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# An efficient production planning approach based demand driven MRP under resource constraints

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Production plans based on Material Requirement Planning (MRP) frequently fall short in reflecting actual customer demand and coping with demand fluctuations, mainly due to the rising complexity of the production environment and the challenge of making precise predictions. At the same time, MRP is deficient in effective adjustment strategies and has inadequate operability in plan optimization. To address material management challenges in a volatile supply-demand environment, this paper creates a make-to-stock (MTS) material production planning model that is based on customer demand and the demand-driven production planning and control framework. The objective of the model is to optimize material planning output under resource constraints (capacity and storage space constraints) to meet the fluctuating demand of customers. To solve constrained optimization problems, the demand-driven material requirements planning (DDMRP) management concept is integrated with the grey wolf optimization (GWO) algorithm and proposed the DDMRP-GWO algorithm. The proposed DDMRP-GWO algorithm is used to optimize the inventory levels, shortage rates, and production line capacity utilization simultaneously. To validate the effectiveness of the proposed approach, two sets of customer demand data with different levels of volatility are used in experiments. The results demonstrate that the DDMRP-GWO algorithm can optimize the production capacity allocation of different types of parts under the resource constraints, enhance the material supply level, reduce the shortage rate, and maintain a stable production process.

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## 1. Introduction

In the context of manufacturing globalization, the production activities of various manufacturing enterprises have become more complex. Fluctuations in supply and demand have intensified, customer requirements for product timeliness have increased, production processes have become more complicated, and production plans face increasing uncertainties. The uncertainty and complexity in the production environment require adopting effective methods and strategies for planning, organizing, and controlling the production of various materials to achieve maximum benefits and utilization of resources. Traditional planning methods represented by MRP are suitable for production environments that balance customer demand and material supply. When the supply and demand fluctuations are severe, the demand quantity of the final products planned by master production schedule (MPS) cannot accurately reflect the actual customer demand. The material requirements plan often deviates from the actual situation. Changes in demand lack effective means to promote the timely update of the material requirements plan, and the feasibility of production plans deteriorates (Kortabarria et al., 2018). Failure of timely supply leads to production downtime due to material shortages and lower production efficiency. Many enterprises adopt Lean or DBR pull production methods to deliver products quickly and reduce waste, but the fluctuations in supply and demand affect the implementation effect of pull production. For the corresponding pull production mode, only a timely supply of materials can

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be guaranteed to maintain a smooth production process, creating favorable conditions for implementing Lean or TOC. For some critical materials that cannot be supplied on time, a certain amount of inventory must be held to avoid material shortages during the production process, which is especially important in markets with large fluctuations in customer demand. Whether the order point method (OPM) or the MRP material management method, they are mainly suitable for stable sales and relatively simple supply chain environments. Their effects cannot meet the needs of enterprises for rapidly changing and complex market demand and supply chain environments. At the same time, both formulate material plans based on demand forecasts, and the accuracy of predictions in uncertain environments is difficult to guarantee. Material requirements plans based on this approach cannot effectively supply production needs, resulting in inventory building or the loss of sales opportunities (Shofa et al., 2017). DDMRP, which was launched in 2011, integrates the advantages of MRP, distribution requirement planning (DRP), constraint theory, and lean principles and realizes the decoupling of material demand and supply by setting buffers for critical materials, reducing the impact of supply and demand fluctuations on enterprise production, ensuring the rapid supply of materials during the production process, eliminating and reducing production downtime caused by material shortages, improving the smoothness of the production process, and providing a better foundation for the implementation of management systems such as Lean or TOC (Miclo et al., 2019). This paper investigates the problem of optimizing production planning under resource constraints based on the DDMRP material management strategy. We fully exploit the effectiveness of DDMRP in managing materials in a volatile supply-demand environment and the advantages of metaheuristic algorithms in solving constrained optimization problems by integrating the material management strategy of DDMRP with the Grey Wolf Optimizer (GWO) algorithm to propose the DDMRP-GWO algorithm for solving the studied problem.

The remainder of this article is organized as follows: Section 2 reviews the development history of production planning and control methods, as well as the new changes in the production environment in recent years. Section 3 constructs a mathematical model for the material production planning optimization problem under resource constraints based on DDMRP. Section 4 proposes the DDMRP-GWO algorithm to solve the problem model in this article. Section 5 designs a set of instances to verify the effectiveness of the DDMRP-GWO algorithm in solving the production planning optimization problem under resource constraints. Section 6 summarizes the research content of this article.

## 2. Literature Reviews

Production planning and control theory is part of production and operations management and is the core of production and operations management. With the continuous changes in the market environment and production technology, production planning and control theory have also been constantly evolving and developing to meet the needs of current-stage enterprise production management and help enterprises improve their management level. Starting from Taylor's proposal of scientific management in the early 20th century, the manufacturing industry has undergone different production modes, from manual workshops and mass production to multi-variety, small-batch production. Correspondingly, production planning and control methods have also developed from qualitative to quantitative, extensive to refined, and flexible (Shofa & Widyarto, 2017). In addition to the early OPM, currently, enterprises use more production planning and control methods, including Material Requirement Planning (MRP)(Benton & Shin, 1998), Manufacturing Resource Planning (MRP-II) (Godinho Filho et al., 2004), Enterprise Resource Planning (ERP) (Ali & Miller, 2017), Lean production (Glass et al., 2016), Theory Of Constraints (TOC) (Watson & Patti, 2008) and DDMRP (Azzamouri et al., 2021), etc.

Before the 1960s, MRP had already been applied in some enterprises (Plossl, 1995). The MRP system at this stage is a calculation method for material demand and lead time. In the late 1970s, due to the improvement in computer capabilities, capacity planning was added to MRP, known as closed-loop MRP. Both MRP and closed-loop MRP only consider material flow. However, in modern enterprise operations management, material flow, capital flow, and information flow are essential. Therefore, in the Manufacturing Resource Planning (MRPII) that appeared in the late 1970s and 1980s, financial analysis and cost control were added to closed-loop MRP, and material and capital flow were combined to further develop into Enterprise Resource Planning (ERP). In the early 1990s, software companies further enriched the functions of MRPII. Based on Manufacturing Resource Planning, they also considered quality management, human resource management, project management, and other enterprise resource planning, further developing into ERP. Whether it is MRP, MRPII, or the most mature ERP, their core has not changed, and the calculation method of material demand has always been based on the basic MRP calculation logic, which is a top-down push production planning logic based on demand forecasting. A feasible plan can be obtained by repeatedly adjusting the production plan based on rough capacity planning (Yue et al., 2019). Forecasting is prone to deviation when the business environment is unstable, and the feasibility of production plans based on it is difficult to guarantee. When there are bottlenecks in the production system, MRP/MRPII/ERP performs the worst compared to TOC and JIT (Thürer et al., 2020). At the same time, MRP/MRPII/ERP have not been able to involve specific production scheduling at the workshop operation level, only focusing on rough capacity planning and have not involved specific production operation plans at the workshop level. It is difficult to achieve full consideration of macro and micro plans, so it is difficult to solve planning and material management in unstable production environments. However, their theoretical and practical research results have laid a solid foundation for the production operation and information management of manufacturing enterprises.

In the 1980s, the Massachusetts Institute of Technology (MIT) conducted in-depth research on the production system originated from Toyota in Japan, believing that it is more resource-saving and efficient, they named it lean production, which differs from the management ideas of mass production (Kandebo, 1997). It is a leap in the manufacturing mode and the development trend of production methods in the 21st century. However, when the production system is complex, the information transmission cycle may be long, and there may be information errors in each production link, which cannot respond to demand changes promptly. Some companies instinctively increase inventory to deal with demand fluctuations and build buffer zones to respond to demand, but this approach does not align with the concept of JIT.

In the 1980s, Dr. Goldratt proposed the Theory of Constraints (TOC), a holistic management philosophy based on the principle that complex systems exhibit inherent simplicity (Luebbe et al., 2010). Drum-Buffer-Rope (DBR) is the core control mechanism of the TOC constraint theory. Using DBR methods to manage planning and buffering can reduce inventory, ensure rapid delivery of customer orders, improve inventory turnover, and enhance enterprise profitability.

JIT or DBR is suitable for manufacturing companies with relatively stable production. Otherwise, their potential cannot be fully realized due to the characteristics of their pull production method. In complex production environments, if material management is improper and shortages occur frequently, the effectiveness of pull production execution will be affected, leading to great difficulties. If shortages occur frequently, it will affect the liquidity of the production process. Whether it is MRP/MRPII/ERP, JIT, or TOC, none can fully exert their advantages. To adapt to production management in a volatile supply and demand environment, current research on production planning and control theory mainly focuses on integrating existing theories to achieve complementary advantages, supplementing and improving existing theories, and deeply integrating relevant theories and production systems. These studies are conducted in a certain production context to solve specific production management problems in specific fields or backgrounds.

Chen and Peng (2004) constructed an integrated production planning and control model that combines the "Push" system led by the MRP II production planning system based on TOC and the “Pull” system led by the JIT production control system. The model aims to maximize bottleneck resource utility , dynamically optimize and adjust production planning based on demand prediction and pulling of JIT producing, and implement dual control of the production process using procurement planning, supplier’s capability planning, and Kanban systems. Cheikhrouhou et al. (2009) proposed a mixed production planning and control method for high-speed production lines combining JIT, Kanban, and MRP, and modeled it. Their performance was compared and evaluated with traditional production planning and control methods. Yu and Wang (2012) proposed a production model and execution plan that combines MRP and JIT based on their characteristics in production management. The effectiveness of this production model has been proven through its application in enterprises. Ming et al. (2005) proposed an integrated production management model that synthesizes the advantages of MRPII and JIT/TOC, the three typical production planning and management methods. Yue deeply integrated the TOC/DBR control concept with the production organization method of a hybrid production system and proposed an operation control framework for a hybrid production system based on constraint theory. They also conducted research on issues such as bottleneck resource-based hybrid manufacturing system scheduling, batch control and scheduling based on hybrid parallel processing lines, and integrated rolling planning and scheduling for hybrid production lines based on DBR and established mathematical optimization models with various complex constraints. In summary, each manufacturing company should formulate and choose appropriate production planning and control methods according to the current market environment and its own production status, which is crucial for the efficient operation of the enterprise (Orue et al., 2020).

In recent years, the production and market environment of enterprises has presented some new characteristics: products are more complex and personalized, prediction errors have increased, product life cycles are gradually shortening, customer tolerance time is also decreasing, the supply chain is more complex, shortages occur in the production process, and inventory backlog is severe. These have brought great challenges to the production management of enterprises. Therefore, there is an urgent need for new production management theories to cope with the challenges brought by supply and demand fluctuations and to improve the level of enterprise production operation and management. DDMRP emerged in response to this demand. DDMRP is a multi-level production planning and execution method proposed in 2011 (Ptak, 2016). It is a significant reflection on the logic and methods of MRP since 1974, a new development of MRP, and an innovation based on integrating multiple production planning and control theories. It is also a further development of MRP technology.

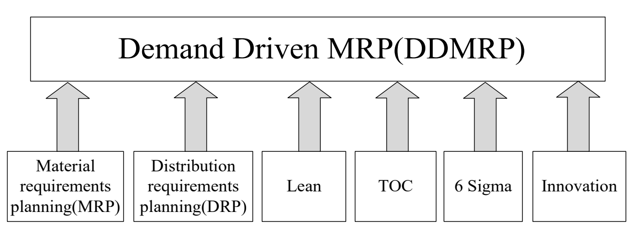


**Fig. 1.** The methodological basis of DDMRP

DDMRP integrates traditional MRP, pull-based replenishment strategies, and demand-driven concepts into a dynamic and highly visual system, providing a production planning and materials management solution that can resolve complex supply chain and materials management challenges in today’s manufacturing environment. DDMRP is a production planning and materials management solution that integrates various traditional methods while incorporating appropriate innovations to address the characteristics of the manufacturing environment. In addition to the core MRP, it also includes the advantages of distribution requirement planning (DRP), constraint theory, and lean principles, as shown in Fig. 1. DDMRP is a multi-level pull-based planning tool whose core is to decouple the demand and supply of strategic materials by setting inventory buffers, improving the visibility of the supply chain to achieve better customer experiences with less inventory.

Through the vigorous promotion of APICS, DDMRP has been applied in some enterprises. The results show that DDMRP can improve materials management and significantly reduce inventory levels while ensuring material consumption, achieving better application effects. Kortabarria et al. (2018) used a qualitative method to study and analyze the situation of a company using MRP after DDMRP implementation. After DDMRP implementation, inventory levels decreased by 52.53%, with a material consumption increase of 8.7%. The results indicate that using DDMRP can effectively improve the level of materials management and increase the visibility of the supply chain. Abdelhalim et al. (2021) expanded previous research on inventory management before DDMRP by improving its existing model to make its manufacturing strategy suitable for MTO/MTS. Compared with various validated, enhanced models, they showed that better solutions could be obtained in a shorter computing time. Thürer et al. (2020) used simulation experiments to evaluate the performance of four production planning and control (PPC) systems: Kanban, MRP, optimized production technology (OPT), and DDMRP, in a multi-stage assembly system with different bottleneck conditions and delivery dates. The results verified that DDMRP performed the best, especially in inventory management, under bottleneck conditions in severe bottleneck systems. When calculating inventory buffers, DDMRP requires the setting of subjective parameters, such as lead time factor and variability factor, which can affect the consistency of inventory levels. Lee and Rim (2019) proposed a mathematical approach to determine safety stock levels for existing DDMRP inventory replenishment models. This approach generates lower inventory levels than current DDMRP methods while keeping the stockout rate near zero. Miclo et al. (2019) introduced and explored DDMRP through a series of structured computer simulation experiments, evaluating its effectiveness relative to the widely accepted methods of MRP-II and Kanban/Lean. The experimental results proved the superiority of DDMRP, which is a motivation for further research. Achergui et al. (2020) applied the strategic positioning method of DDMRP to MTO/MTS manufacturing systems to solve the optimization problem of minimizing storage costs without capacity buffer location and buffer allocation under service time constraints and proposed a heuristic algorithm solution. The effectiveness and performance of the proposed algorithm were proved by comparative experiments, showing that it can provide effective approximate solutions in a more reasonable time than b and nonlinear solvers.

According to the existing applications of DDMRP, it is very effective in production management and material control. It has brought positive changes to the production management level in implementing enterprises. However, compared to traditional methods, the application of DDMRP is minimal, especially in the comparative study with conventional methods, and there is a lack of convincing research results; In addition, no research results on the application of DDMRP under resource constraints have been found in the literature reviewed. In the face of complex and diverse production environments, the current research on DDMRP still has limitations and needs further exploration. Therefore, scholars need to conduct further research and exploration in this field to assess its performance and limitations, better understand its internal logic and how relevant computing methods and parameters affect the implementation of the theory and make appropriate improvements and innovations to help enterprises better respond to the challenges posed by the new manufacturing environment.

## 3. Problem description and mathematical model

In the increasingly volatile production environment of supply and demand, organizing the production of some essential parts of a mainframe computer through MTO can better control inventory costs and reduce unnecessary waste. However, to respond quickly to production orders, a certain amount of inventory must be held for critical components with long lead times and limited production resources to avoid MTO interruptions due to the lack of materials. This section introduces the related methods of DDMEP, which handle material planning optimization problems under fluctuating demand. A mathematical model is established for optimizing production planning under resource constraints. Then an improved GA algorithm is used to optimize resource allocation in each production planning cycle to minimize tardiness penalties. A general description of the production planning optimization problem under capacity and storage space constraints is as follows:

There are $T$ different types of jobs produced in a mixed-model manner on the production line $l$ $(1 \leq l < L)$, and these $t$ types of jobs are key components of the final product $F$. In planning cycles $h$, the required quantity of $t$-th type of job is $AN_{h,t}$ $(h = 1,2,\cdots,H, t = 1,2,\cdots,T)$, the total available production capacity of production line $l$ is $PC_l$, and the production capacity required for one job with type $t$ is $UC_{l,t}$. Due to the capacity constraints of production line $l$ and the uncertainty of demand, an inventory buffer is established for the jobs produced on production line $l$. The total available storage space is $IB_l$. Uncertainties in customer demand led to distorted demand forecasts, so obtaining the planned demand for final products from MPS is inaccurate. Therefore, the production plan for production line $l$ obtained through MRP deviates from actual demand, and optimizing the production plan within each planning cycle based on changes in actual demand is necessary. By setting an appropriate planned production quantity for $t$ types of jobs, it is ensured that under capacity and storage space constraints, the shortage rate of jobs and penalties for violating constraints are minimized.

The following assumptions are made for this problem to make the mathematical model more general:

(1) Any production line is considered as a processing center, and its production capacity is the comprehensive capacity after considering the processing capacity of each process of the production line;

(2) All parameters are known and determined during the planning cycle;

(3) Material transportation time is negligible;

(4) When applying DDMRP, the time elapsed from the release of a manufacturing or purchase order to the start of order execution is not considered.

(5) Ignore the time required for order placement.

(6) The fluctuation of manufacturing lead time caused by equipment failure is not considered.

The relevant notations used in the mathematical model of production plan optimization problems under capacity constraints and storage space constraints are listed in the following table:

| Notation | description |
|---|---|
| $PC_l$ | Total available capacity of production line $l$ |
| $IB_l$ | Total available inventory buffer quantity for production line $l$ |
| $RIB_{L,h}$ | The remaining available storage space of the production line $L$ when the planning horizon is $h$ |
| $H$ | The number of planning horizons |
| $h, h'$ | The planning horizon index, $h = 1,2,\cdots,H$ |
| $T$ | Total number of job types |
| $t$ | Job type index, $t = 1,2,\cdots,T$ |
| $ADU_{h,t}$ | The average daily usage of job $t$ when the planning horizon is $h$ |
| $DLT_t$ | The decoupling lead time for job $t$ |
| $LTF_{h,t}$ | The lead time factor for a job $t$ with a planning cycle $h$ |
| $VF_{h,t}$ | The variability factor for a job $t$ with a planning cycle $h$ |
| $MOQ_t$ | The MOQ of job type $t$ |
| $BL_{h,t}$ | The buffer level for a job $t$ with a planning cycle $h$ |
| $G_{h,t}$ | The green zone size for a job $t$ with a planning cycle $h$ |
| $Y_{h,t}$ | The yellow zone size for a job $t$ with a planning cycle $h$ |
| $R_{h,t}$ | The red zone size for a job $t$ with a planning cycle $h$ |
| $RB_{h,t}$ | The red base size for a job $t$ with a planning cycle $h$ |
| $RS_{h,t}$ | The red safety size for a job $t$ with a planning cycle $h$ |
| $OST_{h,t}$ | The order spike threshold for a job $t$ with a planning cycle $h$ |
| $OSH_{h,t}$ | The order spike horizon for a job $t$ with a planning cycle $h$ |
| $NFP_{h,t}$ | NFP (Net Flow Position) for a job $t$ with a planning cycle $h$ |
| $OH_{h,t}$ | On-hand stock quantity for a job $t$ with a planning cycle $h$ |
| $O_{h,t}$ | On-order stock quantity for a job $t$ with a planning cycle of $h$, i.e., open supply orders |
| $Q_{h,t}$ | The confirmed actual demand quantity for a job $t$ that is due within a planning cycle $h$ |
| $AN_{h,t}$ | The number of job orders of type $t$ that are due today within a planning cycle of $h$ |
| $DN_{h,t}$ | The number of overdue jobs within a planning cycle $h$ |
| $SN_{h,t}$ | The number of qualified order spikes for a job $t$ with a planning cycle $h$ |
| $RN_{h,t}$ | The upper replenishment quantity for a job t with a planning cycle $h$ |
| $IN_{h,t}$ | The number of jobs received by the buffer zone with a planning cycle $h$ |
| $CP_t$ | The production capacity penalty factor for jobs of type $t$ |
| $UC_{h,t}$ | The required production capacity to produce one unit of job of type $t$ with a planning cycle $h$ |
| $BP_{h,t}$ | The inventory buffer penalty factor for jobs $t$ |
| $BE_{h,t}$ | The quantity of planned production that exceeds the total capacity for jobs $t$ with a planning cycle $h$ |
| $X'_{h,t}$ | A binary variable indicating the planned production quantity for a job $t$ within the planning cycle $h$ |
| $X_{h,t}$ | The planned production quantity for jobs $t$ with a planning cycle $h$ |

Use the above notations to establish a mathematical model for the constrained production planning optimization problem. When optimizing the planned production volume of different types of materials within each planning cycle, the optimization objective is shown in formula (1):

$$\min f_h = \sum_{t=1}^{T} \left| X_{h,t} - RN_{h,t} \right| + \sum_{t=1}^{T} CP_t BE_{h,t} UC_{h,t} + \sum_{t=1}^{T} BP_t BE_{h,t} \tag{1}$$

The objective function is based on the following considerations: generating replenishment orders using the DDMRP method, which can maximize the impact of fluctuating customer demand on enterprise production at a reasonable inventory level. However, under capacity constraints and storage space, the planned production volume of each material can be smaller than the replenishment volume generated by the DDMRP method, which cannot be avoided. Therefore, when production plans are affected by constraints, a more practical approach is to make the planned production volume of each material as close as possible to the replenishment volume calculated using the DDMRP method, which helps to minimize the impact on subsequent production and sales. In Eq. (1), the first item is the proximity of the planned production volume of each type of job to the proposed order calculated based on the net flow equation (NFE). The second item is the penalty for exceeding the available production capacity, where $CP_t$ is the penalty coefficient for the excess of production capacity of the jobs of type $t$ . The third item is the penalty for exceeding the storage space of the planned production quantity, where $BP_{h,t}$ is a penalty coefficient for exceeding the storage space of jobs of type $t$ in the planning cycle $h$, where $BE_{h,t}$ represents the difference between the optimized planned production quantity and the replenishment quantity calculated based on NFE. The calculation method is shown in Eq. (2):

$$BE_{h,t} = \begin{cases} X_{h,t} - RN_{h,t}, & RN_{h,t} < X_{h,t} \\ 0, & RN_{h,t} \geq X_{h,t} \end{cases} \tag{2}$$

The constraints for the production planning optimization model based on the DDMRP material management strategy are listed as follows:

$$G_{h,t} = max\{MOC_t ADU_{h,t},\ ADU_{h,t} DLT_t LTF_{h,t}, MOQ_t\} \tag{3}$$
$$Y_{h,t} = ADU_{h,t} DLT_t \tag{4}$$
$$RB_{h,t} = ADU_{h,t} DLT_t LTF_{h,t} \tag{5}$$
$$RS_{h,t} = RB_{h,t} VF_{h,t} \tag{6}$$
$$R_{h,t} = RB_{h,t} + RS_{h,t} \tag{7}$$
$$BL_{h,t} = G_{h,t} + Y_{h,t} + R_{h,t} \tag{8}$$

Eqs. (3-7) define the sizes of the green, yellow, and red buffer zones, respectively. Eq. (8) is used to calculate the total inventory buffer. From Eqs. (3-7), the inventory buffer level for any type of job is determined by the global attributes and individual attributes of the job. When these attributes change, it is necessary to modify the relevant content in the buffer-level configuration file and then re-adjust the size of the three-color buffer.

$$NFP_{h,t} = OH_{h,t} + O_{h,t} - Q_{h,t} \tag{9}$$
$$Q_{h,t} = AN_{h,t} + DN_{h,t} + SN_{h,t} \tag{10}$$

It can be noted from the above equations that for available quantity does not use sales forecast but actual demand, specifically the qualified actual demand calculated using Equation (10). Where, $SN_{h,t}$ represents the peak value of confirmed orders. If enterprises do not pay attention to the peak confirmed orders soon, it will threaten the reliability of the buffer system. The order peak is the sum of the order demand quantities, which is typically summarized in days. That is, the order quantities of all orders on a day are summed up to determine the order peak on that day. The confirmed order peaks in a peak order range are calculated using Eq. (11). In the current model, if an order peak satisfies the conditional Eq. (12), it can become a confirmed order peak. If enterprises do not pay attention to the peak of the confirmed order soon, it will threaten the reliability of the buffer system.

$$SN_{h',t} = \sum_{h=(h'+1)}^{(h'+OSH_t-1)} X'_{h,t}\, \mathrm{A}N_{h,t} \tag{11}$$
$$\mathrm{A}N_{h,t} \geq \frac{R_{h,t}}{2} \tag{12}$$

The NFP of the job $t$ in the planning cycle $h$ can be calculated using Eq. (9). When the NFP is below the top of the yellow buffer, a replenishment order is generated, and the replenishment quantity is calculated through Eq. (13):

$$RN_{h,t} = BL_{h,t} - NFP_{h,t} \tag{13}$$

Replenishment orders refill the existing inventory to the top of the green zone. However, in practice, due to considerations such as economic batch size or transportation costs, the inventory may exceed the top of the green buffer zone after replenishment. Therefore, when optimizing each material production plan, the quantity of replenishment orders generated must meet the constraints (14)-(16):

$$\sum_{t=1}^{T} UC_t X_{h,t} \leq PC_L \tag{14}$$

$$\sum_{t=1}^{T} X_{h,t} \leq RIB_{L,(h+DLT_t)} \tag{15}$$

$$X_{h,t} \leq RN_{h,t} \tag{16}$$

$$RIB_{L,(h+DLT_t)} = RIB_{L,h} + \sum_{h=h'}^{(h'+DLT_t)} IN_{h,t} - \sum_{h=h'}^{h'+DLT_t} TN_{h,t} - DN_{h,t} \tag{17}$$

Constraint (14) ensures that the total capacity required to produce a planned number of pieces within a planning cycle cannot exceed the maximum available capacity of the production line $L$. Constraint (15) is a spatial constraint that ensures that the total quantity of each job in a planned order cannot exceed the available storage space in the buffer. It is noted that the DLT can be different for different types of jobs, which will result in different calculation values for the available buffer size for each type of job when completing demand orders. Constraint (16) Defines the value range of manufacturing orders (purchase orders) for different types of jobs generated within each planning cycle. Constraint (17) defines the calculation method for the available storage space of the buffer when the current manufacturing order (or purchase order) is completed. Where $RIB_{L,(h+DLT_t)}$ is the on-hand inventory of a type $t$ job materials after a DLT and can be calculated using Eq. (17).

## 4. Outcomes of production plan optimization under resource constraints

Conventional material planning is based on demand forecasting. When the market demand environment is complex, it is difficult to verify and ensure the accuracy of the forecast, which results in deviations between material production and actual conditions, affecting the average production and business activities of the enterprise. To improve the accuracy of plans, some enterprises are keen to improve prediction accuracy by improving prediction algorithms and developing mature prediction technologies. However, the overall accuracy of prediction has not been significantly improved because the intensification of market fluctuations has offset various efforts of enterprises in prediction work. Even though the accuracy of enterprise forecasts has improved, it is hard to control inventory levels effectively. Due to the significant instability of the global manufacturing and supply environment, the difficulty of material management is increasing. The most accurate form of demand input is a customer order. A customer order is a clear intention and commitment, which refers to the quantity and timing of products purchased from actual customers. It is highly accurate and relevant information. DDMRP provides a reliable way to use this more accurate demand information. Under resource constraints, the material plan calculated by the NFE in DDMRP cannot be directly used in production due to resource constraints. Intelligent optimization algorithms are the best means to solve constrained optimization problems. In this article, the material plan generation method of DDMRP is combined with the GWO algorithm to propose a novel DDMRP-GWO algorithm and solve the constrained production plan optimization problem.

### *4.1 Grey Wolf Optimization Algorithm (GWO)*

Grey Wolf Optimizer (GWO) is a metaheuristic optimization algorithm based on swarm intelligence proposed by Mirjalili et al. of Griffith University in Australia in 2014 (Mirjalili et al., 2014). This algorithm has the characteristics of an ordinary search principle, fast convergence speed, fewer parameters, and easy implementation. In recent years, it has attracted more attention. Various improvements have been made to solve related problems in multiple fields, such as production scheduling and image processing, and have achieved quite good results. GWO's inspiration comes from the leadership and hunting behavior of gray wolves. In the GWO algorithm, the initial population is used to simulate a pack of gray wolves, can be divided into four levels: the gray wolf with the best, second-best, and third-best fitness values are labeled as α, β, and δ, respectively, while the rest of the gray wolves are labeled as $\omega$, the optimal solution is sought by simulating the hunting process of gray wolves. During hunting, the location of the prey is unknown. Therefore, to simulate the hunting behavior and prey behavior of gray wolves from a mathematical modeling perspective, it is assumed that α, β and δ are the potential location closest to the prey. Guided by α, β and δ, the position vectors are updated to approach the optimal solution in the search space.

When hunting, gray wolves gradually approach and surround their prey, the mathematical model for this behavior is as follows:

$$\vec{D} = \left|\vec{C} \cdot \overrightarrow{X_p}(t) - \vec{X}(t)\right| \tag{18}$$

$$\vec{X}(t+1) = \overrightarrow{X_p}(t) - \vec{A} \cdot \vec{D} \tag{19}$$

$$\vec{A} = 2\vec{a} \cdot \overrightarrow{r_1} - \vec{a} \tag{20}$$

$$\vec{C} = 2\vec{r_2} \tag{21}$$

In the above equations, $\vec{D}$ represents the distance between the current candidate gray wolf and the prey; $\vec{X_p}$ is the position vector of the prey, and $\vec{X}(t)$ represents the position vector of the gray wolf; $\vec{A}$ and $\vec{C}$ are the collaborative coefficient vectors, and the calculation method is shown in Eq. (20) and Eq. (21). The gray wolf searches for prey by changing the value of the vector $\vec{A}$. When $|\vec{A}| > 1$: α, $\beta$ and δ stay away from each other, which is conducive to global search; when $|\vec{A}| < 1$: $\alpha$, $\beta$ and $\delta$ tending to converge to the location of the prey, facilitating local search. The parameter $\vec{C}$ is randomly generated, which is beneficial for the gray wolf search to jump out of the local optimum.

In Eq. (20) and Eq. (21), $\vec{r_1}$ and $\vec{r_2}$ pick random values from [0,1], and the value of parameter $\vec{a}$ decreases linearly from 2 to 1 during the search iteration process. During the search process of the algorithm, the updated method of the position vector is as follows:

$$\vec{X_1} = \vec{X_\alpha} - \vec{A_1} \cdot |\vec{C_1} \cdot \vec{X_\alpha} - \vec{X}| \tag{22}$$

$$\vec{X_2} = \vec{X_\beta} - \vec{A_2} \cdot |\vec{C_2} \cdot \vec{X_\beta} - \vec{X}| \tag{23}$$

$$\vec{X_3} = \vec{X_\delta} - \vec{A_3} \cdot |\vec{C_3} \cdot \vec{X_\delta} - \vec{X}| \tag{24}$$

$$\vec{X}(t+1) = \frac{\vec{X_1} + \vec{X_2} + \vec{X_3}}{3} \tag{25}$$

In Eqs. (22-25), $\vec{X_\alpha}$, $\vec{X_\beta}$and $\vec{X_\delta}$ are position vectors of $\alpha$, $\beta$ and $\delta$. $\vec{X}$ indicates the current position vector that needs to be updated. Fig. 2 shows how the search agent updates its location based on $\alpha$, $\beta$, and $\delta$ in a two-dimensional search space. It can be observed that the final position will be located at a random position within a circle defined by $\alpha$, $\beta$, and $\delta$ positions in the search space. In other words, $\alpha$, $\beta$, and $\delta$ estimate the location of the prey, and other wolves randomly update the location around the prey.

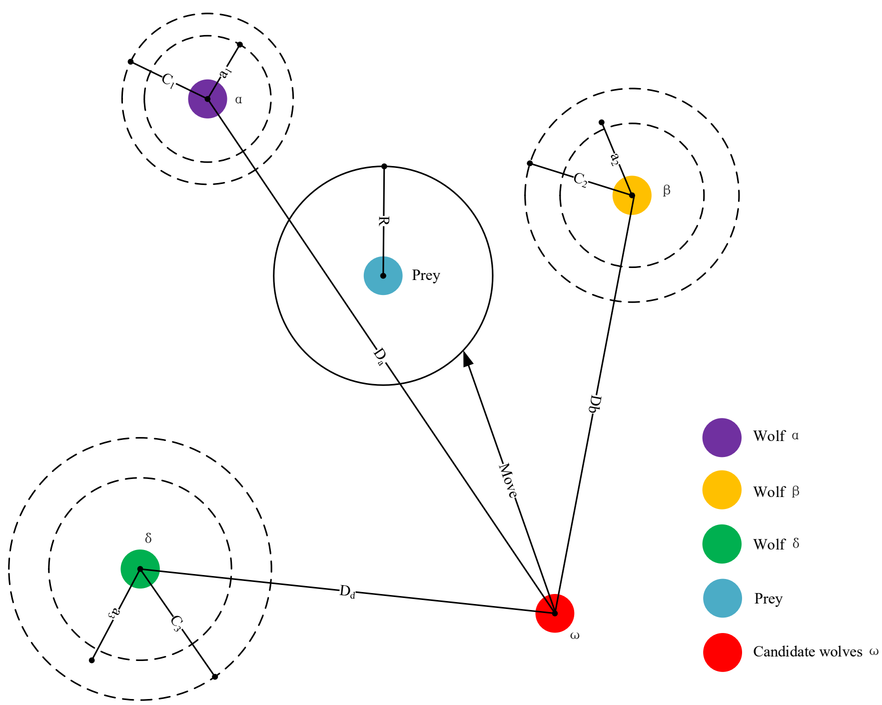


**Fig. 2.** Gray Wolf position update diagram

GWO algorithm has the advantages of simple parameters, easy implementation, fast convergence speed, and good robustness, and it is suitable for optimizing various types of nonlinear single-objective optimization problems. In this paper, the DDMRP material management strategy is combined with it to solve the production planning optimization problem under resource constraints.

### *4.2 DDMRP-GWO Optimization Algorithm*

To address the constraints of capacity and storage space buffer constraints, DDMRP-GWO is proposed. In the proposed algorithm, if the capacity and storage space can meet the demand for manufacturing orders in the current cycle, the planned production quantity of each type of job is calculated according to Eqs. (3-13). Otherwise, it is a constrained optimization problem. The GWO algorithm is used to optimize the planned production capacity of various jobs under constraint conditions because GWO adopts real number coding and has a simple coding format. At the same time, it is easy to control the numerical range of the solution and has relatively balanced global search and local search capabilities. The optimization process of the DDMRP-GWO algorithm in the form of process flow is shown in Fig. 3.

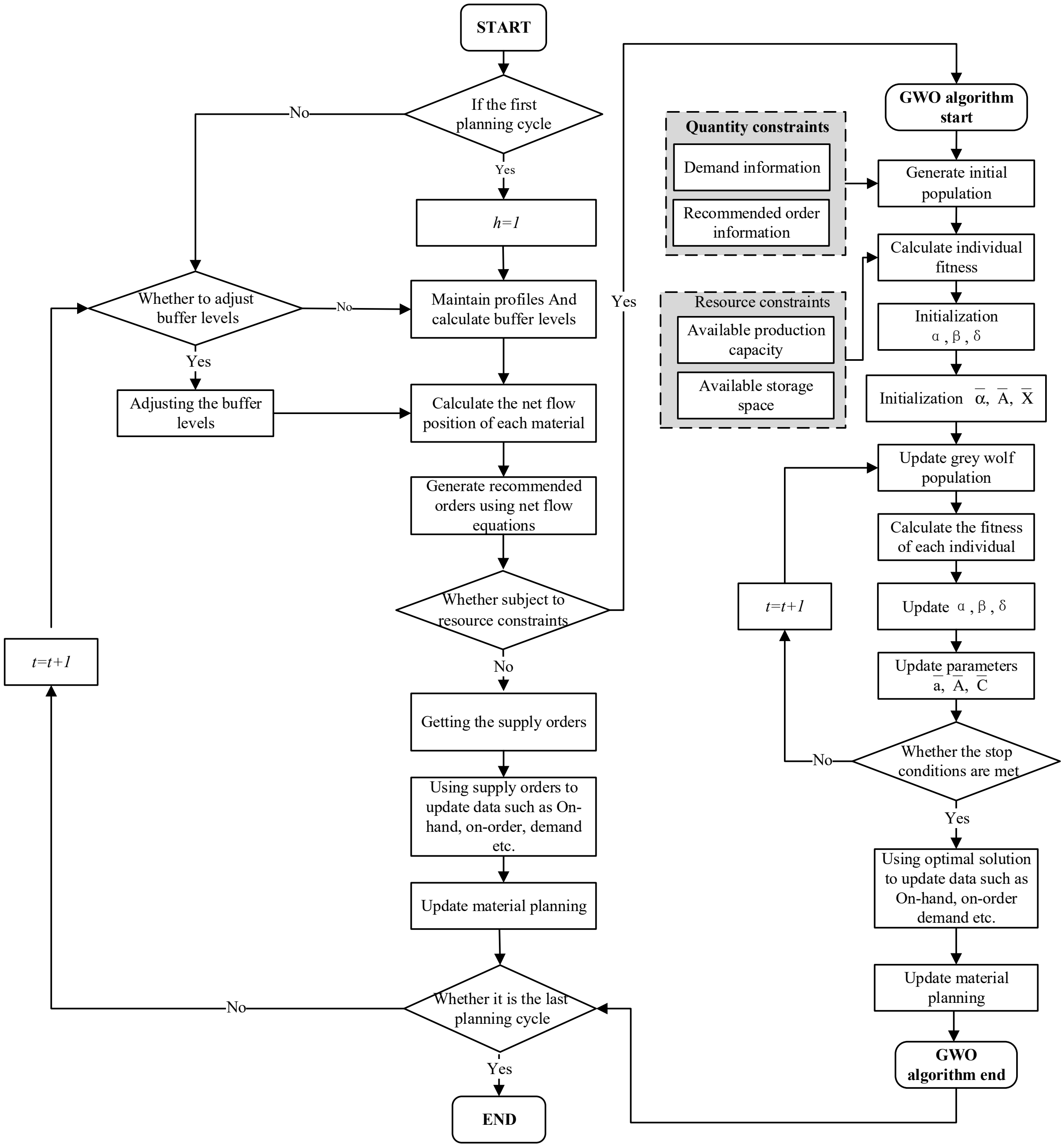


**Fig. 3.** Production plan optimization flow chart

It can be seen from Fig. 3 that for the production plan optimization problem constrained by production capacity and storage space. A material management method based on DDMRP calculates the optimal replenishment quantity of strategic materials as the upper limit of the value randomly generated by the initial solution. If the required production capacity for the obtained material production quantity is met, the production plan is formulated and organized according to the quantity; otherwise, the GWO algorithm optimization process is transferred. The production plan optimization problem studied in this paper is a multi-planning cycle, rolling, and continuous optimization process. The modification of production plans for various materials in the subsequent cycle is based on the results of the previous cycle. Therefore, the proposed DDMRP-GWO algorithm is an iterative optimization process based on the number of planned weeks. The specific operation steps of the algorithm are discussed below:

**Step 1:** Maintain inventory buffer configuration files for each material group, which mainly include parameters such as Average Daily Usage (ADU), Decoupled Lead Time (DLT), Lead Time Factor (LTF), Desired Order Cycle (DOC), and Variability Factor (VF), with the current planning cycle index $h = 1$.

Step 2: If $h > 1$, check whether the inventory buffer configuration files need to be modified. If modification is necessary, adjust the relevant data accordingly.

Step 3: Calculate the recommended replenishment quantity $V_t$ for each material using Equations (3) to (13), where $t = 1,2,\cdots,T$ represents the length of the position vector, which is equal to the number of materials being optimized in the production plan.

Step 4: Use Equations (14) and (15) to determine whether production based on the recommended replenishment quantity violates capacity and storage space constraints. If there is no violation, adjust the planned production quantity for each cycle according to the value of $V_t$ and proceed to Step 13. Otherwise, proceed to Step 5.

Step 5: Generate an initial population. Use a random method to generate values for each position vector, where the $t$-th value within any position vector follows a discrete uniform distribution DU(0,$V_t$), where $t = 1,2,\cdots,T$.

Step 6: Initialize parameter vector $\vec{a}$, as well as the collaborative coefficient vectors $\vec{A}$ and $\vec{C}$.
Step 7: Calculate the fitness values for the position vectors in the population and select the three best position vectors with the highest fitness values as $\overrightarrow{X_\alpha}$, $\overrightarrow{X_\beta}$ and $\overrightarrow{X_\delta}$.
Step 8: Update parameter vector $\vec{a}$, as well as the collaborative coefficient vectors $\vec{A}$ and $\vec{C}$.
Step 9: Use Equations (22) to (25) to update the position vectors of each location in the population based on the current $\overrightarrow{X_\alpha}$, $\overrightarrow{X_\beta}$, and $\overrightarrow{X_\delta}$.
Step 10: Calculate the fitness values for the position vectors of each location in the population.
Step 11: Update $\overrightarrow{X_\alpha}$, $\overrightarrow{X_\beta}$, and $\overrightarrow{X_\delta}$ based on the fitness values of the position vectors in the population.
Step 12: If the optimization stopping criterion for this planning cycle is met, proceed to Step 13; otherwise, proceed to Step 6.
Step 13: If the algorithm stopping criterion is met, output the optimization results and stop the algorithm. Otherwise, set $h = h + 1$, transmit the optimization results to the planning cycle $h$, and proceed to Step 2.

In the DDMRP-GWO algorithm, the encoding length is equal to the number of job types produced in each planning cycle. Each digit value represents the planned production quantity of the corresponding type of job. Since the production quantity of each material is a positive integer, the algorithm uses decimal rounding method for decoding. The DDMRP-GWO algorithm is adopted to solve the material planning optimization problem under resource constraints, which fully leverages the advantages of metaheuristic algorithms in solving constraint optimization problems and the effectiveness of DDMRP in materials management in complex environments. By integrating the two methods, an optimized solution for material production planning can be obtained, which can better optimize resource allocation under fluctuating demand, avoid significant discrepancies between material production and actual outputs, reduce the output efficiency of the final products, and consequently cause production capacity waste and delayed orders. This will affect the on-time fulfillment rate of customer orders for final products.

## 5. Experimental design

This section contains numerical experiments using the proposed DDMRP-GWO algorithm to verify the effectiveness of solutions. To demonstrate the superiority of the proposed algorithm over traditional methods in solving production planning optimization problems in complex environments, the OPM material management strategy is combined with the GWO algorithm as a comparative algorithm, referred to as OPM-GWO. In the experiment, both the DDMRP-GWO algorithm and the OPM-GWO algorithm used for comparison were implemented through Java programming. The experimental running environment was Apple M1 pro, with 16GB of memory, and the MacOS Ventura 13.0.1 operating system.

### *5.1 Experimental data*

In this section of the experiment, four sets of test instances were designed, and each instance included demand data for 3 different types of jobs over 22 production planning cycles. The demand data for various types of jobs within different planning cycles are generated using a uniform distribution method. The volatility rate of the demand data is controlled by fixing the upper and lower limits of the uniform distribution values. The four sets of test data are shown in Table 1. From Fig. 4, we can see the changes in the demand for different types of jobs over the 22 planning cycles. Overall, there is significant variability in the demand data for each type of part across different periods, which poses a challenge for production planning. The DDMRP-GWO and OPM-GWO algorithms combine the traditional OPM to optimize the material planning for each type of part over different planning cycles under resource constraints. The shortage situation, buffer and inventory levels for each material are observed.

**Table 1**
Demand data for each instance

| Instance | Type | Demand quantity | | | | | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 | 16 | 17 | 18 | 19 | 20 | 21 | 22 |
| D1 | T1 | 36 | 45 | 35 | 31 | 48 | 46 | 34 | 41 | 45 | 39 | 30 | 44 | 31 | 50 | 46 | 44 | 44 | 38 | 30 | 39 | 46 | 48 |
| | T2 | 37 | 48 | 49 | 45 | 43 | 45 | 44 | 36 | 45 | 50 | 31 | 48 | 40 | 46 | 46 | 49 | 32 | 49 | 33 | 35 | 35 | 39 |
| | T3 | 48 | 33 | 42 | 33 | 49 | 41 | 46 | 40 | 42 | 49 | 47 | 47 | 44 | 35 | 46 | 46 | 33 | 48 | 33 | 41 | 38 | 44 |
| D2 | T1 | 32 | 62 | 43 | 31 | 58 | 69 | 38 | 57 | 39 | 33 | 44 | 34 | 33 | 35 | 56 | 55 | 43 | 36 | 50 | 67 | 70 | 48 |
| | T2 | 51 | 48 | 68 | 53 | 51 | 66 | 53 | 44 | 48 | 39 | 69 | 52 | 38 | 70 | 56 | 56 | 45 | 69 | 30 | 66 | 48 | 44 |
| | T3 | 35 | 48 | 45 | 45 | 32 | 65 | 63 | 42 | 53 | 65 | 62 | 67 | 33 | 58 | 45 | 46 | 48 | 52 | 65 | 31 | 68 | 61 |
| D3 | T1 | 74 | 46 | 52 | 48 | 22 | 62 | 44 | 52 | 57 | 22 | 60 | 74 | 44 | 72 | 44 | 21 | 70 | 37 | 45 | 27 | 47 | 28 |
| | T2 | 65 | 76 | 78 | 30 | 70 | 26 | 21 | 76 | 47 | 53 | 50 | 60 | 30 | 47 | 65 | 59 | 26 | 31 | 45 | 67 | 52 | 66 |
| | T3 | 41 | 44 | 26 | 35 | 50 | 41 | 77 | 72 | 58 | 31 | 53 | 38 | 41 | 41 | 74 | 50 | 51 | 56 | 40 | 35 | 43 | 72 |
| D4 | T1 | 16 | 50 | 40 | 70 | 37 | 31 | 28 | 36 | 76 | 34 | 76 | 15 | 17 | 52 | 89 | 54 | 90 | 58 | 73 | 72 | 74 | 89 |
| | T2 | 37 | 73 | 75 | 27 | 75 | 32 | 40 | 82 | 46 | 69 | 80 | 15 | 61 | 11 | 61 | 68 | 31 | 36 | 56 | 85 | 38 | 59 |
| | T3 | 84 | 30 | 65 | 24 | 74 | 58 | 40 | 86 | 38 | 61 | 34 | 46 | 40 | 64 | 23 | 14 | 62 | 14 | 31 | 40 | 66 | 33 |

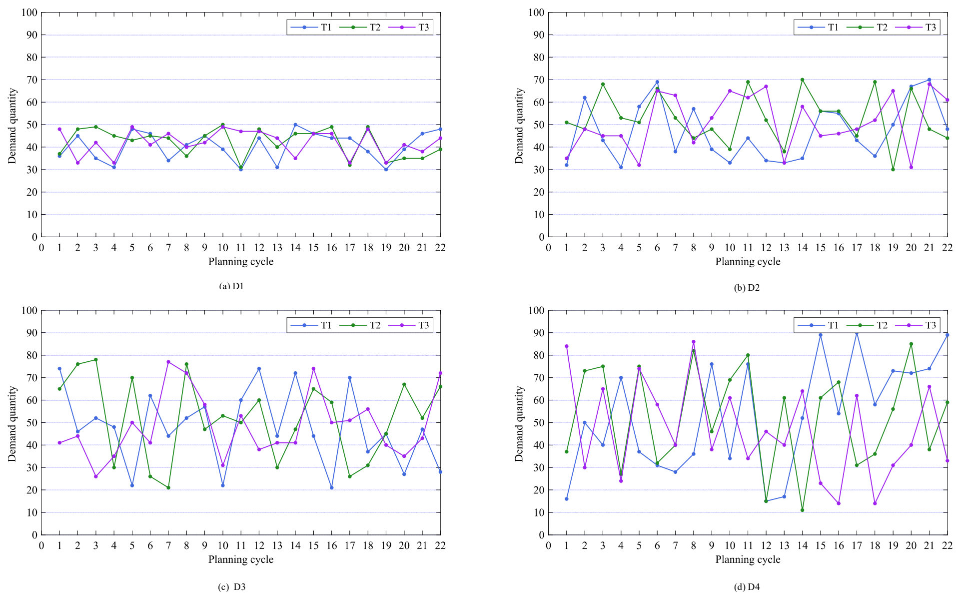


**Fig. 4.** Demand variation for different types of jobs in each instance

## *5.2 Performance evaluation indicators*

In comparative experiments, we used two evaluation indicators to assess the advantages and disadvantages of two production plan optimization methods: shortage rate and inventory level.

(1) Shortage rate: the shortage rate indicates the degree to which the number of existing jobs meets the required jobs by calculating through Eq. (6).

$$SR_{h,t} = \frac{B_{h,t}}{R_{h,t}} \tag{26}$$

$$B_{h,t} = \begin{cases} R_{h,t} - OH_{h,t} & R_{h,t} > OH_{h,t} \\ 0 & R_{h,t} \le OH_{h,t} \end{cases} \tag{27}$$

$$R_{h,t} = AN_{h,t} + DN_{h,t} \tag{28}$$

In Eq. (26), $B_{h,t}$ represents the shortage quantity of type $t$ jobs during planning period $h$, which is calculated by Eq. (27). $R_{h,t}$ represents the actual demand quantity for jobs of type $t$ during planning cycle $h$, which is calculated by Eq. (28). The smaller the value of $SR_{h,t}$, the closer the inventory level for jobs of type $t$ during that planning period. When the value of $SR_{h,t}$ is 0, it indicates that the existing inventory completely meets the demand quantities and production activities can be carried out according to the production plan without delay caused by material shortages.

(2) Inventory (buffer) level: refers to the total inventory of various types of jobs in a planning cycle. The calculation method is shown in Eq. (29):

$$IL_h = \sum_{t=1}^{T} OH_{h,t} \tag{29}$$

The smaller the value of $IL_h$, the less storage space each part occupies during that planning period. Maintaining the same service level, the lower the inventory level is, the higher the material management level of the enterprise is considered.

$$VR_t = \frac{\sigma_t}{\overline{Q_t}} \tag{30}$$

In Eq. (30), $\sigma_t$ represents the standard deviation of type t jobs, $\overline{Q_t}$ represents the average value of the quantity of type t jobs over each planning period, and the calculation method of $\sigma_t$ is shown in Eq. (31):

$$\sigma_t = \sqrt[2]{\frac{\sum_{t=1}^{T}\left(Q_{h,t} - \overline{Q_t}\right)^2}{N_t}} \tag{31}$$

In Eq. (31), $Q_{h,t}$ is the demand quantity of type t jobs during planning period h and $N_t$ is the total number of statistical periods for type t jobs in the experimental data. $VR_t$ reflects the degree of demand volatility, and it is a relative indicator. When $VR_t$ is relatively small, it indicates that the demand quantity for this type of job in each planning period is not significantly different, which makes it easier to ensure the stability of production planning and processes. When $VR_t$ is larger, it means that the demand quantity for the job varies significantly in different planning periods, which can have a significant impact on production planning and capacity allocation for the enterprise. $VR_t$ can better reflect the degree of data volatility relative to $\sigma_t$.

*5.3 Parameter settings*

The numerical experiment in this section aims to verify the effectiveness of the DDMRP-GWO algorithm in dynamically adjusting production plans for varying customer demand fluctuations. In Section 5.1, four sets of demand data with different volatility levels are given randomly. The volatility rate of different types of jobs in these four examples can be calculated using Eq. (30), as shown in Table 2.

**Table 2**
The volatility rate of demand for different types of jobs in each instance

| Instance | Demand volatility rate | | |
|---|---|---|---|
| | T1 | T2 | T3 |
| D1 | 0.10 | 0.14 | 0.12 |
| D2 | 0.27 | 0.21 | 0.23 |
| D3 | 0.35 | 0.34 | 0.29 |
| D4 | 0.45 | 0.41 | 0.45 |

It can be seen from Table 2 that in the four instances, the volatility rate of each material demand data varies significantly from 0.10 to 0.45, which can better test the effectiveness of DDMRP-GWO against different fluctuation level demand data.

**Table 3**
Instance and Parameter Settings

| Instance | Initial inventory (For OPM) | Order point (For OPM) | Initial on-hand (For DDMRP) | LTF (For DDMRP) | VF (For DDMRP) |
|---|---|---|---|---|---|
| D1 | 260 | 260 | 260 | 0.7 | 0.5 |
| D2 | 260 | 260 | 260 | 0.7 | 0.5 |
| D3 | 260 | 260 | 260 | 0.7 | 0.7 |
| D4 | 260 | 260 | 260 | 0.7 | 0.7 |

It is necessary first to determine some relevant parameters for calculating the strategic material buffer level while using DDMRP-related methods. According to the volatility rate of materials in each example, the settings of relevant parameters are given in Table 3. In this experiment, the resource constraints of the production system (capacity and storage space) must be considered. The settings of the parameters related to resources are shown in Table 4.

**Table 4**
Production capacity and resource constraints information related to T1, T2 and T3

| Parameter names | Value |
|---|---|
| Total available production capacity of the production line for each planning cycle | 960 |
| Total storage space of T1, T2 and T3 | 800 |
| Capacity required for the production of a unit quantity of T1 | 4 |
| Capacity required for the production of a unit quantity of T2 | 3 |
| Capacity required for the production of a unit quantity of T3 | 2 |

### 5.4 Analysis of experimental results

We independently run DDMRP-GWO and OPM-GWO algorithms 20 times on each of the four instances and compare the results by selecting the run with the lowest average stockout rate. The statistical results are shown in Table 5, where NOS represents the number of times of material stockout, SR represents the average stockout rate, and IL′ is the average inventory level.

**Table 5**
Results obtained by DDMRP-GWO and OPM-GWO

| Instance | Type | DDMRP-GWO | | | OPM-GWO | | |
|---|---|---|---|---|---|---|---|
| | | NOS | SR | IL′ | NOS | SR | IL′ |
| D1 | T1 | 0 | 0 | 547 | 7 | 0.25 | 531 |
| | T2 | 0 | 0 | | 7 | 0.21 | |
| | T3 | 0 | 0 | | 7 | 0.23 | |
| D2 | T1 | 0 | 0 | 509 | 6 | 0.16 | 621 |
| | T2 | 0 | 0 | | 8 | 0.21 | |
| | T3 | 0 | 0 | | 6 | 0.20 | |
| D3 | T1 | 1 | 0.01 | 505 | 8 | 0.24 | 586 |
| | T2 | 0 | 0 | | 10 | 0.32 | |
| | T3 | 0 | 0 | | 6 | 0.22 | |
| D4 | T1 | 3 | 0.06 | 515 | 10 | 0.26 | 499 |
| | T2 | 0 | 0 | | 11 | 0.35 | |
| | T3 | 0 | 0 | | 6 | 0.20 | |

From Table 5, the planning scheme obtained by the DDMRP-GWO algorithm performs significantly better than the OPM-GWO algorithm over 22 planning cycles. When the volatility rate is less than 0.3, there is no shortage of materials. In instance D3 and D4, despite material shortages, the number of occurrences during the entire cycle is very small, and the average shortage rate is far less than 0.1. Correspondingly, the results of the OPM-GWO algorithm are not satisfactory. In four instances, the frequency of material shortages for each type of job in any planning cycle is no less than 6. The average shortage rate is above 0.2, which is significantly higher than the results of DDMRP-GWO. In terms of average inventory level, the performance of the two algorithms is not significantly different. In summary, the DDMRP-GWO algorithm has advantages in solving material planning optimization problems in demand fluctuations and resource constraints. Of course, from the statistical data, as the volatility rate of demand data increases, the solution results of the OPM-GWO algorithm gradually deteriorate. That is, the order point method is more suitable for material management in stable demand environments. In contrast, the DDMRP method is suitable for material management in complex and volatile demand environments. To observe the experimental results more intuitively, we present the statistical values of the evaluation indicators obtained by the two algorithms on each instance in a graphical form. Fig. 5 and Fig. 6 respectively show the line charts of the shortage rate and average on-hand inventory quantity obtained by DDMRP-GWO and OPM-GWO algorithms on the four instances.

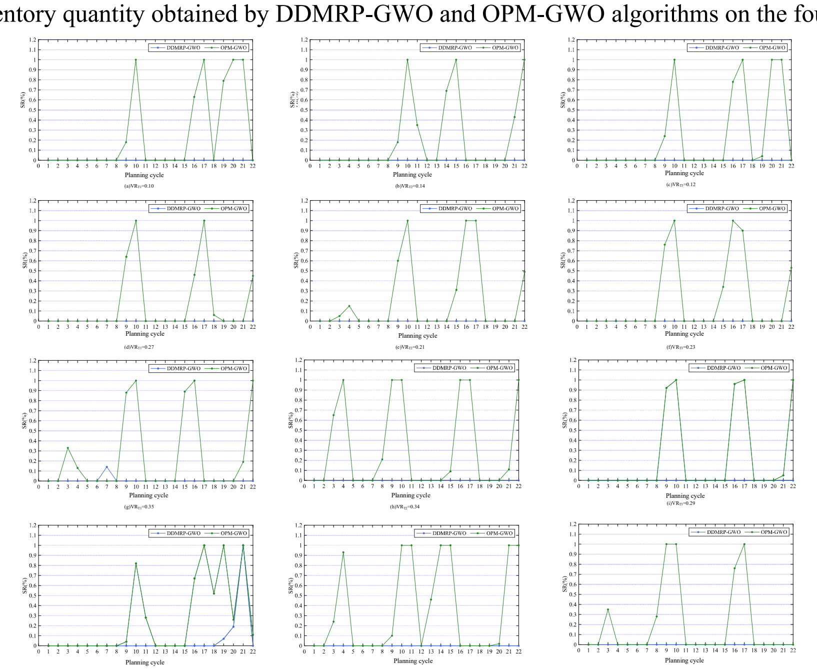


**Fig. 5.** Line chart comparing stockout rates of different types of jobs in each instance

In Fig. 5, the comparison of the material production plans obtained by the DDMRP-GWO algorithm and the OPM-GWO algorithm in 22 planning cycles based on the shortage rate indicator can be intuitively seen. In the four instances with different volatilities, the DDMRP-GWO algorithm obtains significantly lower statistical values of shortage times and shortage rates during the planning execution than the OPM-GWO algorithm. Only a few jobs experienced shortages in the 22 planning cycles, proving that the DDMRP method can better adjust material production planning and manage material inventory in complex production environments, reducing and suppressing shortages.

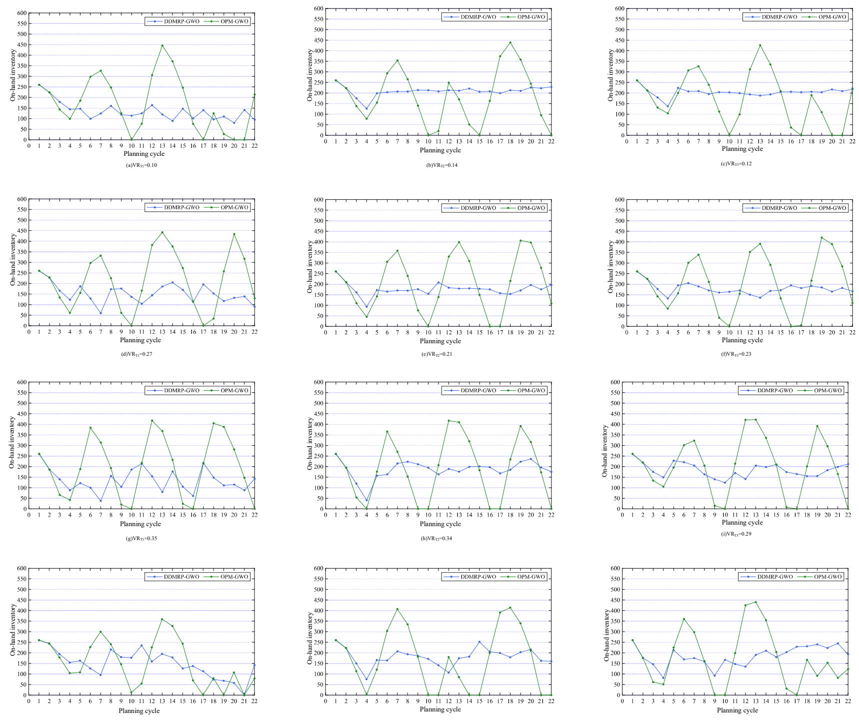


**Fig. 6.** Line chart comparing on-hand inventory of different types of jobs in each instance

Similarly, in Fig. 6, the four rows correspond to four instances, and the three graphs for each row show the changes in the inventory of three types of artifacts in an instance. It can be seen from Fig. 6. that: (1) For any given test instance, the results obtained by DDMRP-GWO algorithm show that the change in the quantity of on-hand inventory is relatively small. This indicates that the level of work-in-process remains in a stable status, which can better ensure the timely supply of materials during the production process and avoid material shortages. (2) In the results obtained by the OPM-GWO algorithm, there is a situation where the line intersects the horizontal axis in multiple line charts, i.e., the inventory is 0, which is consistent with the results in Table 5. That means the material plan obtained by the OPM-GWO algorithm will frequently experience material shortages during implementation due to the volatility of demand. The DDMRP method can effectively dynamically adjust the planned production volume, ensuring the smooth progress of production. (3) For four instances, as shown in Table 2, there are significant differences in volatility among the instances. However, it can be seen from Fig. 6 that the inventory level in the DDMRP-GWO solution remains relatively stable, and the line intersects with the x-axis very little (only occurring when $VR_{T1} = 0.46$ in instance D4). In general, DDMRP-GWO can obtain better material production planning and the generated planning can ensure the smoothness of the production process and material inventory, thereby improving the management level and service quality of the enterprise.

Using the DDMRP-GWO algorithm has achieved relatively good results for fluctuating customer demands. This is because the fluctuating market demand of DDMRP is generated by using the net process equation to generate new supply orders to meet the demands of production plan adjustment. In the net process equation (9), when calculating supply orders, it considers order peaks that threaten the stability of production plans within the peak range. It helps to make it possible to maximize the absorption and suppression of the impact of demand fluctuations on enterprise production compared to traditional forecast-based planning while maintaining a stable production process and meeting various random demands of customers. When considering resource constraints, the implementation effect of DDDMR will be affected to a certain extent, and the related materials and planned production volumes will be subject to bulk constraints from the net flow calculation results and resource constraints. The combination of DDMRP and metaheuristic algorithms can better achieve the application of DDMRP methods under resource constraints. Compared to traditional planning methods, it can improve the material planning and management of enterprises in complex environments by shortening the delivery time and improving the performance rate. It should be noted that, if an enterprise's production planning is frequently constrained by existing production resources such as capacity and storage space during execution, it means that the enterprise's production resource configuration can no longer match the current customer needs. In this case, it is necessary to re-plan production resources to fundamentally solve the current problem.

## 6. Conclusion

In a complex market environment, the traditional material planning method based on forecasting cannot timely respond to the impact of frequent changes in demand. The DDMRP solution can effectively solve the production planning and material management problems under the fluctuation of supply and demand. When the demand fluctuates more severely, resource constraints will restrict the execution of unreasonable material plans. Heuristics are suitable for solving constraint optimization problems. Therefore, a combined material management method based on DDMRP and the GWO algorithm is constructed for the complex production environment to propose the DDMRP-GWO algorithm. DDMRP-GWO algorithm helped to solve the production plan optimization problem under constraints and designed a numerical experiment to verify the effectiveness of the proposed algorithm. It can be seen from the experimental results that the DDMRP-GWO method is more optimized for solving the production plan optimization problem under fluctuating demand conditions. The DDMRP method can dynamically adjust the quantity of material demand and buffer level, which can better ensure the smoothness of the production process and absorb and suppress the impact of the material shortage on enterprise production. At the same time, the smooth production process also lays a good foundation for pull methods such as DBR/JIT to play to their potential.

Production planning optimization has always been an important issue in production management. In future research, existing algorithms will continue to be improved or new algorithms will be developed to improve planning optimization efficiency and accuracy, considering different production environments, scales, and optimization goals. Meanwhile, for complex material supply networks, future research can consider the collaborative optimization of multiple material plans, extend the scope of material plan optimization to the supply chain, integrate supply chain management with production planning optimization, and establish more comprehensive optimization models to reduce costs and improve operational efficiency.

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