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Solving Process Planning, Weighted Earliest Due Date Scheduling and Weighted Due Date Assignment Using Simulated Annealing and Evolutionary Strategies

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Abstract**—**Traditionally, three important manufacturing functions which are process planning, scheduling and due-date assignment are performed sequentially and separately. Although there are numerous works on the integration of process planning and scheduling and plenty of works focusing on scheduling with due date assignment, there are only a few works on integrated process planning, scheduling and due-date assignment. Although due-dates are determined without taking into account of weights of the customers in the literature, here weighted due-date assignment is employed to get better performance. Jobs are scheduled according to weighted earliest due date dispatching rule and due dates are determined according to some popular due date assignment methods by taking into account of the weights of each job. Simulated Annealing, Evolutionary Strategies, Random Search, hybrid of Random Search and Simulated Annealing, and hybrid of Random Search and Evolutionary Strategies, are applied as solution techniques. Three important manufacturing functions are integrated step-by-step and higher integration levels are found better. Search meta-heuristics are found to be very useful while improving performance measure.

Keywords**—**Evolutionary strategies, hybrid searches, process planning, simulated annealing, weighted due-date assignment, weighted scheduling.

I. Introduction

TRADITIONALLY three important manufacturing functions, process planning, scheduling and due-date assignment are processed separately. Although there are plenty of works on IPPS (Integrated Process Planning and Scheduling) and SWDDA (Scheduling with Due Date Assignment) problems, there are only a few works focusing on the IPPSDDA (Integrated Process Planning and Scheduling and Due Date Assignment) problem.

The job shop scheduling problem belongs to the NP-Hard problem class without any integration; integrated problems are even harder to solve. Thus, metaheuristics are commonly utilized in literature. In this research, OS (Ordinary Solution), RS (Random Search), SA (Simulated Annealing), ES (Evolutionary Strategies), RS/SA (Random Search and Simulated Annealing) Hybrid and RS/ES (Random Search and Evolutionary Strategies) Hybrid techniques are used.

According to the Society of Manufacturing Engineers, process planning is the systematic determination of the methods by which a product is to be manufactured economically and competitively. Scheduling allocates resources to tasks and considers timing information [1]. According to Gordon et al. [2], SWDDA problems have received considerable attention recently. According to classical inventory management strategy, only tardiness is an undesired outcome. On the other hand, according to JIT (Just-in-Time) both tardiness and earliness are undesired outcomes.

Since long due dates are unwanted it is reasonable to penalize due dates along with tardiness and earliness. In this study all of the weighted due-date, earliness and tardiness related costs are punished.

The weight of each customer is not considered when designating due dates in the literature. Contrary to this, important customers are given closer due dates and scheduled earlier and relatively less important customers are given long due dates and scheduled later in this study. In this way substantial improvement can be obtained for weighted penalty function. There can be substantial improvement in all of the weighted due-date, earliness and tardiness related costs if more important customers are given close due dates and scheduled earlier. These three important manufacturing functions are interrelated and outputs of upstream functions are inputs of downstream functions. For example, process plans become input to the scheduling function. Poorly prepared process plans become bad inputs to the downstream scheduling functions and may not be followed at the shop floor.

Independently performed functions try to reach local optimum and do not care about global optimum. For instance process planners may frequently select same desired machines but may not select some undesired machines at all. Therefore machine loading across production lane becomes unbalanced. But, if both the process planning and scheduling is taken into account simultaneously, process planners may be able to prepare more appropriate process plans and improve machine balancing at the shop floor. On the other hand, given due-dates may be unrealistic, as they might be given excessively far or insufficiently close, where they cannot be fulfilled.

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Unintegrated solution of the problem considerably degrades the performance function.

The problem is represented as a chromosome and every chromosome consists of (n+2) genes. The first two genes represent the due-date assignment and dispatching rules. The remaining genes represent the actively selected route of every job. Since the first two genes have a high impact on performance compared to the remaining genes, they have given higher probabilities to be selected for mutation, as the dominant gene approach is utilized in this research.

Problems are tested for each integration level. Initially, the unintegrated level is tested and later the integration degree is increased step-by-step by adding more functions to the problem. Higher integration levels give better results. All three functions are integrated at the highest integration level in which the best results are obtained. Full integration with directed search is found to be the best of all combinations, as expected.

II. Background and Literature Survey

In this study, three important manufacturing functions are integrated step-by-step. There are numerous works on IPPS and plenty of works on SWDDA, but only a few works focusing on the IPPSDDA problem.

Some important literature survey on IPPS can be found in [3], [4]. Although it is better to have alternative process plans, marginal benefit of alternative plans reduce sharply, and thus, the number of process plans should be determined wisely. Usher [4] studied the impacts of alternative process plans on manufacturing performance. Selecting a process plan among alternatives becomes more difficult as the number of process plans increases. Bhaskaran [5] studied process plan selection in his work.

Scheduling problem alone belongs to the NP-Hard class, and integrated problems are even harder to solve. Many of the researchers used some metaheuristics in their solution, as [6]-[14]. Some earlier works on IPPS can be found as [1], [15]-[22], [6]. Some recent works on IPPS can be found in [3], [4], [7], [9], [10], [13], [14], [23]-[31].

There are numerous works on SWDDA in the literature, which is another popular research problem. Again, it is better to look at literature surveys on this problem before mentioning other researches. A survey on scheduling with common due date assignment is prepared by Gordon et al. [2].

Sometimes common due dates are tried to be assigned for the parts to be assembled together or shipped to the customer at the same time. In this case, we should assign common due-date for the parts. The following works can be given as an example on scheduling with common due date assignments; [2], [32]-[40]. Some of the works are on scheduling with separate due date assignments. Following works can be given as an example to this problem; [41]-[47], [37].

There are several works on SMSWDDA (Single machine scheduling with due date assignment) such as [33], [44], [35], [2], [37], [38], [47], [48].

Reference [49] can be given as an example to two machine flow shop scheduling with due date determination. References [43], [2], [50], [39] are examples to works on parallel machine scheduling with due date determination. References [51], [45], [52] are examples to job shop scheduling with due date determination. There are also works on MMSWDDA (Multi machine scheduling with due date assignment). References [41], [53], [54], and [36], can be given as an example to this problem.

III. Problem Definition

In this research, the IPPSDDA problem is studied. Although plenty of works were conducted on the IPPS and SWDDA problems, research into the IPPSDDA problem is very new area and there are few studies available on this topic [55]–[58].

In order to solve the problem, simulated annealing and evolutionary strategies and some hybrid strategies are used. The problem is represented as a chromosome. Each chromosome is represented with (n+2) genes which represent due-date assignment rules, dispatching rules and actively selected routes of every job.

Integrated process planning, WEDD (Weighted Earliest Due Date Scheduling) scheduling, and WDUE (Weighted Due-Date Assignment) assignment problems are tested. Starting with the unintegrated problem where all functions are performed sequentially, every integration combination is tested and step-by-step functions are integrated with each other. Finally, all of the three functions are integrated and this level is found as the best integration level.

Four shop floors are tested in this research. The largest shop floor has 175 jobs, 35 machines and every job has 10 operations in every route. The first smaller two shop floors have five alternative routes and the other larger two shop floors have three alternative routes. The processing times of each operation of every job in every route changes according to normal distribution with a mean of 12 and a standard deviation of 6, according to the formula $[(12+z*6)]$. Processing times assume integer values, and so, they take values in between 1 and 30.

The characteristics of all shop floors are tabulated and presented in Table I, where SF is for Shop Floor, # of MC is for number of machines, # of J is for number of Jobs, # of R is for number of alternative routes, PT is for processing time and # of O is for number of operations.

TABLE I
CHARACTERISTICS OF SHOP FLOORS

SF	SF 1	SF 2	SF 3	SF 4
# of MC	5	15	25	35
# of J	25	75	125	175
# of R	5	5	3	3
PT	$\lfloor(12+z*6)\rfloor$	$\lfloor(12+z*6)\rfloor$	$\lfloor(12+z*6)\rfloor$	$\lfloor(12+z*6)\rfloor$
# of O	10	10	10	10

Initially, the unintegrated version is tested where all functions are performed separately. After that, WEDD dispatching is integrated with process plan selection but due dates are determined randomly. Later, WDUE assignment is

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integrated with process plan selection, but this time, jobs are scheduled randomly. Finally, all functions are integrated and process plan selection, WEDD dispatching and WDUE assignments are performed concurrently.

In this study, one shift is assumed per day and it makes 480 minutes per day. As a penalty function, all of the weighted earliness, tardiness and due-date related costs are penalized according to the following formulas (1)-(5).

$$\mathrm{PD(j)} = \mathrm{weight\ (j)} * 8 * (\mathrm{Due\ date}/480) \quad (1)$$

$$\mathrm{PE(j)} = \mathrm{weight\ (j)} * \big(5 + 4 * (\mathrm{E}/480)\big) \quad (2)$$

$$\mathrm{PT(j)} = \mathrm{weight\ (j)} * \big(10 + 12 * (\mathrm{T}/480)\big) \quad (3)$$

$$\mathrm{Penalty(j)} = \mathrm{PD(j)} + \mathrm{PE\ (j)} + \mathrm{PT(j)} \quad (4)$$

$$\mathrm{Total\ Penalty} = \textstyle\sum_{\mathrm{j}} \mathrm{Penalty(j)} \quad (5)$$

where PD is for penalty for due date, PE is for penalty for earliness, PT is penalty for tardiness, $\mathrm{Penalty(j)}$ is the total penalty occurred for job j and $\mathrm{Total\ Penalty}$ is the total penalty occurred for all jobs which is the ultimate desired value.

IV. Metaheuristics Used

In this study OS, RS, SA, RS/SA, ES, and RS/ES results are compared. OS represents initial random poor solutions, and RS is undirected search and scans solution space randomly. SA and ES are directed searches and gain benefit from earlier solutions and are better heuristics compared to RS. RS/SA and RS/ES are hybrid heuristics and are initially undirected, but later become directed searches. The reason for selecting hybrid searches is to benefit from both the power of an undirected search at the very beginning of the iterations, and later converting to the directed search and using the power of the directed search. The search techniques that have been utilized in this study are explained below.

Ordinary Solution (OS): Initially, totally a random chromosome is produced and this solution is assumed as ordinary solution. This is done to observe how ordinary solutions are poor and how directed and undirected search metaheuristics are powerful.

Random Search (RS): In this search, new chromosomes as many as in Evolutionary strategies are produced randomly. At every iteration, 13 new chromosomes are produced randomly. To be fair, in comparison with other search techniques, the same number of new chromosomes is produced for each search technique during the program execution.

Simulated Annealing (SA): SA was developed by Kirkpatrick et al. [59] in 1983 and used in many problems in numerous disciplines. Instead of working on population, this research focuses on a single chromosome in each iteration. For this reason, more iterations are made to be fair with other search techniques. The iteration parameters are tabulated and presented in Table II below.

Random and Simulated Annealing (RS/SA): In this research, an initial 10% of iterations are random iterations and remaining 90% of iterations are SA iterations. Solution space is scanned with random search initially to be able to get a better improvement on the solution. After initial random iterations we continued with SA search. At Evolutionary strategies we work on population with size 10 and we produce new 13 chromosomes. Here at SA we work on single chromosome and produce one new chromosome. That is why to be fair in comparison, in this search iteration, size is 13 times as many as in the iteration size of Evolutionary strategies.

Evolutionary Strategies (ES): Evolutionary strategies were developed in the early 1960s. Two students from the Technical University of Berlin, Germany, introduced evolutionary strategies while solving optimization problems [60], [61]. Unlike genetic algorithms, ES uses only mutation operator. At every iteration, 13 new chromosomes produced; thus, fewer iterations are applied compared to the SA heuristics.

Random and Evolutionary Strategies (RS/ES): The initial 10% of iterations are random iterations and the remaining 90% of iterations are ES iterations; 13 new chromosomes are produced at every iteration. Thus, fewer iterations are applied compared to the SA and RS/SA search heuristics, but the same number of chromosomes is tested during the program execution.

RS, ES, and RS/ES hybrid searches are population based and 13 new chromosomes are produced at each iteration. For RS, ES, and RS/ES hybrid searches 200, 150, 100, and 50 iterations are applied, respectively. SA and RS/SA hybrid searches use only one chromosome at each iteration. Thus, to be fair with other methods, 2600, 1950, 1300 and 650 iterations are applied for four shop floors, respectively.

CPU times required for RS, SA, RS/SA, ES, and RS/ES search heuristics are summarized in Table V.

TABLE II
Iteration Numbers for Pure and Hybrid Searches

	RS	SA	RS/SA Hybrid		ES	RS/ES Hybrid	
SF	Random Iter.	SA Iter.	Random Iter.	SA Iter.	ES Iter.	Random Iter.	ES Iter.
1	200	2600	260	2340	200	20	180
2	150	1950	195	1755	150	15	135
3	100	1300	130	1170	100	10	100
4	50	650	65	585	50	5	50

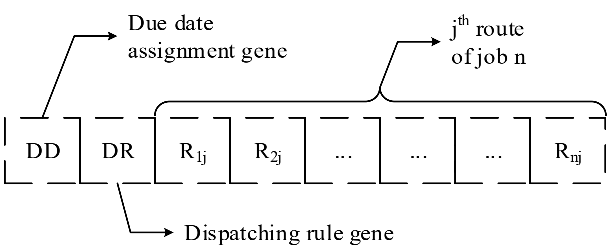

Fig. 1 Sample chromosome

Gene representation of the problem is illustrated in Fig. 1.

There are $(n+2)$ genes in a chromosome and the initial two genes represent the due-date assignment rules and dispatching rules, and remaining n genes represent the actively selected routes of every job.

The dominant gene approach is used in this study. Since initial two genes have higher impact on performance measure, higher probability for mutation is given. Remaining n genes have less effect on penalty function. Thus, lower probability is given to be selected for mutation.

Five types of rules are used while assigning due dates, which are the WTWK (Weighted Total Work), WSLK (Weighted Slack), WPPW (Weighted Process Plus Wait), WNOP (Weighted Number of Operations), and RDM (Random) rules. With the different multipliers and constants, 19 rules are used to assign due dates. These rules are tabulated in Table III and explained in Appendix A.

TABLE III
DUE-DATE ASSIGNMENT RULES

Method	Multiplier k	Constant q_x	Rule no
WTWK	k = 1, 2, 3		0, 1, 2
WSLK		$q_x = q_1, q_2, q_3$	3, 4, 5
WPPW	k =1, 2, 3	$q_x = q_1, q_2, q_3$	6, 7, 8, 9, 10, 11, 12, 13, 14
WNOP	k = 1, 2, 3		15, 16, 17
RDM			18

TABLE IV
DISPATCHING RULES

Method	Rule No
WEDD	1
SIRO	2

The second gene is about scheduling rule and takes one of two values. Two rules are used, which are WEDD (Weighted Earliest Due Date) and SIRO (Service In Random Order) rules. These rules are summarized in Table IV and explained in Appendix B.

V. SOLUTIONS COMPARED

In this study, OS, RS, SA, RS/SA, ES, and RS/ES search solutions are compared with each other. At every integration level, six search heuristics are compared. There are four different integration levels and in total, 24 different combinations for each one of the four shop floors compared. The results are summarized in Table V. Next, each integration level is summarized.

SIRO-RDM (OS, RS, SA, RS/SA, ES, RS/ES): This is the lowest level of integration, where all functions are disintegrated. All search techniques which are OS, RS, SA, RS/SA, ES, and RS/ES heuristics are compared.

WEDD-RDM (OS, RS, SA, RS/SA, ES, RS/ES): Here, the WEDD dispatching rule is integrated with process plan selection, but the due dates are still determined randomly. Here substantial improvements are observed. All search techniques which are OS, RS, SA, RS/SA, ES, and RS/ES heuristics are compared, where OS solutions are very poor and searches are found useful. Directed searches and hybrid searches are found superior compared to the undirected search.

SIRO-WDUE (OS, RS, SA, RS/SA, ES, RS/ES): Later, WDUE assignment is integrated with process plan selection, but this time, jobs are dispatched in random order. Although integrating WDUE improves the global performance substantially, SIRO dispatching sharply deteriorates the global performance back.

WEDD-WDUE (OS, RS, SA, RS/SA, ES, RS/ES): Finally, three important manufacturing functions are integrated, and this is the highest integration level that gives the best global performance.

VI. EXPERIMENTATION

The integrated problem is coded using C++ programming language and run using a Borland C++ 5.02 compiler on a laptop with a 2 GHz processor, 8 GB Ram, and CPU times are recorded and summarized at Table V.

A chromosome is used to represent the integrated problem. Each chromosome consists of $(n+2)$ genes to represent due-date assignment rules, dispatching rules and selected routes of every job. Five different rules are used in due date assignment with various multipliers and constants which sums up to 19 different rules. WEDD and SIRO are used as dispatching rules.

Four shop floors in which the characteristics are given at Table I are tested. Initially, an unintegrated combination, which is SIRO-RDM, is tested. Later, the WEDD-RDM combination is tested, where WEDD scheduling and process plan selection are integrated. After that, the SIRO-WDUE combination is tested and WDUE due date assignment methods are integrated with process plan selection. Finally, the WEDD-WDUE combination is tested, where all three functions are integrated. Here, weighted due date assignment and weighted scheduling are applied and important customers are given closer due dates and scheduled earlier. This provides substantial improvement in performance function, which is weighted penalty on earliness, tardiness and due-date related costs.

Four shop floors are tested for 24 different solution combinations and the results summarized in Table V. At the first shop floor there are 25 jobs and 5 machines. Every job has 10 operations at each route. It took approximately 20 seconds CPU time to run the program. The results are summarized in Table V and Fig. 2. Full integration level was found to the best integration combination. At the integration levels, SA heuristic gave the best result once, ES gave the best result once and RS/ES hybrid heuristic gave the best results three times. At the full integration level, the best results are shared between ES and RS/ES heuristics.

At the second shop floor, it took approximately about 200 seconds to complete the run of the program. The results are summarized in Table V and Fig. 3. According to the results, SA found twice the best solutions in integration levels and ES found twice the best solutions in the remaining two levels of integration. Again, full integration level is found as the best integration level.

At the third shop floor it took in between 200 and 300 seconds to complete the run of the program. The results are illustrated in Table V and Fig. 4. In two levels of integration, RS/SA gave best results, while the remaining two levels ES gave best results and ES and RS/ES shared best result in one level of integration. Again, at this shop floor the full integration level is found as the best combination as expected.

At the fourth shop floor, which is the largest shop floor with 175 jobs and 35 machines, it took about 300 seconds to complete the run of the program. The results are summarized in Table V and Fig. 5. According to the results, SA gave the best result in one level, ES gave the best results in two levels and RS/ES gave the best result in the remaining level. Full integration level was found the best integration level, as expected.

TABLE V
COMPARISON OF TWENTY FOUR SOLUTION COMBINATIONS FOR ALL OF THE SHOP FLOORS

Level of Integration (Combination)	Approaches	Shop Floor 1				Shop Floor 2				Shop Floor 3				Shop Floor 4			
		Best	Avg.	Worst	CPU	Best	Avg.	Worst	CPU	Best	Avg.	Worst	CPU	Best	Avg.	Worst	CPU
SIRO-RDM	OS	293	293	293	-	906	906	906	-	1413	1413	1413	-	2020	2020	2020	-
	RS	268	273	275	37	853	864	870	392	1355	1372	1378	286	1908	1925	1934	296
	SA	256	260	261	35	825	838	844	196	1358	1365	1369	240	1882	1896	1903	247
	RS/SA	258	263	266	34	846	857	864	346	1292	1318	1326	238	1876	1888	1899	246
	ES	256	260	263	37	826	838	844	405	1315	1323	1329	276	1860	1871	1879	286
	RS/ES	248	252	255	38	827	835	839	379	1322	1325	1327	276	1861	1875	1885	289
WEDD-RDM	OS	226	226	226	-	683	683	683	-	1122	1122	1122	-	1616	1616	1616	-
	RS	212	214	215	18	666	675	677	214	1060	1070	1081	286	1500	1513	1520	294
	SA	204	206	207	17	658	661	663	194	1041	1050	1052	245	1474	1489	1495	249
	RS/SA	207	208	209	17	663	668	670	195	1030	1040	1047	243	1484	1501	1508	255
	ES	205	206	207	17	652	654	655	207	1040	1046	1048	274	1469	1480	1487	286
	RS/ES	208	208	208	18	653	657	659	209	1031	1041	1045	276	1467	1479	1485	287
SIRO-WDUE	OS	337	337	337	-	1032	1032	1032	-	1570	1570	1570	-	2265	2265	2265	-
	RS	271	273	276	20	865	872	877	225	1328	1339	1349	299	1886	1907	1923	306
	SA	265	270	273	19	861	868	873	203	1312	1333	1342	254	1876	1900	1915	260
	RS/SA	268	276	278	19	851	862	868	202	1319	1328	1336	255	1894	1907	1920	260
	ES	257	262	265	20	823	848	855	222	1295	1313	1324	294	1879	1896	1907	299
	RS/ES	255	258	260	20	842	852	858	222	1302	1320	1327	294	1880	1896	1909	302
WEDD-WDUE	OS	271	271	271	-	865	865	865	-	1318	1318	1318	-	1894	1894	1894	-
	RS	192	197	199	20	610	622	627	225	948	957	963	303	1357	1376	1386	314
	SA	188	190	192	18	599	610	615	206	943	953	958	265	1355	1373	1386	273
	RS/SA	189	191	193	18	601	609	613	206	947	955	959	268	1357	1378	1386	273
	ES	185	187	188	20	588	595	599	221	931	939	944	294	1345	1363	1375	309
	RS/ES	185	188	189	20	593	602	606	222	931	939	944	297	1349	1369	1380	310

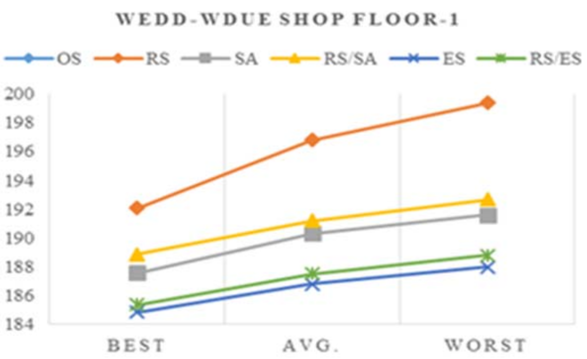

Fig. 2 Results of Shop Floor 1 (25x5x5)

At the highest level of integration, we repeated the experiments five times where at the lower levels of integration we applied only single experiment. Five different random number seeds are used to test the highest level of integration for five replicas. Thus, for four shop floors, 20 experiments are applied, where ES gave the best results in 11 replicas, RS/SA gave the best results in 4 replicas, RS/ES gave best results in 3 replicas, SA gave best results in one replica and RS gave the best results once. Through the experiments, just once best result are obtained from random search which is totally a random result rather than the power of random search.

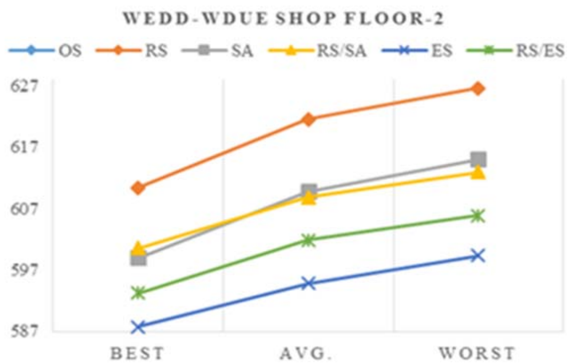

Fig. 3 Results of Shop Floor 2 (75x15x5)

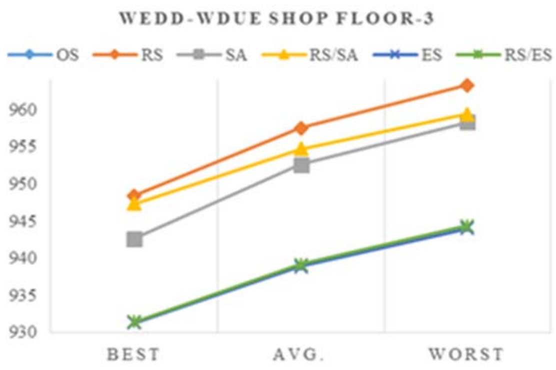

Fig. 4 Results of Shop Floor 3 (125x25x3)

Fig. 5 Results of Shop Floor 4 (175x35x3)

VII. Conclusion

Although there are only a few researches have focused on the IPPSDDA problem, there are numerous works on the sub integrated levels such as IPPS and SWDDA problems. Some of the researches addressing the IPPSDDA problem are mentioned in this research. Since all of these three important manufacturing functions are highly interrelated, it is better to consider them concurrently. A separate solution of the functions causes local optimization for each function, but substantially deteriorates the global optimum. If process plans are prepared separately, then poor and unrealistic process plans can be sent to the downstream scheduling function and this may cause unbalanced machine loading and reduce overall shop floor utilization. Independently performed scheduling function may not consider due date constraint and process plans wisely. Independently given due-dates may be unrealistic for shop floors and unreasonably too close due dates may be designated such that firms may not keep their promise to the customer, and therefore, the reputation of firms may be effected negatively. On the other hand, firms may give unnecessarily long due-dates to customers; this sharply increases, due-date and earliness related costs.

In this study, weighted due date assignment techniques are used where important customers are given closer due dates and are scheduled earlier. As a result, substantial improvements in overall weighted earliness, tardiness and due-date related costs are obtained.

In this research, some pure and hybrid metaheuristics are utilized while solving the integrated problem, namely RS, SA, RS/SA, ES, RS/ES metaheuristics. None of the metaheuristics gave the best results in every experiment. As expected, a fully integrated combination is found as the best integration level. Directed search heuristics are found better than random search. Since random search is marginally attractive only at the beginning of the iterations, combining with other search methods and making hybrid searches was found to be promising metaheuristics.

Initially, the SIRO-RDM combination is tested, and as expected, this lowest level of integration is found to be very poor. At this level process plans are selected independently, due dates are determined randomly and jobs are scheduled in random order. After that, the WEDD-RDM combination is tested; where, scheduling is integrated with process plan selection but due dates are still determined randomly. Substantial improvements are observed at this level of integration.

Later, the SIRO-WDUE combination is tested; where, weighted due-date assignment is integrated with process plan selection, but this time jobs are dispatched in random order. Although weighted due-date assignment provides substantial improvements at the performance function, SIRO dispatching severely deteriorates the penalty function back.

Finally, the WEDD-WDUE combination is tested where the three functions are fully integrated. Process plan selection is integrated with WEDD dispatching and with weighted due date assignment. As expected, this level is found as the best combination and gave the best improvements in the penalty function.

Appendix

A. Due-Date Assignment Rules

WTWK (Weighted Total Work)→ $\text{Due} = w_1 * k_x * \text{TPT}$

WSLK (Weighted Slack)→ $\text{Due} = \text{TPT} + w_1 * q_x$

WPPW (Weighted Process Plus Wait)→Due

$$= q_x * w_1 + w_2 * k_x * \text{TPT}$$

WNOP (Weighted Number of operations)→$\text{Due} = \text{NOP} * w_1 * k_x$

RDM (Random due date assign.)→Due

$$= N \sim (3 * P_{avg}, (P_{avg}/2)\, 2)$$

where; w_1, w_2 are determined according to the weights of the customers; TPT is total processing time; P_{avg} is mean processing time of all jobs waiting.

B. Dispatching Rules

WEDD: Weighted Earliest Due Date

SIRO (Service in Random order): A job among waiting jobs is selected randomly to be processed.

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