On Innovation-Based Triggering for Event-Based Distributed Material Optimization Dispatching Algorithm

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Abstract. This paper investigates the problem of material dispatching for the logistics system. Traditional optimization algorithms are too costly to establish clock synchronization when solving large-scale material dispatching problems. At the same time, small changes in each area can trigger global information interactions, resulting in significant communication costs. For this reason, construct ETAMD (Event-triggered asynchronous material dispatch) distributed optimization algorithm to solve the problem using an asynchronous communication event-triggered model. This algorithm, firstly, eliminates the reliance on clock synchronization. Secondly, reduces meaningless communication between participants and reduces the amount of computation for minimizing the total cost of material dispatching. In the end of the thesis, the effectiveness of the proposed algorithm is verified by simulation results.

Keywords: material dispatching · asynchronous communication · event triggering · distributed optimization · ETAMD algorithm

1 Introduction

Material dispatching existed in the early stage in a market economy with randomness in production and sales, which may easily lead to an imbalance between supply and demand. A centralized and optimal dispatching approach for maintaining a balance between supply and demand has appeared in order to increase the economic efficiency of businesses. Guangzhu Zheng [1] employed a genetic algorithm to calculate the ideal distribution quantity of providers and a dynamic planning method for time sequencing to achieve the optimization target of lowest total supply chain cost. To reduce the scale of material distribution, S. Lee [2] devised a model of material distribution in a real-time setting on the shop floor and separated the workstations into work centers. Xu Zhang [3] considered the degree of demand matching, built an adaptation function to improve the genetic algorithm, and robustly optimized to improve the system's average matching degree. Jinyu Wang [4] improved the genetic algorithm to solve for the optimal material distribution quantity from the supplier's perspective, taking into account the supplier's proportional supply and the time complexity of production. Lin Y [5] proposed an improved particle swarm optimization algorithm embedded in a deconstruction

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algorithm from the demand point of view, taking into account the urgency of demand for various emergency supplies. Ke Xu [6] considers a single material supply constraint and a transshipment balance constraint, and solves the problem with a discrete particle swarm algorithm with inertia weights. Guofu Zhang [7] created a hybrid optimization algorithm based on two-dimensional NSGA-II and ant colony optimization, which can improve the algorithm's search capability and solve the material multi-objective allocation and dispatching integration optimization problem. In comparison to the traditional market economy dispatching mode, the centralized dispatching method transforms manual dispatching into information processing, transmits information such as production capacity and distribution capability of each participant to the central node for decision making, and adjusts the material volume distribution scheme, which not only solves the problem of supply and demand imbalance, but also improves the efficiency of material transportation.

The centralized approach requires all information to be concentrated at a single point, which is too stressful for the control center's communication computation. In order to deal with large amounts of data and changing demands, most researchers employ evolutionary class algorithms, which makes it difficult to find the best solution. To avoid falling into local optimality and relieve communication pressure at the central point, research on distributed optimization methods has emerged. Davidsson [8] concluded that the application of intelligent body technology to many logistics problems is closely related. Pei Xie [9] listed several distributed convex optimization algorithms and stated that this class of algorithms is suitable for model predictive control and large-scale dispatching problems. Chun Jin [10] combined ant colony algorithms with distributed algorithms to solve vehicle path problems with time windows, overcoming the traditional centralized methods' trade-off between algorithmic accuracy and speed. Firdausiyah [11] proposed adaptive dynamic planning based on reinforcement learning for multi-intelligent body simulation to replicate potential behaviors in uncertain environments and improve the accuracy of intelligent body decisions. Malus [12] implemented real-time order dispatching of autonomous mobile robots using a multi-intelligent body reinforcement learning approach. To avoid becoming trapped in local optima, Mei-Feng Shi [13] created adaptive balancing factors to solve distributed constrained optimization problems using parallel search algorithms. Binetti et al. [14] proposed distributed economic dispatching algorithms with losses that can handle different network sizes and calculate the number of nodes in a distributed approach. Distributed methods, as opposed to centralized methods, can find the global optimal solution through local optimization and collaboration among nodes without sending all data to the central node, which is more economical in terms of communication costs [15].

Although the distributed methods used in the preceding studies can avoid centralized data processing in large systems in order to solve the material dispatching problem, they all use synchronous communication mode. Synchronous communication necessitates the establishment of synchronous clocks, and all nodes must communicate and interact simultaneously. For logistics systems, node decentralization is strong, synchronous communication implementation is difficult, and there is a lot of unnecessary communication due to redundant information. Asynchronous communication is accomplished by creating event triggers and only interacting with messages when the trigger conditions are met. The asynchronous communication mode has a filtering function for massive communication, which prevents meaningless communication. The triggering between nodes becomes less and less with the local convergence of results until the global convergence, at which point the triggering ceases, further reducing computation and avoiding reliance on synchronous clocks. This paper proposes an event-triggered distributed material optimization dispatching algorithm based on the inspiration mentioned above. The following are the study's main contributions:

1) By using event-triggered asynchronous communication to reduce communication pressure and cost, the event-triggered conditions are introduced using the distributed method to calculate the optimal material price and the best material distribution plan.
2) The risk management in the supplier distribution process is considered. Since the amount of the overdraft and loss is uncertain, to avoid the error between the actual transportation amount and the demand amount, adding overdraft and loss costs to the supplier cost function can improve overall risk resistance.
3) The optimality of demand-side storage costs is considered. It is found that the existence of an optimal storage volume within the storage range in this paper, which minimizes the storage cost when the optimal storage volume is reached.

2 Problem Description and Modeling

2.1 Problem Description

The material dispatching problem investigated in this paper is formulated as multiple suppliers supplying multiple materials to one demand side, with the suppliers obtaining timely information on the demand side's requirements for multiple materials. To ensure adequate material distribution, we develop a material dispatching and optimal price adjustment plan, allocate a certain proportion of total demand to each supplier, and the same material can also be distributed through multiple suppliers. When production capacity falls short of the actual allocated transportation volume, suppliers face overdraft and distribution costs. Furthermore, because vehicles loss during transportation, demand may not be met in accordance with the original distribution plan, and loss can result in additional transportation costs as well as decreased customer satisfaction.

This paper proposes a price-oriented material optimization dispatching method to address the aforementioned issues. The method is to determine the optimal distribution quantity of each supplier based on the prices of multiple materials that must be distributed and the suppliers' production capacity, as well as to consider the existence of substitution relationships between different materials, so that even in the event of an unexpected situation, the materials can be replenished and distributed in accordance with the planned demand to ensure a balance between supply and demand.

2.2 Modeling

The actual transportation volume of each supplier is determined and the price of materials is derived based on the demand for multiple materials on the demand side. We develop a mathematical model with the overall goal of minimizing the total cost of material distribution, taking into account supplier transportation costs, overdraft costs, and loss costs, as well as demand side storage costs.

Parameter description:

i indicates the material number, $i = 1, 2, \cdots n$;
j indicates the participant number,$j = 1, 2, \cdots m$;
T indicates dispatche cycle;
In which min, max indicates lower bound and upper bound;
x indicates the amount of material transportation;
q indicates the amount of material production;
y indicates the amount of material depletion;
l indicates the amount of material taken out and put in;
w indicates the amount of material stocks at the previous moment;
Q indicates transportation costs;
U indicates overdraft costs;
G indicates loss costs;
O indicates storage costs;
Z indicates total costs;
K indicates total quantity demanded;
k indicates quantity of material distribution;
R indicates[0,1]trust matrix;
pr indicates unit price of materials;
λ indicates trigger factor.

Objective functions.

The supplier and demand-side cost functions are as follows:

1) Transportation cost function

The transportation cost incurred in the process of transporting materials is determined by the transportation volume, which primarily includes distribution vehicle energy costs and labor costs, among other things. The formula for calculation is:

$$Q(x_{ij,T}) = a_{ij} \times (x_{ij,T})^2 + b_{ij} \times (x_{ij,T}) + c_{ij} \tag{1}$$

a_{ij}, b_{ij} and c_{ij} indicate unit cost coefficients, all of them are positive constants, and transportation costs are shown as a convex function. The constraint on the transport volume is $x_{ij,T}^{\min} \le x_{ij,T} \le x_{ij,T}^{\max}$. The amount of material transported cannot exceed the supplier's maximum overdraft, taking into account its own limited production capacity and the existence of competition among multiple suppliers, as well as meeting the minimum amount of transport in the case of demand-side distribution.

2) Overtraft cost function

The supplier takes out a certain amount of materials to provide to the demand side, and the transportation volume taken away is also expressed as the supplier's own overdraft volume, which brings risk to the supplier, and the higher the overdraft risk cost, the more overdraft volume taken out. This part of the cost calculation formula is:

$$U(x_{ij,T}) = d_{ij} \times x_{ij,T} + p_{ij} \times e^{f_{ij} \times x_{ij,T}} \tag{2}$$

d_{ij} and p_{ij} indicate cost coefficient, f_{ij} indicates risk factor. The initial overdraft at the first moment is the transport volume $x_{ij,T}$. The amount of production per unit of time is fixed and expressed as $q_{ij,T}$. The overdraft at the next moment is $(x_{ij,T} - q_{ij,T})$, this value is also used as the initial transport volume for the next moment.

3) Loss cost function

The process of vehicle transportation and loading and unloading, which is influenced by the material's properties as well as encountering unexpected situations, may result in unavoidable material loss. The amount of loss is forecasted to compensate for this amount of material. The excess quantity is transported to the demand side within a certain range to ensure that the demand is met to the greatest extent possible. The following is the attrition cost function:

$$G(y_{ij,T}) = \alpha_{ij} \times y_{ij,T} + \beta_{ij} \times e^{\mu_{ij} \frac{y_{ij,T}^{\max} - y_{ij,T}}{y_{ij,T}^{\max} - y_{ij,T}^{\min}}} \tag{3}$$

$\alpha_{ij} > 0$ and $\beta_{ij} > 0$ indicate loss coefficient, $\mu_{ij} < 0$ indicates risk factor. Loss costs and overdraft costs are both risk costs that are used for risk management during transportation in an uncertain environment. The less loss and overdraft it has, the more economical it is. The constraint on the amount of loss is $y_{ij,T}^{\min} \le y_{ij,T} \le y_{ij,T}^{\max}$. To develop a suitable range of values, consider the past transportation loss situation; if the forecast loss is too low, it will not play a role in risk reduction; if the forecast loss is too high, it will not improve economic efficiency.

4) Storage cost function

Given the presence of both take and put of materials in warehousing, a distinction is made using plus and minus signs for the demand-side warehousing cost problem. The cost of warehousing varies with the amount of warehouse storage available, and there is an optimal point in the confidence interval where the cost per unit of inventory is minimized. The formula for calculating storage costs is:

$$\begin{aligned} O(l_{ij,T}) = {} & \varepsilon_{ij} \times w_{ij,T-1}^2 + v_{ij} \times w_{ij,T-1} + \theta_{ij} \\ & - [\varepsilon_{ij} \times (w_{ij,T-1} - l_{ij,T})^2 + v_{ij} \times (w_{ij,T-1} - l_{ij,T}) + \theta_{ij}] \end{aligned} \tag{4}$$

ε_{ij}, v_{ij} and θ_{ij} indicate nonnegative cost coefficient, $w_{ij,T-1}$ indicates optimal storage volume at the previous moment, $(w_{ij,T-1} - l_{ij,T})$ indicates the optimal storage volume at this moment, the difference of the function is the cost of storage at this moment. The constraint on the amount of taken out and put in is $l_{ij,T}^{\min} \le l_{ij,T} \le l_{ij,T}^{\max}$. The demand side can mobilize a portion of the supplies for emergency purposes, and the suppliers adjust their respective transport quantities based on the change, which has a small fluctuation, with a positive change indicating the amount of supplies taken out and a negative change indicating the amount of supplies put in. Furthermore, the optimal storage quantity varies as the take out quantity changes, and the constraint is $(w_{ij,T-1} - l_{ij,T})^{\min} \le w_{ij,T-1} - l_{ij,T} \le (w_{ij,T-1} - l_{ij,T})^{\max}$. The values of w change from one moment to the next and must be updated.

Mathematical model.

$$\min Z = \sum_{i=1}^{n}\sum_{j=1}^{m} Q(x_{ij,T}) + \sum_{i=1}^{n}\sum_{j=1}^{m} \mathrm{U}(x_{ij,T}) + \sum_{i=1}^{n}\sum_{j=1}^{m} G(y_{ij,T}) + \sum_{i=1}^{n}\sum_{j=1}^{m} C(l_{ij,T}) \tag{5}$$

$$s.t. \quad x_{ij,T}^{\min} \le x_{ij,T} \le x_{ij,T}^{\max} \tag{6}$$

$$y_{ij,T}^{\min} \le y_{ij,T} \le y_{ij,T}^{\max} \tag{7}$$

$$l_{ij,T}^{\min} \le l_{ij,T} \le l_{ij,T}^{\max} \tag{8}$$

$$(w_{ij,T-1} - l_{ij,T})^{\min} \le w_{ij,T-1} - l_{ij,T} \le (w_{ij,T-1} - l_{ij,T})^{\max} \tag{9}$$

$$k_{1j,T} + k_{2j,T} = x_{1j,T} + y_{1j,T} + l_{1j,T} + x_{2j,T} + y_{2j,T} + l_{2j,T} \tag{10}$$

$$K = \sum_{i=1}^{n}\sum_{j=1}^{m} x_{ij,T} + \sum_{i=1}^{n}\sum_{j=1}^{m} y_{ij,T} + \sum_{i=1}^{n}\sum_{j=1}^{m} l_{ij,T} \tag{11}$$

Including transportation cost, overdraft cost, loss cost and storage cost; the relevant explanations of Eqs. (6) to (9) have been given in the objective function analysis; Eq. (10) indicates the case of considering substitutes, assuming that there is a mutual substitution relationship between material 1 and material 2, when one of the materials is out of stock due to production shortage or unexpected events, it can be replaced by another material, and the total amount of transportation of the two materials is kept constant to meet the overall material demand as much as possible; Eq. (11) indicates that the sum of the total transportation is the demand, and the material allocation always meets the supply-demand balance condition.

3 Algorithm Design

3.1 The ETAMD Distributed Optimization Algorithm

The basic logistics activities require dealing with a variety of information, such as material transportation and storage, and the transportation network and various material distribution nodes comprise a complex logistics network, whereas the distributed optimization method is to assign the complex network large-scale optimization problem to a single node for distributed computation, and examine the local interaction relationship, which is suitable for solving the informa. Each participant in the distributed system must be able to communicate, but continuous communication is difficult to achieve and must rely on synchronous clocks. To address this issue, event-triggered conditions are introduced into the distributed optimization process in order to avoid reliance on global clocks via asynchronous communication.

To avoid infinite triggers in a limited time, a trust matrix is built between suppliers, and a cooperative relationship exists between them prior to information interaction. The price difference of the same material is compared to the triggering factor, and the information interaction between two participants is triggered only when the difference is greater. Each participant triggers only when necessary, resulting in a faster convergence speed, and maximizes the common benefit by coordinating the trust relationship of suppliers and the needs of customers.

3.2 Algorithm Steps

Based on the above description,the specific steps for implementing the ETAMD distributed optimization algorithm designed in this paper are as follows:

Step 1 Initialize the base data. Based on the value of total demand K, set the initial shipping volume of multiple materials for participants $k_{ij,T}$, set the optimal storage volume at the previous moment $w_{ij,T-1}$. Construct a $m*m$ [0,1] trust matrix R between participants;
Step 2 Determine the cost of material. If there is a mutual substitution relationship between materials 1 and 2, where the demand side does not take substitutes into account, derive the functions of the participants so that the derivatives are consistent. The constraint is $x_{1j,T}+x_{2j,T}+y_{1j,T}+y_{2j,T}=k_{1j,T}+k_{2j,T}$, and then export prices of different materials $Q'=U'=G'=C'=pr_{ij,T}$.
Step 3 The first trigger condition. Every two participants interact and there is a trust relationship, the output value of the matrix R is 1, and the next trigger judgment is performed. Two participants do not have a trust relationship, the matrix R output value is 0, then the two participants do not trigger.
Step 4 The second trigger condition. The difference between the prices of the first material of the two participants is determined whether the square of the difference is greater than the square of the trigger factor λ, and the condition is met so that all derivatives of the two participants are the same, and the sum of the two participants k is satisfied. Consider the mutual replacement relationship between materiel 1 and materiel 2, and output the new price $pr_{ij,T}$ with the new k value of the two participants, so that the total amount of transportation of the two materiel remains unchanged. If the difference between the first and second materials is less than the trigger factor, compare the prices of the third and fourth materials, and so on, keeping track of the number of triggers.
Step 5 Update the data. After all triggers are completed, update the material prices and material quantities for each participant as the initial values for the next iteration and record the data.
Step 6 Determine whether the algorithm ends. Multiple material prices converge to the same, the trigger count is 0. At this time, the algorithm ends, and the optimal result is output, while it is used as the initial value for the next moment. If the price difference of the material is still greater than the trigger factor, then continue to iterate for event triggering.

4 Simulation Results

In order to verify the effectiveness and feasibility of the algorithm, this paper conducts simulation analysis on a material dispatching system containing six suppliers and one demand side, where the suppliers jointly distribute three kinds of materials, among which there is a mutual substitution relationship between material 1 and material 2. In addition, this paper writes the running program of the proposed algorithm in Matlab environment with a uniform trigger factor $\lambda = 0.5$ yuan/ton, specific data are shown in Tables 1, 2, 3, 4, and 5.

4.1 Simulation Results of Asynchronous Communication

From Fig. 1(a)–(c), the unit prices of the three supplies from the six suppliers converge to the same price for each of the three supplies, yielding the optimal price for each of the three supplies. The multiple suppliers and the demand side adopt an asynchronous communication mode in information processing, which converges only within ten iterations. Considering the total demand for the three materials on the demand side, the material prices and material allocation schemes are adjusted by combining the trust relationship among suppliers and the substitution relationship among materials. There is a substitution relationship between material 1 and material 2, which can be expressed as the same type of product, and the prices of the two are closer, 73.7789 yuan/ton and 81.2561 yuan/ton, respectively. Material 3 is different from the first two types of materials and cannot produce substitution with the first two materials, and the final material unit price of material 3 here is RMB 14.8645/ton.

Table 1. Initial correlation data.

Participant Number	Material 1 distribution volume	Material 2 distribution volume	Material3 distribution volume
Supplier1	126	223	590
Supplier2	214	186	380
Supplier3	152	179	625
Supplier4	145	278	450
Supplier5	207	184	859
Supplier6	185	298	645
	Material 1 warehouse storage volume	**Material 2 warehouse storage volume**	**Material 3 warehouse storage volume**
Demand side7	880	2000	1300

Table 2. Supplier transport function correlation coefficient and constraints.

Material 1	**Participant Number**	a_{ij}	b_{ij}	c_{ij}	$x_{ij,T}^{\min}$	$x_{ij,T}^{\max}$
	Supplier1	0.040	14.5	25	30	150
	Supplier2	0.011	20.5	31	66	180
	Supplier3	0.023	24.5	28	30	166
	Supplier4	0.054	11.9	27	50	130
	Supplier5	0.031	28.0	33	50	150
	Supplier6	0.026	26.5	23	40	180
Material 2	Supplier1	0.032	36	32	40	180
	Supplier2	0.015	24	36	58	326
	Supplier3	0.021	22	34	49	285
	Supplier4	0.010	18.5	26	80	450
	Supplier5	0.041	11	43	77	376
	Supplier6	0.035	30	26	63	350
Material 3	Supplier1	0.043	4	50	100	1500
	Supplier2	0.013	3	80	80	1400
	Supplier3	0.015	9	40	60	1500
	Supplier4	0.022	3	35	45	1350
	Supplier5	0.028	5	50	80	1650
	Supplier6	0.019	4	60	40	1260

Influenced by the constraints related to the storage cost function, when the warehouse storage volume reaches the maximum value of the range of values, the material price is no longer affected by the trigger conditions and changes, Fig. 1(d) indicates the convergence prices of three materials on the demand side, which are 63.9979 yuan/ton, 75.5408 yuan/ton and 16.1584 yuan/ton, respectively. Compared with the convergence results of the material prices of the six suppliers, although they cannot reach complete agreement, the direction of change of the material prices is the same, which meets the basic requirements of the optimal theory when the prices are consistent.

The amount of material transported in the first moment is the supplier's overdraft, and the overdraft risk of material 3 is small; only the overdraft risk costs of material 1 and 2 are considered here. Figure 2 represents the re-dispatching of two materiel by six suppliers, which converges at the same price, and the materiel overdraft volume/transportation volume tends to be smooth. Based on the change of the material volume of each supplier, it can be seen that the cooperation between suppliers with trust relationship exists, and the best distribution plan is derived by comparing the price difference of the material and the overdraft risk cost to improve the risk resistance in general.

Table 3. Supplier overdraft function correlation coefficient and constraints

Material 1	**Participant Number**	d_{ij}	p_{ij}	f_{ij}	$x_{ij,T}^{\min}$	$x_{ij,T}^{\max}$
	Supplier1	99	50	0.010	30	150
	Supplier2	85	45	0.021	66	180
	Supplier3	110	45	0.008	30	166
	Supplier4	50	28	0.013	50	130
	Supplier5	60	35	0.008	50	150
	Supplier6	30	30	0.010	40	180
Material 2	Supplier1	150	45	0.011	40	180
	Supplier2	124	40	0.009	58	326
	Supplier3	250	35	0.010	49	285
	Supplier4	167	35	0.022	80	450
	Supplier5	146	40	0.018	77	376
	Supplier6	155	60	0.003	63	350

4.2 Simulation Results of Synchronous Communication

The traditional distributed algorithm uses a synchronous communication mode for information interaction, where multiple nodes need to communicate simultaneously, independent of the trigger factor, until the prices are fully aligned to output the final results. To demonstrate the superiority of asynchronous communication, the results of the distributed optimal dispatching algorithm are compared with those of synchronous communication.

As can be seen from Fig. 3, the number of convergence iterations and price changes for the three supplies in the synchronous communication mode, the convergence results are 73.2527 yuan/ton, 80.7936 yuan/ton and 14.9586 yuan/ton, respectively. Compared with the simulation results of the asynchronous communication mode, the final pricing of the materials by the six suppliers achieves complete consistency, and the results are closer to the theory of consistent optimal prices. The difference between the calculated results of the two modes is not large, but the difference in calculation volume is huge, which is analyzed as follows.

4.3 Contrast Analysis

Table 6 lists the comparison results under the two communication modes, and it can be seen that the number of convergence iterations of event-triggered asynchronous communication mode is significantly less than the case of synchronous communication, and the asynchronous communication mode avoids a large number of meaningless communications and reduces the computation in terms of information interaction between

Table 4. Supplier loss function correlation coefficient and constraints.

Material 1	**Participant Number**	α_{ij}	β_{ij}	μ_{ij}	$y_{ij,T}^{\min}$	$y_{ij,T}^{\max}$
	Supplier1	0.11	748	-1.1	84.3	103.5
	Supplier2	0.15	1200	-1.2	76.2	84.5
	Supplier3	0.11	1215	-1.5	71.3	88.4
	Supplier4	0.10	1550	-0.5	56.4	72.4
	Supplier5	0.20	1800	-1.4	78.6	111.6
	Supplier6	0.16	1060	-1.3	60.5	98.7
Material 2	**Participant Number**	α_{ij}	β_{ij}	μ_{ij}	$y_{ij,T}^{\min}$	$y_{ij,T}^{\max}$
	Supplier1	0.12	534	-1.3	133.2	148.2
	Supplier2	0.15	526	-1.1	68.1	98.5
	Supplier3	0.18	1263	-1.9	44.5	69.5
	Supplier4	0.11	1030	-1.2	55.6	88.2
	Supplier5	0.22	925	-1.7	49.7	74.6
	Supplier6	0.17	1155	-1.5	72.4	99.1
Material 3	Supplier1	0.23	625	-0.5	100.8	150.5
	Supplier2	0.13	384	-1.8	83.2	108.2
	Supplier3	0.15	951	-1.4	48.9	83.6
	Supplier4	0.25	397	-1.3	45.5	84.4
	Supplier5	0.28	526	-1.5	64.1	96.7
	Supplier6	0.19	431	-1.6	37.8	73.6

Table 5. Demand-side storage function correlation coefficient and constraints.

	ε_{ij}	ν_{ij}	θ_{ij}	$l_{ij,T}^{\min}$	$l_{ij,T}^{\max}$	$(w_{ij,T-1} - l_{ij,T})^{\min}$	$(w_{ij,T-1} - l_{ij,T})^{\max}$
Material 1	0.98	0.028	535	-100	100	450	1500
Material 2	0.95	0.021	721	-60	60	820	3500
Material 3	0.84	0.032	636	-45	45	660	2300

participants. Therefore, the introduction of event-triggered asynchronous communication mode on the distributed optimal dispatching algorithm in this paper can effectively reduce the communication pressure and communication cost, and improve the economic efficiency as a whole.

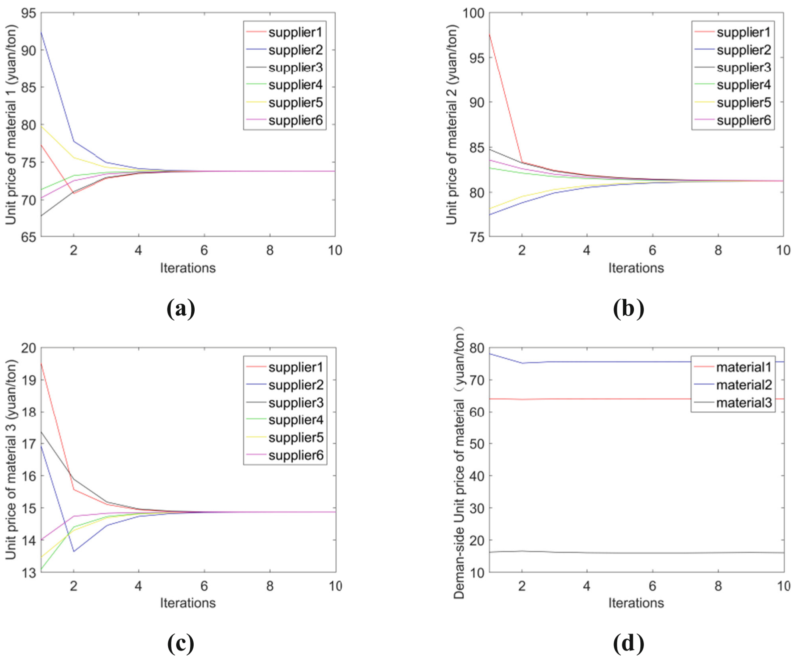

Fig. 1. Asynchronous communication material prices consistent. (**a**) represents the unit price of material 1; (**b**) represents the unit price of material 2; (**c**) represents the unit price of material 3; (**d**) represents the unit price of materials on the demand side.

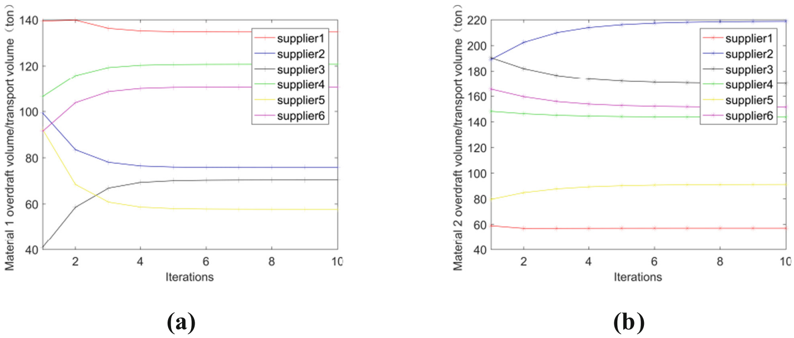

Fig. 2. Overdraft volume / transport volume of material. (**a**) represents the volume of material 1; (**b**) represents the volume of material 2.

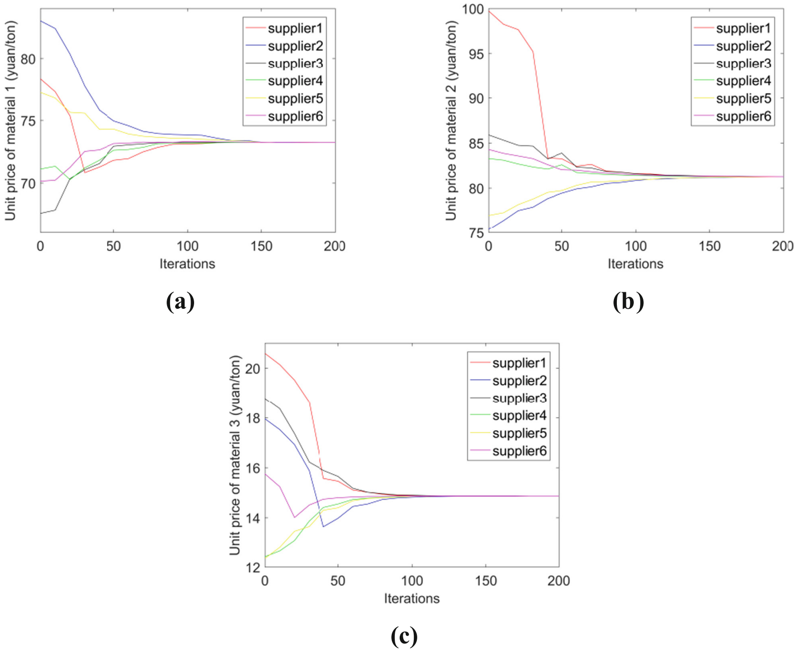

Fig. 3. Synchronous communication materials prices are consistent. (**a**) represents the unit price of material 1; (**b**) represents the unit price of material 2; (**c**) represents the unit price of material 3.

Table 6. Asynchronous communication and synchronous communication

Communication Category	Trigger factor (yuan/ton)	Convergence iterations	Total number of triggers
synchronous communication	0	200	4800
asynchronous communication	0.5	10	240

5 Conclusions

The problem of optimal dispatching of materials with constraints for multiple suppliers was addressed in this paper. The ETAMD distributed optimization algorithm is proposed to realize collaborative optimal dispatching among each participant in the mode of event-triggered asynchronous communication by designing the trust relationship between participants, the comparison relationship between price difference and trigger factor as the event trigger condition. The ETAMD distributed optimal dispatching algorithm is based on a distributed algorithm with asynchronous collaboration, which significantly reduces unnecessary triggers and delays. The synchronous clock constraint was avoided, and the global computational pressure was reduced. Finally, the proposed algorithm was applied to a multi-supplier single-demand-side material dispatching model, and simulation results show that prices of multiple materials converge to the same level and can converge to the global optimal solution. The material optimization dispatching model in this paper considered only the case where the cost functions are all convex, and the non-convex problem was ignored. On the basis of this paper, non-convex optimization can be considered in the future to solve the large-scale material dispatching problem with non-convex cost functions.

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