Energy-efficient Job Shop Scheduling Problem with Transport Resources considering Speed Adjustable Resources

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Abstract

This work addresses the energy-efficient job shop scheduling problem with transport resources. It introduces two types of speed adjustable resources - machines where jobs are processed and vehicles which transport jobs - and aims to find solutions that balance makespan and total energy consumption. This problem involves determining the processing speed, sequence of operations, allocation of transport tasks to vehicles, vehicle traveling speed, and sequence of tasks for each machine and each vehicle. The paper presents a bi-objective mixed-integer linear programming model and a novel multi-objective multi-population biased random key genetic algorithm (mpBRKGA) to solve the problem. Computational experiments demonstrate the effectiveness and efficiency of the novel algorithm, even for larger problem instances and compared to NSGA-II. An extensive analysis of time and energy trade-offs is included, providing insights for managers facing similar complex problems.

1. Introduction

Due to stricter environmental regulations, volatile energy prices, and the increasingly growing energy demand, manufacturing companies need to reduce their energy consumption. Therefore, energy efficiency has recently become the research focus in manufacturing systems, particularly regarding scheduling problems. Although energy efficiency in manufacturing systems can be addressed in many ways, such as adopting renewable resources, using improved machinery, and redesigning products and production processes, researchers have proved energy-efficient scheduling to be an effective way of reducing energy consumption. Additionally, scheduling optimization is easier to apply to existing systems and requires far less capital investment, if at all, making it more widely applicable; especially for small and medium enterprises (Fernandes, Homayouni, and Fontes 2022; Para, Del Ser, and Nebro 2022; Gahm et al. 2016).

2. Literature review and Problem description

The Job shop scheduling problem (JSP) is a well-known combinatorial optimization problem, which can be described as follows: consider a set of *J* jobs and a set of *M* machines. Each job is comprised of several operations that must be processed in a specified order. Each operation requires a pre-determined amount of time and must be processed by a pre-determined machine. Each machine can only process one operation at a time, and operations cannot be interrupted once started.
A solution to the JSP consists of a sequence of operations for each machine while respecting the stated restrictions, such that a given performance measure is optimized, which is most commonly the makespan (Cmax), i.e. the time interval from the start of the first scheduled operation to the end of the last one.

In recent years, many works have tackled extensions of JSP with energy considerations. Several authors have referred to the energy-focused extension of JSP as the Energy-efficient Job Shop Scheduling Problem (EEJSP), namely Dai et al.(2019) and He et al. (2021). In the EEJSP, each operation requires a specific amount of energy in addition to its processing time and required machine. Thus, in EEJSP, energy-related objectives, such as total energy consumption (TEC), are commonly considered.

As described in a literature review regarding EEJSP by Fernandes et al. (2022), numerous papers have introduced additional problem features such as variable machine operation speeds (MS) (Salido et al., 2016), which considers machines may complete operations faster or slower by using more energy or less energy respectively; or vehicle transportation with a limited number of vehicles (VS) (Zhou & Lei, 2021), which incorporates vehicle routing decisions into the EEJSP. However, papers seldom combine multiple of these features at once. However, by doing so, it is possible to more accurately model the operations of a shop floor, through a more complex problem, which formed the basis for the work in Fontes et al (2022).

This work is the first EEJSP paper featuring not only MS, but also VS and vehicles with multiple speed settings, thus introducing a new EEJSP extension – the EEJSP with transportation constraints and variable machine and vehicle speed (EEJSPT-MS). The remainder of this poster details the methodology, results and conclusions from this work.

3. Methodology

Two solution methods were developed to solve the proposed EEJSPT-MS: a bi-objective mixed-integer linear programming model (MILP), and a multi-objective multi-population biased random key genetic algorithm (mpBRKGA). MILP's can provide exact optimal solutions but are usually too computationally demanding and slow to solve large instances in a reasonable timeframe, and thus are deemed unsuitable for real-world applications for this problem. Thus, heuristic methods, such as the proposed mpBRKGA are employed to find good solutions for larger problems significantly faster.

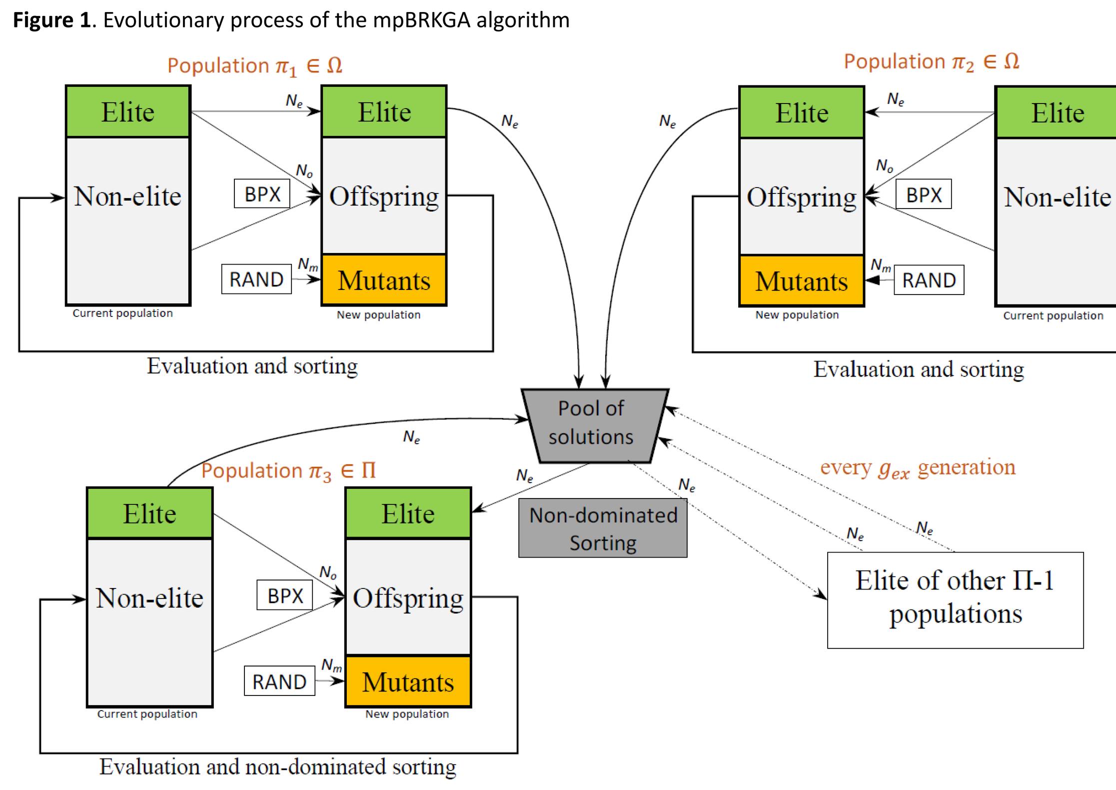
The proposed mpBRKGA is a multi-population algorithm based on the BRKGA initially proposed by Gonçalves and Resende (2011). The mpBRKGA uses a set Ω of single-objective populations and a set Π of multi-objective populations. It features one single-objective population per each objective in the problem (which are Makespan and TEC in this case), and a variable number of bi-objective populations minimizing both objectives (minimum of 1).
Each population is initially generated through vectors of random keys uniformely drawn from [0,1], which are each decoded into feasible solutions for which the makespan and TEC are calculated.

Each iteration, the populations are ranked by using a non-dominated sorting algorithm and, within each non-dominated set, according to crowding distance. Afterwards, for each population, the top N_e solutions are deemed the elite solutions for this iteration and the remaining ones are non-elite.

The number of solutions within each population is constant. Each iteration, the next generation of each population is constructed using solutions from three sources : i) elite solutions are copied onto the next population, ii) new solutions (mutants) are randomly generated to maintain the diversity of the next population, iii) the remaining solutions of the next population are filled up with offspring, generated through biased parameterized uniform crossover (BPX).

However, for the multi-objective populations, the elite solutions are chosen from a pool containing not only their own elite solutions, but also the ones of the single objective populations. This pool has a size of a pool of solutions containing up to $(1 + \Omega) \times N_e$ solutions
For each population, $\pi \in \Pi$ the pool of solutions is obtained by joining the best N_e solutions of the current generation of population π and those of each of the Ω single objective populations and then removing repeated solutions. Additionally, multi-objective populations exchange solutions after a pre-determined number of generations (g_{ex}). Thus, every g_{ex} generations, the pool of solutions also contains the best N_e solutions of the other multi-objective populations; having up to $(\Pi+\Omega)\times N_e$ solutions. Figure 1 depicts, at a high level, the evolutionary process just described.

Figure 1. Evolutionary process of the mpBRKGA algorithm



4.Results

Computational experiments were conducted on a set of 22 small-sized instances (Yin01, Yin02 and Sal01~Sal20) and 11 large-sized instances (Yin03 and Sal21~Sal30). Small instances were solved using the proposed MILP and mpBRKGA, as well as a non-dominated sorting genetic algorithm (NSGA-II), which is a commonly used and well-performing algorithm in multi-objective EEJSP problems. Large instances were solved using the mpBRKGA and NSGA-II, as they were too large for the MILP to solve.
The results are presented in the following tables (Table 1 and Table 2). For the algorithm results, the size of each population was set to 500 and the algorithm ran 10 times per each instance, each time for 300 iterations. The data for the instances used is freely available through the website in section 7. Further details on the algorithm parameters may be found in the full paper.
The size of each instance is noted under J-N-M: J is the number of jobs, N the total number of operations and M the total number of machines.

Measures for best values of TEC and makespan:

- δ_C: variation of makespan
- $\delta_\mathcal{E}$: variation of TEC

Measures for quality of Pareto Front (PF) – small instances

- $\overline{GD^+}$ - Generational Distance
  - Measures deviation from best known PF
- $\overline{\Delta}$ - Spread:
  - Measures PF solution diversity

Measures for quality of Pareto Front (PF) – large instances

- C^*_{max} : best Makespan
- C_{max}: average makespan

- $\mathcal{E}^*$: best TEC
- $\mathcal{E}$: average TEC
- HV: hypervolume; larger value of HV indicates better performance regarding diversity and convergence

Table 1. Results for small-sized problem instances: mpBRKGA performance evaluation - comparison with MILP and NSGA-II.

Instances		MILP		mpBRKGA				NSGA-II			
Ins	J-N-M	C^*_{max}	$\mathcal{E}^*$	δ_C	$\delta_\mathcal{E}$	$\overline{GD^+}$	$\overline{\Delta}$	δ_C	$\delta_\mathcal{E}$	$\overline{GD^+}$	$\overline{\Delta}$
Yin01	4-12-5	25.3	4.86	0.00	0.00	0.002	0.658	0.00	0.00	0.002	0.654
Yin02	10-40-6	43.9	17.89	0.00	0.00	0.026	0.493	0.00	0.00	0.205	0.698
Sal01	3-15-3	39.9	79.0	0.00	0.00	0.015	0.396	0.00	0.00	0.014	0.370
Sal02	3-15-3	55.4	116.1	0.00	0.00	0.011	0.472	0.00	0.00	0.003	0.509
Sal03	3-15-3	45.9	73.1	0.00	0.00	0.006	0.309	0.00	0.00	0.008	0.312
Sal04	3-15-3	45.7	70.1	0.00	0.00	0.008	0.399	0.00	0.00	0.011	0.505
Sal05	3-15-3	41.3	80.1	0.00	0.00	0.003	0.402	0.00	0.00	0.009	0.461
Sal06	3-15-3	47.2	88.1	0.00	0.00	0.007	0.426	0.00	0.00	0.001	0.423
Sal07	3-15-3	46.3	69.1	0.00	0.00	0.013	0.424	0.00	0.00	0.001	0.414
Sal08	3-15-3	45.6	68.1	0.00	0.00	0.005	0.327	0.00	0.00	0.004	0.362
Sal09	3-15-3	54.6	105.1	0.00	0.00	0.003	0.414	0.00	0.00	0.005	0.404
Sal10	3-15-3	56.1	96.1	0.00	0.00	0.009	0.444	0.00	0.00	0.002	0.351
Sal11	3-30-7	664.0	1309.2	0.00	0.00	0.007	0.511	0.00	0.00	0.012	0.657
Sal12	3-30-7	639.4	1542.1	0.00	0.00	0.010	0.478	0.00	0.00	0.032	0.805
Sal13	3-30-7	755.7	2162.1	0.00	0.00	0.009	0.563	0.00	0.00	0.015	0.838
Sal14	3-30-7	551.5	1396.1	0.00	0.00	0.008	0.530	0.00	0.00	0.020	0.799
Sal15	3-30-7	649.7	1485.2	0.00	0.00	0.006	0.368	0.00	0.00	0.008	0.633
Sal16	3-30-7	708.4	1722.2	0.00	0.00	0.004	0.416	0.00	0.00	0.007	0.698
Sal17	3-30-7	600.3	1301.1	0.00	0.00	0.005	0.483	0.00	0.00	0.006	0.616
Sal18	3-30-7	648.9	1818.2	0.00	0.00	0.004	0.498	0.00	0.00	0.017	0.796
Sal19	3-30-7	603.5	1595.1	0.00	0.00	0.011	0.522	0.00	0.00	0.009	0.710
Sal20	3-30-7	621.3	1384.2	0.00	0.00	0.010	0.490	0.00	0.00	0.007	0.654
Mean				0.00	0.0	0.008	0.456	0.00	0.0	0.010	0.566

Table 2. Results for large-sized problem instances: mpBRKGA performance evaluation - comparison with NSGA-II.

Instances		mpBRKGA					NSGA-II				
Ins	J-O-M	C^*_{max}	$\mathcal{E}$	C_{max}	$\mathcal{E}^*$	$\overline{HV}$	C^*_{max}	$\mathcal{E}$	C_{max}	$\mathcal{E}^*$	$\overline{HV}$
Yin03	20-60-5	63.1	23.5	112.1	21.3	0.0977	63.1	23.5	112.1	21.4	0.0940
Sal21	3-75-3	1556.8	6078.3	2605.1	3542.3	0.4227	1678.0	6444.3	2586.1	3542.3	0.3832
Sal22	3-75-3	1999.9	7603.4	3210.3	4458.3	0.4148	2133.8	7589.4	3843.3	4458.3	0.3811
Sal23	3-75-3	1702.1	6338.3	3210.8	3469.3	0.4577	1822.3	6299.4	3616.6	3469.3	0.4236
Sal24	3-75-3	1727.1	6466.3	3047.9	3758.3	0.4148	1842.9	6848.4	4364.9	3758.3	0.3887
Sal25	3-75-3	1628.4	6389.3	2794.7	3889.3	0.4012	1731.3	6213.3	3028.7	3889.3	0.3583
Sal26	3-75-3	1556.4	6416.3	1776.1	3739.3	0.4046	1644.6	6072.3	2947.0	3739.3	0.3768
Sal27	3-75-3	1546.0	5938.3	2766.5	3158.3	0.4664	1618.1	5644.4	3196.7	3158.3	0.4304
Sal28	3-75-3	1635.0	6719.3	2889.5	4000.3	0.4143	1761.0	6805.3	3494.4	4000.3	0.3833
Sal29	3-75-3	1837.3	7172.3	3390.2	4056.3	0.4321	1920.1	6997.4	3870.9	4056.3	0.3917
Sal30	3-75-3	1899.0	6791.3	3265.9	4202.3	0.4124	1957.2	6998.3	3662.3	4202.3	0.3472
Mean						0.3944					0.3598

The mpBRKGA finds Pareto fronts (PF) that closely lie on the true Pareto front (PF∗), as the average generational distance is only 0.008, and are well spread and uniformly distributed over the PF∗, as the average spread is only 0.456. Additionally, the mpBRKGA outperforms the NSGA-II since the NSGA-II average generational distance and average spread are, respectively, 0.01 and 0.566. For the set of larger problem instances (with three jobs, 75 operations, and three machines and with 20 jobs, 60 operations, and five machines) the mpBRKGA also outperforms the NSGA-II as the average hyper volume (HV) is 0.3944 for the former while it is 0.3598 for the latter. Additionally, the mpBRKGA always finds better boundary solutions.

5.Conclusions

The EEJSPT addressed in this paper is harder than most scheduling problems, since it involves not only scheduling production operations and transport tasks but also allocating each task to a vehicle as well as determining processing and transport speed levels of each operation and each task, respectively. Therefore, we also propose a bi-objective mpBRKGA that is capable of finding good solutions efficiently. For comparison purposes, a Non-dominated Sorting Genetic Algorithm II (NSGA-II) was implemented that makes use of the encoding, decoding, and crossover operators we propose for the multi-objective mpBRKGA.

For a more in-depth explanation of the mpBRKGA, as well as the calculation for the performance measures and result analysis, please refer to the full paper.

6. Publication and presentation information

The information in this poster pertains to the paper "Energy-efficient Job Shop Scheduling Problem with Transport Resources considering Speed Adjustable Resources", by Fontes et al (2022), and was presented in the French German Portuguese Conference on Optimization in Porto in May 2022.

Full information:
Fontes, D. B. M. M., Homayouni, S. M., & Fernandes, J. C. (2023). Energy-efficient job shop scheduling problem with transport resources considering speed adjustable resources. *International Journal of Production Research*, 1–24. https://doi.org/10.1080/00207543.2023.2175172

Full paper QR code:

7. Data availability

The data that support the findings of this study are openly available at: https://fastmanufacturingproject.wordpress.com/problem-instances.

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