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Integrating Process Planning, WMS Dispatching, and WPPW Weighted Due Date Assignment Using a Genetic Algorithm

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***Abstract*—**Conventionally, process planning, scheduling, and due-date assignment functions are performed separately and sequentially. The interdependence of these functions requires integration. Although integrated process planning and scheduling, and scheduling with due date assignment problems are popular research topics, only a few works address the integration of these three functions. This work focuses on the integration of process planning, WMS scheduling, and WPPW due date assignment. Another novelty of this work is the use of a weighted due date assignment. In the literature, due dates are generally assigned without considering the importance of customers. However, in this study, more important customers get closer due dates. Typically, only tardiness is punished, but the JIT philosophy punishes both earliness and tardiness. In this study, all weighted earliness, tardiness, and due date related costs are penalized. As no customer desires distant due dates, such distant due dates should be penalized. In this study, various levels of integration of these three functions are tested and genetic search and random search are compared both with each other and with ordinary solutions. Higher integration levels are superior, while search is always useful. Genetic searches outperformed random searches.

***Keywords*—**Process planning, weighted scheduling, weighted due-date assignment, genetic algorithm, random search.

I. Introduction

Although the important manufacturing functions of process planning, scheduling, and due date assignments are performed separately, research is often conducted on IPPS (Integrated Process Planning and Scheduling) and SWDDA (Scheduling with Due Date Assignment), as well as with IPPSDDA (Integrated Process Planning, Scheduling, and Due Date Assignment). Due to the high interdependence among these functions, they should be considered concurrently. If these functions are performed independently, then each function tries to obtain local optima while neglecting the global optimum. However, the outputs of upstream functions become inputs to downstream functions. For instance, the outputs of process planning become the inputs of scheduling. Poor process plans may decrease global performance, reducing shop floor utilization and causing unbalanced machine loading. If process planning is performed independently of other factors, process planners may select the same machines repeatedly, perhaps not selecting other, undesired machines at all. As a result, some machines may become bottlenecked while others experience starvation.

If due dates are determined separately, they may be unnecessarily far, increasing penalty function, incurring reputational damage, increasing customer ill will, and potentially causing high due date and earliness related costs. If due dates are unreasonably close, promises may not be kept, damaging reputations, increasing customer ill will, reducing prices and increasing tardiness related costs. On the other hand, if scheduling is performed separately we may schedule close due dates later and vice versa, leading to high earliness and tardiness related costs, increased customer ill will, and higher stock-keeping costs.

Tardiness may cause price reductions, loss of customer goodwill, reputational damage, and ultimately loss of customers. Earliness may lead to higher inventory holding costs, spoilage, and other miscellaneous costs related to earliness and stock keeping. Far due dates are undesirable date as they may cause price reductions, customer ill will, and loss of customers.

Although tardiness alone is typically punished, according to JIT (Just in Time), both earliness and tardiness should be punished. In this study, we penalized all weighted earliness, tardiness, and due date related costs. These functions have been extensively defined in the literature. The Society of Manufacturing Engineers defines process planning as the systematic determination of the methods by which a product is to be manufactured economically and competitively. Reference [1] defines production scheduling as a resource allocator that considers timing information while allocating resources to tasks. According to [2], problems related to due date determination have received considerable attention in the last 15 years due to the introduction of new methods of inventory management, such as just-in-time (JIT) related concepts. In JIT systems, jobs are to be completed neither too early nor too late, which leads to the scheduling problems with both earliness and tardiness costs, as well as due date assignment.

Since only scheduling the function is NP-Hard, integrated problems are even harder to solve. Although there are

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numerous works on IPPS and SWDDA problems, there are only a few works on IPPSDAA problems in the literature. Researchers have used heuristics to find a good solution in a reasonable amount of time to the integrated problems instead of exact solutions. Exact solutions are only possible for very small sized problems. In this research we used metaheuristics to solve the integrated problem and we applied genetic search and random search to find a good solution in a reasonable amount of time.

The problem is represented as a chromosome with (n+2) genes, where the first two genes represent the due date assignment rule used and the second gene is used to represent the dispatching rule used. Remaining *n* genes represent the selected route of each job. Since the first two genes highly affect the performance measure, it is better to apply the dominant gene approach and increase the probability of these genes higher compared to probability of the remaining *n* genes. Thus, dominant genes have much higher probability to be selected for crossover and mutation operators in a genetic search.

In the literature, due dates are assigned without taking into account the weights of the jobs [2]-[8], but in this study the researchers took into account the importance of each customers. Since more important customers are given close dates and scheduled earlier, we save substantially from the penalty function which is sum of weighted earliness, tardiness and due date related costs. By assigning important customers earlier we save from weighted due date related costs and by scheduling important customers earlier we save from weighted tardiness related costs.

We tested a fully unintegrated solution and step by step we integrated three functions. Finally, we tested a full-integrated combination. Full integration with genetic search is found to be the best combination, as expected.

II. Literature Research

In this study, we attempted to integrate three important manufacturing functions which are process planning, scheduling and due date assignment. Although this integration is new, there are numerous works on IPPS integration and hundreds of works on SWDDA problem.

For IPPS problem it is better to see some reviews made on this problem. References [3]-[5] presented a literature survey on the IPPS problem. As we mentioned earlier, there are hundreds of works on the IPPS problem. Earlier works on IPPS include [6]-[13]. More recent works concerning IPPS include [3]-[5], [14]-[25].

As stated above, exact solutions are only possible for very small problems. Larger problems require the use of heuristics. Reference [26] stated that the literature shows that it is difficult to solve integrated problems. Some solutions are only possible for small problems. For IPPS in the literature, genetic algorithms, evolutionary algorithms, or agent based approaches are used for integration. Additionally, problems may be decomposed due to their inherit complexity. Problems are decomposed into loading and scheduling sub problems. They use mixed integer programming in the loading part and heuristics in the scheduling part.

Another popular research topic is the SWDDA problem. Here scheduling is tried to be integrated with due date assignment. There are hundreds of works on SWDDA problem as well. For a good review of SWDDA problem, see [27]. If we disintegrate due date assignment from the scheduling function, then we may assign poor due dates which are unnecessarily far due dates or unrealistically close due dates. On the other hand, if scheduling is performed independently, we may schedule close dates later and schedule far due dates earlier, unnecessarily increasing weighted earliness and tardiness costs.

Conventionally, tardiness is punished, but according to the JIT environment, we should penalize both earliness and tardiness costs. As nobody desires far due dates, they cause loss of customer goodwill, price reductions, loss of a firm's good reputation, and greater customer loss. That is why in this research we penalized all weighted earliness, tardiness and due date related costs. In the literature, due dates are given without considering the importance of the customers, but in this research we assigned due dates according to the weights of the jobs. Important jobs are assigned closer due dates, allowing for substantial improvement in the overall penalty function.

The literature for SWDDA problems includes SMSWDDA [3]-[7], [33]-[39] (Single Machine scheduling with Due Date Assignment) and MMSWDDA (Multiple Machine Scheduling with Due Date Assignment) problems. In the former case, there are single machines and multiple jobs to be scheduled with due date assignment. In the latter case, there are multiple machines and multiple jobs to be scheduled and due dates to be assigned.

In this research, there are *m* machines and *n* jobs to be scheduled and due dates to be assigned. Unlike many works in the literature, [2], [8], we assigned separate due dates for each jobs. So, our problem is job shop scheduling with separate due date assignments for each job integrated with process plan selection. Here, we assigned earlier due dates to more important customers.

SMSWDDA problems are addressed by [27]-[39]. MMSWDDA problems are addressed by [40]-[44].

Numerous works have considered common due date assignment [2]-[8]. For example, if we give a due date for jobs to be assembled, we assign a common due date. However, in this research, we assigned unique due dates for each customer. More recent works on SWDDA problems include [39], [45]-[57]. Although there are plenty of works on IPPS and SWDDA problems, there are only a few works on IPPSDDA problems. Some works on IPPSDDA problems include [58]-[60], [26].

III. Problem Studied

Although, conventionally process planning, scheduling and due date assignments are separately and sequentially handled, IPPS and SWDDA problems are very popular research topics during the last couple of decades. Furthermore integration of these three functions is a new fertile research area where only a few works are done [32], [58]-[60]. In this study, we tried to integrate these three functions using metaheuristics, namely genetic and random search.

To implement genetic and random searches, we represented problems as chromosomes with (n+2) genes. The first two genes represent due date assignment and scheduling rules. The remaining *n* genes are used to represent the actively selected route of the *n* jobs.

We tested integrated process planning with WMS (Weighted minimum slack) scheduling and WPPW (Weighted process plus wait) due date assignment. We studied three shop floor sizes, which are small, medium, and large. The features of each shop floor are summarized in Table I. As an example, small shop floor consists of 20 machines, 50 jobs and five different routes for each job. Each route has 10 operations and operation times change randomly in between one and 30 according to a normal distribution, with a mean of 12 and a standard deviation of six, according to the formula [(12+z*6)]. Processing times assume integer values.

TABLE I
SHOP FLOORS

Shop floor	Shop floor 1	Shop floor 2	Shop floor 3
# of machines	20	30	40
# of Jobs	50	100	200
# of Routes	5	5	3
Processing Times	$\lfloor(12+z*6)\rfloor$	$\lfloor(12+z*6)\rfloor$	$\lfloor(12+z*6)\rfloor$
# of op. per job	10	10	10

At first, we tested an unintegrated version. Process plan selection was performed separately, while jobs scheduled in random order and due dates were randomly assigned. As expected, this combination was very poor. After that, we integrated WMS scheduling with process plan selection, but due dates are determined randomly and we observed improvements by this integration. Later, we integrated process plan selection with WPPW due date assignments, but with jobs scheduled in random order. Although this integration allows for substantial improvements, SIRO scheduling results in strict deterioration again. Finally, we tested full integration. This integration showed the highest improvements. Here, we tested both random and genetic searches. Genetic search was found to be better than random search.

We assumed a day to consist of one shift per day with 480 minutes. As a penalty function, we penalized due date, earliness, and tardiness related costs in proportion to their importance to customers. For earliness and tardiness, we used both fixed and variable costs. Due dates were assigned according to the importance of the jobs, with important customers getting closer dates.

Each term of the penalty function is given below. PD(j) is the penalty for due date for job j; PE(j) is penalty for earliness for job j; PT(j) is penalty for tardiness for job j; and penalty of a job is Penalty(j). The total penalty of all jobs is calculated as:

$$P.D(j) = weight\ (j)*8*(Due\ date/480) \tag{1}$$

$$P.E(j) = weight\ (j)*\ (5+4*(E/480) \tag{2}$$

$$P.T(j) = weight\ (j)*(10+12*(T/480)) \tag{3}$$

$$Penalty(j) = P.D(j) + P.E\ (j) + P.T(j) \tag{4}$$

$$Total\ Penalty = \textstyle\sum_j Penalty(j) \tag{5}$$

IV. Solution Techniques Used

At this study we compared ordinary solutions with a directed (genetic) and undirected (random) search. As expected genetic and random search provided substantial improvements compared to the ordinary solutions. Also we observed genetic search superior compared to random search.

Since the scheduling problem alone belongs to the NP-Hard problem and integrated problems are even harder to solve, we applied genetic and random search over the problem. We represented problem as chromosomes which are illustrated in Fig. 1.

Below each solution techniques are explained in detail:

Ordinary Solution: We compared ordinary solutions with genetic and random search to prove the benefits of search techniques. At genetic and random searches, we used predetermined number of iterations according to the three tested shop floors. To be fair, at every solution technique we used for the same size of populations. For genetic search for example, we used main population, crossover population and mutation population. Sizes of the populations were 10, eight and five chromosomes, respectively. Thus, at every iteration, we have totally 23 chromosomes and at the end of each iteration we select best 10 chromosomes out of three populations with 23 chromosomes as the current main population.

As ordinary solutions, we select best 10 chromosomes of the initially randomly produced three populations. We used best, worst and average results of first iteration results which initially selected the 10 best chromosomes for the first step main population as the ordinary solutions.

As expected ordinary solutions were the poorest solutions. Since it is the first step solutions, we did not record CPU times and it instantly obtained ordinary results. These results for small, medium and large shop floors according to the different integration levels are summarized in Tables IV, V and VI, respectively.

Random Search: As it is mentioned earlier, we used the same sizes of populations in random and genetic search. This is because we wanted to be fair in comparison of these two search techniques. We had a population with size of 10 as the main population, a population as big as crossover population with size of eight and finally a population as great as mutation population with size of 5. Genetic search crossover population is reproduced using crossover operator and main population, but here we produced the same size of population, purely randomly. At genetic search mutation population is produced by using mutation operator from main population but here we produced five chromosomes totally randomly as brand new random solutions. We applied 200, 100 and 50 purely random iterations instead of genetic iterations for the three shop floors respectively. CPU times and results of random search are given at the last column of Tables IV, V and VI and illustrated at Figs. 2, 3 and 4, respectively, according to the three shop floors.

Genetic Search: Here we applied genetic iterations and genetic operators instead of random iterations. Since random search scans solution space randomly it is an undirected search. Random search always produces brand new solutions and does not realize the benefit of earlier solutions. Although at the beginning marginal improvements of random iterations are high, later marginal improvements reduce sharply and the random search becomes poor. In contrast to random search, genetic search uses earlier best solutions to produce new solutions with the hope of finding better solutions. Since genetic search realizes the benefit of earlier solutions, it is a directed search and is superior to random search. We have a main population with size 10 chromosomes which represent the best 10 chromosomes found so far. By using four pairs of chromosomes from the main population and using crossover operators, we produce four new pairs of children to find eight chromosomes of crossover population. Similarly, we select five chromosomes from the main population and by using mutation operator; we produce five new chromosomes which constitute the mutation population. By using the old main population, the new crossover population and the new mutation population, we produce the new main population. The new main population has the 10 best chromosomes of the three populations.

We applied 200, 100 and 50 genetic iterations for the three shop floors, respectively. Since the genetic search is a directed search and attains the benefits of earlier best solutions so far, it is superior compared to random search. Again, to be fair in the comparison with the random search, we applied the same number of iterations and used the same sizes of populations at every iteration.

CPU times and the results of the genetic search are given in the last column of Tables IV, V and VI and illustrated in Figs. 2, 3 and 4, respectively, according to the three shop floors.

The problem is represented as chromosome and we used (n+2) genes. The first two genes are used to represent due date assignment and dispatching rules. The remaining n genes represent the selected routes of each job. The chromosome model is illustrated in Fig. 1.

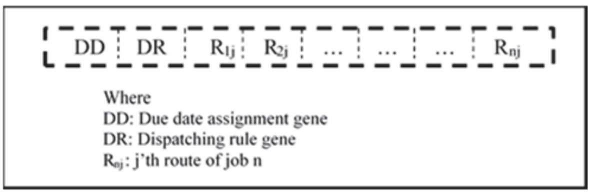

Fig. 1 Sample chromosome

We used dominant genes while solving the problem. Since the effects of the first and second genes over performance function are very high, we gave high probability to these genes to be selected as crossover or mutation points compared to the remaining n genes.

We used two types of rules while assigning due dates, which are the WPPW and RDM (Random) rules. With the different multipliers and constants, we used 10 rules while assigning due dates. These rules are summarized in Table II and explained in Appendix A.

TABLE II
DUE DATE ASSIGNMENT RULES

Method	Multiplier	Constant	Rule No
WPPW	k_x =1,2,3	q_x =q_1,q_2,q_3	1,2,3,4,5,6,7,8,9
RDM			10

The second gene takes one of two values. Two rules are used, which are WMS and SIRO (Service in random order) rules.

TABLE III
DISPATCHING RULES

Method	Rule No
WMS	1
SIRO	2

V. SOLUTIONS COMPARED

In this study we compared ordinary solutions, genetic and random search solutions with each other to prove the benefits of search solutions and to show superiority of directed search over undirected search. For different integration levels we tested ordinary solutions and genetic search solutions and for the full integration level we also tested random search. In total we compared nine solutions, where the first four are ordinary solutions, the next four of them are genetic search results and the last of them are random search results. Each integration level is explained in detail below.

SIRO-RDM (Genetic): Here every function is disintegrated and this is the lowest level of integration. Process plan selection is made separately and jobs are scheduled in random order and due dates are assigned randomly. Here Genetic algorithm is used.

WMS-RDM (Genetic): Later we integrated WMS scheduling with process plan selection but due dates are still determined randomly. We used genetic algorithm here.

SIRO-WPPW (Genetic): After that we integrated weighted due date assignment with process plan selection but this time jobs are scheduled in random order and genetic algorithm used as solution technique. Although this integration provides substantial improvements SIRO scheduling deteriorates performance measure strictly.

WMS-WPPW (Genetic): This is the ultimate goal of our study. Three manufacturing functions are integrated. Process planning is integrated with WMS scheduling and WPPW weighted due date assignment and genetic algorithm is used.

WMS-WPPW (Random): Since this was our goal and best combination, we wanted to test random search with this combination also.

The nine solutions are compared with each other; four of them were ordinary solutions, four of them were genetic search solutions and one is a random search solution. Each technique is tested for different level of integrations.

VI. Experiments and Results

The problem is coded using C++ Programming language. The coded program performs the genetic search, random search, perform scheduling according to the two rules used and assigns due dates according to 10 rules. The program is run using Borland C++ 5.02 compiler on a laptop with a 2 GHz processor, 8 GB Ram which uses the Windows 8.1 operating system. CPU times are recorded at the end of each run and recorded CPU times are summarized in Tables IV, V and VI, respectively.

The problem is represented as chromosomes consisting of (n+2) genes. The first two genes are used to represent due date assignment and scheduling rules, and the remaining genes represent the selected routes of every jobs. As due date assignment rules, mainly WPPW and RDM rules are used. With different multipliers and constants, a total of 10 due date assignment rules are used. As scheduling rules, WMS and SIRO rules are used.

Three shop floors are tested which are small, medium and large shop floors. The characteristics of the shop floors are summarized in Table I. For three shop floors in the genetic and random search, we applied 200, 100 and 50 genetic or random iterations, respectively.

At the beginning we tested unintegrated solutions. SIRO-RDM (Ordinary) and SIRO-RDM (Genetic) combinations are tested at the beginning. Later we integrated WMS scheduling with process plan selection, and WMS-RDM (Ordinary) and WMS-RDM (Genetic) combinations are tested. After that we integrated process plan selection with WPPW weighted due date assignment, and tested SIRO-WPPW (Ordinary) and SIRO-WPPW (Genetic) combinations. Finally, we tested full integrated combinations, and we solved WMS-WPPW (Ordinary), WMS-WPPW (Genetic) and WMS-WPPW (Random). A total of nine solutions are compared and full integration with genetic search is found as the best combination. We interpreted the results and made conclusions on this study in the conclusion section of this paper.

Three shop floors are tested for nine different solution combinations. The characteristics of the shop floors are summarized and explained in Table I and Section III. The nine solutions compared are explained in Section V.

The smallest shop floor had 50 jobs and 20 machines, and we applied 200 random or genetic iterations and recorded the CPU times, as summarized in Table IV. It took approximately 100 to 200 seconds to complete 200 genetic or random iterations. All the results for the small shop floor are summarized in Fig. 2 and Table IV. According to the results, full integration with genetic search is found to be the best combination and ordinary solutions are found to be the poorest.

All the results related to the medium shop floors can be found in Fig. 3 and Table V. Here we obtained similar results and searches are always found to be useful, and genetic search outperformed random search. Ordinary solutions are found to be the poorest combinations. Full integration level found the best integration level and full integration with directed search as the best combination. It took approximately 300 to 600 seconds to finish 100 genetic or random iterations.

TABLE IV
COMPARISON OF NINE TYPES OF SOLUTIONS FOR SMALL SHOP FLOOR

	Worst	Average	Best	CPU Time
SIRO-RDM(O)	464,82	447,55	432,15	
WMS-RDM(O)	411,7	383,54	366,88	
SIRO-WPPW(O)	516,42	473,76	434,37	
WMS-WPPW (O)	464,32	406,14	332,62	
SIRO-RDM(G)	397,38	395,98	393,46	117 sec
WMS-RDM(G)	356,59	356,02	354,25	191 sec
SIRO-WPPW(G)	385,82	382,59	375,76	148 sec
WMS-WPPW (G)	298,15	297,42	296,46	149 sec
WMS-WPPW (R)	308,62	306,98	303,45	162 sec

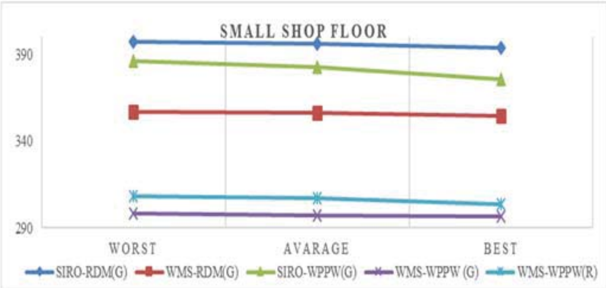

Fig. 2 Small Shop Floor Results

TABLE V
COMPARISON OF NINE TYPES OF SOLUTIONS FOR MEDIUM SHOP FLOOR

	Worst	Average	Best	CPU Time
SIRO-RDM(O)	1124,6	1076,26	1038,92	
WMS-RDM(O)	1067,6	995,63	938,1	
SIRO-WPPW(O)	1246,71	1092,69	1006,8	
WMS-WPPW (O)	1091,88	915,22	781,92	
SIRO-RDM(G)	973,91	968,86	960,46	650 sec
WMS-RDM(G)	816,48	811,87	805,3	295 sec
SIRO-WPPW(G)	952,61	947,95	936,41	425 sec
WMS-WPPW (G)	722,84	721,72	720,48	426 sec
WMS-WPPW (R)	760,2	753,27	741,12	444 sec

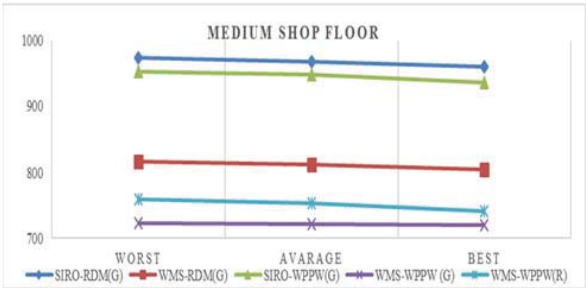

Fig. 3 Medium Shop Floor Results

The largest shop floor had 200 jobs and 40 machines and we applied 50 directed and undirected search iterations. It took approximately 600 to 800 seconds to finish the genetic or random iterations. We obtained similar results here too. Full integration with genetic search is found to be the best combination, genetic search outperformed random search and ordinary solutions were the poorest.

TABLE VI
CO COMPARISON OF NINE TYPES OF SOLUTIONS FOR LARGE SHOP FLOOR

	Worst	Average	Best	CPU Time
SIRO-RDM(O)	2736,06	2698,08	2623,78	
WMS-RDM(O)	2450,23	2411,84	2388,78	
SIRO-WPPW(O)	2858,88	2676,36	2546,17	
WMS-WPPW (O)	2385,39	1990,61	1708,09	
SIRO-RDM(G)	2510,6	2505,37	2492,86	635 sec
WMS-RDM(G)	2257,37	2252,82	2247,2	735 sec
SIRO-WPPW(G)	2486,87	2479,78	2458,71	734 sec
WMS-WPPW (G)	1671,42	1669,83	1667,24	690 sec
WMS-WPPW (R)	1745,96	1721,09	1684,17	834 sec

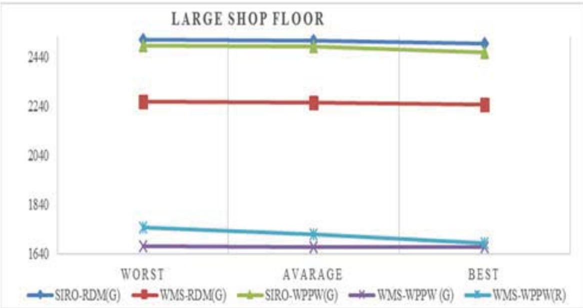

Fig. 4 Large Shop Floor Results

VII. CONCLUSION

Although the three important manufacturing functions are treated separately, there are numerous works on IPPS recently, and the SWDDA problem is also a very popular research topic as well. Even though these two research topics are very popular lately, there are only a few works on the IPPSDDA problem, making this area of study a very fertile research area. Some works on IPPSDDA are listed in the reference part of this study. Since there are high interrelations between these three functions it is better to integrate these functions. If we integrate these three functions, then each function tries to get global optima and substantial improvements could be provided; otherwise, each function tries to get local optima and does not care about global optima. This strictly reduces global performance measures. In this study we tried to integrate these three important manufacturing functions. We started from the unintegrated combination and step by step we integrated three functions and tried to observe the benefits of a higher integration level and prove that full integration is the best combination. We also tried to observe the improvements made by genetic and random searches and show how poor the ordinary solutions are. We also wanted to show the superiority of a directed search over an undirected search.

When we see IPPS and SWDDA problems, due dates are assigned externally or internally. For the internal due date assignments, the importance of the customers was not taken into account. In this study we assigned important customers closer dates which provided substantial improvements in the overall performance measure.

In this study, we assigned closer dates for important customers by applying the WPPW due date assignment rule and scheduled important customers with earlier due dates first using the WMS scheduling rule.

Conventionally only tardiness is punished, but according to JIT philosophy, both earliness and tardiness should be punished. Since nobody wants far due dates and far due dates cause customer ill will, price reduction, loss of firm reputation, and worse, loss of customers, this is why we should assign closer due dates as much as possible. For this reason, we penalized all of weighted earliness, tardiness and due date related costs.

We used genetic search and random search metaheuristics as solution techniques and compared the search results with each other and with ordinary solutions. By comparing the search results with ordinary solutions, we tried to prove improvements made through the search techniques. We also wanted to observe the superiority of genetic search over random search.

To start, we tested full unintegrated combinations, where process plan selection is performed separately and jobs are scheduled in random order and due dates are assigned randomly. Here we tested SIRO-RDM (Ordinary) and SIRO-RDM (Genetic) combinations.

Later we integrated WMS scheduling with process plan selection and tested this integration level. Due dates are still determined randomly here and at this level of integration we tested WMS-RDM (Ordinary) and WMS-RDM (Genetic) combinations. Here we observed substantial improvements through this integration. After that, this time due date determination is integrated with process plan selection. WPPW weighted due date assignment is integrated with process planning, and due dates are determined internally, but jobs are scheduled in random order. Although this integration provided substantial improvements, SIRO scheduling highly deteriorated the overall performance back. Here we studied SIRO-WPPW (Ordinary) and SIRO-WPPW (Genetic) combinations.

To end, we integrated all three functions and process plan selection is integrated with WPPW due date assignment and WMS scheduling. As expected this level of integration is found as the best combination. At this step we tested WMS-WPPW (Ordinary), WMS-WPPW (Random) and WMS-WPPW (Genetic) combinations. Genetic search is found to be superior compared to random search and full integration with genetic search found to be the best combination.

Although traditionally these three functions are performed separately and sequentially, high interrelations between these three functions force us to consider integration. Although there are numerous works on IPPS and SWDDA problems, there are only a few works on the IPPSDDA problem. Outputs of upstream functions become inputs to the downstream functions. For instance, poorly prepared process plans become very poor inputs to scheduling function. In the end we may not completely follow plans at the shop floor level and poor process plans may cause unbalanced machine loading and reduce shop floor performance. For example, if process plans are prepared separately then process planners may repeatedly select same desired machines and may not select some undesired machines at all. This causes highly unbalanced machine loading and substantially reduces shop floor utilization. Similarly, if due dates are assigned independently from scheduling, we may give far due dates unnecessarily especially for important customers, which greatly increases weighted due date assignment and earliness related costs. On the other hand, if we give unreasonably very close due dates, this time we highly pay for high weighted tardiness related costs because of unrealistic close due dates.

If scheduling is performed independently from due date assignment, we may schedule closer dates later or vice versa. In the former case we pay for high weighted tardiness related costs or in the latter case we pay for weighted high earliness related costs. So logically it is better to consider these three functions concurrently and improve overall performance measures. In this research we observed highest integration level as the best combinations.

As a summary we integrated process planning with WPPW weighted due date assignment and WMS scheduling. We selected better routes for overall performance and assigned closer dates for important customers using WPPW, and we scheduled these important customers using WMS scheduling. As a result, we obtained high improvement in overall performance, which is the sum of weighted earliness, tardiness and due date related costs.

Full integration with genetic search gave the best results and is found to be the best combination. Genetic search outperformed random search and ordinary solutions are found to be very poor and this proved the benefits of the search techniques.

APPENDIX

A. Appendix A: Due date Assignment Rules

- WPPW (Weighted Process Plus wait)
- Due = q_x * w_1 + w_2*k_x*TPT (w_1, w_2 are determined according to weights) $q_x = q_1$, q_2 or q_3, q_1=0.5*P_{av}, q_2=P_{av}, q_3=1.5*P_{av}, k_x= 1,2,3
- RDM (Random due assign.)Due = N ~ (3*P_{av}, (P_{avg})2)
- TPT= total processing time
- P_{avg}= mean processing time of all job waiting

B. Appendix B: Dispatching Rules

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

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