International Journal of Mechanical, Industrial and Aerospace Sciences
ISSN: 2517-9950
Vol:11, No:7, 2017

Solving Process Planning and Scheduling with Number of Operation Plus Processing Time Due-Date Assignment Concurrently Using a Genetic Search

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Abstract**—**Traditionally process planning, scheduling and due date assignment are performed sequentially and separately. High interrelation between these functions makes integration very useful. Although there are numerous works on integrated process planning and scheduling and many works on scheduling with due date assignment, there are only a few works on the integration of these three functions. Here we tested the different integration levels of these three functions and found a fully integrated version as the best. We applied genetic search and random search and genetic search was found better compared to the random search. We penalized all earliness, tardiness and due date related costs. Since all these three terms are all undesired, it is better to penalize all of them.

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

I. Introduction

ALTHOUGH on IPPSDDA (Integrated process planning, scheduling and due date assignment) problems there are only a few studies, while there are numerous works on IPPS (Integrated process planning and scheduling) and plenty of works on SWDDA (Scheduling with due date assignment). There is a high interrelation between process planning, scheduling and due date assignment functions. Thus, it is better to consider these three functions simultaneously in order to improve global performance.

Output of upstream functions becomes input for downstream functions. For instance, output of process planning becomes an input for scheduling. If process plans are prepared independently from scheduling then process planners may select the same desired machines repeatedly and may not select some undesired machines at all. This causes unbalanced shop floor loading and poor process plans may not be followed at the shop floor level.

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This research is supported by the Sakarya University Scientific Research Projects Commission with the project number 2017.

In the case of unexpected occurrences, if we prepared alternative routes, jobs may be redirected to overcome them. Performance measures also highly depend on scheduling and due date assignment integration. Independently prepared scheduling may substantially deteriorate performance measures and we may end up with severe earliness and tardiness costs.

Similarly independently assigned due dates severely increase performance measures. If we integrate due date assignment with process planning, we can improve performance measure substantially. By doing so, we may assign better due dates and save up from due date related costs, and we may give more reasonable due dates and keep our promise and also save from earliness and tardiness related costs.

Before going further, if we give definitions of these three functions, we may find the following definitions: Society of Manufacturing Engineers defined process planning. According to their definition process planning is a systematic determination of the methods by which a product is to be manufactured economically and competitively. Production scheduling is defined by Zhang and Mallur [1] as a resource allocator which considers timing information while allocating resources to the tasks. According to Gordon et al. [2] "The scheduling problems involving due dates are of permanent interest. In a traditional production environment, a job is expected to be completed before its due date. In a just-in-time environment, a job is expected to be completed exactly at its due date".

Only the scheduling problem belongs to the NP-Hard class problems and integrated problems are even harder to solve. For this reason, some heuristics are used in the solution. Exact solutions are only possible for very small problems, for the large problems, we look for a reasonable solution. In this research we used metaheuristics for the solution. We used genetic search and random search to find a good solution in a reasonable amount of time.

As a result of developments in hardware, software and algorithms, it is possible to solve the problems which could not be solved earlier or to solve some problems easier, which were in the past difficult to solve. Similarly, now it is easier to prepare alternative and quality process plans to improve the global performance. Developments in computers lead to the development in CAPP (Computer Aided Process Planning).

NOP (Number of operation) is a method used in the literature to find due dates for the jobs being considered. In this study, we tried a new method NOPPT (Number of operations plus processing time) to assign due dates to jobs. Here, we tried to integrate process planning, scheduling with NOPPT due date assignment, as well as processing time and number of operations simultaneously while determining due dates.

According to the literature, traditionally tardiness is punished, but according to JIT philosophy, both tardiness and earliness should be punished. However, according to this study, we penalized all of weighted earliness, tardiness and due date related costs. Since nobody wants far due dates, we penalized due dates with some proper parameters. Far due dates may cause customer ill will, price reduction and worse customer loss. Earliness can result in stock storage problems, spoilage and inventory holding costs. Tardiness may cause loss of customer good will and price reductions, and worse, loss of the customer in case we may not keep our promise on time.

II. Background and Related Researches

Process planning, scheduling and due date assignment are three important manufacturing functions which are treated separately. Although there are plenty of works on IPPS and on SWDDA, there are only a few works on IPPSDDA. Demir and Taskin [3] worked on IPPSDDA in a PhD thesis and later Ceven and Demir [4] studied the benefit of integrating due date assignment with the IPPS problems in a Master's Thesis. Later Demir et al. [5] continued to study the IPPSDDA problem.

If we look at integrated solutions of these three functions we can find numerous works on sub integrations. There are many works on IPPS problem. For a good review on IPPS problem it is better to see Tan and Khosnevis [6]. Also Li [7] and Phanden et al. [8] can be read as IPPS review.

According to the literature, since scheduling is an NP-Hard class problem, the integrated problem is even harder to solve. That is why in the solution of IPPS problem some heuristics, metaheuristics are used. Exact solutions are only possible for very small problems, and as problems get bigger, it becomes practically not possible to find exact solutions to the problem. In this case, we need to find a good solution instead of the best solution. Since integrated problems are even more complex, researchers decomposed the IPPS problem into loading and scheduling sub problems. Demir and Wu [9] decomposed problem into loading and scheduling sub problems and solved the IPPS problem in a Master's Thesis. While solving the integrated problem, some researchers applied evolutionary algorithms, genetic algorithms or agent based solutions to the problem.

Since the IPPSDDA problem is even more complex, we used genetic search and random search while solving the problem.

As we mentioned, there are numerous works on IPPS problem and [1], [10]-[15] are some examples to earlier IPPS researches.

If we give a list of some current researches on IPPS, [6]-[8], [16]-[22] are more recent examples .

Another important research topic is the SWDDA problem. This problem is also more complex compared to the scheduling problem, and here, we assign better due dates and schedule jobs simultaneously that gives better performance measure. For a good review it is better to see Gordon et al. [2].

Due dates can be determined as endogenous or exogenous. If dates are determined as exogenous then a firm has no control over the due dates. On the other hand, if dates are determined endogenous, then firm tries to find better due dates that give better global performance.

Some works are on SMSWDDA (Single machine scheduling with due date assignment) and some works are on MMSWDDA (multiple machine scheduling with due date assignment). In the former case, jobs are scheduled with due date assignment before a single machine. At the latter case, some jobs are scheduled with due date assignment before some machines. In this research, we have m machines and n jobs to be scheduled with due date assignment before these m machines.

Some researches assign common due date for jobs to be scheduled. This may be possible for those jobs waiting to be assembled together. But in this research, we assigned separate due dates for each job.

References [23]-[33] are some examples of the SMSWDDA problem. On the other hand, the following works address the MMWDDA problem. References [34]-[36] are some examples to these kinds of problems.

In the literature, conventionally tardiness is penalized. But according to JIT, both earliness and tardiness should be punished. While in this study, we penalized all weighted earliness, tardiness and due date related costs, since nobody wants late due dates, it was decided to penalize due date related costs. Long due dates cause customer ill will, price reduction and even customer loss. In the JIT environment and in reality, earliness is also undesired. Earliness causes unnecessarily stock storage, spoilage and inventory holding costs. Similarly, in due date related costs, tardiness is also undesired and means that we could not keep our promises. Nobody wants tardiness and it can damage a firm's reputation, cause loss of customer good will, and result in price reduction, and at worse, the loss of the customer.

III. Problem Studied

In this study, we tried to integrate process plan selection with scheduling and NOPPT due date assignment. We studied three shop floors with the characteristics summarized in Table I. Small shop floor with 20 machines and 50 jobs; where each job has five alternative routes and each route has 10 operations. Medium shop floor has 30 machines and 100 jobs; where each job has five alternative routes and each route has 10 operations. Large shop floor has 40 machines and 200 jobs; where each job has three alternative routes and each route has 10 operations. For each shop floor, every operation has processing time determined randomly according to the formula $\lfloor(12 + z * 6)\rfloor$. Practically every operation assumes a random integer value in between 1 and 30, according to normal distribution with mean of 12 and standard deviation of 6.

We used genetic search and random search in the solution. We used the well-known dispatching rules given in Table III as the scheduling rules and the NOPPT due date assignment rule as the due date determination method. For the NOPPT rule, we use the number of operations and processing times of each job while determining the due dates. We compared search solutions with ordinary solutions to illustrate how search techniques are well compared to ordinary solutions.

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

We assumed a day is 480 minutes. We assumed one shift with eight hours, as such 8*60 = 480 minutes is the duration of one shift and one day. We punished all weighted earliness, tardiness and due date related costs. The penalty function is summarized below.

Where *weight(j)* is the weight of job j. *D* is the due date, *E* is the earliness and *T* is the tardiness of job j. *P.D(j)* is penalty for due date, *P.E(j)* is the penalty of earliness and *P.T(j)* is the Penalty of tardiness of job j. *Penalty(j)* is the total penalty of a job j. Finally, we determine *Total Penalty,* which is the total penalty for all of the jobs.

IV. SOLUTION TECHNIQUES USED

We used genetic search and random search as the solution technique, and we compared the search results with each other and against ordinary solutions. Each technique is explained below:

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

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

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

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

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

Ordinary Solution: At every iteration of genetic and random search we use three populations. Main population with size 10, Crossover population with size 8 and mutation population with size 5. To be fair in the comparison of random search and genetic search, we used the same size of populations. In order to determine the current main population, we used the previous step's main population and current crossover population and current mutation population, and out of 23 chromosomes, we select the best 10 chromosomes for the current main population. At the first iteration for the first main population, we select best 10 chromosomes of randomly produced 23 chromosomes. The results of this first step's main population are used as ordinary solutions.

Random Search: For this search, we applied random iterations. For three shop floors we applied 200, 100 and 50 random iterations, respectively. To be fair with genetic search, we randomly produced the same size populations as we genetically produced in the genetic search. At every iteration we select the best 10 chromosomes of the previous main population, and a current population as big as the crossover population, and a current population as big as the mutation population. Out of these three populations and 23 chromosomes, we select current a main population with size 10.

Genetic search: For this search, we applied genetic operators to produce crossover and mutation populations. At every iteration we select four pairs of chromosomes according to the probability produced according to the performance measure of the chromosomes. By using these four pairs of chromosomes, we produced four new pairs of chromosomes, which make eight chromosomes for the crossover population. For the mutation population, we select five chromosomes according to the probability produced by using the performance measure of the chromosomes. We apply mutation operators over the selected five chromosomes and produce five new chromosomes for the mutation population. Out of previous main population, for a new crossover population and new mutation population, we select the best 10 chromosomes and produce a new main population with size 10.

As in Fig. 1, we have *(n+2)* genes in a chromosome. First, two genes are used for the due date assignment rule and dispatching rule. Since these two genes substantially affect the performance measure of the chromosome, we assumed these genes as the dominant genes and gave high probability to these genes while selecting for crossover and mutation operators. The remaining *n* genes are about the active route of the jobs. Since these genes have less effect on performance measure, we gave a lower probability for these genes while selecting crossover and mutation operators. According to the literature on IPPS, we can say that initially marginal benefits of alternative process plans are very high and later marginal benefits of alternative process plans decrease sharply.

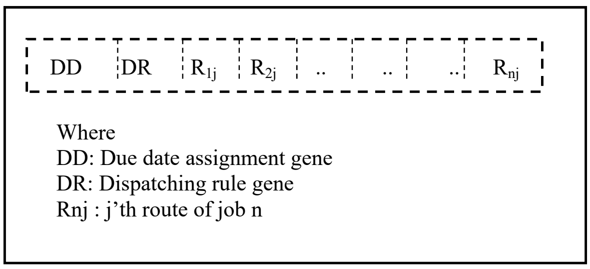

Fig. 1 Sample chromosome

Due dates are determined according to the rules summarized in Table II. Mainly, we have two rules which are NOPPT and RDM due date assignment rules. With the

International Journal of Mechanical, Industrial and Aerospace Sciences
ISSN: 2517-9950
Vol:11, No:7, 2017

multipliers, there are 10 rules in total. For the NOPPT rule, we use the number of operations and processing times while determining due dates. This is endogenous due date determination, where the firm has control over due dates. For the RDM rule, we randomly determine due dates, which represents exogenous due date determination where the firm has no control over due dates.

TABLE II
DUE-DATE ASSIGNMENT RULES

Method	Multiplier1	Multiplier2	Rule no
NOPPT	k_x =1,2,3	k_y =1,2,3	1,2,3,4,5,6,7,8,9
RDM			10

Second gene represents the dispatching rules, where second gene may take one of 21 different values. Mainly, we used nine different dispatching rules, and with the multipliers we used 21 rules. These rules are summarized in Table III.

TABLE III
DISPATCHING RULES

Method	Multiplier	Rule no
WATC	k_x =1,2,3	1,2,3
ATC	k_x =1,2,3	4,5,6
WMS, MS		7,8
WSPT, SPT		9,10
WLPT,LPT		11,12
WSOT,SOT		13,14
WLOT,LOT		15,16
WEDD,EDD		17,18
WERD,ERD		19,20
SIRO		21

V. SOLUTIONS COMPARED

In this research, we compared nine different solutions for different levels of integrations, and according to the search results or ordinary solutions, we compared random search with genetic search and with ordinary solutions. Since genetic search is more powerful, we only used random search for the best combination. The first four solutions are ordinary solutions, the next four solutions are genetic search solutions and the final solution is for random search for the best integration level.

We list ordinary solutions according to integration levels as: *SIRO-RDM (Ordinary), SCH-RDM (Ordinary), SIRO-NOPPT (Ordinary), and SCH-NOPPT (Ordinary)* for the ordinary solutions.

If we summarize the genetic search solutions according to the different integration levels of the three functions, we may give the following explanations:

SIRO-RDM (Genetic): This is the un-integrated level of the three functions. Due dates are determined randomly and jobs are scheduled in random order. We apply a predetermined number of genetic iterations, which are 200, 100 and 50 genetic iterations to the shop floors, respectively.

SCH-RDM (Genetic): Here we integrated the scheduling function with process plan selection, but due dates are still determined randomly. Here, again, we applied 200, 100 and 50 iterations for the shop floor, respectively.

SIRO-NOPPT(Genetic): This time we integrated NOPPT due date assignment rule with different multipliers with the process plan selection but jobs are scheduled in random order. Although integrating due date assignment rule is very useful, SIRO rule substantially deteriorates the results. Again we applied predetermined number of iterations for each shop floor, as explained previously.

SCH-NOPPT (Genetic): This is the highest level of integration. Three functions are fully integrated. Process plan selection is integrated with 21 dispatching rules and NOPPT due date assignment rules. As expected, this level of integration gave the best results. The results are given in Section VI and interpreted in the conclusion section.

Finally, we used random search for the full integration level. This is the ninth compared solution.

SCH-NOPPT (Random): For the best integration level, we also tested random search for the comparison. Here, we integrated process plan selection with the scheduling and NOPPT due date assignment rule and random search is applied. We applied 200, 100 and 50 random iterations for the shop floors, respectively.

Nine different solutions are compared. The first four of them are ordinary solutions, the next four use genetic search and final combination uses random search for different integration levels. The search results are compared with each other and with ordinary solutions to see how well the searches compared to ordinary solutions. We also tested the power of genetic search compared to random search, and attempted to observe the results of different integration levels to prove the benefits of higher integration levels.

VI. RESULTS

The program is coded using the C++ Language. The program performs due date assignment, genetic and random iterations and scheduling. The program is run with a Laptop 2 GHz processor and 8 GB ram with windows 8.1 and Borland C++ 5.02 compiler. CPU times are collected and summarized in Tables IV-VI.

Three shop floors are tested for nine different solutions. These solutions are explained in Section V. First, un-integrated combinations are tested and solved for SIRO-RDM (Genetic) and SIRO-RDM (Ordinary) combinations. Later, we integrated 21 scheduling rules with process plan selection and tested SCH-RDM (Genetic) and SCH-RDM (Ordinary) combinations. After that, we integrated NOPPT due date assignment with process plan selection and tested SIRO-NOPPT (Genetic) and SIRO-NOPPT (Ordinary) combinations. Finally, we integrated all three functions and tested SCH-NOPPT (Genetic), SCH-NOPPT (Random) and SCH-NOPPT (Ordinary) combinations.

For the smallest shop floor we assumed 20 machines and 50 jobs. Each job has five alternative routes and each route has 10 different operations. We compared ordinary solutions with random search and genetic search. The results of the initial populations are used instead of ordinary solutions, and for every level of integration we tested genetic search, but only for the full level of integration we tested random search. This was because genetic search is superior compared to random search and we just used random search for the best combination.

For small shop floor, 200 genetic or random iterations are applied. Small shop floor results are summarized in Table IV and Fig. 2. It took approximately 100 to 300 seconds to complete 200 iterations. According to the results, search solutions are found to be far better than ordinary solutions. Genetic search outperformed random search and full integration level with genetic search found to be the best combination.

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	
SCH-RDM(O)	451.96	407.88	363.21	
SIRO-NOPPT(O)	499.17	447.53	400.05	
SCH-NOPPT (O)	475.32	438.37	396.67	
SIRO-RDM(G)	397.38	395.98	393.46	117 sec
SCH-RDM(G)	352.74	352.06	351.31	210 sec
SIRO-NOPPT(G)	366.95	365.37	359.64	186 sec
SCH-NOPPT (G)	319.15	318.40	316.35	320 sec
SCH-NOPPT (R)	352.07	346.11	330.52	190 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	
SCH-RDM(O)	1002.05	937.32	851.84	
SIRO-NOPPT(O)	1134.24	1007.49	957.90	
SCH-NOPPT (O)	1013.53	944.06	881.27	
SIRO-RDM(G)	973.91	968.86	960.46	475 sec
SCH-RDM(G)	804.39	799.78	794.21	835 sec
SIRO-NOPPT(G)	898.44	895.20	890.46	654 sec
SCH-NOPPT (G)	810.84	809.04	806.62	896 sec
SCH-NOPPT (R)	866.96	862.77	850.39	664 sec

Similar results are obtained for the medium shop floor. The results of this shop floor are listed in Table V and summarized in Fig. 3. CPU times are summarized in Table V and show it took about 400 to 900 seconds to complete 100 random or genetic iterations. Again, the integration level is found to be substantially useful and genetic search outperformed random search. The search results were far better than ordinary solutions. Full integration with genetic search was found as the best combination.

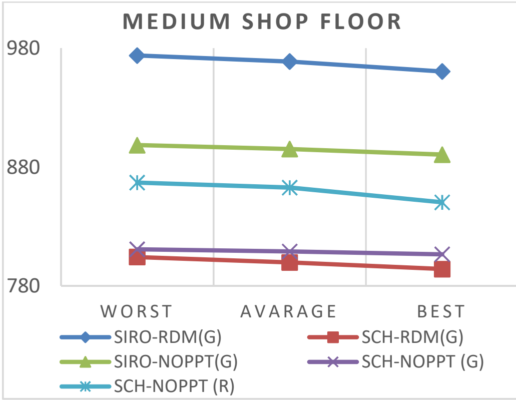

Fig. 3 Medium shop floor results

For the largest shop floor with 40 machines and 200 jobs we obtained similar results. Genetic search outperformed random search. The search results were substantially better than ordinary solutions. Full integration with genetic search gave the best result and was found as the best combination. CPU times were in between 600 to 1100 seconds approximately to finish 50 random or genetic iterations. The results of this shop floor are listed in the Table VI and summarized in Fig. 4.

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

	Worst	Average	Best	Cpu time
SIRO-RDM(O)	2736.06	2698.08	2623.78	
SCH-RDM(O)	2543.38	2352.13	2190.29	
SIRO-NOPPT(O)	2732.63	2594.17	2503.12	
SCH-NOPPT (O)	2598.94	2289.47	2084.73	
SIRO-RDM(G)	2510.6	2505.37	2492.86	1084 sec
SCH-RDM(G)	2046.25	2045.02	2043.82	1065 sec
SIRO-NOPPT(G)	2330.68	2319.86	2308.07	638 sec
SCH-NOPPT (G)	2026.62	2020.00	2004.35	785 sec
SCH-NOPPT (R)	2088.63	2082.91	2068.73	1039 sec

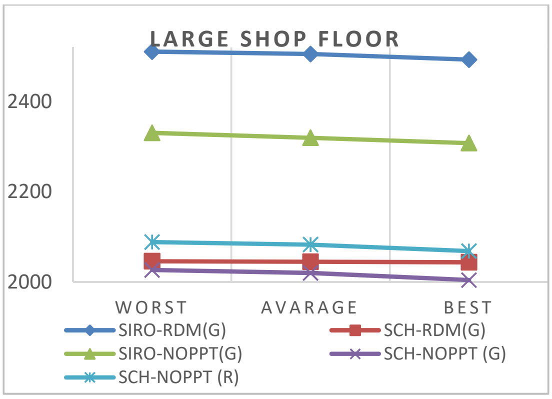

Fig. 4 Large shop floor results

VII. Conclusion

At this study we tried to observe the benefits of integration of three important manufacturing function. We tried to integrate process planning with scheduling and with NOPPT due date assignment. At the process planning function we assumed alternative routes are available. Since after developments in software, hardware and algorithms it is easier and faster to prepare process plans and alternative plans compared to the past. At the scheduling function we used mainly 9 different dispatching rules with different multipliers and weights of jobs 21 different is used at the scheduling gene of the chromosomes. At the due date assignment gene we used NOPPT rule instead of internal due date assignment and RDM rule for the external due date assignment rule. With different multipliers due date assignment gene assumes one of 10 different values.

At the beginning we tested fully un-integrated combinations to see how poor they are. At this level we tested SIRO-RDM (Genetic) and SIRO-RDM (Ordinary) combinations. We also assumed due dates are determined randomly and jobs are dispatched in random order and three functions are fully un-integrated. As expected we found this level very poor compared to higher level of integrations.

After that, we integrated scheduling with process planning and observed how solutions are improved. We integrated 21 dispatching rules with process plan selection, while due dates are still determined randomly. At this level we tried SCH-RDM (Genetic) and SCH-RDM (Ordinary) combinations.

Later, we tested the integration of process planning and due date determination. Here, jobs are dispatched in random order and due dates are determined according to NOPPT rules. Although the integration of process planning and due date assignment substantially improves performance, on the other hand, the SIRO rule strictly deteriorates the overall performance back. At this level, we tested SIRO-NOPPT (Genetic) and SIRO-NOPPT (Ordinary) combinations.

Finally, we tested fully integrated level, where we have alternative routes available to choose from and we used 21 dispatching rules and 9 due date assignment rules, with the exception of the RDM rule. Thus, process planning, scheduling and NOPPT due date assignment are all integrated. As expected, this level of integration was found the best integration. For this reason, we also tested random search as well as genetic search. At this level, we tested *SCH-NOPPT (Ordinary), SCH-NOPPT (Random),* and *SCH-NOPPT (Genetic)* combinations. As a result of the experiments, the *SCH-NOPPT (Genetic)* combination is found to be the best combination. The full integration level was the best level and genetic search outperformed random search, and the searches were far better than ordinary solutions.

According to the literature, IPPS alternative routes are very beneficial at the beginning; however, the marginal benefits of the alternative routes decrease. We used five alternative routes for the small and medium shop floors, but in order to reach a solution in a reasonable amount of time and the reduce memory consumption of the program, we assumed three alternative routes for the largest shop floor. In order to reach a good solution in a reasonable amount of time we reduced the iteration size as the shop floor gets bigger. We used 200, 100 and 50 genetic and random iterations, respectively. Since these three functions highly affect each other, it was better to consider all of them concurrently. If process planning, scheduling and due date assignment functions are performed separately, this means they all try to attain local optima and are not concerned about global optima, which substantially reduces global performance. Since the output of upstream functions become downstream functions, we should consider the entire chain simultaneously; otherwise, lack of integration causes poor inputs to downstream functions. For instance, if process plans are made independently then process planners may select the same desired machines repeatedly and may not select undesired machines at all. This causes unbalanced load at the shop floor level and can result in some bottleneck machines and some starving machines, and this can substantially reduce shop floor performance. Furthermore, some poorly prepared process plans may not be followed at the shop floor level. Similarly, if due dates are prepared independently from other functions we may give unrealistic and poor due dates. If due dates are too early then we may pay severely for weighted tardiness; otherwise, due date and earliness related costs greatly increase the penalty function. If scheduling is performed without considering due dates then we may schedule later for early due dates, and again, we substantially pay for weighted tardiness related costs. On the other hand, if we schedule late due dates earlier, then we unnecessarily pay for weighted earliness substantially.

In conclusion, as the integration level gets higher, the solutions become better and the highest integration level is shown to be the best. Genetic search outperforms random search, which is why the full integration level with genetic search is proven as the best combination. Ordinary solutions are very poor and searching for better solutions is very useful.

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