.1080/21681015.2020.1729877

[10] Zhang, L., Yan, Y., Xu, W., Sun, J., & Zhang, Y. (2022). Carbon emission calculation and influencing factor Analysis based on industrial big data in the "double carbon" era. *Computational Intelligence and Neuroscience*, *2022*. https://doi.org/10.1155/2022/2815940

[11] Hu, X., Wang, G., Li, X., Zhang, Y., Feng, S., & Yang, A. (2018). Joint decision model of supplier selection and order allocation for the mass customization of logistics services. *Transportation Research Part E: Logistics and Transportation Review*, *120*, 76-95. https://doi.org/10.1016/j.tre.2018.10.011

[12] Gao, X., Chen, S., Tang, H., & Zhang, H. (2020). Study of optimal order policy for a multi-period multi-raw material inventory management problem under carbon emission constraint. *Computers & Industrial Engineering*, *148*, 106693. https://doi.org/10.1016/j.cie.2020.106693

[13] Zheng, Q., Zhou, L., Fan, T., & Ieromonachou, P. (2019). Joint procurement and pricing of fresh produce for multiple retailers with a quantity discount contract. *Transportation Research Part E: Logistics and Transportation Review*, *130*, 16-36. https://doi.org/10.1016/j.tre.2019.08.013

[14] Vigoroso, M. (1998). Buyers pare down supplier rosters. *Purchasing*, *125*(6), 20-21.

[15] Essig, D. A., Alderson, N. L., Ferguson, M. A., Bartoli, W. P., & Durstine, J. L. (2000). Delayed effects of exercise on the plasma leptin concentration. *Metabolism*, *49*(3), 395-399. https://doi.org/10.1016/S0026-0495(00)90396-2

[16] Gunasekaran, A., McGaughey, R. E., Ngai, E. W. T., & Rai, B. K. (2009). E-Procurement adoption in the Southcoast SMEs. *International Journal of Production Economics*, *122*(1), 161-175. https://doi.org/10.1016/j.ijpe.2009.05.013

[17] Faratin, P., Sierra, C., & Jennings, N. R. (2002). Using similarity criteria to make issue trade-offs in automated negotiations. *Artificial Intelligence,142*(2), 205-237. https://doi.org/10.1016/S0004-3702(02)00290-4

[18] Pan, L., Luo, X., Meng, X., Miao, C., He, M., & Guo, X. (2013). A two-stage win-win multi-attribute negotiation model: optimization and then concession. *Computational Intelligence*, *29*(4), 577-626. https://doi.org/10.1111/j.1467-8640.2012.00434.x

[19] Pazhani, S., Ventura, J. A., & Mendoza, A. (2016). A serial inventory system with supplier selection and order quantity allocation considering transportation costs. *Applied Mathematical Modelling*, *40*(1), 612-634. https://doi.org/10.1016/j.apm.2015.06.008

[20] Xia, W. & Wu, Z. (2007). Supplier selection with multiple criteria in volume discount environments. *Omega*, *35*(5), 494-504. https://doi.org/10.1016/j.omega.2005.09.002

[21] Jiang, G. R. & Lv, X. (2012). A multi-attribute negotiation model based on artificial immune algorithm. *Computer Engineering*, *38*(7), 139-144.

[22] Gao, S., Liang, M., & Zhang, H. (2015).Multi-agent automatic negotiation model for e-commerce based on artificial bee colony algorithm. *CAAI Transactions on Intelligent Systems*, *10*(3), 476-481. https://doi.org/10.3969/j.issn.1673-4785.201405023

[23] Ritzel, B. J., Eheart, J. W., & Ranjithan, S. (1994). Using genetic algorithms to solve a multiple objective groundwater pollution containment problem. *Water Resources Research*,

30(5), 1589-1603. https://doi.org/10.1029/93WR03511
[24] Horn, J., Nafpliotis, N., & Goldberg, D. E. (1994). A niched Pareto genetic algorithm for multi-objective optimization. *Proceedings of the First IEEE Conference on Evolutionary Computation (ICEC '94), Piscataway. IEEE Service Center*, *1*, 82-87. https://doi.org/10.1109/ICEC.1994.350037
[25] Erickson, M., Mayer, A., & Horn, J. (2002). Multi-objective optimal design of groundwater remediation systems: application of the niched Pareto genetic algorithm (NPGA). *Advances in Water Resources*, *25*(1), 51-65. https://doi.org/10.1016/S0309-1708(01)00020-3
[26] Deb, K., Agrawal, S., Pratap A, & Meyarivan, T. (2000). A fast elitist non-dominated sorting genetic algorithm for multi-objective optimization: NSGA-II. *International conference on parallel problem solving from nature. Springer, Berlin, Heidelberg*, *1917*, 849-858. https://doi.org/10.1007/3-540-45356-3_83
[27] Song, M. & Chen, D. (2018). An improved knowledge-informed NSGA-II for multi-objective land allocation (MOLA). *Geo-spatial Information Science*, *21*(4), 273-287. https://doi.org/10.1080/10095020.2018.1489576
[28] Meng, J. L. (2021). Demand Prediction and Allocation Optimization of Manufacturing Resources. *Journal of Simulation Modelling*, *20*(4), 790-801. https://doi.org/10.2507/IJSIMM20-4-CO20
[29] Zhou, Y., Cao, S., Kosonen, R., & Hamdy, M. (2020). Multi-objective optimization of an interactive buildings-vehicles energy sharing network with high energy flexibility using the Pareto archive NSGA-II algorithm. *Energy conversion and management*, *218*, 113017. https://doi.org/10.1016/j.enconman.2020.113017
[30] Dong, W., Huang, Y., Lehane, B., & Ma, G. (2022). Multi-objective design optimization for graphite-based nanomaterials reinforced cementitious composites: A data-driven method with machine learning and NSGA-Ⅱ. *Construction and Building Materials*, *331*, 127198. https://doi.org/10.1016/j.conbuildmat.2022.127198
[31] Zhang, Z., Liao, C., Chai, H., Ni, X., Pei, K., Sun, M., Wu, H., & Jiang, S. (2021). Multi-objective optimization of controllable configurations for bistable laminates using NSGA-Ⅱ. *Composite Structures*, *266*, 113764. https://doi.org/10.1016/j.compstruct.2021.113764
[32] Xiao, W., Cheng, A., Li, S., Jiang, X., Ruan, X., & He, G. (2021). A multi-objective optimization strategy of steam power system to achieve standard emission and optimal economic by NSGA-Ⅱ. *Energy*, *232*, 120953. https://doi.org/10.1016/j.energy.2021.120953
[33] Aljinović, A., Bilić, B., Gjeldum, N., & Mladineo, M. (2021). Prediction of Surface Roughness and Power in Turning Process Using Response Surface Method and ANN. *Tehnički vjesnik*, *28*(2), 456-464. https://doi.org/10.17559/TV-20190522104029
[34] Blank, J. & Deb, K. (2020). Pymoo: Multi-objective optimization in python. *IEEE Access*, *8*, 89497-89509. https://doi.org/10.1109/ACCESS.2020.2990567
[35] Hojaeefard, M. H., Hosseini, S. E., & Zare, J. (2019). CFD simulation and Pareto-based multi-objective shape optimization of the centrifugal pump inducer applying GMDH neural network, modified NSGA-II, and TOPSIS. *Structural and Multidisciplinary Optimization*, *60*(4), 1509-1525. https://doi.org/10.1007/s00158-019-02280-0
[36] Zitzler, E. & Thiele, L. (1999). Multi-objective evolutionary algorithms: a comparative case study and the strength Pareto approach. *IEEE transactions on Evolutionary Computation*, *3*(4), 257-271. https://doi.org/10.1109/4235.797969
[37] Deb, K. (2011). Multi-objective optimisation using evolutionary algorithms: an introduction, *Multi-objective evolutionary optimisation for product design and manufacturing. Springer, London*, 3-34. https://doi.org/10.1007/978-0-85729-652-8_1
[38] Trung, D. D. & Thinh, H. X. (2021). A multi-criteria decision-making in turning process using the MAIRCA, EAMR, MARCOS and TOPSIS methods: A comparative study. *Advances in Production Engineering & Management*, *6*(4), 443-456. https://doi.org/10.14743/apem2021.4.412

Contact information:

Fengxia DING
1) School of Economics and Management,
Beijing Jiaotong University,
2) China Energy Investment Corporation Limited,
NO. 3, Shangyuancun, Haidianqu Beijing Jiaotong University,
Beijing 100044, China
E-mail: 14113123@bjtu.edu.cn

Shifeng LIU
(Coresponding author)
School of Economics and Management,
Beijing Jiaotong University,
NO. 3, Shangyuancun, Haidianqu Beijing Jiaotong University,
Beijing 100044, China
E-mail: shfliu@bjtu.edu.cn

Name Xuewei LI
School of Economics and Management,
Beijing Jiaotong University,
NO. 3, Shangyuancun, Haidianqu Beijing Jiaotong University,
Beijing 100044, China
E-mail: xwli@bjtu.edu.cn