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A MODIFIED SPEA2 ALGORITHM FOR SEQUENCING PROBLEM WITH SEQUENCE DEPENDENT SETUP CONSTRAINT IN MIX-MODEL ASSEMBLY LINE

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Abstract. *This paper deals with sequencing problems with assembly plan in the assembly to order production system. A multi-objective optimization model is developed based on a typical mix-model assembly sequencing model and important constraints such as order release time, delivery time and sequence-dependent setup time, with the objective to minimize overall delay time and to minimize maximum completion time. A corresponding lexicographic multi-objective constraint programming model is constructed with application of ILOG CPLEX optimizer to get precise solutions. To deal with the deficiency of CPLEX, a modified SPEA2 algorithm is proposed. By improving the local search of SPEA2 and making a Pareto optimization of the problem, the new method gets a front solution set and is more efficient than CPLEX.*
Keywords: Constraint programming, Mixed-model assembly line, Sequence-dependent setup, Sequencing, SPEA2

1. **Introduction.** An increasing number of enterprises turn to assemble-to-order (ATO) for help which enables reasonable arrangement for order discoupling points and corresponding production strategy in line with production cycle and lead time. ATO is increasingly adopted in mix-model assembly line in attribution to its efficiency in saving delivery time and cutting stock of finished goods. Researches on production sequencing for mix-model assembly line mainly deal with two aspects, namely, decision model and solution algorithm [1]. Most researches on decision models concentrate on the five objectives such as production load balancing, material consumption leveling, efficiency maximization, cost minimization and completion time minimization [2-9]. And researchers mainly employed three methods to study the solution algorithm for model of production sequencing of mix-model assembly line, namely, exact algorithm, rule-based heuristic algorithm and AI-based meta-heuristic algorithm. Damodaran et al. [10] implemented simulated annealing (SA) algorithm and a particle swarm optimization (PSO) algorithm to solve the optimization problems dedicated to anti-lock braking systems and to obtain optimal Takagi-Sugeno-Kang (TSK) fuzzy models. On the other hand, AI-based meta-heuristic algorithm is the focal point of current academic research. Chutima and Naruemitwong [11] presented biogeography-based Pareto optimization (BBO) to solve mix-model sequencing model with learning effect for two-sided assembly lines. The searching and solving performance of the algorithm were reinforced with the adoption of self-adapting BBO. The

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self-adoption-based BBO algorithm can decide if the next-generation adaptive parameter should be adjusted.

According to abovementioned literature, exact algorithms, though efficient in finding exact solutions, fail to show its superiority in computational efficiency. Rule-based heuristic algorithm, based on actual conditions of production sites and by applying specific priority-based rules, is quick in finding feasible solutions while the quality of such solutions is unpredictable. AI-based meta-heuristic algorithms are the hotspot of recent researches and its advantages lie in its speediness in finding feasible solutions, though the quality of such solutions is as well unguaranteed.

Thus, in this paper, we propose a modified strength Pareto evolutionary algorithm (SPEA2) to deal with the deficiency of exact solution by CPLEX when resolving the sequencing problems with assembly plan in the assembly to order production system. Moreover, the solution approach provides high quality solutions in a very short time with respect to the performance period. The remainder of this paper is organized as follows. Section 2 describes the production process and the objectives of the work. The multi-objective model of the sequencing problems with assembly plan is discussed in Section 3. Section 4 represents the CPLEX resolution of the problem. Section 5 details the SPEA2 approach used for the investigation and presents experimental results. Finally, Section 6 summarizes the work.

2. Problem Description.

Chassis assembly is organized production based on assembly-to-order model while four key parts, namely axle, reducer shell, differential shell and bearing pedestal, are manufactured based on production-to-inventory model. The final assembly is based on make-to-order model. The assembly process has direct influence on customer delivery lead time.

For chassis products, four types of platforms are available, namely Sub-P1, Sub-P2, Sub-P3 and Sub-P4, and there exist 8 product categories. As shown in Figure 1, all these product categories are provided with the same process route. During the assembly process, cross-platform model switchover takes more time than that for products of the same platform.

In general conditions, requirements on important job of an assembly line are to be satisfied by inventory at order discoupling point, thus ensuring the constraint of assembly material arrival to a certain extent. Assembly process is flexible and assembly line may

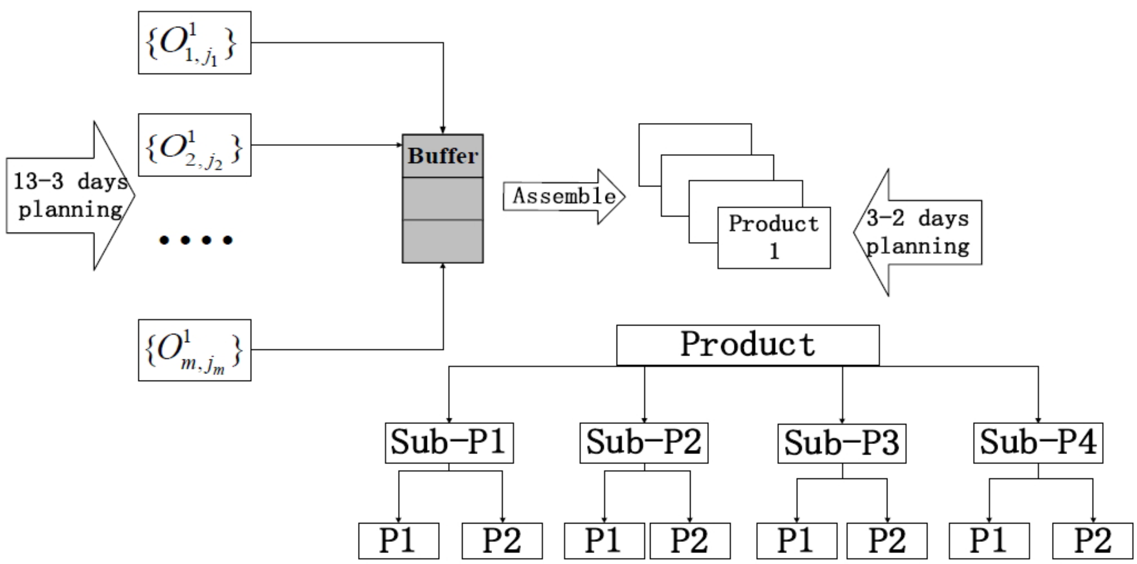

FIGURE 1. Sketch map of ATO model and the product categories

undergo line/model switchover based on different customer requirements on product models. Such switchover is likely to disturb workshop assembly process, therefore, planning shall not be based simply on assembly balancing issues.

The problem adopts general hypotheses regarding permutation flow shop scheduling, which means job on each station of the assembly line moves downward in the same order. Therefore, job assembly sequence is to be decided and objective of the problem is to optimize overall delay time and maximum completion time of the order so as to shorten customer response time.

A mathematical model is developed for this problem and the following hypotheses are proposed:

(1) The size of production sequence is decided by planning cycle, and order demand of each cycle is known, namely, product model and category, quantity, order release time and delivery time;

(2) Each station is available at time zero;

(3) At each station, only one job can be assembled;

(4) Once started, the assembly process of each job on the station shall not be interrupted;

(5) One job can be assembled only on the same station at one time;

(6) Processing sequence of job on each station shall be the same;

(7) Fault time and maintenance time of each station are not to be considered.

3. **Multi-Objective Modelling of the Sequencing Problems with Assembly Plan.** Based on features of the problem, the following symbols are defined as follows:

O	Total number of customer order included in the production batch, $o = 1, 2, \ldots, O$
M	Total quantity of job models of the batch production plan, $m = 1, 2, 3, \ldots, M$
Z	Total quantity of demanded job of the batch production plan
S	Total number of stations of assembly line, $s = 1, 2, \ldots, S$
$t_{z,o} = \begin{cases} 1 \\ 0 \end{cases}$	$t_{z,o} = 1$ when job z belongs to order o, otherwise 0, $z = 1, 2, \ldots, Z$, $o = 1, 2, \ldots, O$
$g_{z,m} = \begin{cases} 1 \\ 0 \end{cases}$	$t_{z,m} = 1$ when production model of job z is m, otherwise 0, $z = 1, 2, \ldots, Z$, $m = 1, 2, 3, \ldots, M$
rd_o	Release time of order o, $o = 1, 2, \ldots, O$
dd_o	Delivery time of order o, $o = 1, 2, \ldots, O$
$P_{m,s}$	Standard time of job of m model at station s, $m = 1, 2, 3, \ldots, M$, $s = 1, 2, \ldots, S$
$Setup_{m,n,s}$	Setup time required by station s to switch from model m to model n, $m, n = 1, 2, 3, \ldots, M$, $s = 1, 2, \ldots, S$
rel_z	Release time of job z, $z = 1, 2, \ldots, Z$
due_z	Delivery time of job z, $z = 1, 2, \ldots, Z$
$pt_{z,s}$	Standard time of job z at station s, $z = 1, 2, \ldots, Z$
$st_{p,q,s}$	Setup time required by station s to switch from job p to job q, $p, q = 1, 2, \ldots, Z$, $s = 1, 2, \ldots, S$
$Start_{z,s}$	Start time of job z at station s, $z = 1, 2, \ldots, Z$, $s = 1, 2, \ldots, S$
$Comp_{z,s}$	Completion time of job z at station s, $z = 1, 2, \ldots, Z$, $s = 1, 2, \ldots, S$
Tar_z	Delay time of order o, $z = 1, 2, \ldots, Z$

For features of the problem, the following decision variables are introduced:

$$\pi = \{\pi(1), \pi(2), \ldots, \pi(Z)\} \qquad \text{job assembly sequence}$$

The key of the problem is to further optimize maximum completion time by applying lexicographic multi-objective optimization method and minimizing overall delay time of all job. The model is proposed as follows:

$$\text{Min} \quad f = \sum_{z=1}^{Z} Tar_z \tag{1}$$

$$\text{Min} \quad f = \max\left\{Comp_{\pi(i),S}\right\} \tag{2}$$

s.t.

$$rel_z = \sum_{o \in O} t_{z,o} \cdot rd_o \qquad \forall z \in Z \tag{3}$$

$$due_z = \sum_{o \in O} t_{z,o} \cdot dd_o \qquad \forall z \in Z \tag{4}$$

$$pt_{z,s} = \sum_{m \in M} g_{z,m} \cdot P_{m,s} \qquad \forall z \in Z, \quad \forall s \in S \tag{5}$$

$$st_{p,q,s} = \sum_{m \in M} \sum_{n \in M} g_{p,m} \cdot g_{q,n} \cdot Setup_{m,n,s} \qquad \forall p, q \in Z, \quad \forall s \in S \tag{6}$$

$$Comp_{\pi(0),s} = 0 \qquad \forall i \in Z \tag{7}$$

$$Comp_{\pi(i),0} = rel_{\pi(i)} \qquad \forall i \in Z \tag{8}$$

$$Start_{\pi(i),s} = \max\left(Comp_{\pi(i),s-1}, Comp_{\pi(i-1),s} + st_{\pi(i-1),\pi(i),s}\right) \qquad \forall i \in Z, \quad \forall s \in S \tag{9}$$

$$Comp_{\pi(i),s} = Start_{\pi(i),s} + pt_{\pi(i),s} \qquad \forall i \in Z, \quad \forall s \in S \tag{10}$$

$$Tar_z = \max\left\{0, Comp_{\pi(i),S} - due_{\pi(i)}\right\} \qquad \forall i \in Z \tag{11}$$

Equations (1) and (2) are the objective of the problem and represent respectively minimizing overall delay time of all job and minimizing maximum completion time. Lexicographic priority of objective (1) is higher than objective (2), meaning that maximum completion time should be minimized based on the minimization of overall delay time of all job. Equations (3), (4), (5) and (6) acquire basic data which include order release time, delivery time, processing time and setup time by addressing some scenario elements, such as order release time, delivery time, processing time and setup time, and combining associated data of order and product model of the job. Equation (10) implies that basic constraints to be satisfied for job start time, including general constraints for flow shop scheduling problems and that start time of job on a certain station shall not be earlier than completion time of previous process of such job. Meanwhile, start time of job on such station shall not be earlier than completion time of adjusting/switchover process. To ensure that Equation (9) is a consistent expression, Equations (7) and (8) appoint boundary conditions of the equation, namely, the position of virtual sequence "0" and completion time of virtual station "0". Completion time of all stations at the position of sequence "0" shall be 0, reflecting that all stations are available at time 0 and can provide assembly directly for arrived job without setup time. Completion time of job at time 0 is order release time of such job, implying that start time of first process of the job shall satisfy the constraint of order release time of such job and no assembly in advance is allowed. Equation (10) represents that completion time of a job on the station shall be start time of such job on such station plus assembly time of such job. Equation (11) shows that delay time of a job shall be completion time of the last process of such job minus delivery time of corresponding order, while delay time is 0 in case the order is completed in advance.

4. **Constraint Programming Method Using ILOG CPLEX.** In this paper, firstly, we resolve the model by applying ILOG CPLEX. Exact solution to the problem is figured out with the application of "CP" engine. Data of standard time are organized based on research results of manufacturers and refer to Tables 1-6.

Table 1. Data of product process time

Platform	Product model	Assembly station 1	Assembly station 2	Assembly station 3	Assembly station 4
Sub-P1	P1	30	32	28	25
	P2	32	35	30	29
Sub-P2	P1	43	40	35	35
	P2	45	38	38	35
Sub-P3	P1	48	45	40	40
	P2	45	46	38	38
Sub-P4	P1	50	49	45	45
	P2	50	50	46	45

Table 2. Data of line/product switchover time at station 1

Model		Sub-P1		Sub-P2		Sub-P3		Sub-P4	
		P1	P2	P1	P2	P1	P2	P1	P2
Sub-P1	P1								
	P2	6							
Sub-P2	P1	20	25						
	P2	25	20	8					
Sub-P3	P1	22	28	25	30				
	P2	28	22	30	25	9			
Sub-P4	P1	25	30	28	30	28	32		
	P2	30	25	30	28	32	28	10	

Table 3. Data of line/product switchover time at station 2

Model		Sub-P1		Sub-P2		Sub-P3		Sub-P4	
		P1	P2	P1	P2	P1	P2	P1	P2
Sub-P1	P1								
	P2	7							
Sub-P2	P1	21	26						
	P2	24	21	7					
Sub-P3	P1	23	29	24	31				
	P2	27	23	29	26	8			
Sub-P4	P1	24	31	27	31	27	29		
	P2	29	26	29	29	31	27	9	

Table 4. Data of line/product switchover time at station 3

Model		Sub-P1		Sub-P2		Sub-P3		Sub-P4	
		P1	P2	P1	P2	P1	P2	P1	P2
Sub-P1	P1								
	P2	6							
Sub-P2	P1	20	25						
	P2	25	20	7					
Sub-P3	P1	22	28	25	30				
	P2	28	22	30	25	8			
Sub-P4	P1	25	30	28	30	28	32		
	P2	30	25	30	28	32	28	9	

Table 5. Data of line/product switchover time at station 4

Model		Sub-P1		Sub-P2		Sub-P3		Sub-P4	
		P1	P2	P1	P2	P1	P2	P1	P2
Sub-P1	P1								
	P2	8							
Sub-P2	P1	21	26						
	P2	24	21	8					
Sub-P3	P1	23	29	24	31				
	P2	27	23	29	26	7			
Sub-P4	P1	24	31	27	31	27	29		
	P2	29	26	29	29	31	27	9	

Table 6. Order data

Order No.	Order demand		Order demand							
	Release time	Delivery time	Sub-P1		Sub-P2		Sub-P3		Sub-P4	
			P1	P2	P1	P2	P1	P2	P1	P2
Order1	0	550	1		1		2			
Order2	0	650		2		1		1		
Order3	50	1000	2	1	2					
Order4	60	1250			1	1	1			
Order5	100	1000		2		1				
Order6	100	1100					1		1	
Order7	150	1400						1		2

Solver is invoked to solve the problem and to optimize assembly planning in 174.89 seconds. The optimized assembly sequence of to-be-assembled job is 2-3-7-4-5-8-0-9-1-11-6-18-14-13-12-17-10-16-20-19-15-21-22-23. Overall delay time of such assembly batch is 0 and maximum completion time is 1323. Thus, assembly production is arranged based on optimized assembly plan and requirement on delivery time of all customer orders can then be guaranteed.

CPLEX gets the precise solution of the problem actually is not robust for the decision making in real case, and it will run a long time when the problem scale gets larger.

5. **Improved SPEA2 Based on Neighborhood Search.** Zitzlr et al. [12] proposed SPEA2 algorithm and the algorithm was improved from the aspect of fitness value assignment mode. Individual fitness was evaluated according to individual's dominating information, dominated information and neighbor distance information of k (k is related to the summation of the size of population P and archive Q). Fitness value consists of $R(i)$ and $D(i)$. $R(i)$ is the summation of $S(j)$ of all dominated individuals of individual i in population P and non-dominated set and the value of $S(j)$ is the total number of individuals dominated by individual i in population P and external archive Q. In $D(i)$, σ_i^k is the kth neighbor Euclidean distance of individual i.

$$Fitness(i) = R(i) + D(i)$$

$$R(i) = \sum_{j \in P + NDSet, j \succ i} S(j)$$

$$S(i) = |\{j\,|j \in P + Q \wedge i \succ j\}|$$

$$D(i) = \frac{1}{\sigma_i^k + 2}$$

$$k = \sqrt{|P| + |Q|}$$

With adoption of highly random crossover and mutation operators in evolution process, the algorithm is equipped with global searching ability and higher rate of convergence and decreased probability of local optimization. With local searching capability compromised, searching precision of the algorithm is constrained when solution space is irregular. Local search algorithm starts with initial solution and generates neighbor archive according to the defined neighborhood structure and then selects based on fitness value of neighboring solution; the iteration will proceed until termination conditions are satisfied. Primal local search algorithm is prone to plunge into local optimal and stops the searching; however, tabu search records the searching process by establishing a tabu list and such record has further influence on follow-up searching process, thus improving the defect to a large extent.

Therefore, the improvement is based on the idea of enforcing local searching capability of the algorithm and bringing in local searching process by establishing an archive of local search results which involves in fitness assignment and environment selection process of SPEA2 algorithm. When SPEA2 has undergone main process, neighborhood search is to be conducted by adopting sparse point in objective domain and single-objective optimal point of Pareto front. And the archive is to be updated based on search results.

SPEA2 algorithm is improved according to the process listed below:

Step 1: repeat individual initialization Ne times to generate initial population P_o of the size of Ne; define external archive Q_o and neighborhood search set R_o; set the size of Q_o and R_o as N and N' respectively;

Step 2: assign the fitness of P_t, Q_t and R_t;

Step 3: conduct non-dominated sorting for $P_t \cup Q_t \cup R_t$ and copy the non-dominated solution of result of the sorting to Q_{t+1} and ensure that the number of individuals in Q_{t+1} remains N; truncate the number of individuals in Q_{t+1} if $Q_{t+1} > N$; fill it up if $Q_{t+1} \leq N$;

Step 4: neighborhood search (tabu search): perform local search with tabu search based on the individual of the greatest fitness and the individual with optimal single-objective value selected from Pareto front solution set; conduct non-dominated sorting on the search result and copy it to R_{t+1}.

Step 5: output all individuals in Q_{t+1} as the quasi-optimal Pareto front if iteration times if $t > T$; continue the iteration if $t \leq T$;

Step 6: conduct binary tournament selection, crossover, mutation operation on individual in Q_{t+1}; update P_{t+1} with newly generated individuals;

Step 7: make $t = t + 1$ and switch to Step 2.

The introduced tabu search involves parallel search on $Num_o + 1$ initial individuals in $2Num_o$ directions; neighborhood structure of the tabu search shall be in line with crossover operator and Num_o represents total number of objective of Num_o model. In the tabu search, $Num_o + 1$ initial solutions represent respectively Num_o single-objective optimal individuals and the solution at the most sparse position at the front; sparsity of the solution at the front is decided based on the kth neighbor distance. For Num_o single-objective optimal individuals, the tabu search is conducted in the optimal direction of each single objective; for individual at the most sparse position at the front, parallel and tabu search is conducted in the optimal direction of each objective.

Solution to the abovementioned production case with the improved SPEA2 algorithm and the front solution set is shown in Figure 2, including 6 front solutions, namely $(1268, 235)$, $(1272, 177)$, $(1283, 63)$, $(1297, 11)$, $(1299, 4)$ and $(1238, 0)$. Among these solutions, solution $(1238, 0)$ is approximate to CPLEX solution $(1232, 0)$ with deviation rate less than 0.5%.

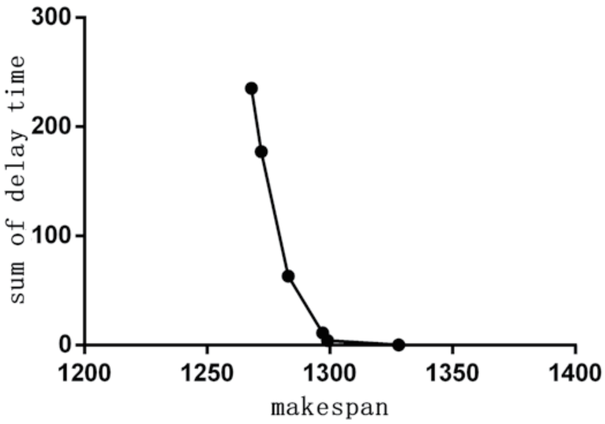

Figure 2. Pareto front resolution

6. Conclusions.

The paper deals with the planning problem of the assembly line assembly shop. A multi-objective model for mix-model assembly plan under ATO production model is developed based on deep research on typical production sequencing problems, customer order scenario and sequence-dependent setup time and other features are considered in our model with the objective to minimize overall delay time and to minimize maximum completion time. We propose 2 methods to resolve the model with the real case data. First, a lexicographic multi-objective constraint programming model is proposed by applying optimization tool ILOG CPLEX to getting the exact solution. In this method, constraint propagation is used to shrink the searching space which enhanced the searching efficiency. However, it needs to traverse the entire searching space and a long time to get the best result. Then, we provide another method by improving the local search of SPEA2 algorithm. In this method the Pareto optimization was carried out and a set of forward solutions was obtained, and the single objective result is almost the same as CPLEX's solution. Compared with the CPLEX solution, the improved SPEA2 algorithm is faster and with more candidate solutions, which can be used for further decision.

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