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The hybrid metaheuristic scheduling model for on-demand garment manufacturing

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ABSTRACT

The latest technology milestone drives the fashion industry to implement on-demand garment manufacturing. This study presents the hybrid metaheuristic for scheduling by combining the genetic algorithm and tabu search. The various method was introduced since this type of scheduling is categorized as an NP-hard optimization problem and very interesting. The goal of this study is to minimize makespan. First, to make a genetic algorithm keep the diversity of the solution, we introduce a double swap mutation approach as a genetic operator which reproduces four offsprings from two selected parents. After the reproduction process, the algorithm is guided by tabu search scanning its neighborhood to improve the solution accuracy. As we know, the genetic algorithm is quickly falling to local optima because the advantages are to perform global exploration. Tabu search is used as a local search strategy to exploit the solution space. We conducted experimental results using the Taillard instance. We compared them to the other three hybrid algorithms such as re-blocking adjustable memetic procedure, hybrid genetic algorithm simulated annealing, and hybrid evolution strategy simulated annealing resulted in improvement by 0.16%, 4.50%, and 0.06%, respectively. Also, have the lowest relative percentage deviation of 0.28%. Then we applied the proposed algorithm to the real-world case study and compared the hybrid metaheuristic method with current approaches. The experimental results demonstrate that the hybrid metaheuristic approach can yield very efficient solutions to the scheduling problem; it can save production completion time by 22.6%; it shows promising performance compared to the existing methods.

1. Introduction

Technology has changed the way people shop from the traditional market into social media applications and marketplace channels [1], [2]. The digital lifestyles, digital marketing strategies, and digital platforms coupled with the impact of Covid-19 during the last 2021 allows companies to engage consumers digitally [3], [4], and taking over apparel production becomes on-demand manufacturing since the fluctuated purchase intentions [5].

The garment industry has a dynamic, complex manufacturing sector, with a long supply chain under conditions of rapidly changing market demand, competitive market prices, short product cycles, large product variety, and uncertain demand [6]. Flexible or on-demand manufacturing is needed because it increases utilization [7], and the total completion time of a product manufacturing can be minimized to optimize resources [8]. Thus, companies have to rebuild their scheduling manufacturing process to achieve greater business agility [9].

Scheduling becomes the main aspect of the company's success factor to help the decision-making process in production [10]. The scheduling in garment manufacturing (characterized as flow shop), which is dynamic, stochastic, and very complex, makes many researchers conduct various methods to address this type of scheduling. First, from the exact approach such as linear programming [11] also branch and bound algorithm [12] are very good to find solution optimally, but very time consuming when the problem to solve getting bigger. Second, from the heuristic category, there are Iterated Greedy [13], Palmer and Gupta [14], and Nawaz-Enscore-Ham (NEH) by [15], designed to be faster and more efficient than the exact method, unfortunately, have lower solution accuracy. So the third, from the metaheuristic category that balances the algorithm speed and solution accuracy, receives more attention as a scheduling optimizer [16].

The genetic algorithm (GA) from metaheuristic is the most implemented [17] for optimization problems because it provides the ability to explore search space and find the solution better at reasonable computation time [18]. The GA has been hybridized with problem-oriented heuristic [19] and tabu search [20] to provide deep exploitation in the search area and escape the GA from early convergence. Because the solution accuracy depends not only on tabu search but also on the genetic operator, other studies also consider modifying the operator used [21] and improving the algorithm. The initial solution of GA can also be adjusted using biased random sampling [21] called re-blocking adjustable memetic procedure (RAMP) to minimize makespan. Not only combining the two algorithms but the initial GA solution was also generated with the min-max and NEH algorithms, then exploited the solution space using simulated annealing [22], but there seems to be an algorithm that competes with it, namely hybrid evolution strategy simulated annealing (HESSA) [23] which perform initialization using improved evolution strategy and compared the result to another hybrid algorithm.

Local search method like tabu search is another efficient optimization approach and are freaquently used to address the flow shop scheduling problem, such as [24]–[26] very promising to scan the solution space. Since there is no one method or algorithm that can solve all problems [27], then hybridization is a solution because it incorporates the superiority between two or more algorithms to address specific problems [28]. Thus, this paper's contribution is to hybridize the tabu search into GA by increasing the generated offspring number twice, considering that the studied literature only generates two offspring numbers [29], [30]. This study aims to look up the quickest time to complete jobs called makespan by determining the optimal scheduling sequence. This study applies to companies that manufacture clothes, and then the comparison with the current method is also provided.

For the rest of this paper, we present the central concept in scheduling and on-demand manufacturing, providing a backbone for our approach. Also, we present how a hybrid metaheuristic algorithm should be integrated into on-demand manufacturing in section 2; then we present the result and discussion available through section 3; and lastly, the conclusion of this paper is provided in section 4.

2. Method

This section describes the integration hybrid metaheuristic as a production scheduling algorithm for on-demand garment manufacturing.

2.1. Garment Scheduling

Define abbreviations and acronyms the first time they are used in the text, even after they have been defined in the abstract. Abbreviations such as IEEE, SI, MKS, CGS, sc, dc, and rms do not have to be defined. Do not use abbreviations in the title or heads unless they are unavoidable.

One of the main problems within the fashion industry today is the long production time frame [31]. In today's complicated manufacturing environment, various product lines are involved with different stages and machinery. The manufacturing plant's decision-maker must effectively handle resources in order to make products as efficiently as reasonably possible [32]. The decision-maker must develop a plan in the form of a schedule which provides the maximum on-time delivery and reduces the needed time for job completion [33].

Scheduling challenges occur when determining the optimal schedule for a variety of goals, the sequence of the machine, and also task constraints [34]. Production scheduling in the garment industry is categorized as flow shop since the task is reordering the jobs over the same machining process with the goal is to minimize makespan or lower the overall finished time of every task [35]. A shorter production time is better for apparel production because this business needs to deliver the goods to the consumer as quickly as possible [36].

The following is a definition of a garment scheduling problem:

"Provided a collection of jobs J = (J1, J2, J3, …) and machinery M = (M1, M2, M3, …), then assign a job to resources in achieving the objective (minimizing the completion time)."

One of the usually investigated objectives is the effort to minimize the total production time, usually called makespan and generally denoted by Cmax [37]. The constrain of this work is that every machine or workstation can be processed only one job at a single machine. So if only one machine is available and a job cannot be finished in time (because it takes too long to complete or the resource was busy for too much time), there is simply no way to make progress.

With the increasing competition in global markets, manufacturers are constrained to meet their customers' deadlines to win new business. So, they have limited time for producing any order or task to cater to the customer requirements on time [38]. The limited time allocated for the job makes scheduling necessary to optimize the resources [39]. Many algorithms were developed to address this scheduling type. One of them is a hybrid metaheuristic, which refers to a combination of metaheuristic methods, a set of techniques and ideas studied in various scientific disciplines before [40]. Hybrid metaheuristic algorithms for scheduling take advantage of different optimization techniques, such as local searches like tabu search and evolutionary algorithms like genetic algorithms.

Due to the increasing pressure to improve service operations, the service sectors have analyzed to the manufacturing industry a milestone on how to shift to on-demand manufacturing, a customer-oriented service [41]. On-demand manufacturing is a group of concepts and capabilities that enable the production of goods with minimal or no inventory [42]. On-demand manufacturing reduces capital costs by reducing the need for fixed assets such as spare parts and machinery. The concept can also lower warehousing costs because there is no finished goods inventory to store [43]. It can reduce other costs by allowing greater flexibility in meeting volatile or seasonal product demand while avoiding stockouts requiring expensive rebuilding activities.

Fig. 1. provides an overview of how the developed method works. Consumers interact digitally with fashion manufacturers using the marketplace, social media, or another digital channel. These platforms then communicate to the company's enterprise resource planning (ERP) system, which facilitates them to handle inventory control, order received, finance, and human resource management. It will help the production sector make products for customers according to customer orders quickly.

The ERP will send the received order for production. If the company has a digital garment platform facility, it will be done automatically by the machine. Otherwise, it will be done by a human then the finished product will be delivered. The hybrid metaheuristic approach will play a role in the on-demand garment manufacturing platform to make optimal production scheduling decisions that minimize the makespan.

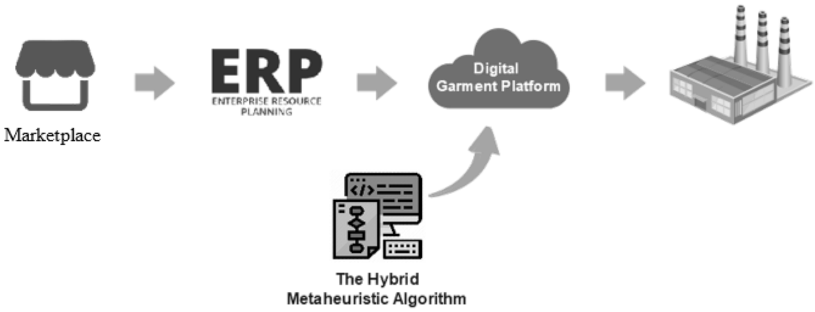

Fig. 1.GATS for on-demand manufacturing

The on-demand manufacturing will enable the factory to consistently produce on-trend designs that satisfy consumer demand, thus standing out from the competition. On-demand manufacturing is now preferred to assist societies and ensure availability [44]. On-demand manufacturing also requires that companies integrate data on suppliers' capabilities, real-time customer demand for products, manufacturing inventories, and equipment availability to determine whether a particular order needs to be built using inventory components or made by a specific machine [45].

2.2. Proposed Method

The proposed hybrid metaheuristic scheduling follows the generation incorporation framework between genetic algorithm and tabu search by increasing four produced offspring. The various steps with parameter settings are revealed as follows:

Step 1 Encode the solution by treating the job set as genes and the chromosome's sequence. Then distribute the required time over gene.

Step 2 Generate the 100 population by random, then split them into the left and right parts. Take part and choose the best fitness by comparing the opposite point using a partial opposition-based approach.

Step 3 If the allowed generation 1000 is not satisfied, check and evaluate the fitness objective, which is to minimize the makespan (min C_{max}); better fitness will update the solution.

Step 4 Choose to parent to reproduce the child or offspring using the tournament method with size 5 to balance the speed and convergence. The winner will update the elitist, which contains the best fitness so far.

Step 5 Offspring reproduction using two-point crossover, which selects two chromosomes by random and decides the barrier to exchange the chromosome between the barrier and the 0.5 for crossover probability. Then our innovation is a double swap mutation that can reproduce four offspring from two selected parents with the 0.1 mutation probability. This can be done by the 1+2 reproduction approach, which is one parent results in two offspring, see Fig. 2.

Step 6 Next, the tabu search uses fitness function as aspiration criteria, tabu size length is five, and stop criteria is the allowed generation. This tabu search performs a move by insertion and swap strategy to scan its neighborhood to exploit the solution locally.

Step 7 The proposed algorithm will initialize the Gantt chart structure by retrieving the job sequence and processing time over the machining process. After all, the Gantt chart will be loaded.

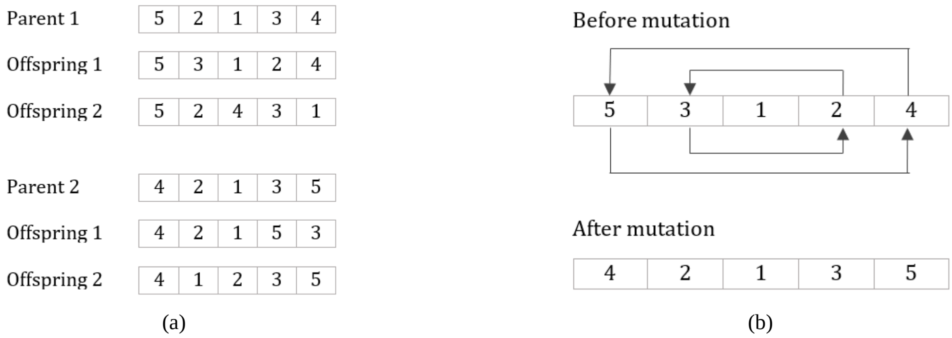

Fig. 2.(a) Reproducing four offspring from 2 parents, (b) Double swap method

This study has constrained and can be stated as:

- Not of all jobs will be processed on all machines; the job can have 0 processing time continued to the subsequent machining
- Every operation from the associated job could be performed on a single piece of machinery at every time
- Operation from a job can be started after the operation completed the previous job
- For all jobs that have the same machining process sequence, the task is finding a job schedule that minimizes completion time

3. Results and Discussion

This study used the Taillard dataset consisting of 120 instances as a computational experiment material so that the results can be compared with other studies, namely RAMP [21], GASA [22], and HESSA [23]. Ten repetitions of the experiment using a 1.9 GHz computer processor, 4 GB of RAM, and coded in the Python programming language the experiment results can be summarized in Table 1, which provides the relative percentage deviation (RPD), calculated as:

$$RPD = \frac{\sum_{i=1}^{N}(\frac{GATS-UB}{UB} x\ 100)}{N} \tag{1}$$

N represents the used instances, GATS shows the best solution from the proposed hybrid heuristic algorithm, and UB is upper bound for Taillard, representing the best-known solution for Taillard. We can sum the RPD column to 33,48, so the PRD for GATS is 1 / 120 x 33,48 = 0.28% which show the error rate; the lower indicates a better result.

Table 1. Computational result on Taillard

Instance	Size	Upper Bound	RAMP	GASA	HESSA	GATS	PRD
Tai001	20 * 5	1278	1278	1324	1278	1278	0,00
Tai002	20 * 5	1359	1359	1442	1359	1359	0,00
Tai003	20 * 5	1081	1081	1098	1081	1081	0,00
Tai004	20 * 5	1293	1293	1469	1293	1293	0,00
Tai005	20 * 5	1235	1235	1291	1235	1235	0,00
Tai006	20 * 5	1195	1195	1391	1195	1195	0,00
Tai007	20 * 5	1239	1239	1299	1239	1239	0,00
Tai008	20 * 5	1206	1206	1292	1206	1206	0,00
Tai009	20 * 5	1230	1230	1306	1230	1230	0,00
Tai010	20 * 5	1108	1108	1233	1108	1108	0,00
Tai011	20 * 10	1582	1582	1713	1582	1582	0,00
Tai012	20 * 10	1659	1659	1718	1659	1659	0,00
Tai013	20 * 10	1496	1496	1555	1496	1496	0,00
Tai014	20 * 10	1377	1377	1516	1377	1377	0,00
Tai015	20 * 10	1419	1419	1573	1419	1419	0,00
Tai016	20 * 10	1397	1397	1457	1397	1397	0,00
Tai017	20 * 10	1484	1484	1622	1484	1484	0,00
Tai018	20 * 10	1538	1538	1749	1538	1538	0,00

Instance	Size	Upper Bound	RAMP	GASA	HESSA	GATS	PRD
Tai019	20 * 10	1593	1593	1624	1593	1593	0,00
Tai020	20 * 10	1591	1591	1722	1591	1591	0,00
Tai021	20 * 20	2297	2297	2331	2297	2297	0,00
Tai022	20 * 20	2099	2099	2280	2099	2099	0,00
Tai023	20 * 20	2326	2326	2480	2326	2326	0,00
Tai024	20 * 20	2223	2223	2362	2223	2223	0,00
Tai025	20 * 20	2291	2291	2507	2291	2291	0,00
Tai026	20 * 20	2226	2226	2375	2226	2226	0,00
Tai027	20 * 20	2273	2273	2341	2273	2273	0,00
Tai028	20 * 20	2200	2200	2279	2200	2200	0,00
Tai029	20 * 20	2237	2237	2410	2237	2237	0,00
Tai030	20 * 20	2178	2178	2401	2178	2178	0,00
Tai031	50 * 5	2724	2724	2731	2724	2724	0,00
Tai032	50 * 5	2834	2834	2934	2836	2834	0,00
Tai033	50 * 5	2621	2621	2638	2621	2621	0,00
Tai034	50 * 5	2751	2751	2785	2751	2751	0,00
Tai035	50 * 5	2863	2863	2864	2863	2863	0,00
Tai036	50 * 5	2829	2829	2907	2829	2829	0,00
Tai037	50 * 5	2725	2725	2764	2725	2725	0,00
Tai038	50 * 5	2683	2683	2706	2686	2683	0,00
Tai039	50 * 5	2552	2552	2610	2552	2552	0,00
Tai040	50 * 5	2782	2782	2784	2782	2782	0,00
Tai041	50 * 10	2991	3025	3198	3024	3024	1,10
Tai042	50 * 10	2867	2877	3020	2882	2882	0,52
Tai043	50 * 10	2839	2852	3055	2852	2852	0,46
Tai044	50 * 10	3063	3063	3124	3063	3063	0,00
Tai045	50 * 10	2976	2979	3129	2982	2982	0,20
Tai046	50 * 10	3006	3006	3293	3006	3006	0,00
Tai047	50 * 10	3093	3098	3232	3122	3099	0,19
Tai048	50 * 10	3037	3038	3390	3042	3038	0,03
Tai049	50 * 10	2897	2902	3237	2911	2902	0,17
Tai050	50 * 10	3065	3078	3251	3077	3077	0,39
Tai051	50 * 20	3850	3873	4105	3889	3889	1,01
Tai052	50 * 20	3704	3714	3992	3714	3720	0,43
Tai053	50 * 20	3640	3649	3900	3667	3667	0,74
Tai054	50 * 20	3720	3739	3921	3754	3754	0,91
Tai055	50 * 20	3610	3625	4020	3644	3644	0,94
Tai056	50 * 20	3681	3695	3971	3708	3708	0,73
Tai057	50 * 20	3704	3715	4093	3754	3754	1,35
Tai058	50 * 20	3691	3709	4090	3711	3711	0,54
Tai059	50 * 20	3743	3765	4107	3772	3772	0,77
Tai060	50 * 20	3756	3773	4113	3778	3778	0,59
Tai061	100 * 5	5493	5493	5536	5493	5493	0,00
Tai062	100 * 5	5268	5268	5302	5268	5268	0,00
Tai063	100 * 5	5175	5175	5221	5175	5175	0,00
Tai064	100 * 5	5014	5014	5044	5014	5014	0,00
Tai065	100 * 5	5250	5250	5358	5250	5250	0,00
Tai066	100 * 5	5135	5135	5197	5135	5135	0,00
Tai067	100 * 5	5246	5246	5414	5246	5246	0,00
Tai068	100 * 5	5094	5094	5130	5094	5094	0,00
Tai069	100 * 5	5448	5448	5546	5448	5448	0,00
Tai070	100 * 5	5322	5322	5480	5322	5322	0,00
Tai071	100 * 10	5770	5770	5964	5776	5770	0,00
Tai072	100 * 10	5349	5349	5596	5360	5349	0,00
Tai073	100 * 10	5676	5676	5796	5677	5677	0,02
Tai074	100 * 10	5781	5781	5928	5792	5781	0,00
Tai075	100 * 10	5467	5467	5748	5467	5467	0,00
Tai076	100 * 10	5303	5303	5446	5311	5304	0,02
Tai077	100 * 10	5595	5596	5679	5596	5596	0,02
Tai078	100 * 10	5617	5623	5723	5625	5625	0,14
Tai079	100 * 10	5871	5875	5934	5891	5875	0,07
Tai080	100 * 10	5845	5845	5998	5845	5845	0,00
Tai081	100 * 20	6202	6336	6395	6257	6257	0,89
Tai082	100 * 20	6183	6271	6433	6223	6223	0,65

Instance	Size	Upper Bound	RAMP	GASA	HESSA	GATS	PRD
Tai083	100 * 20	6271	6363	6689	6342	6325	0,86
Tai084	100 * 20	6269	6334	6419	6303	6303	0,54
Tai085	100 * 20	6314	6394	6536	6380	6380	1,05
Tai086	100 * 20	6364	6482	6527	6427	6431	1,05
Tai087	100 * 20	6268	6350	6542	6306	6306	0,61
Tai088	100 * 20	6401	6530	6712	6472	6472	1,11
Tai089	100 * 20	6275	6381	6760	6380	6330	0,88
Tai090	100 * 20	6434	6496	6621	6485	6456	0,34
Tai091	200 * 10	10862	10872	11120	10872	10872	0,09
Tai092	200 * 10	10480	10499	10658	10487	10487	0,07
Tai093	200 * 10	10922	10934	11224	10941	10922	0,00
Tai094	200 * 10	10889	10889	11075	10889	10889	0,00
Tai095	200 * 10	10524	10527	10793	10524	10526	0,02
Tai096	200 * 10	10326	10334	10467	10346	10330	0,04
Tai097	200 * 10	10854	10866	11394	10868	10868	0,13
Tai098	200 * 10	10730	10743	11011	10741	10731	0,01
Tai099	200 * 10	10438	10438	10725	10451	10454	0,15
Tai100	200 * 10	10657	10685	10786	10680	10680	0,22
Tai101	200 * 20	11195	11379	11642	11287	11280	0,76
Tai102	200 * 20	11203	11453	11683	11277	11272	0,62
Tai103	200 * 20	11281	11510	11930	11418	11378	0,86
Tai104	200 * 20	11275	11462	11791	11376	11376	0,90
Tai105	200 * 20	11259	11397	11728	11365	11310	0,45
Tai106	200 * 20	11176	11413	11690	11330	11265	0,80
Tai107	200 * 20	11360	11549	11958	11398	11430	0,62
Tai108	200 * 20	11334	11526	11730	11433	11398	0,56
Tai109	200 * 20	11192	11432	12138	11356	11266	0,66
Tai110	200 * 20	11288	11479	12084	11446	11355	0,59
Tai111	500 * 20	26059	26387	26859	26187	26187	0,49
Tai112	500 * 20	26520	26890	27220	26799	26779	0,98
Tai113	500 * 20	26371	26692	27511	26496	26496	0,47
Tai114	500 * 20	26456	26688	26912	26612	26618	0,61
Tai115	500 * 20	26334	26590	26930	26514	26500	0,63
Tai116	500 * 20	26477	26753	27354	26661	26647	0,64
Tai117	500 * 20	26389	26595	26888	26529	26529	0,53
Tai118	500 * 20	26560	26812	27229	26750	26772	0,80
Tai119	500 * 20	26005	26346	28103	26223	26223	0,84
Tai120	500 * 20	26457	26687	27290	26619	26617	0,60

From Table 1, we can see a very close outcome between RAMP, HESSA, and GATS. The printed bold result is the lowest makespan among the three algorithms compared. If we calculate it, we find that RAMP has 26 times the lowest makespan, HESSA 20 times, and GATS 41 times. We ignore GASA because it has one time the lowest makespan. When visualized, the results of Table 1 can be seen in Fig. 3.

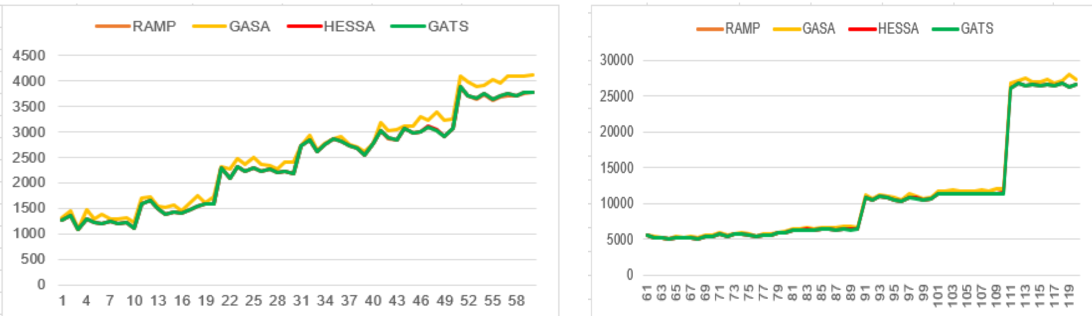

Fig. 3.(a) Comparison Taillard instance 1-60, (b) Comparison Taillard instance 61-120

We use two indicators to compare, the PRD that shows the error rate and the percentage of increase (PI), representing the improvement made by GATS compared to other algorithms. PI formulated as:

$$PI = \frac{GATS-UB}{UB} x100 \quad (2)$$

First, we can measure the increase of hybrid metaheuristic GATS in Table 2:

Table 2. PI achievement

Instance Size	Improvement GATS to		
	RAMP	***GASA***	***HESSA***
20 x 5	0,00	7,53	0,00
20 x 10	0,00	7,35	0,00
20 x 20	0,00	6,34	0,00
50 x 5	0,00	1,31	0,02
50 x 10	-0,02	6,70	0,12
50 x 20	-0,37	7,79	-0,02
100 x 5	0,00	1,49	0,00
100 x 10	-0,01	2,71	0,09
100 x 20	0,72	3,39	0,14
200 x 10	0,03	2,34	0,04
200 x 20	1,12	4,45	0,31
500 x 20	0,40	2,61	0,01
Average	0,16	4,50	0,06

In other words, a hybrid metaheuristic can improve the RAMP algorithm by 0.16%, improve the GASA by 4.50%, and improve the HESSA by 0.06%. The PI achievement can be visualized out as Fig. 4.

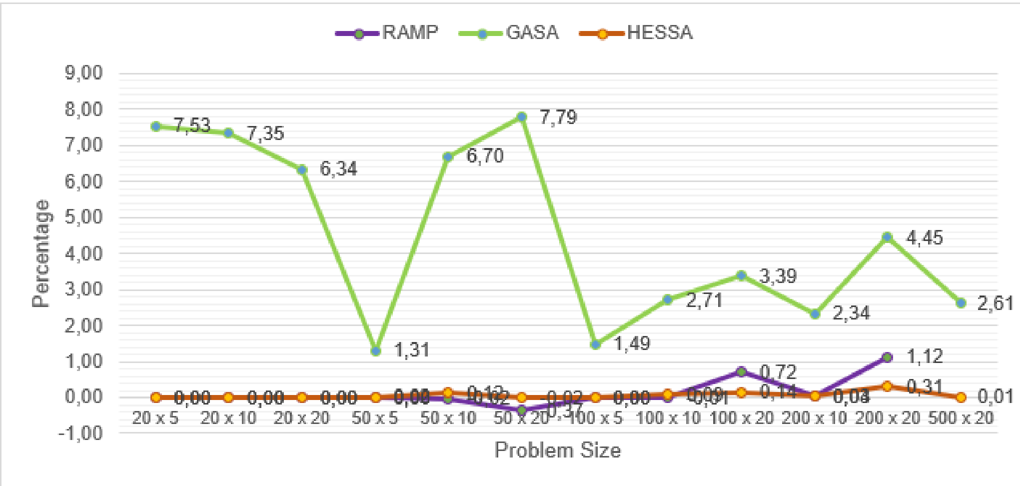

Fig. 4. The PI of GATS compared to other algorithms

Next, we provide the percentage of PRD in Table 3 and can be visualized as Fig. 5 lower value indicate lower error rate.

Table 3. Percentage of PRD

Algorithm	Instance	∑ PI	PRD (%)
RAMP	120	52,22	0,44%
GASA	120	576,60	4,81%
HESSA	120	40,67	0,34%
GATS	120	33,48	0,28%

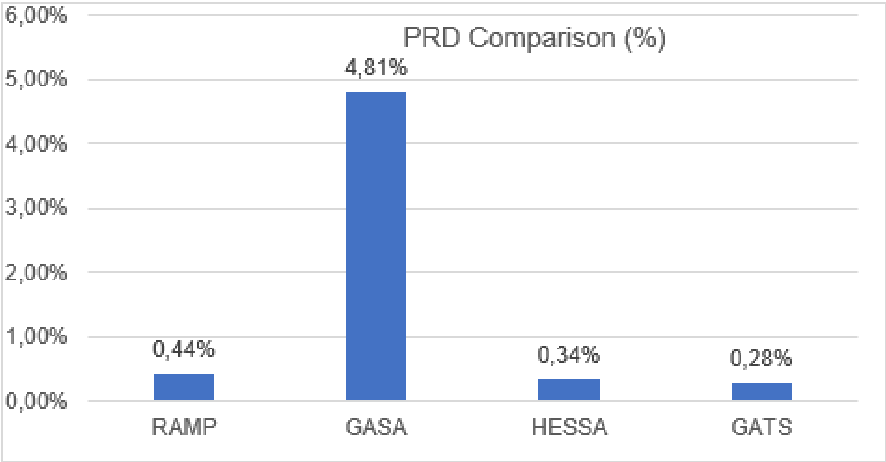

Fig. 5. The PRD comparison among hybrid algorithm

Lastly, the proposed algorithm solved an accurate word on-demand garment manufacturing. Customer orders, a routing matrix is containing the order of 10 machining tasks, and the processing obtained through observation provided in Table 4 and Table 5.

Table 4. The customer order

No.	Product List	Order Quantity
1	A	2.300
2	B	3.000
3	C	2.700
4	D	3.200
5	E	3.300
6	F	1.900
7	G	2.050
8	H	2.000
9	I	4.000
10	J	3.600

Table 5. Routing matrix

Machines	Jobs									
	J_{00}	J_{01}	J_{02}	J_{03}	J_{04}	J_{05}	J_{06}	J_{07}	J_{08}	J_{09}
Machine 1 (M_0)	45	45	45	45	45	45	45	45	45	45
Machine 2 (M_1)	60	60	60	60	60	40	50	60	60	55
Machine 3 (M_2)	120	100	100	100	120	100	120	130	120	105
Machine 4 (M_3)	80	58	60	60	80	60	60	40	50	55
Machine 5 (M_4)	300	150	275	280	300	100	180	110	120	115
Machine 6 (M_5)	60	60	60	60	240	180	140	180	120	180
Machine 7 (M_6)	60	70	45	65	95	35	85	75	80	40
Machine 8 (M_7)	60	60	48	65	90	35	85	75	75	35
Machine 9 (M_8)	60	50	60	55	70	30	45	40	50	45
Machine 10 (M_9)	25	25	25	25	25	25	25	25	25	25

In our problem, there are ten machining processes or called with workstation: fabrication checking, pattern making, cutting, overlocking, needle lock stitching, embroidering, button attaching, buttonhole stitching, ironing, and labeling. These are numbered as 0, 1, 2, …, 9, respectively. The current scheduling uses first in first out (FIFO) scheduling that can't handle when the problem is more complex. Fig. 6 shows a Gantt chart of the current scheduling from the factory based on Table 4 and Table 5. The completion time is presented horizontally and different colors show different machining processes. Meanwhile, the vertical is job sequence to be ordered to have makespan as minimal as possible.

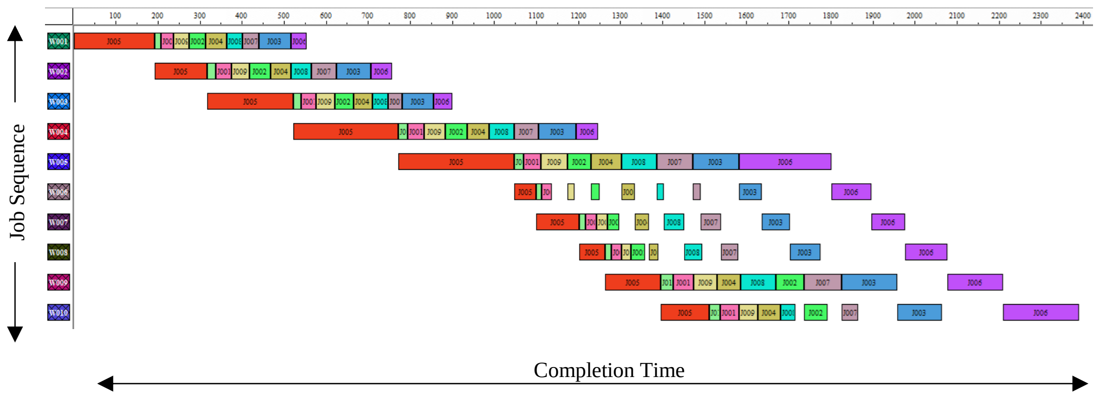

Fig. 6. Gantt chart based on existing scheduling

The illustration above shows that the time needed to complete ten jobs is 2.361 with [5, 10, 1, 9, 2, 4, 8, 7, 3, 6] job sequence. We can see that job 4 (the fifth order from up) causes too long a time gap for the following three jobs, namely jobs 5, 6, and 7, which means that the idle time of the machine is considerable. The current approach is that several jobs cannot be completed daily. As a result, the work cannot meet the delivery schedule to the customer or is said to be late. In order to improve overall system performance, a new approach is used, namely using a hybrid metaheuristic.

Now, we solve the problem instance from the company by using hybrid metaheuristic GATS, and the calculation resulted in a schedule which can be shown in Fig. 7 as follow:

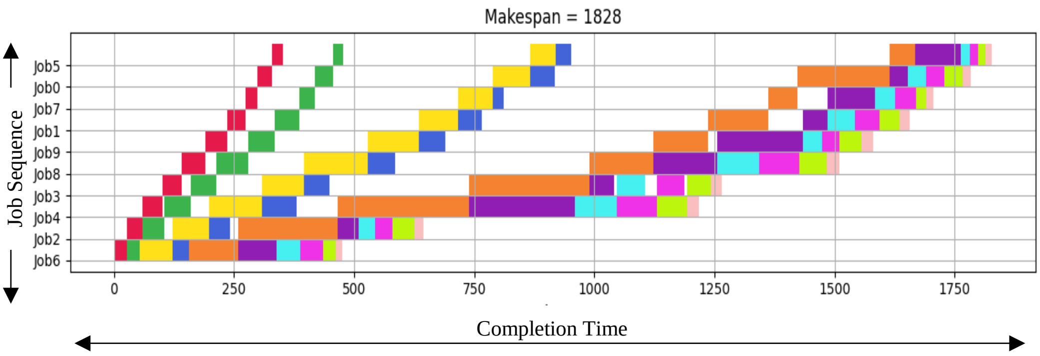

Fig. 7. Gantt chart based on GATS

The problem is solved, the completion time result is 1.828, and the order of job execution is obtained, namely [6, 2, 4, 3, 8, 9, 1, 7, 0, 5]. The different colors represent the machining process for jobs. This is certainly lower than the completion time generated by the company. It can be calculated that there is an increase in performance of (2.361 – 1.828) / 2.361 x 100% = 533 / 2.361 x 100% = 22.6%.

4. Conclusion

This paper started by identifying concerns to integrate the hybrid metaheuristic scheduling into on-demand garment manufacturing. It would be beneficial because it can keep production flexible and efficient without excess or shortage in delivery time. The main benefit is to reduce the makespan in response to changes in demand because there is a never-ending flow of orders. The number of orders can vary from season to season and from month to month. In order to maintain a smooth production process, it is necessary to have an efficient production scheduling system in place. Based on the result, the hybrid metaheuristic GATS algorithm can improve the RAMP, GASA, and HESSA algorithms by 0.16%, 4.50%, and 0.06%, respectively. The GATS also has the lowest PRD by 0.28%, showing a lower error rate. After being implemented at a practical level to on-demand garment manufacturing.

The new proposed model can improve the solution by around 22.6% compared to the current scheduling method in the company, which is FIFO.

Production scheduling is not an easy task; various factors need to be considered, such as labor costs, capacity utilization of machinery, fabric lead time, etc. One algorithm can not fit all. So, the future approach will focus on hybridizing more new methods using metaheuristics since it is more robust to implement under the multi-objective scheme.

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