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Optimization of welding job-shop scheduling problem under variable workstation constraint: an industrial application with Arena simulation based genetic algorithm

Kaynak atölyesi çizelgeleme probleminin değişken iş istasyonu kısıtlaması altında optimizasyonu: Arena simülasyonu tabanlı genetik algoritma ile endüstriyel bir uygulama

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Abstract

Job-shop scheduling is a difficult issue for 'labor-intensive project type manufacturing'. Because in this type of production, the actual processing times are not exactly known until the production is finished and these processing times vary depending on the order's technical specifications. It is an appropriate method to use probability distributions to forecast the processing times. This paper provides an industrial application for the scheduling of a labor-intensive project type working welding job-shop under variable workstation constraints. This constraint is consequence of a special production type that is depending on the length of the products. The aim is minimizing the makespan of a group of waiting orders. Genetic algorithm (GA) is used for this purpose to establish the entry sequence of the job-shop's waiting orders and dispatching them to the 6 identical welding stations. The dynamic conditions of the job-shop are simulated by the Arena simulation program. Stochastic processing times are used as the input data of the algorithm. Using stochastic processing times under variable workstation constraint for welding job-shop scheduling is not investigated previously. According to the experimental results, GA and Arena simulation together effectively reduces the makespan in this type of problem under variable workstation constraint. The GA aided Arena schedule outperforms the schedules proposed without using GA for this problem. Simulation results indicate that the total manufacturing time of pending orders is nearly 9.25% reduced when compared with the schedules proposed without using GA.

Keywords: Arena simulation, Genetic algorithm, Labor-intensive project type production, Makespan minimization, Variable workstation constraint, Welding shop scheduling problem.

Öz

İş atölyesi planlaması, 'emek yoğun proje tipi üretim' için zor bir konudur. Çünkü bu tür bir üretimde, gerçek işlem süreleri üretim bitene kadar tam olarak bilinmez ve bu işlem süreleri siparişin teknik özelliklerine göre değişir. İşlem sürelerini tahmin etmek için olasılık dağılımlarını kullanmak uygun bir yöntemdir. Bu makale, emek-yoğun proje tipi çalışan kaynak atölyesinin değişken iş istasyonu kısıtlamaları altında planlanması için endüstriyel bir uygulama sunmaktadır. Bu kısıt, ürünlerin boyuna bağlı olarak ortaya çıkan özel bir üretim şeklinin sonucudur. Amaç, bir grup bekleyen iş emrinin tamamlanma süresini en aza indirmektir. Genetik algoritma (GA) bu amaçla, atölyeye girmeyi bekleyen iş emirlerinin atölyeye giriş sırasını oluşturmak ve bunları 6 özdeş kaynak istasyonuna göndermek için kullanılır. Atölyenin dinamik koşulları, Arena simülasyon programı ile simüle edilir. Algoritmanın girdi verileri olarak stokastik işlem süreleri kullanılır. Kaynak iş istasyonu çizelgeleme için değişken iş istasyonu kısıtlaması altında stokastik işleme sürelerinin kullanılması daha önce araştırılmamıştır. Deneysel sonuçlara göre, GA ve Arena simülasyonu birlikte, değişken iş istasyonu kısıtlaması altında bu tür problemlerde bir grup işin toplam tamamlanma zamanını etkili bir şekilde azaltmaktadır. GA destekli Arena çizelgesi, bu sorun için GA kullanmadan önerilen çizelgeden daha iyi performans gösterir. Simülasyon sonuçları, bekleyen siparişlerin toplam üretim süresinin, GA kullanılmadan önerilen çizelgelerle karşılaştırıldığında yaklaşık % 9,25 oranında azaldığını göstermektedir.

Anahtar kelimeler: Arena simülasyonu, Genetik algoritma, Emek-yoğun proje tipi üretim, Tamamlanma zamanı minimizasyonu, Değişken iş istasyonu kısıtı, Kaynak atölyesi çizelgeleme problemi.

1 Introduction

It is critical for enterprises to supply customer requirements within due date and to reduce the labor cost for each customer order. Order scheduling is required for various purposes, for example makespan minimization, optimizing the use of resources, etc. Before starting the production, processing times for each job are known in deterministic scheduling and there are no process disruptions, except for a few production adjustments. These production systems can be widely computer-controlled, and the problem can be analytically solved by using linear programming. However, such types of solutions are far from actual production environments. Since so many assumptions are needed to be made to mathematically model the real-life problem, this causes the problem to diverge from real life. Stochastic scheduling on dynamic shop floors is more appropriate for scheduling real life problems. There are many factors that trigger stochastic operating times, such as technical order requirements, operator skills, job-shop bottlenecks, transporters, and so on. The appropriate operations are known but processing times are not exactly known in stochastic scheduling. Stochastic processing times make it harder for order scheduling. In addition to using stochastic operation times, because of the dynamic job-shop environment, the use of simulation provides more important results for real industrial plants.

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The labor intensive project type job-shop has a dynamic production environment. Stochastic operation times and stochastic scheduling are triggered by a dynamic production environment. Heuristics are used to address that issue because of these problems are known as the NP-hard problem. Particle swarm, genetic algorithm, ant colony and so on have been commonly used meta-heuristics in the last decade to solve problems with job-shop scheduling.

Some of the papers selected - those closely relevant to the subject matter of this paper - are as follows: Jia et al. [1] proposed decode select string (DSS) decoding genetic algorithm (GA) for job-shop scheduling problem (JSSP). Azadeh et al. [2] studied on makespan minimization in stochastic JSSP. They used artificial neural networks (ANN) and computer simulation together to select the optimum dispatching rule for each machine under a set of different constraints and rules. Huang et al. [3] studied on process sequence flexibility problem for JSS. They used GA to minimize the makespan. Aydemir and Koruca [4] developed a priority rule-based GA (PRGA) scheduling module to minimize the total completion time. Flexible job-shop scheduling (FJSS) is also a NP hard problem. Ba et al. [5] presented a novel mathematical model for a multi-resource FJSS (MR-FJSS). They used GA to minimize the makespan. Deng et al. [6] studied on bee evolutionary guiding non-dominated sorting GA (NSGA) for multi-objective FJSSP (MO-FJSSP). Ocaktan et al. [7] used GA and Arena simulation together to minimize the makespan of customized orders of a job-shop. Zhang et al. [8] also used GA for MO-FJSSP to minimize the longest makespan of the workpieces and machine loads (for each machine and total machine). The shortest processing time (SPT) and balanced use of machines is considered by them. Hu et al. [9] used improved cuckoo search algorithm (CSA) for JSSP. This algorithm is a hybrid of CSA and particle swarm optimization (PSO) algorithm. The results are compared with PSO and GA. The simulations are performed by using Matlab program. Jiang et al. [10] studied on energy-efficient JSS instead of conventional performance criteria such as production efficiency, makespan etc. To optimize this environmental metric, they used grey wolf optimization (GWO) algorithm. Also they proposed a double-searching mode for GWO to solve this problem. Jiang et al. [11] studied on the same subject by using whale optimization algorithm (WOA). Seng et al. [12] proposed a low-carbon scheduling model for MO and multi-speed (MS) FJSS and used NSGA for optimization. They considered energy consumption, low carbon emissions, and makespan as the performance criteria. Karaoglan et al. [13] studied on JSSP by considering the ergonomic constraints. They used combined GA and Arena simulation to minimize the makespan. Zhang et al. [14] used binary PSO to optimize the multi-technique, multi-response FJSSP. Zhong et al. [15] optimized dual resource constraint JSSP to optimize the makespan and total processing cost. They proposed branch population GA for optimization. Sel and Hamzadayi [16] used simulated annealing (SA) for JSSP and used Arena for simulations. Fu et al. [17] established a multi-objective optimization model for a JSSP and used NSGA to minimize some performance measurements such as the total cost and the total completion time. Tang et al. [18] considered limited starting time interval and tolerated time interval to conduct a MO-FJSSP. They also presented hybrid discrete PSO with simulated annealing (HDPSO-SA) for the optimization of this problem. Liao and Lin [19] studied on optimization of job-shop supply chain scheduling problem using PSO. Wang et al. [20] used hybrid GA-PSO for inverse JSSP and performed discrete event simulation. Zhang et al. [21] used PSO and ANN together for JSSP. They treated each particle in the swarm as a connection in the ANN to minimize the maximum makespan. Zhu et al. [22] used improved WOA for JSSP based on the quantum computing. They optimized maximum makespan, maximum machine load and total machine load. Karaoglan et al. [23] used artificial bee colony (ABC) algorithm to optimize the welding shop scheduling problem (WSSP) to minimize the makespan. They used deterministic processing times. Shi et al. [24] used fuzzy and immune GA for optimizing MO-FJSSP. They considered on minimizing energy consumption, maximum makespan and consumer dissatisfaction. Gu et al. [25] proposed a discrete genetic-grey wolf optimization (GA-GWO) algorithm to solve low-carbon JSSP. Vital-Soto [26] used hybridized bacterial foraging optimization (BFO) algorithm for the FJSSP. To minimize weighted lateness for the FJSSP with sequencing flexibility, they modeled the problem with mixed integer linear programming (MILP). The summary of the related literature is given in Table 1.

The WSSP for JSSP using GA is considered in the current paper. In several industrial fields, including the production of mechanical manufacturing, WSSP can be applied. There are however, just a few studies based on WSSP that include the use of several machines. Rao et al. [27] studied on bi-objective WSSP (BWSSP) to minimize the machine interaction effects and the total tardiness. BWSSP is a concern with special flow-shop scheduling problem (FSSP). In this problem, on a certain stage, more than one machine (or workstation) can process one job. They modeled the problem as mixed integer programming model (MIPM) and then solve the model by NSGA with a restarted strategy. However WSSP for JSSP (which is the subject of the current study) is studied by Karaoglan et al. [23] and a novel problem is established with variable workstation constraint. They solved the problem using ABC algorithm coded by Matlab. Although they assumed that the processing times of the operations are known before starting the operation. This assumption results not able to fully reflect dynamic job-shop conditions.

In the present paper, WSSP is considered for JSSP for probabilistic (stochastic) processing times. This is the first novelty of this research. The optimization is performed by using GA combined with Arena simulation. Using probabilistic processing times and Arena simulation provide to consider the dynamic job-shop conditions and get more applicable solutions. The contributions of this study to the literature are: *(i)* using variable workstation constraint, *(ii)* solving welding shop scheduling problem (WSSP) - which is studied by Rao et al. [27] and Karaoglan et al. [23]-under the stochastic processing times. They used mixed-integer programming model (MIPM). However, if the production line is labor-intensive then using integer programming causes not discussing the dynamic shop conditions. Because in the labor-intensive jobs, there are so many factors those have effect on the processing times of the same jobs processed in different shifts (such as the tempo factor of the workers, material searching, waiting for crane or forklift, and etc.). This is also the motivation of this research. Using stochastic processing times under variable workstation constraint for welding job-shop scheduling is not investigated previously and this is the novelty aspect of this research. Some researchers [24] used fuzzy processing times, however in this study GA aided Arena simulation is used and probability distributions of processing times are suitable for this software.

Table 1. Summary of the literature review.

Author	Method	Problem/Model (or constraints)	Objective
Jia et al. [1]	DSS GA	JSSP	Makespan
Azadeh et al. [2]	ANN	Stochastic JSSP	Makespan
Huang et al. [3]	GA	JSSP with process sequence flexibility	Makespan
Aydemir and Koruca [4]	PRGA, Faborg-Sim	JSSP	Total completion time
Ba et al. [5]	GA	MR-FJSSP	Makespan
Deng et al. [6]	Bee evolutionary guiding - NSGA	MO-FJSSP	Total workload of all machines, makespan, workload of the most loaded machine
Ocaktan et al. [7]	GA, Arena simulation	Stochastic JSSP	Makespan
Zhang et al. [8]	Multi-population GA	FJSSP	Makespan, load of each machine, load of all machines
Hu et al. [9]	Improved CSA	JSSP	Makespan,
Jiang et al. [10]	GWO with double-searching mode	JSSP	Energy efficiency
Jiang et al. [11]	WOA	JSSP	Energy efficiency
Seng et al. [12]	NSGA	Low-carbon scheduling model for MO and MS-FJSS	Makespan, energy consumption
Karaoglan et al. [13]	GA, Arena simulation	JSSP with ergonomic constraints	Makespan
Zhang et al. [14]	Binary PSO	Multi-technique, multi-response FJSSP	Makespan, cost
Zhong et al. [15]	Branch population GA	Dual resource constraint JSSP	Makespan, total processing cost
Sel and Hamzadayi [16]	SA, Arena simulation	Stochastic JSSP	Flowtime, Tardiness
Fu et al. [17]	NSGA	JSSP	Total cost, total completion time
Tang et al. [18]	HDPSO-SA	FJSSP, limited starting time interval and tolerated time interval (TTI)	Total overtime of TTI, total tardiness, completion time
Liao and Lin [19]	PSO	Job-shop supply chain scheduling	Completion time
Wang et al. [20]	Hybrid GA-PSO, discrete event simulation	Inverse JSSP	Total weighted makespan
Zhang et al. [21]	PSO, ANN	JSSP	Makespan
Zhu et al. [22]	Improved WOA, quantum computing	JSSP	Makespan, maximum machine load, total machine load
Karaoglan et al. [23]	ABC	WSSP with deterministic times	Makespan
Shi et al. [24]	Fuzzy and immune GA	MO-FJSSP	Makespan, energy consumption, consumer dissatisfaction
Gu et al. [25]	GA-GWO	Low-carbon JSSP	Sum of energy consumption cost, completion time cost
Vital-Soto [26]	BFO	FJSSP with sequencing flexibility	Weighted lateness
Rao et al. [27]	NSGA	BWSSP with deterministic times	Total tardiness, total penalty

The aim is to minimize the average makespan of a group of waiting orders by using GA aided Arena simulation. The second motivation is presenting the results of GA aided simulation based scheduling of the WSSP under the variable workstation constraint to the readers.

A brief overview of GA aided Arena simulation and the real industrial problem is given in the next section. Then in Section 3, the results and discussions are discussed. Finally, in Section 4, the conclusions are given.

2 Materials and methods

2.1 Problem definition

The case study is being carried out in the mechanical workshop of a transformer manufacturer. The company's manufacturing operations for power transformers consist of five main phases. They are: 1) magnetic core manufacturing, 2) winding, 3) assembly of active parts, 4) mechanical manufacturing (welding shop), and 5) final assembly.

This study is carried out in mechanical manufacturing (welding shop) section. In the welding shop the primary purpose is to perform the production of transformers' vessels. In transformer vessel manufacturing, vessel bottom pan, side walls and top cover are manufactured using st37 black sheet metal. Then, these parts are assembled by welding operation. The welding operations at the shop floor are performed under 4-tasks (task names are not specified for commercial confidentiality). The aim of this study is scheduling the orders at welding shop for makespan minimization. GA specifies the entry sequence of the waiting orders to the mechanical manufacturing (welding shop). ARENA has been used to bring the problem under consideration closer to the dynamic workshop conditions and provide fitness value calculations for GA.

The workshop is a labor-intensive project-type manufacturing process consisting of sequential processes including CNC sheet metal cutting, other semi-product preparation processes, lathe leveling, welding, etc. These operations are presented under the “Task” headings in Table 2. In companies that operate on the basis of project type labor-intensive production, the dynamic production environment causes stochastic times for operations.

Stochastic operation times make it harder for order scheduling. There are several explanations why running times are stochastic, such as technical order requirements, operator expertise, job-shop bottlenecks, and so on. Production times differ according to the characteristics of the materials that will be processed. To determine the distribution of the processing times, random samples were taken, then the probability distributions were fitted by using Arena input analyzer and chi-square goodness-of-fit test was performed to test the significance of these fitted probability distributions. Table 2 gives the determined probability distributions (which are fitted to the processing times observed from the workshop) those can be used for simulation. The chi-square goodness-of-fit test results under 95% confidence level are significant for the distributions given in the Table 2. In Table 2, 8 meters is cut-point for classifying the vessel length (1: vessel length≥8 meters, and 2: vessel length<8 meters). The values are in terms of hours.

For a total of 20 orders, the data was collected from the company's current pending list (list of waiting orders), and provided in Table 3.

Table 2. Task-based probability distributions for orders discussed in the example (hours).

Welding order number (WON)	Product type	Model	Vessel length type	Task 1	Task 2	Task 3	Task 4
1	1	1	1	Uniform (130, 140)	Triangular (80, 90, 100)	Normal (23.8, 5.2)	Normal (811.9, 30.8)
2	1	2	1	Uniform (85, 95)	Triangular (40, 50, 60)	Normal (42.4, 7.2)	Normal (542.8, 22.9)
3	1	3	1	Uniform (110, 120)	Triangular (110, 120, 130)	Normal (26.6, 5.4)	Normal (960.2, 42.8)
4	1	4	1	Uniform (140, 150)	Triangular (30, 40, 50)	Normal (63.6, 8.6)	Normal (371.4, 12.9)
5	1	5	1	Uniform (200, 210)	Triangular (120, 130, 140)	Normal (41.8, 6.3)	Normal (1014.4, 50.7)
6	1	6	1	Uniform (120, 130)	Triangular (110, 120, 130)	Normal (50.8, 7.2)	Normal (606.7, 25.8)
7	2	1	1	Uniform (125, 135)	Triangular (40, 50, 60)	Normal (16.3, 4.1)	Normal (402.5, 18.3)
8	2	2	1	Uniform (230, 240)	Triangular (10, 20, 30)	Normal (24.5, 5.4)	Normal (1667.7, 63.5)
9	3	1	1	Uniform (130, 140)	Triangular (90, 100, 110)	Normal (47.1, 6.2)	Normal (1611.3, 59.4)
10	4	1	2	Uniform (315, 325)	Triangular (200, 210, 220)	Normal (89.8, 10.2)	Normal (2016.4, 70.5)
11	4	2	1	Uniform (360, 370)	Triangular (300, 310, 320)	Normal (73.5, 5.4)	Normal (1017.7, 48.2)
12	4	3	2	Uniform (330, 340)	Triangular (110, 120, 130)	Normal (65.3, 6.2)	Normal (2312.9, 75.2)
13	5	1	1	Uniform (170, 180)	Triangular (60, 70, 80)	Normal (46.1, 4.3)	Normal (676.1, 35.8)
14	6	1	1	Uniform (140, 150)	Triangular (30, 40, 50)	Normal (24.1, 3.2)	Normal (269.7, 12.8)
15	6	2	1	Uniform (210, 220)	Triangular (90, 100, 110)	Normal (96.1, 8.4)	Normal (1157.9, 55.7)
16	6	3	1	Uniform (100, 110)	Triangular (40, 50, 60)	Normal (51.2, 5.4)	Normal (365.4, 9.8)
17	6	4	2	Uniform (330, 340)	Triangular (70, 80, 90)	Normal (73.9, 5.9)	Normal (1230.1, 51.5)
18	6	5	1	Uniform (110, 120)	Triangular (5, 8, 10)	Normal (32.2, 3,5)	Normal (210.9, 6.7)
19	6	6	1	Uniform (90, 100)	Triangular (60, 70, 80)	Normal (64.6, 4.9)	Normal (495.1, 9.8)
20	6	7	1	Uniform (170, 180)	Triangular (50, 60, 70)	Normal (49.1, 5.1)	Normal (510.2, 11.3)

Table 3. Current waiting orders list.

Welding Order Number (WON)	Product Type	Model	Number of Vessels in the Order	Vessel ID (VID)	Length of the Vessel (meters)	Number of Welding Stations Needed (S)	Processing time (Arena Results: Mean of 10 Runs-Rounded)
1	1	1	1	1	4	1	1063
2	1	2	4	2, 3, 4, 5	2	1	709, 720, 729, 718
3	1	3	1	6	7	1	1207
4	1	4	1	7	3	1	625
5	1	5	1	8	7	1	1384
6	1	6	1	9	4	1	913
7	2	1	1	10	4	1	602
8	2	2	2	11, 12	7	1	1945, 2026
9	3	1	1	13	5	1	1980
10	4	1	3	14, 15, 16	11	2	2631, 2579, 2446
11	4	2	1	17	7	1	1762
12	4	3	2	18, 19	13	2	2828, 2829
13	5	1	2	20, 21	4	1	988, 969
14	6	1	1	22	2	1	467
15	6	2	2	23, 24	7	1	1575, 1608
16	6	3	2	25, 26	3	1	546, 539
17	6	4	2	27, 28	11	2	1736, 1724
18	6	5	1	29	2	1	377
19	6	6	2	30, 31	4	1	719, 721
20	6	7	2	32, 33	6	1	798, 731

The given 20 orders in this table is lead to manufacture of a total of 33 vessels (in other words, 20 separate customers demand 33 vessels) and in this case we used 6 identical welding stations for scheduling. Input data is the stochastic order processing times that differ in compliance with the design requirements requested by the customers. In Table 3, also the rounded measured average processing times of 10 simulation runs for each order (that is generated in the simulations given in Section 3) is presented. This study's assumptions and constraints are listed below. General assumptions related with simulation based scheduling:

- It is assumed that production is not interrupted until all scheduled jobs are produced,
- It is assumed that the workers in the workshop are identical,
- Just one task can be processed on a workstation at the same time,
- Since each vessel is quite large and heavy, after placing the vessel once at the welding stations, even if a more urgent job comes, the urgent job is not queued before the current job list is completed. In other words, in order to perform another task, the process cannot be disrupted,
- The factory operates in 3 shifts, each consisting of 8 hours. Each shift is assumed to have 1 hour lunch break and 2 rest breaks (30 minute each),
- Task 1, Task 2, Task 3 and Task 4 should be performed in successive order and one after the other,
- The processing times are probabilistic (as presented in Table 2),
- The number of the orders at the 'pending order list' is fixed at the beginning of the simulation,

Variable workstation constraint (newly added novel constraint for WSSP):

- The number of welding stations varies in compliance with the order's technical requirements. If the length of the transformer vessel is 8 meters or more, two horizontally neighbor stations are combined by removing the mobile sound barrier between these stations and this vessel is assigned to both stations. In addition, the successive stations are merged to match the vessel to the station if the widths of the jobs are 8 meters and over. One order occupies two welding stations at the same time in this situation. Welding stations 1-2, 2-3, 4-5, and 5-6 can be merged. This means, at the same time 6 small or 2 small and 2 large vessels can be operated at the same time. However 3 large vessels cannot be operated at the same time. Figure 1 represents the layout of the welding shop.

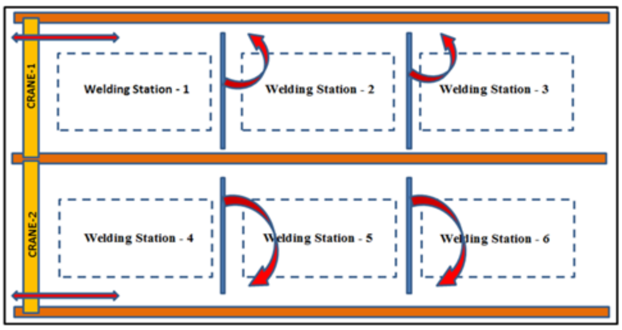

Figure 1. Welding shop layout.

According to Table 3, only one vessel has to be manufactured in the first order, while 4 transformers have to be manufactured in the second order. This implies that there are 4 identical vessels that have to be manufactured. Similarly, the 8th order has 2 identical transformers, which means that this order has 2 identical vessels and so on. To minimize the makespan, GA aided Arena simulation was carried out to dispatch the orders to the welding stations. The problem can also be mathematically represented. The related equations are given below to give an idea to the readers; however the problem is modeled with Arena simulation instead of integer programming (for details see Rao et al. [27]):

Objective:

$$Minimize\ f = Cmax_{avg} \tag{1}$$

Constraints:

$$\textstyle\sum_h Z_{ijh} = N_{ij}\ \&\ N_{ij} \geq 1;\ N_{ij} \leq pN_j;\ \mathrm{i} = 1, \dots, \mathrm{n};\ \mathrm{j} = 1, \dots, \mathrm{m} \tag{2}$$

$$\sum_{i=0}^{n} y_{ii'j} = 1;\ \mathrm{i'} = 1, \dots, \mathrm{n};\ \mathrm{j} = 1, \dots, \mathrm{m} \tag{3}$$

$$\sum_{i'=1}^{n+1} y_{ii'j} = 1;\ \mathrm{i} = 1, \dots, \mathrm{n};\ \mathrm{j} = 1, \dots, \mathrm{m} \tag{4}$$

Where *i* and i' are the index of the jobs, *j* is the index of stages, *h* is the index of the machines used for processing during stage *j, and* N_{ij} is the number of processing machines for *i*th job at stage *j*. If the machine *h* processed *i*th job at stage *j* then the Z_{ijh}=1; and otherwise Z_{ijh}=0. Similarly, $y_{ii'j} = 1$ if job *i* is processed before i' at stage *j*, and $y_{ii'j} = 0$ otherwise. Equation (1) is the objective and represents the minimizing the average makespan, Equation (2) means that a job is processes by at least one machine and also it ensures that the number of processing machines cannot exceed the number of available machines. Equation (3) satisfies that at per stage, each job has just one pre-order job. And finally at each stage, Equation (4) ensures that just one follow-up job can be processed after each job. According to the sample problem given in Figure 1, the constraint for variable workstation can be defined as:

$$\text{if } l \geq 8 \text{ meters than } Z_{ijh} + Z_{ijh+1} = 1; \mathrm{h} = 1{,}2 \text{ or } \mathrm{h} = 4{,}5 \tag{5}$$

Note that the *l* is the length of the transformer vessel. Which means 1 & 2, 2 & 3 welding stations, and 4 & 5, 5 & 6 welding stations can be merged to perform the welding operation of the vessels with those have more than 8 meters length.

2.2 Simulation-based GA

GA is run through the data to find the best customer order sequence that minimizes average makespan. Arena is run to measure processing times of the orders and also to calculate the makespan of operations depend on GA-generated order sequences. Please refer to [28],[29] for a detailed discussion on GA and also refer to [7],[13] for a detailed discussion on simulation based GA. JSSP is well-known as NP hard problem. In this very complex problem type; we search for the best solution because there is no known way to arrive at a final answer. Heuristic algorithms are frequently used in JSSP to find the best solution. However, performances of the heuristics are decreased when the inputs become more complex and varied. GA is well suited to solving JSSP because, unlike heuristic methods, they work on a population of solutions instead of a single solution. This population of solutions in production scheduling consists of several responses with varying and often conflicting goals. For the special types of problems (such presented in WSSP) where the search space is huge but the feasible solutions are limited and also if the discrete optimization is needed, GA is ideal (PSO, GWO, WOA and some other popular algorithms given in the literature review of this study are more suitable for continuous optimization). Also the variable workstation constraint causes additional complexity on the problem. Because of these reasons, GA has been used in this study instead of other population-based algorithms in the solution of this new type of WSSP problem [30],[31],[32].

Simulating the complex systems allows the researchers to analyze and experiment the internal interactions. Numerical experiments are performed on a digital computer in a simulation job, and a general programming language or a special programming language for simulation may be used [33]. There are several simulation-purposed languages for performing a simulation experiment, such as Arena, Promodel, and etc. In order to integrate directly with other systems such as Microsoft Office, Arena uses 'Visual Basic for Applications' (VBA) editor. Arena 14 is used as the simulation software in this paper for the simulation [7],[13],[33].

The suggested GA is coded in the VBA environment, making it hassle-free to link to the Arena simulation program. In VBA, all GA unique elements are implemented. Arena is used to measure, by simulating a complex system, each chromosome's fitness value (FV). The FV is the average makespan calculated by the ARENA for the selected order sequence. The system here corresponds to the welding shop's complex labor-intensive project-type manufacturing structure including different queues, operations, and capacity constraints. The GA-based Arena simulation method proposed is to minimize the average makespan. Average makespan is total completion time for all pending orders. Here, we use GA to tune the sequence of waiting orders to import them into the system. This algorithm starts with generating the initial population randomly, which includes the number of chromosomes in population size (*PopSize*). Each chromosome consists of a permutable sequence of orders ranging from 1 to the total number of orders, where the number of orders corresponds to each gene.

The multiplication of PopSize and mutation rate determines the number of chromosomes to apply mutation. To maximize diversity, the mutation operator is applied to selected chromosomes in two ways: swap and insert. A random number (rnd) between 0 and 1 is generated for each selected chromosome, and if rnd > 0.5, insert is applied; otherwise, swap is applied. For the crossover strategy; two point crossover is used [7]. The pseudocode for this GA aided simulation method is given in Figure 2 [7],[13]. A sample result of this code is given in Figure 3. The flow chart for the proposed GA aided simulation is presented in Figure 4. In this figure, each gene (customer order) is seen on the chromosome only once and Arena dispatches them to the welding stations respectively. ARENA assigns these orders sequentially (according to the sequence at the chromosome) and primarily to the lowest numbered free welding station. This chromosome represents the entry sequence of the orders to the Arena simulation model and determined by using GA.

When an order enters the arena simulation model, it is primarily assigned to a suitable welding station from 1 to 6 (if there is no other constraint such as the welding station is operating at that moment, the assignment order is from 1 to 6). In the simulation model if an order with vessel length≥8 meters is assigned to a welding station, then the available neighbor welding station is also merged to operate this order.

(Step 1) DETERMINE the pending order list.
(Step 2) DETERMINE the GA parameters and initial population.
(Step 3) RUN ARENA to calculate fitness values $\left(P(i) = \frac{1/FV(i)}{\sum_{k=1}^{PopSize} 1/FV(k)}\right)$ of the chromosomes in the initial population.
  (*Step 3.1*) **RUN** Arena Simulation for the selected chromosomes (order sequence of waiting jobs) and calculate the FV values (where FV is the average makespan calculated by Arena for the selected order sequence).
  (*Step 3.2*) **IF** all the FVs are calculated for the initial population **THEN GO TO** ***Step 4.***
(Step 4) RUN GA to generate new individuals (new order sequences: chromosomes) for providing diversity and **CALCULATE** FV of all child chromosomes in the initial population by **RUNNING ARENA**.
  IF Maximum number of iterations is reached, **THEN GO TO** ***Step 5.***
(Step 5) TERMINATE the simulation based GA and **REPORT** the ***optimum entry sequence*** for the waiting orders and the ***minimum average makespan*** for the waiting orders.
END

Figure 2. Pseudo Code used for scheduling by GA aided Arena simulation.

1	2	3	4	5	6	13	10	7	11	12	8	9	14	17	16	18	15	19	22	21	23	20	24	25	26	27	29	30	28	31	32	33

Figure 3. The representation of a sample chromosome.

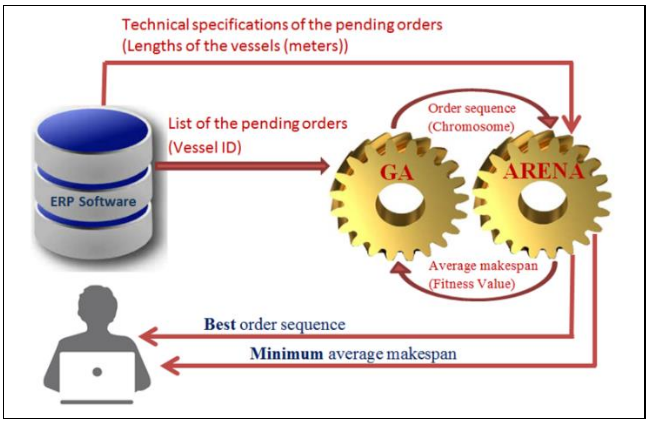

Figure 4. Flow chart of the proposed GA aided simulation.

3 Results and discussions

The input data for the 20 waiting orders was obtained from the company's current list of pending orders, and given in Table 3. The list of these 20 orders corresponds to the manufacture of 33 vessels in total. In the method, six welding stations operate. Constraints relating to the parameters of the technological design of the orders, number of manufacturing resources, resource capability, etc. influence the average makespan of the waiting orders in the competitive manufacturing environment, as studied in previous literature studies. The objective here is to minimize the average makespan of the orders described under the variable workstation constraint in Table 3.

The Gantt chart presents the pure Arena simulation results without using GA is given in Figure 5. The simulations are run on the "Intel Core i5-2430M CPU 2.40GHz with 4 GB RAM PC. The orders are scheduled primarily to their order number. The average makespan is calculated as 11368 hours. Notice that the 2nd and 3rd welding stations are merged while orders 14, 16, 19, and 28 are processed. Owing to the width limit (width of these transformers≥8 meters), the 5th and 6th workstations are also merged during the processing of orders 15, 18, and 27. In other words, the 14th, 16th, 19th, and 28th orders are assigned at the same time to the 2nd and 3rd welding stations. For orders with the numbers 15, 18, and 27, the same problem applies. The idle times of the stations 1st, 4th and 5th are very high, and there is no compliance with the workload balances between the welding stations. The total CPU time is calculated as 56 seconds for this first scenario.

In the second scenario, to reduce the idle times of the welding stations, some stations are reserved for the width vessels and the average makespan of given orders is calculated as 11732 hours with Arena simulation. According to this scenario; as much as possible, the one with the lowest order number was processed first, but when it came time, idle machine time was tried not to be allowed. Therefore, in some cases, orders with larger order numbers are allowed to be processed first to prevent workstations from waiting idle. However, the order with the lowest order number in the queue continues to be assigned to welding stations (to the reserved stations) at the first opportunity. In the simulation the 1st and 2nd welding stations; and the 4th and 5th welding stations are reserved if the width vessels are in the queue. The 1st and 2nd welding stations are merged while orders 15, 18, and 27 are processed. The 4th and 5th welding stations are also merged during the processing of orders 14, 16, 19, and 28. The idle times of stations 1st, 4th and 5th are significantly decreased as compared to the results shown in Figure 5, but there are still idle times at stations 1st, 3rd and 4th. Also the workload balances between the welding stations still are not in accordance. The average makespan is calculated as 11732 hours. The total completion time is increased when it is compared with classical simulation presented in Figure 5. However the total idle times of the welding stations and the total tardiness for the orders are decreased. The Gantt chart for this schedule is given in Figure 6. When the result presented in Figure 5 and Figure 6 are compared; the completion times for the orders (<8 meters) those have order numbers>17 are decreased seriously. However, the completion time of the 28th order is noticeably increased. The total CPU time is calculated as 68 seconds for this second scenario.

Then GA aided Arena simulation is performed to reduce the makespan. The GA parameters are determined after some preliminary trials. Totally 105 trials are performed for this purpose. The levels of the parameters are determined as: population size (PopSize): [40:100] with 10 step size, crossover rate (cr): [0.4:0.6] with 0.1 step size, and mutation rate (mr): [0.1:0.5] with 0.1 step size. The best performing parameter combination between these trials is selected as the GA parameters. The GA run with maximum number of iterations = 100000, *PopSize* = 80, crossover rate (*cr*) = 0.5, and mutation rate (*mr*) = 0.4 parameters. The average makespan of given order is calculated as 10317 hours. The chromosome which gives the best FV (10317 hours) is 1-2-3-4-5-6-14-15-7-9-8-10-11-12-18-16-13-17-19-27-20-21-22-23-28-24-25-26-33-32-29-30-31. The Gantt chart for this schedule is given in Figure 7. The total CPU time is calculated as 36 minutes 28 seconds for this third scenario. According to the results given in Figure 7, the results presented in Figure 5 are improved and by using GA, the balance between the welding stations is provided. Also the dispatching is acceptable when the order numbers are considered. The 95% confidence interval for order sequence generated by GA is calculated as [10270.55 ; 10363.45]. This is quite a narrow confidence interval for this type of production. For the 95% confidence interval the z-critical value is 1.96 according to the statistical tables. This means standard error coefficient is 23.698. So it can be concluded that 10 runs may be enough to validate the results for the presented data for this problem.

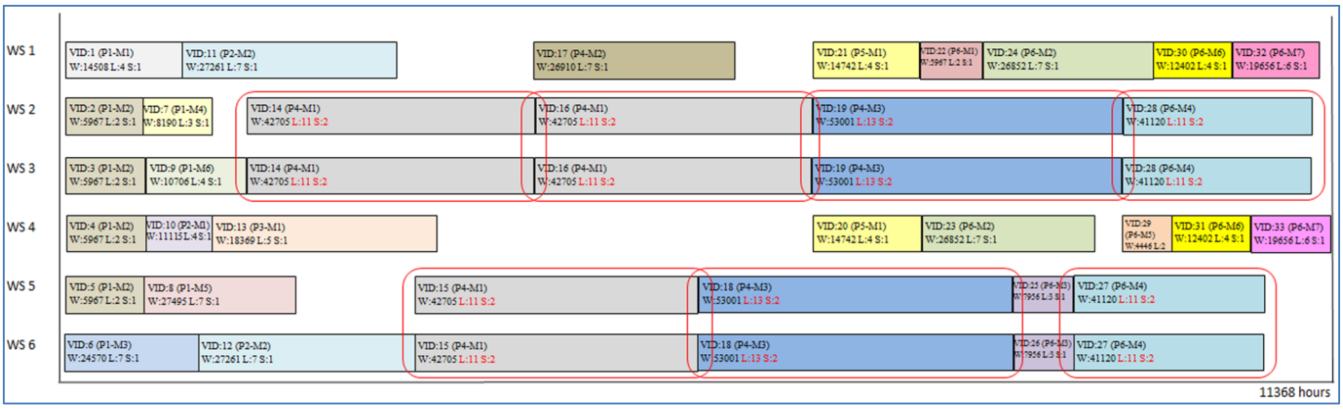

Figure 5. Gantt chart of the schedule with Arena without using GA (order number has priority).

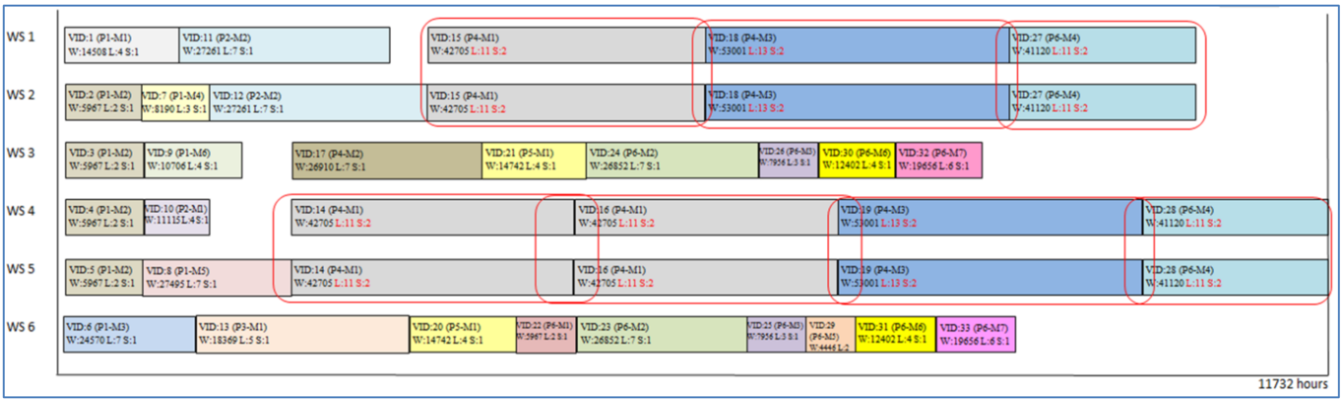

Figure 6. Gantt chart of the schedule with Arena without using GA (reserved stations).

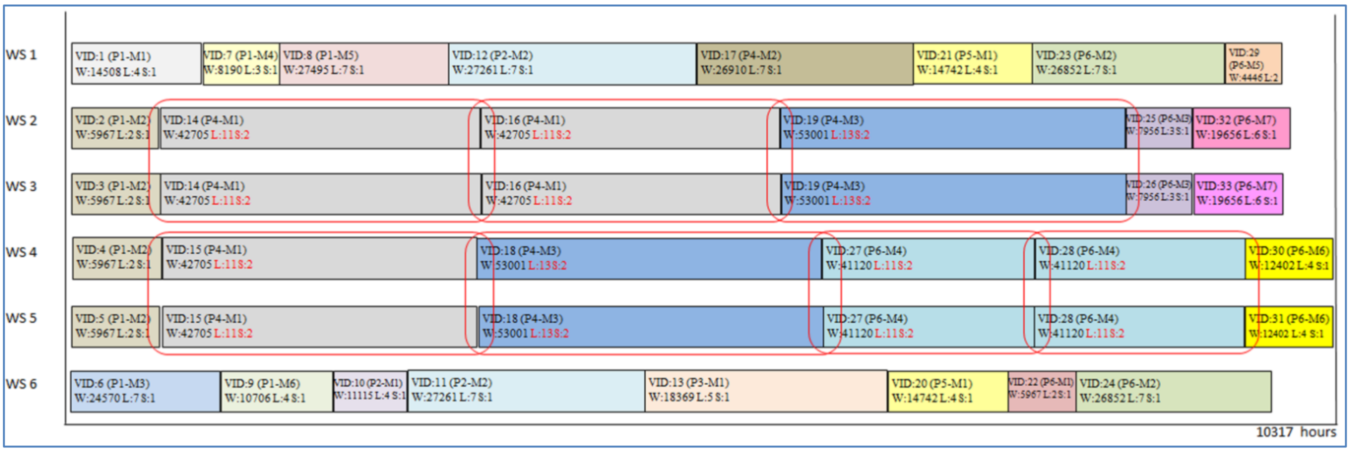

Figure 7. Gantt chart of the schedule with GA aided Arena.

The GA aided Arena schedule outperforms the other schedules, because in this schedule the manufacturing of pending order list is completed much earlier when compared with other schedules. The total completion time is nearly 9.25% and 12.06% reduced when compared with the schedules presented in Figure 5 and Figure 6, respectively. Also total idle times of the welding stations are nearly zero (which is a very important managerial criterion) and unlike the other two approaches the workload of the workstations are balanced. This is very important for the manufacturing cost. Because the main cost items are the material cost, labor cost, and the overhead costs. The overhead costs are dispatched to the customer orders according to the labor times. So idle times and unbalanced workstations will lead to incorrect assignment of overhead cost to orders.

4 Conclusion

The focus of this study was to determine the best possible waiting order schedule to reduce the average makespan under the conditions of the job-shop and some design requirements constraints. The novelty of this study is using variable workstations constraint under stochastic processing times to minimize average makespan of the orders in a labor-intensive and project type manufacturing. GA is used for this purpose. The average makepan is minimized after 100000 iterations for this problem as a result of assignments made under some constraints. It is observed that the algorithm's computational effectiveness is strong. According to the experimental results, it is noted that for the given order set, the GA-based Arena simulation decreased the average makespan by almost 9.25% (from 11368 to 10317 hours). Also idle times of the welding stations are prevented and the balance between the workstations is provided. Total idle times are nearly zero according to the GA-based Arena schedule. The same problem can be addressed in future studies by taking into account additional vessel design constraints and ergonomic constraints that influence processing times. Also as a future research, under variable workstation constraint fuzzy processing times can be considered instead of using probabilistic distribution and solved by using integer linear programming. In addition, a performance comparison can be presented between the results of integer linear programming and Arena simulation.

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6 Author contribution statement

In this study, all of the studies such as creating the idea, making the design, obtaining resources and materials, collecting data, performing analyzes, literature review, writing and critical review were all carried out by Aslan Deniz KARAOĞLAN.

7 Ethics committee approval and conflict of interest statement

There is no need to obtain permission from the ethics committee for the article prepared.

There is no conflict of interest with any person/institution in the article prepared.

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