World Academy of Science, Engineering and Technology
International Journal of Industrial and Manufacturing Engineering
Vol:11, No:1, 2017

Solving Weighted Number of Operation Plus Processing Time Due-Date Assignment, Weighted Scheduling and Process Planning Integration Problem Using Genetic and Simulated Annealing Search Methods

Halil Ibrahim Demir, Caner Erden, Mumtaz Ipek, Ozer Uygun

International Science Index, Industrial and Manufacturing Engineering Vol:11, No:1, 2017 waset.org/Publication/10006048

Abstract**—**Traditionally, the three important manufacturing functions, which are process planning, scheduling and due-date assignment, are performed separately and sequentially. For couple of decades, hundreds of studies are done on integrated process planning and scheduling problems and numerous researches are performed on scheduling with due date assignment problem, but unfortunately the integration of these three important functions are not adequately addressed. Here, the integration of these three important functions is studied by using genetic, random-genetic hybrid, simulated annealing, random-simulated annealing hybrid and random search techniques. As well, the importance of the integration of these three functions and the power of meta-heuristics and of hybrid heuristics are studied.

Keywords**—**Process planning, weighted scheduling, weighted due-date assignment, genetic search, simulated annealing, hybrid meta-heuristics.

I. Introduction

PROCESS planning, scheduling and due date assignment are the three important functions in a modern manufacturing system. First function, which is the process plan, specifies what things are going to be needed to produce a product and their production processes. Process planning consists of two section, the first of them is the selection of operation and the second one is the operation sequencing [1]. Therefore, most manufacturing systems work with alternative process plans because a company needs to be flexible to produce many different products. Once a process plan is done, the outcome of the process planning is the input of scheduling [2]. Although process planning and scheduling are related to each other, traditionally, they are usually considered two separate and different functions. It is assumed that there is no other process plans for each product part in the traditional manufacturing system [3]-[5]; this causes major problems for process planning and scheduling; that is why, to integrate process planning and scheduling has become a crucial problem and received the attention of researchers and engineers. The integration of those two functions contributes positively to the manufacturing system performance system. Only the scheduling problem is categorized as NP-Hard problem. Thus, the integration problems of scheduling are also categorized as NP-Hard problem. In the past 20 years, a significant number of researchers and engineers have studied the integration of process planning and scheduling (IPPS); as well, numerous meta-heuristic approaches have been developed to solve the IPPS. Some of those meta-heuristic algorithms are genetic algorithm (GA), simulated annealing (SA), taboo search (TS), ant colony optimization (ACO), particle swarm optimization (PSO), and the hybrid algorithms.

The other integration problem is to integrate scheduling and due date assignment functions. In scheduling with due date assignment (SWDDA), firstly due dates of jobs are determined and production planning are scheduling according to due dates. In modern manufacturing systems, due dates are determined with the negotiation of customers and manufacturers. Making too short due date assignments may lead to missed due dates. Besides, making too long due date assignments may lead to lost customers for manufacturers. That is why, due date assignment and scheduling should be considered together to make better decisions [6].

In recent years, the study of integration of two (IPPS and SWDDA) or three (IPPS with due date assignment) manufacturing functions has attracted significant attention, due to the advantages of working with alternative process plans. Expanding this research, this study investigates the integration of three manufacturing functions, which are known as integrated process planning, scheduling and due date assignment (IPPSDDA). There are relatively a few published on IPPSDDA in the literature. Integration of three production functions (process planning, scheduling and due date assignment) would show a more efficient way in terms of production management [7]. In this study, various numbers of

H. I. Demir is with the Sakarya University, Department of Industrial Engineering, Sakarya, Turkey (phone: +90-264-295-5675; e-mail: hidemir@sakarya.edu.tr).
C. Erden is with the Sakarya University, Department of Industrial Engineering, Sakarya, Turkey (phone: +90-264-295-7323; e-mail: cerden@sakarya.edu.tr).
M. Ipek is with the Sakarya University, Department of Industrial Engineering, Sakarya, Turkey (phone: +90-264-295-5688; e-mail: ipek@sakarya.edu.tr).
O. Uygun is with the Sakarya University, Department of Industrial Engineering, Sakarya, Turkey (phone: +90-264-295-5890, e-mail: ouygun@sakarya.edu.tr).

meta-heuristic algorithms were applied to solve the integration problem. The methods used are genetic, hybrid random search-genetic algorithm (RS/GA), SA, hybrid random search-simulated annealing algorithm (RS/SA) and random search algorithms. Furthermore, the importance level of the customers was also taken into account, since there is always priority scheduling in real companies.

The remainder of this paper is organized as follows. Section II gives some literature reviews on integration problems. Section III describes the problem. Section IV provides the list of approaches, which are genetic, random-genetic hybrid, simulated annealing, random-simulated annealing hybrid and random search algorithms, for solving integration optimization problems based these algorithms. Then, Section V provides an experimental study and the results. And finally, the conclusions are given in Section VI.

II. Literature Review

Since IPPS provides great improvements for the productivity of manufacturing companies in terms of lead-time, usage rate of resources etc., there have been plenty of studies studied by many researchers. Chryssolouris first used the IPPS term in 1984; and specifies IPPS as (Manufacturing Decision Making Approach (MADEMA) [8]. They generated a decision matrix to choose one from several alternatives. After that Sundara and Fu, proposed a scheduling approach in order to minimize the make span [9]. In addition, Shrihari and Greene proposed a prototype referred to as the computer aided process planning (CAPP) in 1990 [10]. In recent years, many literatures can be found, such as [11]-[13], and some important literature papers [14]-[17], show that the attention on IPPS is very high. Therefore, many approaches have been used to integrate process planning and scheduling, such as GA [18], [19], TS [18], [20]-[24], SA [25]-[27], ACO [7], [28], [29], PSO [15], [30]-[32], evaluation strategy [33], agent-based, and algorithm based .

Kim et al. [33] have studied the merging of two manufacturing functions and proposed a new method by using artificial intelligence on searching methods. Lim and Zhang [34] optimized the system of integration of dynamic process planning and dynamic production scheduling. Kumar and Rajotia [17] proposed a framework for the IPPS g. While Li et al. [11] evaluated the integrated process planning and scheduling.

Besides IPPS, many papers have been published on SWDDA. Due dates given at the same time with other functions can lead to a significant improvement. Therefore, it can be said that integrating due date assignment with scheduling have a growing interest in the today's competitive world. Gordon et al. [35] emphasized the performance of scheduling and due date assignment for an evaluation of an art study. Single machine scheduling with due date assignment (SMSWDDA) problem is also included in SWDDA problems and some studies for SMSWDDA can be listed as [33]-[38].

In previous researches, scheduling multiple jobs with a single machine problem has been studied and completed using various methods. In the paper of [39], the differential evaluation method was utilized to solve job shop problems for the objective of optimizing earliness/tardiness penalty costs. Uncertain processing times were used in [40] to establish job sequence and due date assignment for the purpose of minimizing earliness/tardiness penalty costs. Similarly, in the research of [41], single machine scheduling and due date assignment problems have been studied.

In spite of the great number of scientific research on IPPS and SWDDA, there are few studies on IPPSDDA in the literature. Some studies related to IPPSDDA were given at [42]–[45].

III. Description of the Problem

In this study, the integration of process planning and the due date assignment problem was studied, and an attempt was made to integrate those three manufacturing functions with weighted scheduling and due date assignment. The tests were conducted in four different size shop floors, the details of which are given in Table I. In Table I, there are five machines and 25 jobs in Shop Floor 1. There are five alternative routes for small shop floors and three alternative routes for large shop floors. The time for all operations will be produced randomly and determined with the function of $\lfloor (12+6z) \rfloor$. Furthermore, it is assumed that all jobs have 10 operations.

TABLE I
Shop Floors

Shop Floor	Number of Machines	Number of Jobs	Number of Routes	Operation Time	Number of Operation
1	5	25	5	$\lfloor (12+6z) \rfloor$	10
2	15	75	5	$\lfloor (12+6z) \rfloor$	10
3	25	125	3	$\lfloor (12+6z) \rfloor$	10
4	35	175	3	$\lfloor (12+6z) \rfloor$	10

It is also assumed that one shift is eight hours; this makes 8*8=480 minutes. Weight (j) will be used for all customers. Earliness/tardiness penalties, penalty for due dates and total penalty points are calculated in:

$$PD_j = 8w_j\left(\frac{D}{480}\right) \tag{1}$$

$$PE_j = w_j\left(5+4\left(\frac{E}{480}\right)\right) \tag{2}$$

$$PT_j = w_j\left(10+12\left(\frac{T}{480}\right)\right) \tag{3}$$

$$P_j = PD_j + PE_j + PT_j \tag{4}$$

$$TP = \sum_j P_j \tag{5}$$

The notations to explain the equations are represented as:

- w_j: the importance of job j

- D: the assigned due date of job j
- E: earliness of job j
- T: tardiness of job j
- PD_j: penalty for due date
- PE_j: penalty for earliness
- PT_j: penalty for tardiness of job j
- P_j: total penalty for a job is determined by (4)
- TP: the total penalty for all of the jobs

As mentioned earlier, six different approaches will be used to solve the problem. The sample chromosome is shown in Fig. 1. Here, there are n+2 genes, and the first and second genes represent due date and scheduling, while the rest represents the routes of each of the jobs. Shop Floor 1 and Shop Floor 2 have five routes, and Shop Floor 3 and 4 have three routes. Three alternative routes were chosen for Shop Floor 3 and 4 to run the computer program faster and stronger. Likewise, the marginal gains of the alternative routes reduce, since the alternative number increases. In this way, the first alternative routes are the most advantageous in terms of marginal gains.

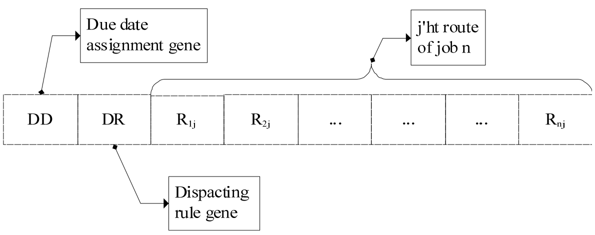

Fig. 1 Chromosome representation

Due date assignment procedure consists of two different rules, which are weighted number of operation plus processing time (WNOPPT) and random due date assignment (RDM). Basically, WNOPPT works internally and conversely RDM works externally. Operations and processing time multipliers are determined and WNOPPT main rules are increased by nine working with different multipliers. Likewise, RDM rules are represented by 10. Those rules are shown in the Table II.

TABLE II
DUE DATE RULES

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

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

The second gene is the dispatching rule, which can be seen in Fig. 1; it has nine different possible rules. Table III shows the scheduling rules. At the second gene of the chromosome, dispatching rules can be one of nine different main rules. With the multipliers and weights of the jobs, the second gene assumes one of 21 values and these rules are listed at Table III. The explanation of the methods can be found in the Appendix section.

IV. Optimization Approaches for IPPSDDA

A. GA

GA is search and optimization method, which works the same with the evolutionary process observed from nature. It searches for the best solution in terms of the best ones survive in the complex multi dimension search space. The essentials of GA were introduced by Holland at Michigan University. Holland gathered all his studies on the book namely, "Adaptation in Natural and Artificial Systems" [46]. Fig. 2 shows the workflow of GA.

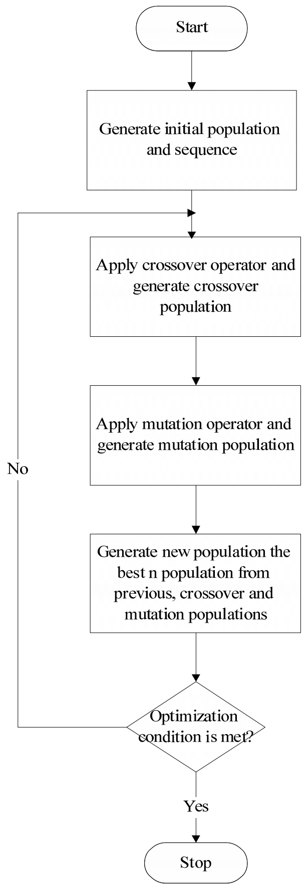

Fig. 2 The workflow of GA

B. Hybrid RS/GA Algorithm

In this approach, both random search and genetic search techniques will be used. First, the solution set will be scanned more efficiently with a random search. Second, it will attempt to take advantage of the power of the directed search by continuing with the genetic search. The same number of iterations is applied for making comparisons fairer. For instance, 200 genetic iterations, 200 random iterations and 20-180 hybrid RS/GA algorithm combinations are used.

The benefit of starting with a random iteration can be summarized as follows: If we generate one random number between 0 and 1,000, 500 (1/2) would be the expected value of this random number and that marginal gains would be 500. Therefore, if we generate two random numbers between 0 and 1,000, and if we take the maximum of it, the expected value of 667 (2/3) and the marginal gains would decrease to 167; however, that is still a high marginal benefit. Likewise, if we generate three random numbers, and if we take the maximum of it, the expected value of 750 (3/4) and the marginal gains would decrease to 83; which is still a high marginal benefit. When we sort the marginal gains that would be 500,167 and 83, the solution set would be scanned more efficient. Fig. 3 shows the workflow of hybrid RS/GA algorithm.

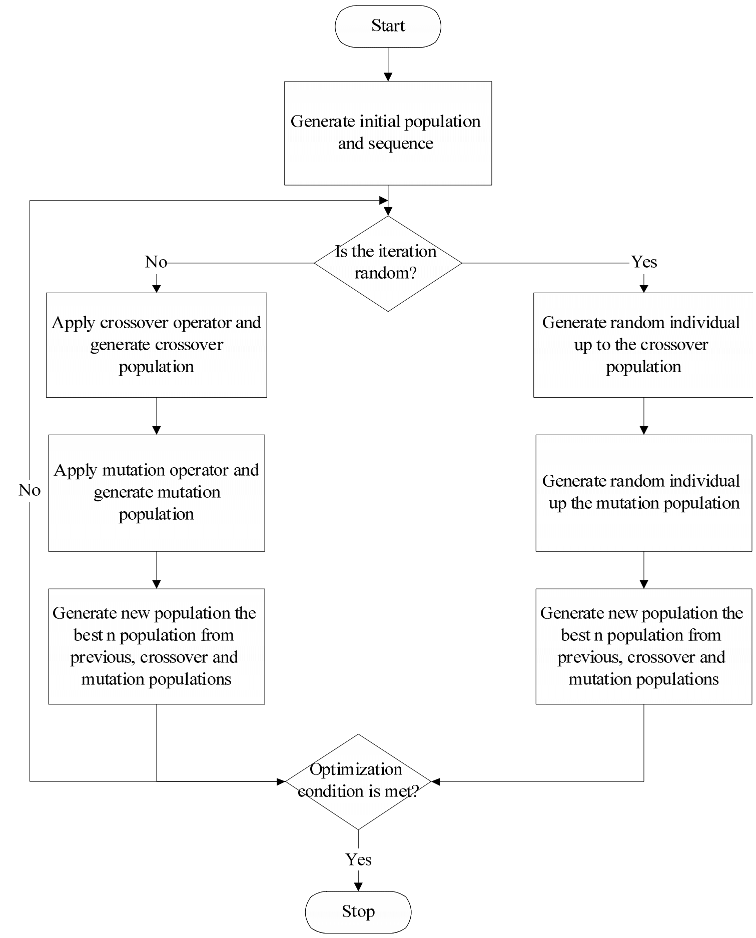

Fig. 3 The workflow of hybrid RS/GA

C. SA

SA was introduced by Kirkpatrick et al. [47] in 1983 and Černý contributed to SA a local search algorithm to solve the complex problems [48]. The origin of the SA was inspired by a similarity with the SA process of solids. This similarity is quite appealing and in SA, it is used as a background. Annealing process is known as the thermal process for taking low energy states of a solid in a heat beat. SA is a strong algorithm uses randomization to escape from local optima. Given a current state i of E_i, the resulting state j is produced by applying a perturbation mechanism that changes the present state into a next state by a little mutilation, for example, by a displacement of a single particle.

$$P_{accept} = e^{\left(\frac{E_i - E_j}{k_B T}\right)} \quad (6)$$

where, T: the temperature of the heat bath, k_B: the Boltzmann constant, E_i: the energy of the current state, E_j: the energy of the next state

The acceptable rate depends on the value of the temperature. When the temperature is high, the acceptable rate of the move that makes an objective function increased, and the temperature drops, this possibility will also be decreased. That is why, it is necessary to begin the search at the highest point of temperature. In the algorithm, while the temperature was slowly reduced, the search process is continued by trying a certain number of moves at each temperature value. Fig. 4 shows the workflow of SA.

D. Hybrid RS/SA Algorithm

In this hybrid search, we start with random search and continue with SA; 10% of the searches are random and 90% of the searches are performed using SA.

E. Random Search

In this search, individuals are produced for each iteration randomly, and an attempt to get a better solution is undertaken by using the random search method. Marginal gain is higher at the first iteration, increasing of the number of iterations would result in reduced increase of the performance. Since the best solutions of the previous search make no contribution to the new individuals, this search method is oriented, unlike the genetic search. Genetic search uses the best solutions of the previous iteration for the next iteration. Fig. 5 shows the workflow of random search.

V. Comparisons Made

Ordinary solutions are the basic solutions; thus, all the solutions are going to be compared with the ordinary solutions. The different integration levels are listed below:

- SIRO-RDM (Ordinary, GA, Hybrid GA/RS, SA, Hybrid SA/RS, RS): This integration level is the lowest one among the all integration levels, where jobs are scheduled in random order and due dates are generated randomly.
- SIRO-WNOPPT (Ordinary, GA, Hybrid GA/RS, SA, Hybrid SA/RS, RS): Although jobs are scheduled randomly, WNOPPT due-date assignment is integrated with process planning.
- WSCH-RDM (Ordinary, GA, Hybrid GA/RS, SA, Hybrid SA/RS, RS): Although due dates are still generated randomly, different number of dispatching rules are worked together with process planning.

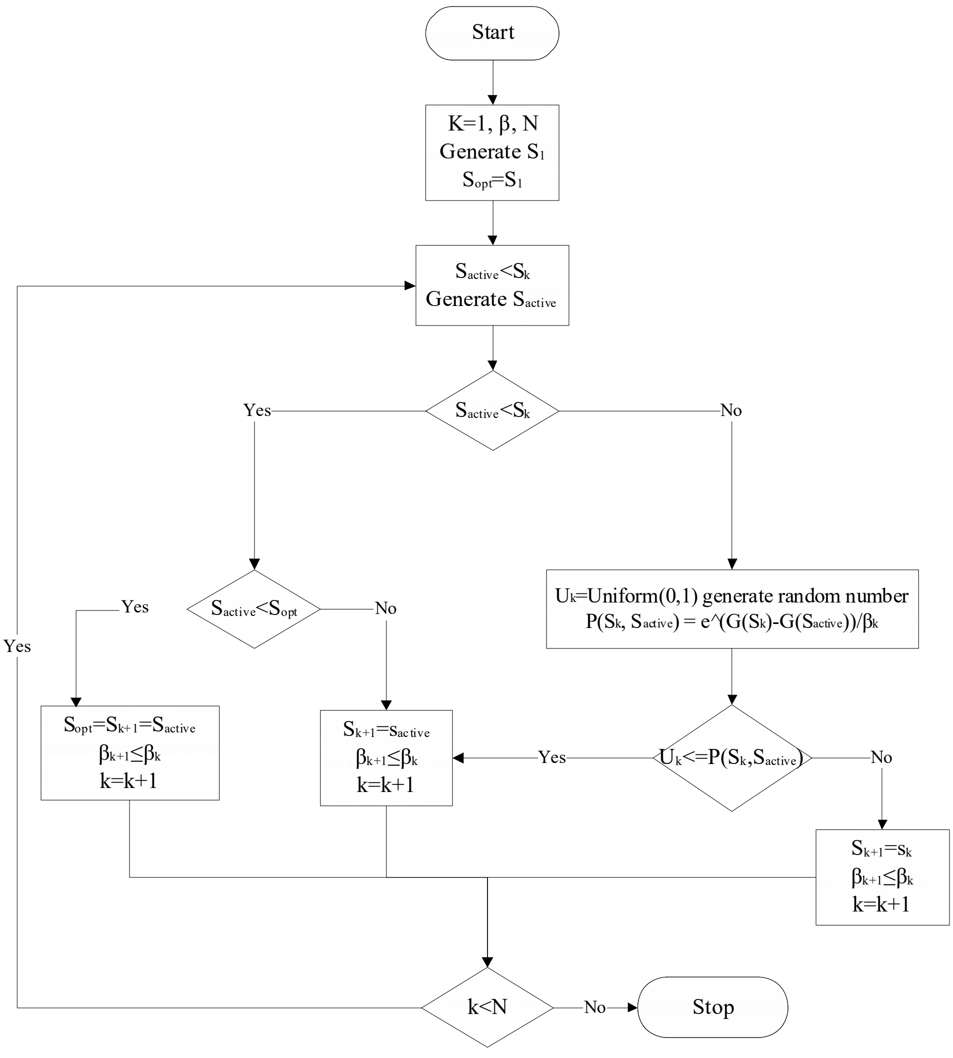

Fig. 4 The workflow of SA

- WSCH-WNOPPT (Ordinary, GA, Hybrid GA/RS, SA, Hybrid SA/RS, RS): The highest level of integration is used here. Process planning, weighted scheduling and WNOPPT weighted due-date assignments are integrated. Table IV shows the number of iterations of GA, RS/GA, RS, SA and RS/GA.

TABLE IV
ITERATION NUMBERS FOR PURE AND HYBRID SEARCHES

	GA	RS/GA Hybrid		RS	SA	RS/SA Hybrid	
Shop Floor	GA Iter.	Random Iter.	GA Iter #	Random Iter.	SA Iter.	Random Iter.	SA Iter.
1	200	20	180	200	2600	260	2340
2	150	15	135	150	1950	195	1755
3	100	10	90	100	1300	130	1170
4	50	5	45	50	650	65	585

As can be seen in Table IV, there are 200 iterations for Shop Floor 1; 10% of the total number is covered with RS iterations for hybrid meta-heuristics. In addition, the number of SA iterations is equal to 13 multiple. Likewise, 10% of the iterations are random for RS/SA hybrid search.

VI. EXPERIMENTAL STUDIES AND DISCUSSION

In this section, the experiments of integration of the process planning, scheduling and due-date assignment were conducted and the results of techniques are given and compared with results of each of the techniques, which are GA, Hybrid RS/GA, Random, SA, Hybrid RS/SA. As the problem was categorized as an NP-Hard problem, different meta-heuristic approaches were applied and the results of the experiments were compared according to their performance levels.

The approaches for IPPSDDA was coded in C++ with Borland 5.02 compiler software and implemented on a computer with 3.3 GHz Intel Core (TM) CPU, 8 GB RAM with the Windows 10 operating system. In the following section, the performance of the chosen meta-heuristic methods is investigated.

A. Comparison of the Used Search Techniques

As stated in literature review section, GA and SA have been successfully utilized to solve the IPPS and SCHWDDA problems. In this section, the main objective is to compare the performance of the GA and SA algorithms with random and ordinary search methods. In this study, five different search methods are used to solve the problem. Table V shows the results, performance measures of costs, as well as the CPU time of each of the methods, separately. The integration levels (SIRO-RDM, WSCH-RDM, SIRO-WNOPPT, WSCH-WNOPPT) with the shop floors (Shop Floor 1-4), and search methods (Ordinary, GA, Hybrid RS/GA, Random, SA, Hybrid RS/SA) and CPU times are given in Table V. Comparisons and improvements are evaluated based on the ordinary technique results.

As can be seen from Table V, optimal solutions are improved by using the higher integration level and optimization techniques. For instance, the ordinary result of Shop Floor 1 with SIRO-RDM level is improved from 292 to 256 by using GA. In Shop Floor 4, optimal solution with WSCH-WNOPPT is improved from 1,463 to 1,290 by using GA, again. An example where Hybrid RS/SA is the most superior among the other techniques can be given as at Shop Floor 1 with WSCH-WNOPPT level. Optimal solution is improved from 208 to 175 at that experiment.

The result obtained by the methods are summarized and illustrated in Figs. 6-9. Results for Shop Floor 1 are shown in Fig. 6. It is seen that methods show similar ranking in Shop Floor 1; however, Hybrid RS/SA and SA methods are outperformed by GA. The performance of GA, Hybrid RS/GA and Hybrid RS/SA are very close to the optimum solution, whereas random search achieved the lowest solution at that floor. The results for Shop Floor 2 are demonstrated in Fig. 7. It is clearly seen that GA is the most superior algorithm to solve the IPPSWDDA problem. The results for Shop Floor 3 support the main outcome of the study and are shown in Fig. 8. Lastly, the results for Shop Floor 4 are shown in Fig. 9.

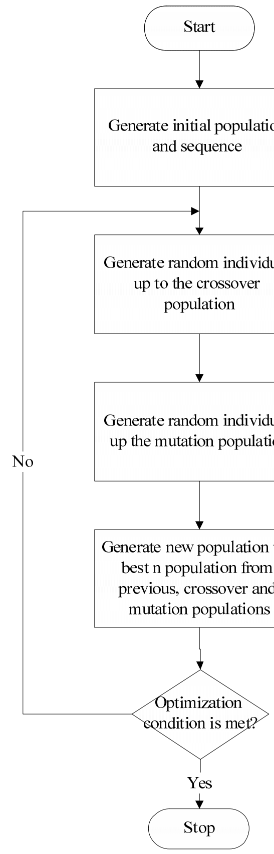

Fig. 5 The workflow of random search

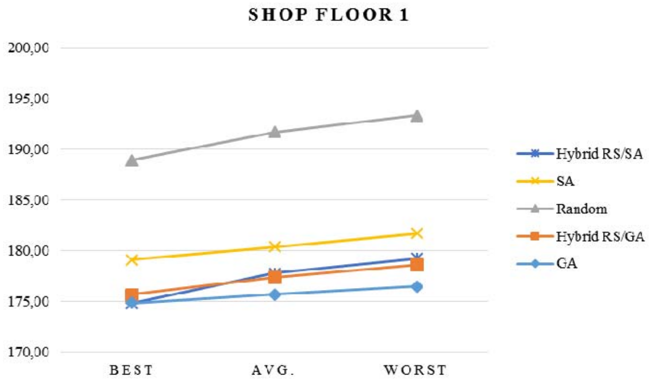

Fig. 6 Results of Shop Floor 1

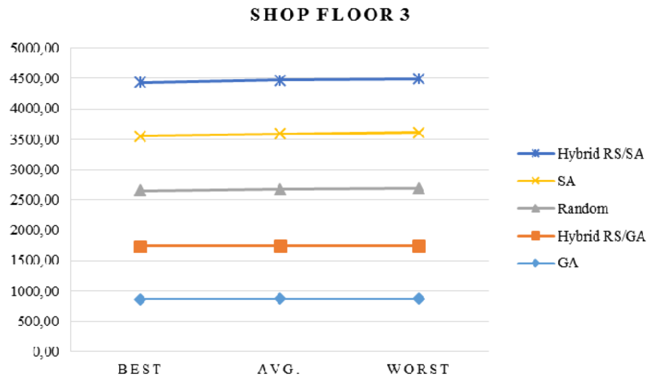

Fig. 8 Results of Shop Floor 3

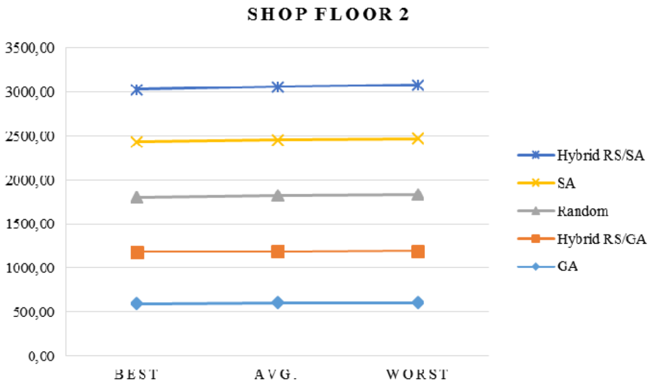

Fig. 7 Results of Shop Floor 2

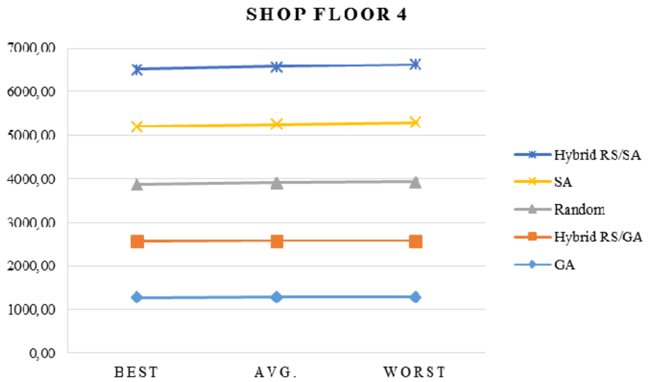

Fig. 9 Results of Shop Floor 4

TABLE V
RESULTS OF THE STUDY

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	Ordinary	292	292	292	18	906	906	906	235	1412	1412	1412	274	2019	2019	2019	278
	GA	249	256	259	16	803	816	820	201	1291	1300	1305	256	1846	1856	1863	268
	Hybrid RS/GA	265	269	272	16	814	818	822	204	1305	1312	1315	260	1856	1869	1878	270
	Random	268	273	275	17	853	864	870	211	1354	1371	1378	274	1907	1925	1934	278
	SA	256	260	261	15	531	547	553	89	1357	1365	1369	234	1881	1896	1903	241
	Hybrid RS/SA	258	263	266	18	846	857	864	235	1292	1317	1325	223	1876	1888	1899	240
WSCH-RDM	Ordinary	276	276	276	27	802	802	802	253	1372	1372	1372	332	1885	1885	1885	338
	GA	218	219	219	17	676	678	679	220	1092	1095	1097	278	1523	1526	1529	292
	RS/GA	215	216	216	17	657	658	659	208	1036	1038	1039	257	1464	1467	1469	282
	Random	213	218	220	20	676	684	689	253	1085	1097	1108	332	1531	1559	1583	338
	SA	205	211	213	27	648	657	661	177	1038	1044	1047	260	1569	1580	1586	248
	Hybrid RS/SA	209	210	210	15	661	665	667	193	1045	1048	1050	247	1484	1497	1503	254
SIRO-WNOPPT	Ordinary	287	287	287	20	874	874	874	233	1315	1315	1315	349	1938	1938	1938	315
	GA	231	238	241	20	749	757	760	230	1228	1242	1249	323	1753	1764	1773	313
	Hybrid RS/GA	240	242	244	20	759	764	765	228	1228	1238	1242	329	1719	1730	1742	310
	Random	252	259	264	20	807	815	821	233	1273	1287	1292	349	1779	1801	1815	315
	SA	247	257	262	19	781	804	810	204	1247	1263	1274	248	1758	1787	1803	250
	Hybrid RS/SA	251	255	257	20	773	797	805	204	1263	1273	1281	259	1781	1793	1805	266
WSCH-WNOPPT	Ordinary	208	208	208	45	654	654	654	367	1009	1009	1009	539	1463	1463	1463	549
	GA	176	176	177	34	599	605	609	218	862	865	866	539	1282	1287	1290	549
	Hybrid RS/GA	176	177	179	33	585	587	588	385	873	877	880	504	1286	1291	1293	541
	Random	189	192	193	25	624	632	636	284	915	930	942	365	1301	1332	1353	379
	SA	179	180	182	45	629	634	636	199	903	916	924	255	1328	1347	1360	262
	Hybrid RS/SA	175	178	179	34	593	604	608	367	883	886	888	452	1312	1322	1328	470

VII. Conclusion

In this paper, five different meta-heuristic methods were utilized and can be adapted to solve the IPPS with due-date assignment problem. Two types of Hybrid methods for the IPPSWDDA problem have been implemented, and consist of random search with GA and random search with SA algorithm. As it can be seen in Figs. 6-9, the performance difference between GA and Hybrid RS/GA is very close. Hybrid RS/SA and Hybrid RS/GA algorithms are outperformed by GA.

As a conclusion, although Hybrid RS/SA and Hybrid RS/GA algorithms can be suitable to solve the IPPSWDDA problem, GA is still the best algorithm to solve the problem with a full integration level.

Acknowledgment

The authors wish to thank the anonymous referees for their detailed comments that led to this improved version of the paper.

Appendix

A. Due-Date Assignment Rules

- WNOPPT: $Due = w_1 \times k_1 \times TPT + w_2 \times k_2 \times NOP$
- RDM: $Due = N \approx \left(3 \times P_{avg}, (P_{avg})^2\right)$
- TPT: Total processing time
- P_{avg}: Mean processing time of all job waiting

B. Dispatching Rules

- WATC/ATC ((Weighted) Apparent Tardiness Cost): This is composite dispatching rule, and it is a hybrid of MS and SPT and takes into account importance of customers.
- WMS/MS: Weighted/Minimum Slack First
- WSPT/SPT: Weighted/Shortest Processing Time First
- WLPT/LPT: Weighted/Longest Processing Time First
- WSOT/SOT: Weighted/Shortest Operation Time First
- WLOT/LOT: Weighted/Longest Operation Time First
- WEDD/EDD: Weighted/Earliest Due-Date First

References

[1] X. Xu, L. Wang, and S. T. Newman, "Computer-aided process planning–A critical review of recent developments and future trends," Int. J. Comput. Integr. Manuf., vol. 24, no. 1, pp. 1–31, 2011.
[2] X. Li, L. Gao, and X. Wen, "Application of an efficient modified particle swarm optimization algorithm for process planning," Int. J. Adv. Manuf. Technol., vol. 67, no. 5–8, pp. 1355–1369, Nov. 2012.
[3] X. Shao, X. Li, L. Gao, and C. Zhang, "Integration of process planning and scheduling—a modified genetic algorithm-based approach," Comput. Oper. Res., vol. 36, no. 6, pp. 2082–2096, 2009.
[4] T. Sauter, J. Peschke, A. Luder, and others, "Distributed automation: PABADIS vs. HMS," in Industrial Informatics, 2003. INDIN 2003. Proceedings. IEEE International Conference on, 2003, pp. 294–300.
[5] H. H. Cheng, F. Proctor, J. L. Michaloski, and W. P. Shackleford, "Real-time computing in open systems for manufacturing," J. Comput. Inf. Sci. Eng., vol. 1, no. 1, pp. 92–99, 2001.
[6] J. Y.-T. Leung, Handbook of Scheduling: Algorithms, Models, and Performance Analysis. CRC Press, 2004.
[7] H. Lee and S.-S. Kim, "Integration of process planning and scheduling using simulation based genetic algorithms," Int. J. Adv. Manuf. Technol., vol. 18, no. 8, pp. 586–590, 2001.
[8] G. Chryssolouris, S. Chan, and N. P. Suh, "An integrated approach to process planning and scheduling," CIRP Ann.-Manuf. Technol., vol. 34, no. 1, pp. 413–417, 1985.
[9] R. M. Sundaram and S. Fu, "Process planning and scheduling—a method of integration for productivity improvement," Comput. Ind. Eng., vol. 15, no. 1, pp. 296–301, 1988.
[10] K. Srihari and T. J. Greene, "MACRO-CAPP: a prototype CAPP system for an FMS," Int. J. Adv. Manuf. Technol., vol. 5, no. 1, pp. 34–51, 1990.
[11] X. Li, L. Gao, C. Zhang, and X. Shao, "A review on integrated process planning and scheduling," Int. J. Manuf. Res., vol. 5, no. 2, pp. 161–180, 2010.
[12] R. K. Phanden, A. Jain, and R. Verma, "Integration of process planning and scheduling: a state-of-the-art review," Int. J. Comput. Integr. Manuf., vol. 24, no. 6, pp. 517–534, 2011.
[13] W. Tan and B. Khoshnevis, "Integration of process planning and scheduling—a review," J. Intell. Manuf., vol. 11, no. 1, pp. 51–63, 2000.
[14] A. Baykasoğlu and L. Özbakır, "A grammatical optimization approach for integrated process planning and scheduling," J. Intell. Manuf., vol. 20, no. 2, pp. 211–221, 2009.
[15] Y. W. Guo, W. D. Li, A. R. Mileham, and G. W. Owen, "Optimisation of integrated process planning and scheduling using a particle swarm optimisation approach," Int. J. Prod. Res., vol. 47, no. 14, pp. 3775–3796, 2009.
[16] A. Jain, P. K. Jain, and I. P. Singh, "An integrated scheme for process planning and scheduling in FMS," Int. J. Adv. Manuf. Technol., vol. 30, no. 11–12, pp. 1111–1118, 2006.
[17] M. Kumar and S. Rajotia, "Integration of process planning and scheduling in a job shop environment," Int. J. Adv. Manuf. Technol., vol. 28, no. 1–2, pp. 109–116, 2006.
[18] A. H. Mantawy, Y. L. Abdel-Magid, and S. Z. Selim, "Integrating genetic algorithms, tabu search, and simulated annealing for the unit commitment problem," IEEE Trans. Power Syst., vol. 14, no. 3, pp. 829–836, 1999.
[19] N. Morad and A. M. S. Zalzala, "Genetic algorithms in integrated process planning and scheduling," J. Intell. Manuf., vol. 10, no. 2, pp. 169–179, 1999.
[20] H.-S. Yan, Q.-F. Xia, M.-R. Zhu, X.-L. Liu, and Z.-M. Guo, "Integrated production planning and scheduling on automobile assembly lines," Iie Trans., vol. 35, no. 8, pp. 711–725, 2003.
[21] W. D. Li, S. K. Ong, and A. Y. C. Nee, "Optimization of process plans using a constraint-based tabu search approach," Int. J. Prod. Res., vol. 42, no. 10, pp. 1955–1985, 2004.
[22] C. Moon, J. Kim, and S. Hur, "Integrated process planning and scheduling with minimizing total tardiness in multi-plants supply chain," Comput. Ind. Eng., vol. 43, no. 1, pp. 331–349, 2002.
[23] X. Li, X. Shao, L. Gao, and W. Qian, "An effective hybrid algorithm for integrated process planning and scheduling," Int. J. Prod. Econ., vol. 126, no. 2, pp. 289–298, 2010.
[24] P. Brandimarte, "Routing and scheduling in a flexible job shop by tabu search," Ann. Oper. Res., vol. 41, no. 3, pp. 157–183, 1993.
[25] G. H. Ma, Y. F. Zhang, and A. Y. C. Nee, "A simulated annealing-based optimization algorithm for process planning," Int. J. Prod. Res., vol. 38, no. 12, pp. 2671–2687, 2000.
[26] W. D. Li and C. A. McMahon, "A simulated annealing-based optimization approach for integrated process planning and scheduling," Int. J. Comput. Integr. Manuf., vol. 20, no. 1, pp. 80–95, 2007.
[27] D.-H. Lee, D. Kiritsis, and P. Xirouchakis, "Search heuristics for operation sequencing in process planning," Int. J. Prod. Res., vol. 39, no. 16, pp. 3771–3788, 2001.
[28] S. Wan, T. N. Wong, S. Zhang, L. Zhang "Integrated process planning and scheduling with setup time consideration by ant colony optimization," HKU Theses Online HKUTO, 2012.
[29] W. D. Li, S. K. Ong, and A. Y. C. Nee, "Hybrid genetic algorithm and simulated annealing approach for the optimization of process plans for prismatic parts," Int. J. Prod. Res., vol. 40, no. 8, pp. 1899–1922, 2002.
[30] M. Yu, Y. Zhang, K. Chen, and D. Zhang, "Integration of process planning and scheduling using a hybrid GA/PSO algorithm," Int. J. Adv. Manuf. Technol., vol. 78, no. 1–4, pp. 583–592, 2015.
[31] Y. Wang and J. H. Liu, "Chaotic particle swarm optimization for assembly sequence planning," Robot. Comput.-Integr. Manuf., vol. 26, no. 2, pp. 212–222, 2010.
[32] F. Zhao, Y. Hong, D. Yu, Y. Yang, and Q. Zhang, "A hybrid particle swarm optimisation algorithm and fuzzy logic for process planning and

production scheduling integration in holonic manufacturing systems," Int. J. Comput. Integr. Manuf., vol. 23, no. 1, pp. 20–39, 2010.
[33] Y. K. Kim, K. Park, and J. Ko, "A symbiotic evolutionary algorithm for the integration of process planning and job shop scheduling," Comput. Oper. Res., vol. 30, no. 8, pp. 1151–1171, 2003.
[34] M. K. Lim and D. Z. Zhang, "An integrated agent-based approach for responsive control of manufacturing resources," Comput. Ind. Eng., vol. 46, no. 2, pp. 221–232, 2004.
[35] V. Gordon, J.-M. Proth, and C. Chu, "A survey of the state-of-the-art of common due date assignment and scheduling research," Eur. J. Oper. Res., vol. 139, no. 1, pp. 1–25, 2002.
[36] J.-B. Wang, "Single machine scheduling with common due date and controllable processing times," Appl. Math. Comput., vol. 174, no. 2, pp. 1245–1254, 2006.
[37] S.-W. Lin, S.-Y. Chou, and S.-C. Chen, "Meta-heuristic approaches for minimizing total earliness and tardiness penalties of single-machine scheduling with a common due date," J. Heuristics, vol. 13, no. 2, pp. 151–165, 2007.
[38] K.-C. Ying, "Minimizing earliness–tardiness penalties for common due date single-machine scheduling problems by a recovering beam search algorithm," Comput. Ind. Eng., vol. 55, no. 2, pp. 494–502, 2008.
[39] A. C. Nearchou, "A differential evolution approach for the common due date early/tardy job scheduling problem," Comput. Oper. Res., vol. 35, no. 4, pp. 1329–1343, 2008.
[40] Y. Xia, B. Chen, and J. Yue, "Job sequencing and due date assignment in a single machine shop with uncertain processing times," Eur. J. Oper. Res., vol. 184, no. 1, pp. 63–75, 2008.
[41] V. S. Gordon and V. A. Strusevich, "Single machine scheduling and due date assignment with positionally dependent processing times," Eur. J. Oper. Res., vol. 198, no. 1, pp. 57–62, 2009.
[42] H. I. Demir, T. Cakar, M. Ipek, O. Uygun, and M. Sari, "Process Planning and Due-date Assignment with ATC Dispatching where Earliness, Tardiness and Due-dates are Punished," J. Ind. Intell. Inf. Vol, vol. 3, no. 3, 2015.
[43] H. I. Demir, O. Uygun, I. Cil, M. Ipek, and M. Sari, "Process Planning and Scheduling with SLK Due-Date Assignment where Earliness, Tardiness and Due-Dates are Punished," J. Ind. Intell. Inf. Vol, vol. 3, no. 3, 2015.
[44] C. E. and D. Halil Ibrahim, "Benefits of integrating due date assignment with process planning and scheduling," Master Thesis, Sakarya University, 2007.
[45] D. Halil Ibrahim and T. Harun, "Integrated process planning, scheduling and due date assignment," PhD thesis, Sakarya University, 2005.
[46] H. John, Holland, Adaptation in natural and artificial systems. MIT Press, Cambridge, MA, 1992.
[47] S. Kirkpatrick, C. D. Gelatt, M. P. Vecchi, and others, "Optimization by simmulated annealing," science, vol. 220, no. 4598, pp. 671–680, 1983.
[48] V. Černỳ, "Thermodynamical approach to the traveling salesman problem: An efficient simulation algorithm," J. Optim. Theory Appl., vol. 45, no. 1, pp. 41–51, 1985.

Halil Ibrahim Demir was born in Sivas, Turkey in 1971. In 1988 he received a full scholarship and entered Bilkent University, Ankara, Turkey, to study in the Industrial Engineering Department. He got his Bachelor of Science degree in Industrial Engineering in 1993. He then went to Germany for graduate study, studying German at the intermediate level. In 1994, he received a full scholarship for graduate study in the USA from the Ministry of Education of Turkey. In 1997 he received a Master of Science degree in Industrial Engineering from Lehigh University, Bethlehem, Pennsylvania, USA. He was then accepted to Northeastern University, Boston, Massachusetts for Ph.D. study. He finished his Ph.D. courses at Northeastern and completed a Ph.D. thesis at Sakarya University, Turkey in 2005 for a Ph.D. in Industrial Engineering. He obtained an academic position at Sakarya University as an Assistant Professor. His Research Areas are Production Planning, Scheduling, Application of OR, Simulation, Artificial intelligence techniques, Genetic algorithms, Artificial Neural Networks, Fuzzy Logic and Decision making.

Caner Erden was born in Istanbul in 1989. He received the B.Sc. degree from Istanbul Commerce University in 2006 and M.Sc. degree from Istanbul University in 2013, respectively. He is currently a Ph.D. student and a research assistant in Industrial Engineering Department, Sakarya University. His research interests include genetic algorithms, neural networks, fuzzy sets and rough sets

Mümtaz İpek was born in Sakarya, Turkey in 1969. He got his Bachelor of Science degree in 1991 and his Master of Science degree in 1995 in Industrial Engineering at İstanbul Technical University. He finished Ph.D. courses and completed Ph.D. thesis at Sakarya, Turkey in 2007 and got Ph.D. degree in Industrial Engineering. He started to his academic position at Sakarya University and works as an Assistant Professor at this university.

Özer Uygun was born in Sakarya, Turkey in 1976. In 1994 he entered Sakarya University, Turkey to Industrial Engineering Department. He got his Bachelor of Science degree in Industrial Engineering in 1999. He got Master of Science degree in 2002 and Ph.D. degree in 2008 in Industrial Engineering from Sakarya University, Turkey.

He started to his academic position at Marmara University and worked as a Lecturer between 2000 and 2003. Then he worked as a Research Assistant at Sakarya University between 2003 and 2008 and now works as an Assistant Professor at this university.

He was a researcher in EU FP6 Network of Excellence (I*PROMS: 2004-2009) and FP6 STREP Project (IWARD: 2007-2009). He has successfully completed the EFQM Assessor Training in Brussels in 2015. His research areas are Multi-criteria decision making, Fuzzy decision making, and Application of Operation research.