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RESEARCH ARTICLE

Multiobjective Lot Sizing and Scheduling of Multiproduct Switching Production in the Process Industry Considering Uncertain Market Information Under Mass Customization

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ABSTRACT With the gradual diversification of customer demand, to improve the rapid response ability of enterprises, this paper fully considers uncertain market information under the background of mass customization and establishes a new process industry multi-product switching production lot sizing and scheduling model with the goal of minimizing the maximum completion time and total switching cost. Fuzzy chance-constrained programming is used to explicitly incorporate market demand with uncertain quantities into the model. Starting from reality, this paper considers the switching cost of equipment when processing multiple varieties of products and skillfully integrates the conversion rate of materials during processing into the novel model, making the entire production system closer to the real state. It provides a new concept to consider cost reduction for actual workshop scheduling management. In addition, this paper proposes an improved multi-objective genetic particle swarm optimization (SMOPSO-IIs) algorithm, and the basic parameters are tested by RSM method. The optimal parameters pc $= 0.6$, pm $= 0.06$, $\alpha = 0.25$, $\beta = 4$ are obtained. They are substituted into SMOPSO-IIs to simulate and solve the model. The operation results show that the Pareto solution obtained by the SMOPSO-IIs algorithm is better overall. Finally, the model is solved by example simulation, and the operation results are analyzed along with a scheduling Gantt chart to verify its applicability and effectiveness. The model presented in this paper can be used to further shorten the gap between production theory and practical application and improve the current workshop scheduling management system of the process industry.

INDEX TERMS Mass customization, process industry lot sizing and scheduling, uncertain market information, product switching.

I. INTRODUCTION

With the wave of the industrial revolution, the demand characteristics of consumers have gradually changed from the original popularization to new personalization and diversification. To actively cater to the market, the production mode of the process industry began to transform from the original small variety and large quantity approach to the current multi-variety and small quantity approach. However, to meet the diverse customer needs and follow the existing lot production model in the process industry, there is a certain contradiction between the two approaches, and a mass customization background is arising at this historic moment. Mass customization is a new production mode that combines the mass production mode with customer-personalized customization needs. In this mode, enterprises need to shift from quality-centered

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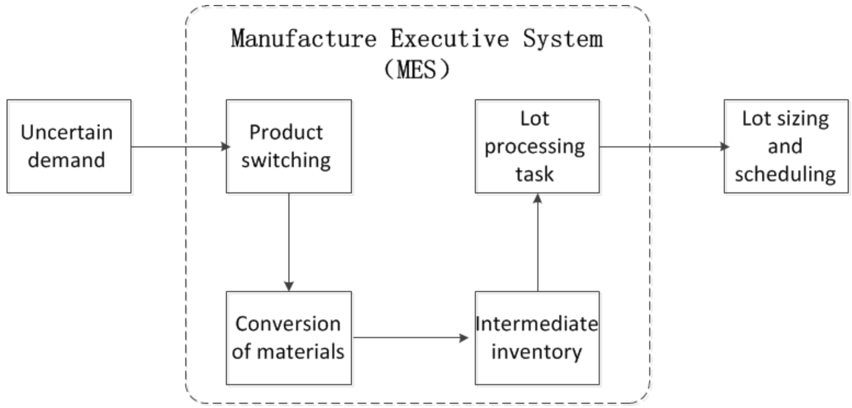

FIGURE 1. Process industrial production system operation flow chart.

to personalized demand-centered, with a timely response to the external dynamic market, by adjusting the lot production plan in the workshop to ensure the production of corresponding orders within the delivery period [1], [2]. However, progress has also led to the gradual complexity and diversity of external market information. Therefore, uncertain market information is a problem that enterprises encounter in actual production. Therefore, how to use uncertain market information to formulate production plans and respond in time within the workshop has become a major challenge for the operation of the process industry in the context of mass customization [3], [4]. Consideration of uncertain market information in the context of mass customization is a background environment worthy of study that has practical application value.

Under this challenging background environment, this paper starts from the internal enterprise to process the uncertain demand orders from the market, and uses the manufacturing execution system (MES) to formulate the corresponding production plan and implement scheduling for the orders [5], [7]. In contrast to previous studies, the novelty and contribution of this paper are in the implementation of product lot sizing and scheduling, in addition to consideration of uncertain demand information, as well as the novel proposition of the problem of product switching in multi-variety process industries. When product switching occurs on the same equipment, workers need to clean and adjust the equipment. Because of the relationship between product purity labeling and chemical properties such as the composition, the time and cost of cleaning and adjustment differ when switching between different types of labeling, and the time and cost of product switching should not be ignored and should be taken into account when formulating production plans for products. In addition, the complete transformation of materials is still an ideal research situation in theory. However, in actual production, 100% conversion of materials is not necessarily possible; that is, for a certain equipment, the input and output of materials can be unequal. Therefore, when multispecies lot sizing and scheduling occur in the process industry in an MES system, production switching and material transformation need to be considered. To reflect the innovation of this paper and the overall context, Fig. 1 shows a flow chart of the industrial process production system.

In summary, when the process industry is facing uncertain market information for mass customization production, how to take into account the practical problems of both product switching and material transformation, as well as the dynamic response of external information, to implement lot scheduling arrangements is key in this study.

II. LITERATURE REVIEW

With the continuous development of the social economy, external competition is becoming increasingly fierce, and the whole market is in a constantly changing environment. Therefore, it is often unrealistic for a single enterprise to obtain information on all of the products in the market, and how to deal with uncertain market demand in the production of products has gradually become a key link in manufacturing research. In the existing research, uncertain market demand is mainly divided into stochastic uncertain demand and fuzzy uncertain demand [8], [11]. For the production problem under stochastic uncertain demand, after considering the dependence of equipment conditions and production rate on output, Zhang *et al.* [12] proposed an integrated decision-making strategy for single-machine production and maintenance under uncertain demand and solved it through a two-stage stochastic programming model. Karakaya and Köksal [13] studied a multiperiod product line mixing problem considering the interdependence between products and the destruction effect of new products in the context of uncertain price, demand and production cost and established a two-stage stochastic programming model for this purpose. Delgoshaei and Ali used the normal distribution in stochastic programming to solve uncertain market demand in dynamic unit production planning [14]. Delgoshaei *et al.* considered the impact of uncertain costs on the unit manufacturing system and used the normal distribution to deal with market demand so that the system could dynamically adjust the scheduling scheme [15]. Frazzon *et al.* proposed and applied a data-driven adaptive planning and control method to determine the most suitable scheduling rules under different conditions in real time [16]. Giordani *et al.* dynamically changed the working position of a robot according to the fluctuations in demand and production cost, thus forming a flexible layout and solving the corresponding scheduling problem [17]. For the production problem under fuzzy uncertain demand, Liu *et al.* [18] used the scenario probability and triangular fuzzy numbers to describe uncertain demand and introduced complexity theory to measure and model the uncertainty of assembly lines. Guo *et al.* [19] constructed a total cost model of a remanufacturing closed-loop supply chain system considering carbon taxes and subsidies under uncertain market demand. To address the uncertainty of the model, they used the fuzzy chance constrained programming method. In the above literature, whether considering the production problem under stochastic uncertain demand or fuzzy uncertain demand, the existing research is mostly from the perspective of planning to achieve the allocation of resources and line planning, and investigation of the production scheduling field under uncertain demand remains to be expanded.

The demand of the market often drives production changes in the manufacturing industry. Mass customization starts from the customization and complex demands of customers in the market and adjusts the original mass production mode to quickly respond to the change in external demand. The specific production problems within enterprises under the background of mass customization are focus areas worthy of attention [20], [21]. Among them, Modrak *et al.* [22] provided an effective solution to optimize batch size to minimize product delivery time and maximize system throughput in mass customization mode. Khan *et al.* [23] focused on generating automated process planning for a single-machine problem under mass customization and focused on reducing the time lead time. Two evolutionary algorithms (EAs) were compared to solve complex process planning problems. To make scheduling research under the background of mass customization more practical, He *et al.* [24] established a flexible manufacturing system of parts input sorting and robot scheduling, developed a mathematical model for a time-based decision-making problem and proposed a method based on a segment set to solve the problem. From the above literature on production research under mass customization, it is apparent that both planning and scheduling arrangements have been developed for a certain system and scale, but they are all based on conditions under demand determination.

Therefore, in view of the current development trend, scholars began to study mass customization production under uncertain market demand. Among them, Song *et al.* [25] developed a product configuration model that fully considers the uncertainty of delivery time in mass customization. Wei *et al.* [26] proposed a flexible design method for product families based on dynamic demand uncertainty analysis to improve the dynamic response ability of product families to market changes. Weskamp *et al.* [27] proposed a two-stage stochastic mixed integer linear programming model that comprehensively considers the delivery time, penalty cost of shortage and inventory decisions under the condition of uncertain demand. The above methods focus on product configuration and production planning, while specific scheduling problems within the workshop are rarely considered.

Since the relationship between market demand and mass customization is considered in the above analysis, what is the relationship between mass customization and production scheduling? The process industry characterized by mass production is able to respond in a timely manner under mass customization [28], [29]. In the existing multi-species production scheduling model of the process industry, scholars mainly consider a series of objectives, such as the completion time and inventory cost. For example, in an intelligent manufacturing environment, Yuan *et al.* [30] studied the workshop problem with machines and workpieces as the object to minimize the maximum completion time, lateness, machine load and energy consumption. Bai *et al.* [31] achieved feasible scheduling under mass customization with the shortest processing time and earliest due date. Gu *et al.* [32] simultaneously considered the economic and environmental factors, studied the permutation flow shop scheduling problem (MOPFSP) to minimize the completion time and carbon emissions, and proposed a hybrid cuckoo search algorithm (HCSA) to solve this problem. Hakeem-Ur-Rehman *et al.* [33] studied multilevel and multistage batch and scheduling demand information updating problems with the objective of minimizing the total production and inventory costs and established a mixed integer programming (MIP) model. To solve the problem of flexible process routes and frequent changes in workshop scheduling schemes in multiple varieties and small batch production modes, Sun *et al.* [34] established a multi-process route scheduling optimization model with carbon emissions and cost as multiple objectives.

Several objectives reflected in the above literature are common in the processing of multi-variety process industries. However, in actual production, the switching costs between various products cannot be ignored. Therefore, in recent years, experts have begun to focus on the switching of products. Among them, Zhou *et al.* [35] described and abstracted the dyeing process scheduling problem in a workshop and constructed a mathematical scheduling optimization model to minimize the delay cost and switching cost. Wu *et al.* [36] focused on the switching product cost generated in the cold rolling process, the ordering cost when the demand was not satisfied, and the inventory holding cost when the inventory was surplus and formulated the production and inventory plan for cold rolling with the goal of minimizing the above costs. Although there are few articles on product switching, it is worth exploring the future directions. In addition, there are many deficits in the literature on the material conversion rate in the multi-variety production scheduling model of the process industry.

In summary, whether focused on uncertain market demand or today's mass customization, the production scheduling problem with time series arrangement is a major issue that is worthy of study. The analysis of the literature indicates that the research of process production scheduling problems with uncertain demand under the background of mass customization is a new field. To resolve the lack of research, this paper also incorporates the two situations of multi-product switching and the material conversion rate, which are less studied at present, into the lot sizing and scheduling of multi-product process industry. Thus, the production control system of the process industry can more closely reflect the actual production situation to adjust the production plan and scheduling to improve the rapid response ability to external market changes.

The organization of this article is as follows. Section III describes the problem. Section IV proposes a multi-objective and multistage lot sizing and scheduling model and explains the objectives and constraints. Section V describes in detail the processes of the coding design stage of the model and the design stage of the multi-objective hybrid particle swarm optimization (SMOPSO-IIs) algorithm. Section VI provides the parameter optimization, performance test of the multi-objective algorithm, simulation test at different scales, and simulation test of the process industry with weekly demand reference value. The conclusion and future research directions are presented in section VII.

III. PROBLEM DESCRIPTION

The gradual diversification of customer demand in the current market conflicts with the existing mass production mode in the process industry. In addition, because of the limits of their business scope, it is not realistic for enterprises to obtain all the definite information on the market. To better meet the customization needs of customers, this paper focuses on how the process industry responds to the external uncertain market demand in the context of mass customization and fully considers the core issues of product switching and material conversion generated in the multi-variety lot production mode when scheduling.

The market needs p products, and each product must go through s production stages in the production process. Among them, $P = \{1, 2, \ldots, p\}$, $S = \{1, 2, \ldots, s\}$. It is assumed that the market demand of product $i \in P$ during the planning period is denoted as De_i. Since the material has a certain conversion rate in the input and output of the process-based production method, the production of the product at each stage is not completely equal. Let θ_{ij} denote the conversion rate of product $i \in P$ at stage $j \in S$. Usually, equipment will process and produce multiple products, so the production of the same product $i \in P$ at any stage $j \in S$ is denoted as Q_{ij}. In the actual production process, the amount of Q_{ij} will be greater than the single production lot of the equipment at this stage, so the product must be produced in lots at any stage.

In the process of lot production, the size of the lot, the number of production switches and the actual capacity of the production container will have different degrees of influence on the planning of the production lot. Therefore, in actual production, the lower limit and upper limit of each processing lot should be stipulated, that is, Bb_{ij}^{max} and Bb_{ij}^{min} represent the maximum upper and minimum lower limits of the processing lot in stage j of product i, respectively. Therefore, the first problem to be solved in multi-variety lot production planning is to determine the production lots and production lots of each product at each stage to meet the requirements of the material dynamic transformation relationship and lot boundary and realize the supply and demand coordination required for production.

The production time of many products $i \in P$ at stage $j \in S$ has a linear relationship with the lot size, and λ_{ij} is recorded as the production processing time coefficient related to the lot size. In addition, at the same stage $j \in S$, if the two lots are processed separately for different varieties of products, there is also time required to adjust and clean the equipment q_{ij}. For the same product $i \in P$, taking into account the actual situation of storing semifinished products and buffer stocks between two adjacent production stages j and $j+1$, the workshop will configure storage devices between the two production stages, with the maximum inventory capacity of the storage device E_{ij}^{max}. Thus, the second problem to be solved in multi-variety lot production planning is to make the lot scheduling that meets the first problem further meet the requirements of the equipment production capacity, intermediate inventory capacity constraints and production punctuality.

IV. MATHEMATICAL MODEL ESTABLISHMENT

A. NOMENCLATURE

index/set	explanation
$i \in P$	product
$j \in S$	stage
$k \in N$	position

symbol	explanation
α_{ijk}	whether the product i is processed at the kth position on stage j, true is 1, false is 0
bb_{ijk}	the volume of production that product i is assigned to the kth location on stage j
bb_{ij}^{max}	the maximum limit for processing lots of product i on stage j
bb_{ij}^{min}	the minimum limit for processing lots of product i on stage j
θ_{ij}	the conversion rate of product i processing lot on stage j
$tstart_{ijk}$	the lot start processing time for product i to be assigned to the kth location on stage j
$tend_{ijk}$	the lot completion time for product i to be assigned to the kth location on stage j
$E_{ijkk'}$	the difference between the total amount of inventory processed for product i at the kth position on stage j and the amount of materials that need to be processed and

	consumed at position k' of stage $j+1$, that is, the intermediate inventory
E_{ij}^{max}	the maximum inventory capacity of product i at stage j
λ_{ij}	the production and processing time coefficient of product i at stage j
q_{ij}	the time required to adjust and clean up the equipment when product i switches on stage j
De_i	the demand for product i
Z	the outlook period
pr	the unit inventory cost of a factory
g_{ij}	the number of lots of product i on stage j
Q_{ij}	the production of a product i at any stage j
$T_{ii'j}$	the adjustment time required for production from product i to product i' on stage j
jm	the total number of equipment
km	the total number of event points
$u_{ijkk'}$	whether the intermediate inventory is greater than 0; true is 1, false is 0
$v_{ijkk'}$	whether the intermediate inventory is less than the maximum capacity limit; true is 1, false is 0
A	a positive number that is sufficiently big
B	a positive number that is sufficiently small

B. PROBLEM ASSUMPTIONS

1) Each piece of reaction equipment in the production line can produce a variety of products.
2) The demand for each product varies with time;
3) Due to the limitation of equipment capacity, the lot size is related to the reactor capacity;
4) Each piece of equipment can produce only one product;
5) When the equipment is switched from the current production process to the next production, the equipment needs to be adjusted. The adjustment time and adjustment cost are related to the product correlation and processing sequence;
6) Each product can be produced in one or more consecutive lots during the planned outlook period.

C. ANALYSIS OF OBJECTIVE FUNCTIONS

1) CONVERSION OF MATERIALS

In addition to the conversion of products described in the previous section, the conversion rate of materials is another key link to be considered. In actual production scheduling, due to problems with the equipment itself, the material may have a certain loss in the production process; that is, the input material received by the equipment does not necessarily equal the intermediate material output after processing. This unequal phenomenon of material production is defined as the conversion of materials [37]. Material conversion is related to the product variety and processing equipment performance. Different products with different equipment conversion rates are not the same, and thus the transformation of materials also affects the production lot.

For example, when the same lot of product i is processed on two adjacent stages j and $j+1$, there will be a transformation relationship between materials. Although they are the same product, their conversion rates at different stages of equipment are not the same, namely, $\theta_{ij} \neq \theta_{i,j+1}$. Then, for stage j, the material produced can be put into stage $j+1$, specific to (3):

$$bb_{i,j+1,k'} = bb_{ijk}\theta_{ij} \tag{1}$$

With the completion of product i in stage j, stage $j+1$ also ushers in a new material, and then a new proportion of the transformation will occur. The transformed material will continue to be put into the next stage of production. Equation (4) can be expressed as:

$$bb_{i,j+2,k''} = bb_{i,j+1,k'}\theta_{i,j+1} \tag{2}$$

The transformation of materials affects the lot production, and the lot production further affects the lot completion time of the product. In this paper, the production time of each lot is not fixed, and is closely related to the lot and conversion rate, forming a linear mapping relationship. For example, when product i is lot-processed at position k of stage j, its processing time $\lambda_{ij}\theta_{ij}bb_{ijk}$ can be expressed by (3):

$$t_{ijk} = \lambda_{ij}\theta_{ij}bb_{ijk} \tag{3}$$

It can be seen that the conversion of materials also has a certain impact on the total completion time when the process industry lots and schedules multiple orders, so the conversion rate of materials should also be included in the establishment of the model.

2) PRODUCT SWITCHING

In the production scheduling problem of the process industry, if it involves multi-product processing, there will inevitably be product switching problems. For enterprises, although there are different types of products in the order information transmitted from the market, there are often certain similarities between multiple products. To facilitate management, according to the similarity between products, enterprises can divide the same or similar products into a product family. In this way, products in the same product family can be divided into the same production line for mass production. Since each piece of equipment can only process one lot of products at the same time, when product switching occurs on the equipment, workers need to clean and adjust the equipment. Because of the relationship between product purity labels and chemical properties such as the composition, the switching requirements between different labels differ. If it is converted from low-grade to high-grade production, the cleaning and adjustment requirements of the equipment will be reduced accordingly, resulting in relatively less more time and cost consumption; if the equipment is converted from high-grade to low-grade production, the cleaning and adjustment requirements of the equipment will be significantly increased compared with the previous situation. The switching from high to low requires more procedures and even the addition of cleaning materials. Therefore, the time and cost consumption will be significantly increased when the equipment is converted from high-grade to low-grade.

From the perspective of time, the lot completion time of each product is composed of three parts, namely, the start time $tstart_{ijk}$ of the lot, the processing time of the material $\lambda_{ij}\theta_{ij}bb_{ijk}$ in the lot and the adjustment and cleaning time $q_{ij}\alpha_{ijk}$ due to product switching. Among them, the first two periods are determined by the lot, and the product switching time $q_{ij}\alpha_{ijk}$ can be regulated by the scheduling scheme to minimize the impact of the switching time on the total completion time. Therefore, the lot completion time of each product can be expressed by (4):

$$tend_{ijk} = tstart_{ijk} + \lambda_{ij}\theta_{ij}bb_{ijk} + q_{ij}\alpha_{ijk} \tag{4}$$

From a cost perspective, different products in the same device will lead to different switching costs due to their different purity labels, which can be expressed as $q_{ij}pr_{ij}$. However, variety switching does not occur every time for the equipment, and thus α_{ijk} must be defined at this time. Therefore, the switching cost of a certain amount of equipment can be expressed by (5):

$$C_{zh} = \sum_{i \in P} \sum_{k \in N} \left(q_{ij}\alpha_{ijk} \times pr_{ij} \right) \tag{5}$$

Product switching has a significant impact on the total completion time and total processing cost when the process industry uses lot sizing and scheduling for multi-product orders. This factor should be included in the establishment and consideration of the multi-product lot sizing and scheduling model of the process industry.

3) ESTABLISHMENT OF OBJECTIVE FUNCTIONS

Definition 1: The processing event of a certain lot at a certain stage of each product is called an event point, which includes all the information of the product in a corresponding lot, such as the number of lots, the lot size, and the lot production time. The lot sizing at different event points is between the maximum upper limit and the minimum lower limit of the reaction capacity at this stage, and the intermediate inventory between the event points shall not exceed the specified maximum intermediate inventory. The sequence of the stages passed by the event points of each product is prescribed in advance.

Definition 2: The event points are connected as a series of lines, and the line connected by each event point is defined as the associated layer. The correlation layer is divided into two types: one is the fully correlated layer, where all devices have event points on the connection, and the other is the incomplete correlation layer, where all devices have no event points on the connection. Incompletely related layers are divided into the front-end and back-end. There is no event point of the first device on the front-end incompletely correlated layer and no event point of the last device on the back-end incompletely correlated layer.

a: MINIMIZING THE MAXIMUM COMPLETION TIME

In the process production control system studied in this paper, the product processing time is not a fixed value and is related to the product variety, lot and stage. The production stage of the product is determined by the process flow of the product. Differing process complexity leads to different process time consumption under the same production task. The lot processing time of the product is determined by the lot and production coefficient of the product at the current stage; the lot of products is determined by market demand. In the actual production process, there is the problem of the material processing conversion rate; that is, the input material cannot be completely converted into the required output. Therefore, when calculating the lot production processing time, the output material after the conversion of the adjacent previous stage is used as the input material in the next stage, as discussed in Section IV.C.1. In addition, since this system can produce multiple products, there will be product switching and cleaning time between many different products at the same stage. This part of the time is defined as the variety switching time and is incorporated into the calculation, as discussed in Section IV.C.2. Based on the above analysis, the completion time of each lot of each product can be obtained. By comparing the completion time of different lots for all products in the whole system, the maximum is the final production and processing end time in a scheduling scheme for this system. To identify the optimal scheme, the shortest total processing time is selected as the criterion to minimize the maximum completion time, as shown in (6):

$$F_1 = min \left\{ max \left\{ tstart_{ijk} + \lambda_{ij}\theta_{ij}bb_{ijk} + q_{ij}\alpha_{ijk} \mid i \in P \right\} \right\} \tag{6}$$

where $tstart_{ijk}$ represents the lot start processing time of product i at position k of stage j; $\lambda_{ij}\theta_{ij}bb_{ijk}$ represents the lot processing time of product i at position k of stage j; and $q_{ij}\alpha_{ijk}$ represents the time that product i requires for adjustment and cleaning of the device during the variety switching at the location of phase j.

b: MINIMIZING THE TOTAL SWITCHING COSTS

There is no parallel machine in this paper, so when different product lots are produced at the same stage, it is necessary to produce multiple varieties in turn. In the actual production process, when different products are switched at the same stage, it is necessary to allow for certain equipment switching and cleaning times rather than a seamless connection, which has rarely been considered in previous studies. Therefore, when the process production control system proposed in this paper is used for lot sizing and scheduling of multiple products, we give the second objective function of this paper based on (5) derived in Section IV.C.2, that is, to minimize the total switching cost, as shown in (7):

$$F_2 = min \sum_{i \in P} \sum_{j \in S} \sum_{k \in N} \left(q_{ij}\alpha_{ijk} \times pr_{ij} \right) \quad (7)$$

$q_{ij}\alpha_{ijk}$ represents the switching time re quired for variety switching of a certain number of products in a certain stage, and the corresponding switching cost can be obtained by multiplying the unit switching cost in this stage. The total switching cost generated in the scheme is obtained by accumulating all the switching generated in the whole scheme. The lower the total switching cost is, the lower the number of switches needed in the scheme is, and the more reasonable the scheduling of the scheme is.

D. ANALYSIS OF CONSTRAINT CONDITIONS

In the process of establishing a multi-objective mathematical model of multi-product switching production in the process industry, this paper mainly focuses on the clarification of uncertain demand, the rationalization of intermediate inventory in the production line and the serialization constraints of each processing task in the production line.

1) THE CLARITY OF UNCERTAIN MARKET DEMAND

There are many levels of uncertain market information, such as the uncertainty in the demands of variety, quantity and price. However, this paper mainly focuses on market demand with an uncertain quantity. the sum of the lot production tasks of each product on the production line in the last machine should be consistent with the market demand for the product, and the uncertain market demand often has certain ambiguity. Here, the product demand is defined as a fuzzy variable [38]. (8) can be used to represent the equality of supply and demand in the production process:

$$\sum\nolimits_{k \in P} bb_{ijk} = \widetilde{De_i}, \quad \forall i \in P, j = jm \quad (8)$$

After this transformation, (8) becomes a conceptual formula, which can represent fuzzy market demand but cannot be solved. Therefore, this chapter introduces the concept of fuzzy chance constrained programming; that is, the decision can be made before the constraints with random variables are realized, and the decision results are allowed to fail to meet the constraints to a certain extent, but the probability of the establishment of the constraints should not be less than the confidence level [39]. The specific form and performance are as follows:

$$Pos \{f(\varphi, \varepsilon)\} \geq \gamma \quad (9)$$

$Pos\{f(\varphi, \varepsilon)\}$ denotes the possibility of an event in $f(\varphi, \varepsilon)$; φ represents clear variables; ε represents fuzzy variables; and γ represents the confidence level. According to (9), (8) can be changed to (10).

$$Pos \left\{ \sum\nolimits_{k \in P} bb_{ijk} = \tilde{De_{ij}} \right\} \geq \gamma, \forall i \in P, j = jm \quad (10)$$

To clarify the fuzzy chance-constrained programming, this chapter refers to the classic α-cut method in the literature [40], that is, if $\tilde{y} = (y_1, y_2, y_3)$ is a triangular fuzzy number, then for any given confidence level $\alpha \in (0, 1)$, there are:

$$\begin{cases} Pos\{\tilde{y} \leq k\} \geq \alpha, & if \quad k \geq (1-\alpha) y_1 + \alpha y_2 \\ Pos\{\tilde{y} = k\} \geq \alpha, & if \quad \begin{cases} k \geq (1-\alpha) y_1 + \alpha y_2 \\ k \leq (1-\alpha) y_3 + \alpha y_2 \end{cases} \\ Pos\{\tilde{y} \geq k\} \geq \alpha, & if \quad k \leq (1-\alpha) y_3 + \alpha y_2 \end{cases} \quad (11)$$

Therefore, according to the principle of the α-cut method, $\widetilde{De_{in}} = (De_{in1}, De_{in2}, De_{in3})$ is a triangular fuzzy number, and (8) can be transformed into (12) and (13):

$$\sum_{k \in P} bb_{ijk} \geq (1-\gamma) De_{i1} + \gamma De_{i2}, \quad \forall i \in P, j = jm \quad (12)$$

$$\sum_{k \in P} bb_{ijk} \leq (1-\gamma) De_{i3} + \gamma De_{i2}, \quad \forall i \in P, j = jm \quad (13)$$

2) RATIONALIZATION OF INTERMEDIATE INVENTORY

Multiple products can be processed on each machine, but when the machine processes each product, each position point can only have at most one lot production task, which can be expressed by (14):

$$\sum\nolimits_{i \in P} \alpha_{ijk} \leq 1, \quad \forall j \in S, k \in N \quad (14)$$

In addition, each location point does not necessarily have many production tasks; that is, there may be virtual location points. If the position point is real, then $\sum_{i \in P} \alpha_{ijk} = 1$, and $\sum_{i \in P} \alpha_{ijk} = 0$. When the previous position point is real, $\sum_{i \in P} \alpha_{ijk} = \sum_{i \in P} \alpha_{ij,k+1}$. Similarly, when the previous location point is virtual, $\sum_{i \in P} \alpha_{ijk} > \sum_{i \in P} \alpha_{ij,k+1}$. Therefore, the relationship between position points can be expressed by (15):

$$\sum_{i \in P} \alpha_{ijk} \geq \sum\nolimits_{i \in P} \alpha_{ij,k+1}, \quad \forall j \in S, k \in N, k \neq km \quad (15)$$

Since this paper considers that the material of each lot of the product between adjacent machines is not completely transformed in the actual situation, the production task lot of the same lot of the same product in the two adjacent stages is not necessarily equal; that is, the input material of a certain lot of the machine should be the intermediate material produced by the same lot after the conversion rate is calculated by the machine in the adjacent previous stage, rather than the input material of the machine in the adjacent previous stage. Therefore, the relationship between reaction amount and production amount in each batch can be expressed by (16):

$$\sum_{k \in N} bb_{ijk}\theta_{ij} = \sum_{k \in N} bb_{i,j+1,k}, \quad \forall i \in P, j \in S, j \neq jm \quad (16)$$

Due to the physical limitations of the machines on the production line, only a limited number of products can be produced at one time. To rationalize the number of products in each lot task, this paper makes a quantitative limitation on the lot; that is, the lot of products should be within the range of the machine's processing capacity at the corresponding stage, which can be expressed by (17):

$$\alpha_{ijk} Bb_{ij}^{min} \leq bb_{ijk} \leq \alpha_{ijk} Bb_{ij}^{max}, \quad \forall i \in P, j \in S, k \in N \tag{17}$$

In the actual production process, the intermediate products produced are not necessarily completely consumed by the next adjacent stage, so there is an intermediate inventory. Due to the limited space in the production workshop, there is also a quantitative limit interval in the intermediate inventory. The intermediate inventory can be expressed by the difference between the production tasks of the same lot of the same product in the two adjacent machines, which can be expressed by (18):

$$E_{ijkk'} = \sum\nolimits_{0 \leq kk \leq k} \theta_{ij} bb_{i,j,kk} - \sum\nolimits_{0 \leq kk \leq k'} bb_{i,j+1,kk}, \quad \forall i \in P, j \in S, j \neq jm, k \in N, k' \in N \tag{18}$$

However, the intermediate inventory is not necessarily within a reasonable range, so it needs to be restricted, as shown in (19) and (20).

Among them, if the intermediate inventory is greater than 0, then $u_{ijkk'} = 1$. $(u_{ijkk'}-1)A = 0$, $u_{ijkk'}A+(u_{ijkk'}-1)B$ are great positive numbers; if the intermediate inventory is less than 0, then $u_{ijkk'} = 0$. Because B is a minimal positive number and A is a maximal positive number, then $(u_{ijkk'}-1)A$ is a minimal negative number and $(u_{ijkk'} - 1)B$ is a maximal negative number, so $u_{ijkk'}A+(u_{ijkk'}-1)B$ must be greater than $(u_{ijkk'} - 1)A$, $(u_{ijkk'} - 1)A \leq E_{ijkk'} \leq u_{ijkk'}A + (u_{ijkk'} - 1)B$, and can be expressed as (19):

$$\left(u_{ijkk'} - 1\right) A \leq E_{ijkk'} \leq u_{ijkk'}A + \left(u_{ijkk'} - 1\right) B, \quad \forall i \in P, j \in S, j \neq jm, k \in N, k' \in N \tag{19}$$

If the intermediate inventory is less than the maximum capacity limit, then $v_{ijkk'} = 1$, $(v_{ijkk'} - 1)A = 0$. $E_{ij}^{max} - E_{ijkk'}$ is a positive number, and $v_{ijkk'}A + (v_{ijkk'} - 1)B$ is a great positive number; if the intermediate inventory is greater than the maximum capacity limit, then $v_{ijkk'} = 0$. Since B is a minimal positive number and A is a maximal positive number, then $E_{ij}^{max} - E_{ijkk'}$ is a negative number, $(v_{ijkk'} - 1)A$ is a minimal negative number, and $(v_{ijkk'} - 1)B$ is a maximal negative number, so $v_{ijkk'}A + (v_{ijkk'} - 1)B$ must be greater than $(v_{ijkk'} - 1)A$, and can be expressed as (20):

$$\left(v_{ijkk'} - 1\right) A \leq E_{ij}^{max} - E_{ijkk'} \leq v_{ijkk'}A + \left(v_{ijkk'} - 1\right) B, \quad \forall i \in P, j \in S, j \neq jm, k \in N, k' \in N \tag{20}$$

3) SERIALIZATION OF PROCESSING TASKS

Since a single machine on each production line can produce only one task at the same time, there is a certain time relationship between the lot production tasks corresponding to each location point.

First, the relationship between the adjacent two position points of the same product on the same machine is determined. If there are many production tasks at the two adjacent position points on a certain machine and the same product is produced at the two position points, the start time of the lot production task at the latter position point should not be less than the end time of the lot production task at the former position point, which can be expressed by (21):

$$tstart_{ij,k+1} \geq tstart_{ijk} + q_{ij}\alpha_{ijk} + \lambda_{ij} bb_{ijk}\theta_{ij}, \quad \forall i \in P, j \in S, k \in N, k \neq km \tag{21}$$

Second, the relationship between two adjacent position points of different products on the same machine is considered. If there are many production tasks at two adjacent position points on a certain machine and different products are produced at two position points, the start time of lot production tasks at the latter position point should not be less than the sum of the end time of lot production tasks corresponding to the former position point and the adjustment time between the two products, which can be expressed by (22):

$$tstart_{i'jk} + q_{i'j}\alpha_{i'jk} + \lambda_{i'j} bb_{i'jk}\theta_{i'j} - Z(1-\alpha_{i'jk}) + T_{i'ij}\alpha_{ij,k+1} \leq tstart_{ij,k+1}, \quad \forall i \in P, i' \in P, j \in S, k \in N \tag{22}$$

Third, the relationship between the same lot of the same product on the adjacent machine is considered: if the same lot of a product has a lot production task on the adjacent machine, the start time of the lot production task on the back machine position point should not be less than the end time of the lot production task on the front position point adjacent to the previous machine, as shown in (23) and (24).

Among them, if there is no lot production task at the position point of the previous machine, the left side of the inequality is a minimal negative value, the right side is a positive value, and the inequality is constant. If there is no lot production task at the position point of the rear machine, the right side of the inequality is a maximum positive value, the left side is a normal positive value, and the inequality is constant; if there are lot production tasks at nonadjacent positions of the two machines, then $Z\left(1-\alpha_{ijk}\right) = 0$. If the intermediate inventory from k to k' is nonnegative and the intermediate inventory from $k-1$ to k' is nonnegative, then $Zu_{ij,k-1,k'}+Z\left(1-u_{ijkk'}\right) \rightarrow \infty$, and the inequality is constant; if the intermediate inventory from k to k' is less than 0 and the intermediate inventory from $k-1$ to k' is less than 0, or if the intermediate inventory from k to k' is less than 0 and the intermediate inventory from $k-1$ to k' is nonnegative, or if the intermediate inventory from k to k' is nonnegative and the intermediate inventory from $k-1$ to k' is less than 0, the above three situations do not satisfy the assumption that there is a lot production task at the nonadjacent position points of the two machines, so the above three situations do not hold. The above analysis can be expressed by (23):

$$tstart_{ijk} + q_{ij}\alpha_{ijk} + \lambda_{ij} bb_{ijk}\theta_{ij} - Z\left(1-\alpha_{ijk}\right) \leq tstart_{i,j+1,k'} + Z\left(1-\alpha_{i,j+1,k'}\right) + Zu_{ij,k-1,k'} + Z\left(1-u_{ijkk'}\right), \quad \forall i \in P, j \in S, j \neq jm, k \in N, k' \in N \tag{23}$$

If there is no lot production task at the position point of the previous machine, the left side of the inequality is a minimal negative value, the right side is a positive value, and the inequality is constant. If there is no lot production task at the position point of the rear machine, the right side of the inequality is a maximum positive value, the left side is a normal positive value, and the inequality is constant; if there are lot production tasks at nonadjacent positions of the two machines, then $Z\left(1-\alpha_{ijk}\right) = 0$. If the intermediate inventory from k to k' is less than the maximum capacity limit and the intermediate inventory from $k-1$ to k' is less than the maximum capacity limit, then $Zv_{ijk,k'-1} + Z\left(1-v_{ijkk'}\right) \rightarrow \infty$, and the inequality is constant; if the incoming intermediate inventory from k to k' exceeds the maximum capacity limit and the incoming intermediate inventory from $k-1$ to k'exceeds the maximum capacity limit, or if the incoming intermediate inventory from k to k' exceeds the maximum capacity limit and the incoming intermediate inventory from $k-1$ to k' is less than the maximum capacity limit, or if the incoming intermediate inventory from k to k' is less than the maximum capacity limit and the incoming intermediate inventory from $k-1$ to k' exceeds the maximum capacity limit, the above three situations do not satisfy the assumption that there are many production tasks at the nonadjacent positions of the two machines, so the above three situations do not hold. The above analysis can be expressed by (24):

$$\begin{aligned} tstart_{i,j+1,k'} - Z\left(1-\alpha_{i,j+1,k'}\right) \leq\, & tstart_{ijk} \\ & + q_{ij}\alpha_{ijk} + \lambda_{ij}bb_{ijk}\theta_{ij} + Z\left(1-\alpha_{ijk}\right) \\ & + Zv_{ijk,k'-1} + Z\left(1-v_{ijkk'}\right) \forall i \in P, j \in S, \\ & \quad j \neq jm, k \in N, k' \in N \end{aligned} \tag{24}$$

In addition to the above constraints, this paper changed event points when dealing with the number constraints of event points, and the process has no aftereffect.

Proof: When dealing with the event point, the supply material constraint is first carried out in order from the beginning to the end; that is, the consumption of the same product in the same lot at the same stage shall not be greater than the production of the same lot in the previous stage. If the supply is insufficient, the corresponding lot of the subsequent product is moved backward to the nearest event point where the same equipment does not conflict. This supply material constraint ensures that the equipment can continuously produce and that the intermediate inventory of the same product between the same lot in the adjacent two stages is greater than or equal to 0. After the supply material constraint is completed, the intermediate inventory constraint is checked from back to front, that is, whether the intermediate inventory of the same product exceeds the maximum intermediate inventory between the same lots in the adjacent two stages. If the maximum inventory is exceeded, the corresponding lot of the preorder product is moved backward to the nearest event point where the same device does not conflict. Additionally, because the product before moving in the adjacent phase of the same lot of intermediate inventory exceeds the maximum limit, that is, $E_{ijkk'} \geq E_{ij}^{max}$, and the maximum capacity of a single device is less than the maximum inventory between devices, that is, $bb_{ij}^{max} \leq E_{ij}^{max}$, moving back the event point will only reduce the number of intermediate inventory, and it is still positive and will not destroy the completed supply constraints, so there is no aftereffect. The proof is complete.

V. IMPROVED MULTI-OBJECTIVE GENETIC PARTICLE SWARM OPTIMIZATION (SMOPSO-IIs) BASED ON MODEL SOLVING

A. CODING OF PARTICLES

The multi-objective lot sizing and scheduling problem in the process industry necessitates determination of the lot number, lot sizing, production sequence and production time at each stage of each product before formal production. To solve the problem of lot planning and scheduling, this paper uses pb_{qlk} to denote the lot of particle q, pX_{qlk} represents the position vector of particle q, and $T = (1, 2, \ldots, t)$ represents the set of tasks. In this article, the particle has two dimensions to store information. The first dimension represents the task information where the particle is located and is composed of two parts of information, the product i and the stage j; when it represents the product i information on the stage j, $l = i+p(j-1)$, where $l \in T$. The second dimension represents the lot position where the particles are located; because a position in each stage can only correspond to many products, the set of variables in the position k of particle q in stage j is $U = \{pb_{qlk} \,| l = i + p(j-1), \ldots, pj\}$.

In the particle encoding process, two main factors are considered: that is, the production volume is equal to the demand, and each product is produced in only one lot at each stage. To solve the above two constraints in a targeted manner, this paper describes two modified sub-strategies for the initialized particle swarm.

1) SUPPLY AND DEMAND REVISION SUBSTRATEGIES

Because there is no intermediate inventory problem after the product has undergone the final lot of the last stage of processing, the sum of the lots converted in all stages of the product should be equal to the demand order quantity of the product. To meet this requirement, this article makes the following adjustments to the initialized particle population:

Step 1. l represents two kinds of information, including products and equipment included in particles, Q_l represents the total processing amount of l, O_l represents the total output of l, and De_i represents the demand for product i. Initialize these variables and let O_l be zero, which is determined according to the actual order requirements.

Step 2. Let j be the final stage number of the product.

Step 3. When the final stage number of product i is e, the total output of product i is:

$$O_l = O_{i+p(e-1)} = \sum_{k=1,\ldots,n} pb_{q,i+p(e-1),k} \times \theta_{i+p(e-1)} \tag{25}$$

Step 4. When the total output O_l is greater than the total demand De_i, reduce the lots that are not 0 from n until they are equal; when the total output O_l is less than the total demand De_i, increase the lot to 0 from the back to the front until the total output is equal to the demands. It should be noted that the new lot cannot exceed the maximum lot limit specified for each lot.

Step 5. Let $j = j - 1$, calculate the output and demand in the phase, and then compare them.

$$O_l = O_{i+p(j-1)} = \sum_{k=1,\ldots,n} pb_{q,i+p(j-1),k} \times \theta_{i+p(j-1)} \quad (26)$$

$$De_i = Q_{i+pj} = \sum_{k=1,\ldots,n} pb_{q,i+pj,k} \quad (27)$$

Step 6. When $j > 1$, repeat Steps 5 to 6 to complete the lot repair of all products in each stage; when $j = 1$, go to Step 7.

Step 7. End.

2) SUBSTRATEGY OF EQUIPMENT PRODUCTION REVISION

Each product is produced in only one lot at each stage; that is, there can only be one nonzero variable in the set U.

Step1 Randomly generate the selection probability of each product.
Step2 Compare the probabilities and record the product number with the highest probability f.
Step3 When $f \neq l$ in the set U, $pb_{qlk} = 0$.

B. DECODING OF PARTICLES

The lot sizing of each product at each stage can be determined through the encoding of particles, but the encoded particles only meet the limitations of capacity and demand. In addition, the particles will be adjusted according to the time correlation and cohesion before and after the process characteristics to further determine the working time of each lot of processing. The particle decoding process is given below:

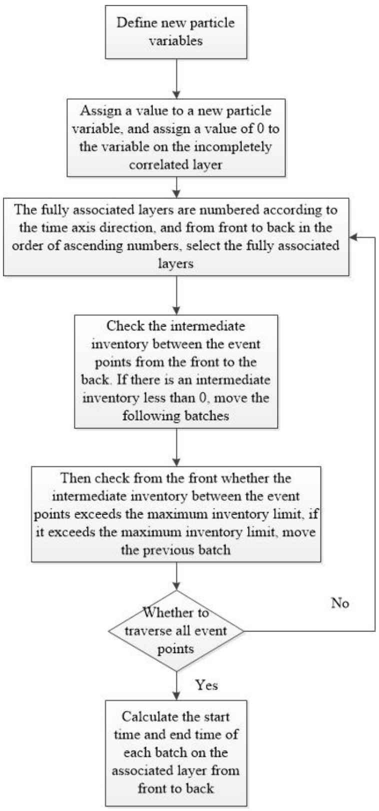

FIGURE 2. Flowchart of particle decoding.

C. STEPS OF THE IMPROVED MULTI-OBJECTIVE GENETIC PARTICLE SWARM OPTIMIZATION (SMOPSO-IIs) ALGORITHM

MOPSO, NSGA-II and SPEA2 are the most common heuristic algorithms for solving multi-objective mathematical models in the past. Among them, the MOPSO algorithm relies on the particle speed to complete the search, the search speed is faster, but the lack of dynamic speed regulation, easy to fall into local optimum. NSGA-II algorithm avoids falling into local optimum by introducing crossover and mutation ideas, but its stability is not high. SPEA2 algorithm can further improve the overall quality of Pareto front, but it has the disadvantage of weak local search ability. To sum up, this paper will improve the MOPSO algorithm, integrate it with NSGA-II algorithm and SPEA2 algorithm for Pareto optimization, and propose a new SMOPSO-IIs algorithm. The specific algorithm steps are as follows:

Step1 Define the population size and iterations and initialize the population.
Step2 Encode and decode particles.
Step3 Calculate the fitness value and determine the individual optimal particles.
Step4 Replace the initialized population with constraint conditions to generate a particle population that meets the requirements of the topic. Initialize the Pareto optimal solution set and find the nondominated liberation into the Pareto optimal solution set in the required particle swarm.
Step5 In the Pareto optimal solution set, according to the degree of congestion, an adaptive grid method is used to select a leader as $Gbest$, and the particle population is updated by using the velocity and position update formula of the particle swarm. If better particles are generated, the individual optimal particle $pbest$ is updated. Continue to update the particle population into the constraints to be adjusted.
Step6 After updating all particles during this iteration, referring to the literature [41], [43], this paper divides the task in each particle into different sets by using the constraint relationship in the production process, where a set represents a stage. Select two particles as the cross parent and the location of the task phase where the cross occurs randomly. When the crossover probability satisfies the condition, the selected crossover task stage and its subsequent stage in particle 2 are exchanged with the same position in

particle 1, that is, the crossover occurs between sets. After the crossover occurs, the mutation probability is generated randomly. When the mutation probability meets the conditions, a set and two positions in the set are randomly selected, and the two positions in the selected set are exchanged, that is, the mutation occurs in the set.

Step7 The parent population and the offspring population are merged, fast nondominated sorting is carried out, and the crowding degree of the individuals in the nondominated solution set is calculated, so the appropriate individuals are selected to form a new population. Further judge whether the new population is better than the individual optimal value of each particle; if better, the update is carried out. If not improved, go directly to Step 8.

Step8 Continue to adjust the updated particle population into constraint conditions. Assign the adjusted population to P_t and initial empty external file A_t, then calculate the fitness values of P_t and A_t individuals.

Step9 Copy all the nondominated solutions in P_t and A_t to P_t and A_{t+1}; if the number of nondominated solutions in A_{t+1} is greater than N, then prune. Otherwise, the dominant solutions in P_t and A_t are added to A_{t+1} until its size is equal to N.

Step10 For external archives A_{t+1}, the binary tournament method with substitution is used to select individuals to enter the mating pool. The crossover and mutation operations are performed on the mating pool, and the population input constraints are adjusted and assigned to P_{t+1}.

Step11 The fitness values of P_{t+1} and A_{t+1} individuals are calculated. Copy all nondominated solution sets in P_{t+1} and A_{t+1} to A_{t+2} to further determine whether the external file A_{t+2} is better than the individual optimal value of each particle and update if better; if not improved, then directly go to Step 12.

Step12 Nondominated sorting of adjusted populations; find the nondominated solution in the new population and put it into the Pareto optimal solution set; further filter in the Pareto optimal solution set and delete the dominant solution.

Step13 Repeat Steps 5-12 until the maximum number of iterations is reached to stop the algorithm.

Step14 Output all particles in the Pareto optimal solution set.

VI. EXPERIMENTS AND DIS CUS SION

A. PARAMETER TEST BASED ON RESPONSE SURFACE METHODOLOGY (RSM)

RSM is a kind of experimental design (DOE) tool that uses a series of experimental quantitative data to explore the relationship between different explanatory variables and one or more response variables, so it is often used in the parameter tuning process [44]. In this paper, the response surface method (RSM) is used to adjust the proposed algorithm parameters to accelerate the convergence rate of the algorithm and improve the quality of the solution. The main idea of RSM is that the software generates a series of experiments through the lower and upper limits of each parameter given in the initial step. According to the experimental data requirements, different results are filled into the software to obtain the best response and parameter level. This paper used Design Expert software version 8.0 for the experiment.

In the SMOPSO-IIs algorithm, there are some parameters that need to be optimized, such as the crossover probability (pc), mutation probability (pm), grid expansion (α) and leadership election pressure (β). Suppose the initial values of pc, pm, α and β are 0.5, 0.06, 0.25 and 3, respectively [45]. The random test table was obtained as shown in Table 1.

TABLE 1. Random experiment around the initial value in the first-order model.

No.	pc	pm	alpha	beta	R
1	0.5	0.06	0.25	3	0.7858
2	0.6	0.05	0.3	4	0.9713
3	0.6	0.07	0.3	4	0.1366
4	0.5	0.06	0.3	4	0.7351
5	0.6	0.07	0.25	3	0.2442
6	0.6	0.06	0.25	4	0.6930
7	0.6	0.06	0.3	5	0.8063
8	0.7	0.05	0.25	4	0.8604
9	0.6	0.06	0.25	4	0.8066
10	0.5	0.05	0.25	4	0.6484
11	0.6	0.05	0.25	5	0.9483
12	0.6	0.06	0.2	5	0.3361
13	0.7	0.06	0.25	3	0.6816
14	0.5	0.07	0.25	4	0.9843
15	0.6	0.05	0.25	3	0.9558
16	0.6	0.06	0.3	3	0.9448
17	0.5	0.06	0.2	4	0.7880
18	0.6	0.07	0.2	4	0.6265
19	0.5	0.06	0.25	5	0.9603
20	0.7	0.06	0.2	4	0.5383
21	0.6	0.06	0.25	4	0.8335
22	0.6	0.06	0.2	3	0.6528
23	0.7	0.07	0.25	4	0.8177
24	0.6	0.06	0.25	4	0.8742
25	0.7	0.06	0.25	5	0.8877
26	0.6	0.06	0.25	4	0.8821
27	0.7	0.06	0.3	4	0.7518
28	0.6	0.07	0.25	5	0.8746
29	0.6	0.05	0.2	4	0.6541

TABLE 2. Variance analysis results generated by the first-order model.

Source	Sum of Squares	df	Mean Square	F value	p value	Prob > F
Model	0.24	4	5.90E-02	1.37	0.2736	not significant
A-pc	1.10E-02	1	1.10E-02	0.26	0.6167	
B-pm	1.50E-01	1	1.50E-01	3.55E+00	0.0716	
C-alpha	4.70E-02	1	4.70E-02	1.09	0.3069	
D-beta	2.50E-02	1	2.50E-02	0.58	0.4528	
Residual	1.03	24	0.043			
Lack of Fit	1.01	20	0.05	8.68	0.0244	significant
Pure Error	0.023	4	5.82E-03			
Cor Total	1.27	28				

TABLE 3. Final variance analysis results after parameter adjustment.

Source	Sum of Squares	df	Mean Square	F value	p value	Prob > F
Model	0.12	4	0.031	2.97	0.0397	significant
A-pc	0.021	1	0.021	2.01	0.1688	
B-pm	2.72E-03	1	2.72E-03	0.27	0.6114	
C-alpha	0.047	1	0.047	4.56	0.0432	
D-beta	0.052	1	0.052	5.06	0.0339	
Residual	0.25	24	0.01			
Lack of Fit	0.21	20	0.01	1.09	0.5251	not significant
Pure Error	0.038	4	9.51E-03			
Cor Total	0.37	28				

In this paper, the ZDT1 multi-objective test function is used as the objective function. Since there is more than one objective function and the obtained results are noninferior solution sets, the expected value of each experiment is set as the product root of the average value of multiple objective functions, and the variance analysis results are shown in Table 2.

Subsequently, the parameter values are continuously adjusted according to the fluctuation of the final parameter level, and the expected values under the new parameters are recalculated. When the computer obtains the analysis of variance table, which shows that the model is explicit and the missing items in Table 3 are not explicit, it stops the experiment and views the corresponding final parameter values, and obtained $pc = 0.6$, $pm = 0.06$, $\alpha = 0.25$, and $\beta = 4$.

1) ZDT1

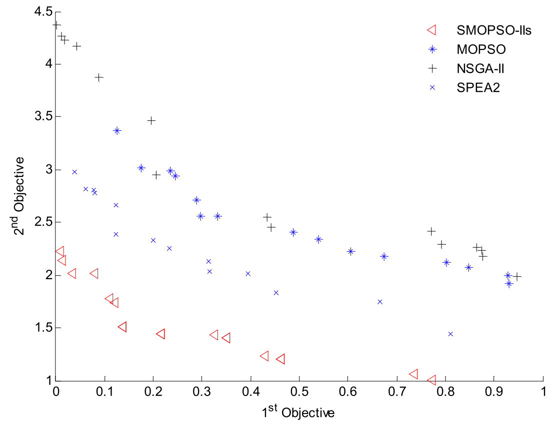

FIGURE 3. Comparison of ZDT1 functions on a 20 × 20 scale.

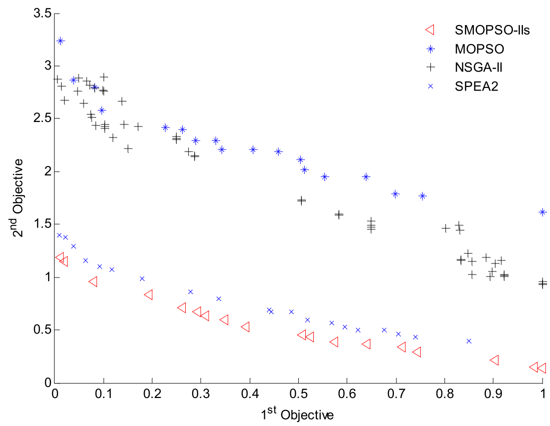

FIGURE 4. Comparison of ZDT1 functions on a 20 × 200 scale.

B. PERFORMANCE TEST OF THE MULTI-OBJECTIVE ALGORITHM

To verify the effectiveness of the SMOPSO-IIs algorithm, this paper compared it with other powerful or advanced algorithms, such as NSGA-II, MOPSO, and SPEA2. NSGA-II and MOPSO were chosen because they are often used by many researchers for flow shop scheduling problems and have proven to be very effective; SPEA2 was selected because it is often used as a control object when comparing multi-objective algorithms. Therefore, this paper selected the NSGA-II, SPEA2, and MOPSO algorithms mentioned above as the comparison objects. The performance test selected the most common ZDT series multi-objective test function. The experimental parameters were selected as in Section 5.1, and the optimal data were obtained by the RSM method. This experiment compared the fronts of different algorithms with the same initial population for 20 iterations in the context of population sizes of 20 and 200, and the maximum running time was used as the stop standard. In addition, for each problem, the computer conducted 10 independent experiments and chose the best one.

1) ZDT2

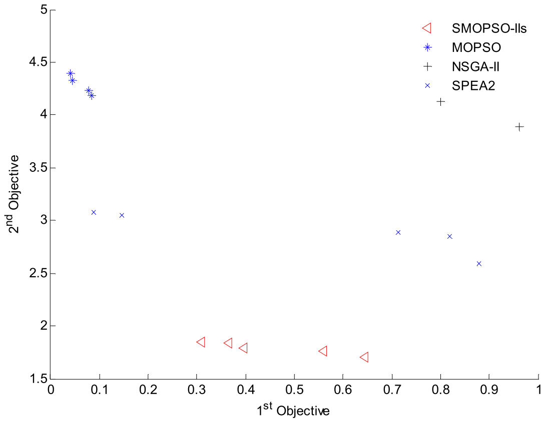

FIGURE 5. Comparison of ZDT2 functions on a 20 × 20 scale.

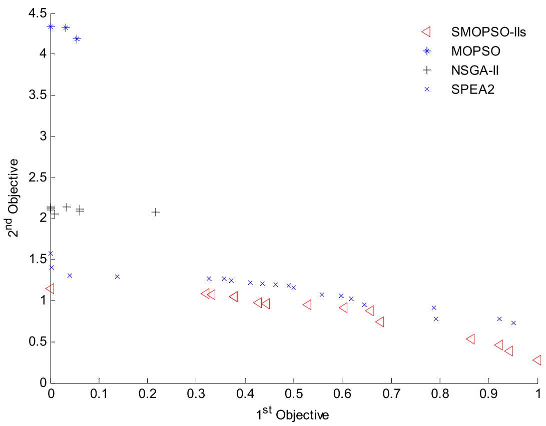

FIGURE 6. Comparison of ZDT2 functions on a 20 × 200 scale.

2) ZDT3

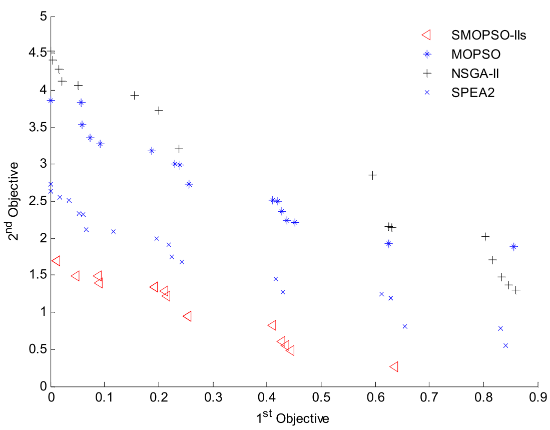

FIGURE 7. Comparison of ZDT3 functions on a 20 × 20 scale.

From the above figures, it can be seen that for different test functions with different scales, the Pareto front obtained by

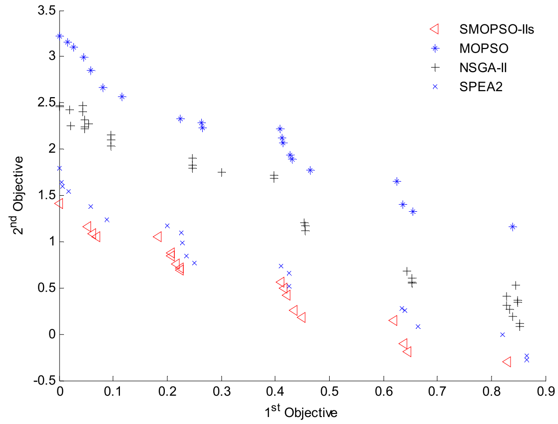

FIGURE 8. Comparison of ZDT3 functions on a 20 × 200 scale.

the SMOPSO-IIs algorithm is better than those of the SPEA2, NSGA-II, and MOPSO functions, and the effect is obvious, which proves that SMOPSO-IIs has good solution stability and effectiveness.

C. SIMULATION ANALYSIS OF THE ALGORITHM

In this paper, this algorithm was applied to the lot planning and scheduling problem of multi-variety continuous production in the chemical industry at different scales. The specific parameters of the experiment were designed as follows:

1) When sizepop=20

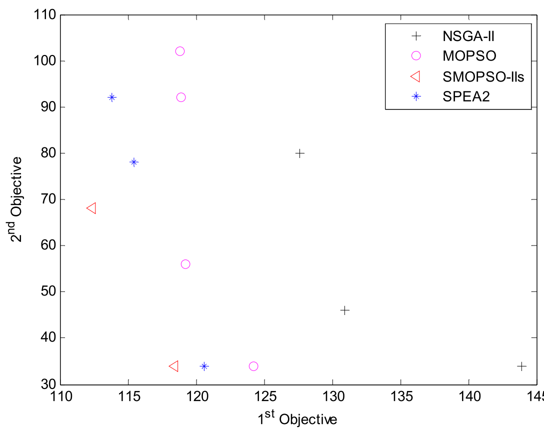

FIGURE 9. Pareto front at 20 × 50.

The total demand D_s for each product is [260,270,280]; the demand De_i of the product is generated randomly in $[0, D_s]$; the number of varieties of products p is 2; the number of production stages e is 3; the minimum lot production Bb_{ij}^{min} is 100; the maximum production lot Bb_{ij}^{max} is 150; the conversion rate of equipment 1 is 1 and the conversion rate of equipment 2 and equipment 3 is 0.9; the production processing time coefficient λ_{ij} are [0.1,0.15;0.2,0.1;0.1,0.1]; the time of adjusting and cleaning the equipment, coefficient q_{ij}, is [1,1.2;1.4,1.2;1,1]; the maximum inventory capacity E_{ij}^{max}

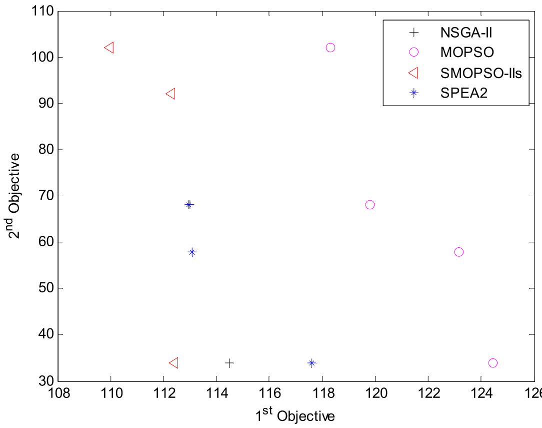

FIGURE 10. Pareto front at 20 × 100.

is 200 and the unit switching cost is 10. The maximum number of iterations is 50 and 100, and the population is divided into large-scale GD, medium-scale GZ and small-scale GX, where GD = 200, GZ = 100, and GX = 20. For particle swarms with different scales, the algorithm is performed to observe the number of particles in the Pareto optimal solution set and the Pareto front trajectory. The algorithm was programmed in MATLAB 2016a using the Windows 7 operating system.

2) When sizepop=100

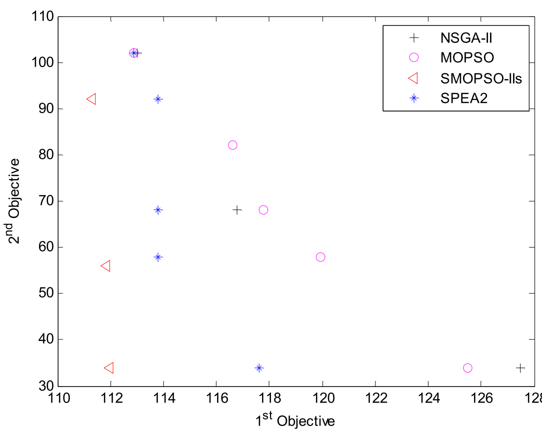

FIGURE 11. Pareto front at 100 × 50.

It can be found from the above results that, regardless of the scale, the Pareto front calculated by the SMOPSO-IIs algorithm is better than that calculated by the other algorithms, followed by the Pareto front obtained by the SPEA2 algorithm, while the MOPSO algorithm and NSGA-II algorithm are equally prominent in the front. In summary, the Pareto front calculated by the SMOPSO-IIs algorithm is significantly better than that calculated by other algorithms.

To more intuitively compare the different Pareto fronts obtained by each algorithm, the following table lists the total number of particles in the Pareto front under different combinations:

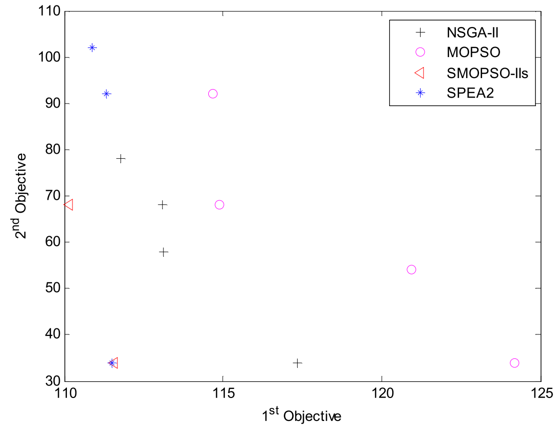

FIGURE 12. Pareto front at 100 × 100.

3) When sizepop=200

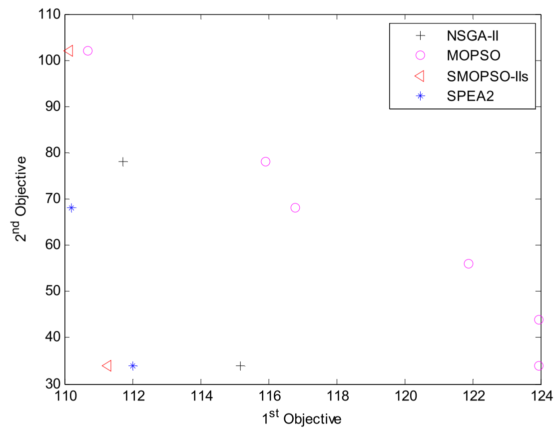

FIGURE 13. Pareto front at 200 × 50.

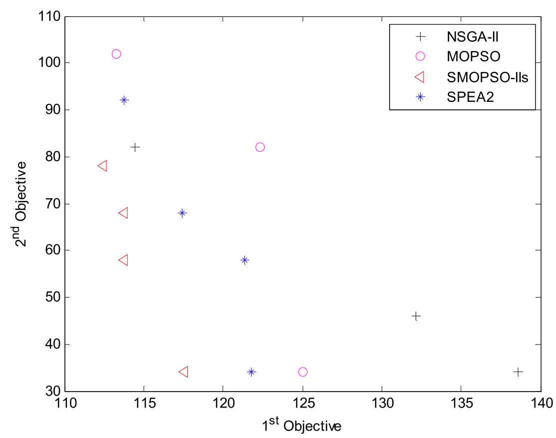

FIGURE 14. Pareto front at 200 × 100.

It can be seen from Table 4 above that when the number of iterations is 50, the number of noninferior solutions of the MOPSO algorithm is always optimal in the four algorithms, and the number of noninferior solutions obtained by the NSGA-II and SMOPSO-IIs algorithms is always stable. However, with the expansion of population size, the number of noninferior solutions of the SPEA2 algorithm fluctuates the most and is in an unstable state. When the number of

TABLE 4. Number of particles in the total Pareto front under different combinations (without repeated solutions).

iterations	sizepop	NSGA-II algorithm	MOPSO algorithm	SMOPSO-IIs algorithm	SPEA2 algorithm
50	20	3	4	2	3
	100	3	5	3	5
	200	2	3	2	1
100	20	2	4	3	3
	100	2	2	4	3
	200	3	3	4	4

iterations is 100, with the increase in population size, the number of noninferior solutions obtained by the SMOPSO-IIs algorithm reaches the optimal value and it performs well among the four algorithms. The number of noninferior solutions of the MOPSO algorithm decreases. Therefore, the SMOPSO-IIs algorithm is relatively good considering the number of particles.

In addition to comparing the total number of particles in the Pareto front under different combinations, dispersion is also a major criterion for testing the distribution of the Pareto front. To better compare the discrete degree of particles in the Pareto optimal solution set under different algorithms, this paper introduces the concept of dispersion. When the dispersion degree of particles in the Pareto optimal solution set is high, that is, the dispersion degree is large, the algorithm does not fall into the local optimal solution and can search the pheromone in the global solution to find the global optimal solution. Based on the above principles and statistical knowledge, this paper uses the standard deviation formula to calculate the dispersion of particles in the Pareto optimal solution set under different algorithms. The specific formula is as follows:

$$fs = \sqrt{\frac{\sum_{i=1}^{n} (f_i - \overline{f})^2}{n}} \tag{28}$$

where f_i represents the fitness value of particle i, $\overline{f}$ represents the average fitness of n particles, and n represents the number of particles in the Pareto optimal solution set. The specific dispersion results are shown in Table 5.

By observing the dispersion of particle populations at different scales, it can be found that when the population size is 20, the dispersion of the NSGA-II algorithm fluctuates greatly while that of the MOPSO algorithm is relatively stable from fs1. From fs2, the dispersion of the SMOPSO-IIs and SPEA2 algorithms fluctuate greatly, while the dispersion of the NSGA-II and MOPSO algorithms are relatively stable. When the population size is 100, from the perspective of fs1, the dispersion of the NSGA-II algorithm fluctuates greatly, while the dispersion of the MOPSO and SMOPSO-IIs algorithms are relatively stable. From fs2, the dispersion of the NSGA-II and SPEA2 algorithms fluctuate greatly, while the

TABLE 5. Dispersion comparison of algorithms under different combinations.

	NSGA-II		MOPSO		SMOPSO-IIs		SPEA2	
	fs1	fs2	fs1	fs2	fs1	fs2	fs1	fs2
20x50	7.03	19.48	2.27	27.37	3.00	17.00	2.90	24.71
20x100	0.74	17.00	2.47	24.43	1.12	29.98	2.16	14.27
100x50	6.12	27.76	4.16	22.82	0.29	23.91	1.65	24.28
100x100	0.46	17.00	3.82	23.8	0.54	17.00	0.00	0.00
200x50	1.71	22.00	4.84	22.43	0.57	34.00	0.90	17.00
200x100	10.19	20.40	5.01	28.53	1.92	16.33	3.26	20.81

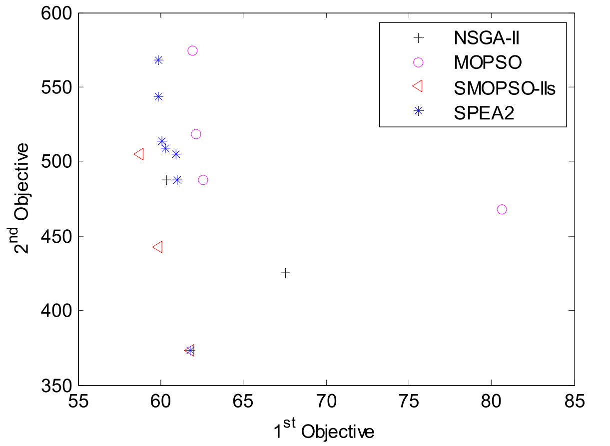

FIGURE 15. Dispersion comparison table of the four algorithms when sizepop = 50 and iteration = 50.

dispersion of the SMOPSO-IIs algorithm is relatively stable. When the population size is 200, from fs1, the dispersion of the NSGA-II algorithm fluctuates greatly, and the dispersion of the other three algorithms are relatively stable. From fs2, the dispersion of the SMOPSO-IIs and MOPSO algorithms fluctuate greatly, while the dispersion of the NSGA-II and SPEA2 algorithms are relatively stable. Based on the above analysis, the dispersion of the SMOPSO-IIs and MOPSO algorithms are relatively stable. However, the overall dispersion value of the MOPSO algorithm is better than that of the SMOPSO-II algorithm.

In summary, this paper combines analyses of the Pareto front graph distribution, the total number of particles in the Pareto front and the dispersion of particles in the Pareto front under the above different algorithms. The results show that the number of noninferior solutions obtained by the MOPSO and NSGA-II algorithms are good overall, but their Pareto fronts are behind, indicating that the schemes obtained by these two algorithms are not the optimal solution set scheme. The number of noninferior solutions obtained by the SPEA2 algorithm fluctuates greatly, and the dispersion is also in a state of fluctuation, but the Pareto front is relatively good, indicating that although the scheme obtained by the SPEA2 algorithm is better, it is not necessary to achieve the best scheme every time, and it has a certain risk. The

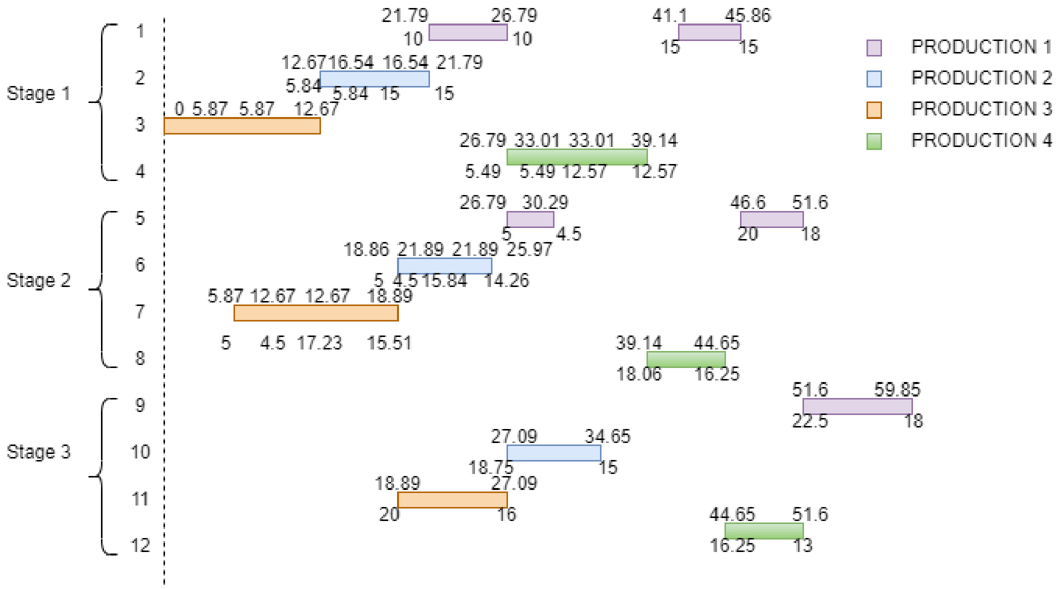

FIGURE 16. A Gantt chart of a nondominated solution in the Pareto optimal solution set.

Pareto front calculated by the SMOPSO-IIs algorithm can reach the optimal value at different scales, and the number of noninferior solutions is also good overall. Although the dispersion is not optimal, it is basically stable. Therefore, the scheme obtained by the SMOPSO-IIs algorithm is less accurate, which can help workshop production personnel reduce unnecessary waste in scheduling. For the multi-objective and multi-variety lot sizing and scheduling model considering product switching and conversion rate, the SMOPSO-IIs algorithm is the optimal algorithm regardless of the group size.

D. CASE SIMULATION ANALYSIS

Based on the data of a mass customization chemical enterprise in Shenyang with two production lines of ten thousand tons per year and one thousand tons per year, this paper simulates and establishes a set of process enterprise production control systems that quickly respond to dynamic market demand. In the system, there is an annual output of ten thousand tons of pipeline, and the pipeline includes the first reaction, the second reaction, and three poly condensation reaction production stages. There are different reactors on the pipeline. The capacity of each reactor is limited: the upper limit is the maximum capacity of the reactor, which is related to the type and specification of the reactor, and the lower limit is determined by the reaction conditions and technical requirements. Due to the different capacities of different reactors in the pipeline, single production lots are not equal. In addition, when the product variety is switched, the reactors at three different production stages need cleaning and other related work, which increase the production time of the whole processing process of the product variety. The following table shows the weekly demand for different products in the chemical enterprise and the related parameter settings.

TABLE 6. Weekly demand for products.

Product Variety	DOP	DINP	DOA	DOTP
Weekly demand	[17,18,19]	[14,15,16]	[15,16,17]	[12,13,14]

TABLE 7. Model parameter settings.

Stage & Production	lot upper and lower limit	conversion rate	Fixed time factor	Variable time factor	Inventory limit
1,1	15,5	1.0	4.0	0.10	16
1,2	15,5	1.0	3.0	0.15	17
1,3	15,5	1.0	5.0	0.12	16
1,4	15,5	1.0	4.5	0.13	16
2,1	20,5	0.9	3.0	0.10	20
2,2	20,5	0.9	2.5	0.10	22
2,3	20,5	0.9	2.6	0.21	21
2,4	20,5	0.9	2.8	0.15	23
3,1	25,5	0.8	6.0	0.10	-
3,2	25,5	0.8	5.5	0.11	-
3,3	25,5	0.8	6.4	0.09	-
3,4	25,5	0.8	5.0	0.12	-

From the case data, this paper establishes a multi-objective multi-variety lot sizing and scheduling model based on a mass customization process with product switching to further verify the correctness of the algorithm comparison. In this simulation example, this paper uses SMOPSO-IIs, MOPSO, SPEA2 and NSGA-II algorithms for calculation. The population size and iteration number were set to 100. The other specific parameters of the learning factor are shown in the experimental parameter description, the product demand in Table 6 and the model parameter setting in Table 7. The Pareto front is as follows:

In addition, the number and dispersion of noninferior solutions obtained by the SMOPSO-IIs algorithm are better, as shown by the data in Tables 8 and 9, and the frontier obtained by the SMOPSO-IIs algorithm is in the front.

TABLE 8. Dispersion comparison table of the four algorithms when sizepop = 100 and iteration = 100.

SMOPSO-IIs		MOPSO		NSGA-II		SPEA2	
fs1	fs2	fs1	fs2	fs1	fs2	fs1	fs2
1.25	53.92	7.96	39.97	3.58	31.50	0.67	57.49

TABLE 9. Comparison table of the front particle numbers of the four algorithms when sizepop = 50 and iteration = 50.

SMOPSO-IIs	MOPSO	NSGA-II	SPEA2
3	4	2	7

To further test whether the entire production scheduling plan of the nondominated solution is reasonable, this paper randomly selected a nondominated solution in the Pareto optimal solution set and generated the Gantt chart from the perspective of the time sequence. In the Gantt chart, different colors correspond to different varieties of products. The length represents the production duration of different products in different lots at different stages. The upper left represents the start time of each lot, the upper right represents the end time of each lot, the lower left represents the reaction amount of each lot, and the lower right represents the production amount of each lot. Each lot of the nondominated solution meets the requirements of the production process and the undertaking of each stage. The specific situation is shown in Fig. 16.

It can be seen from the Fig. 16 that there is no production conflict in the time scheduling arrangement for each lot of products, and the conversion ratio between the input and output of each batch, as well as their respective batch and intermediate inventory all meet the data in Table 7. In addition, it can be seen throughout the Gantt chart that the number of switching between different lots of the same product is significantly reduced. This shows that the scheduling scheme solved by this model is effective.

VII. CONCLUSION

This paper analyzes the background of mass customization resulting from customer demand individuation in the process industry and analyzes specific lot sizing and scheduling problems under this background. With the development of the economy, the number of products required by the market is often uncertain. Therefore, the quantity of product demand is defined as a fuzzy variable. To clarify this, this paper uses the fuzzy chance programming constraint in data processing. Based on these data, to minimize the maximum completion time and total switching cost, a multi-objective lot sizing and scheduling model for multi-product switching production in the process industry is established.

In the lot scheduling model established in this paper, the following key findings are noted: 1) The switching cost and switching time of products in the production process are considered for the first time; 2) material transformation was considered in the production process and combined with the production lot and processing time; 3) The model considers a series of basic constraints such as inventory and production constraints in the establishment process to reduce costs and shorten the processing time to best meet the diversified needs of customers; 4) An improved multi-objective genetic particle swarm algorithm (SMOPSO-IIs) is proposed to simulate and solve the model. Compared with the current common scheduling methods, the proposed method retains the original fast convergence ability and guiding iteration mechanism of the particle swarm algorithm but also introduces NSGA-II to avoid particles falling into a local optimal solution. In addition, SPEA2 allows for the existing Pareto front to be further optimized, which is not considered in the literature.

For the process industry, the establishment of this model is conducive to dealing with complex uncertainties and environments and is also conducive to the production and scheduling of multiple products. In future work, in addition to dealing with uncertain external information such as market demand, a series of internal uncertainty problems such as machine aging, wear and failure that may exist in the workshop could also be incorporated into the model so that it can carry out model predictive control before the occurrence of uncertain events to reduce unnecessary risk losses.

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