ADVANCES IN DATA SCIENCE AND AI CONFERENCE 2022

GENETIC ALGORITHMS IN MANUFACTURING SYSTEMS DESIGN

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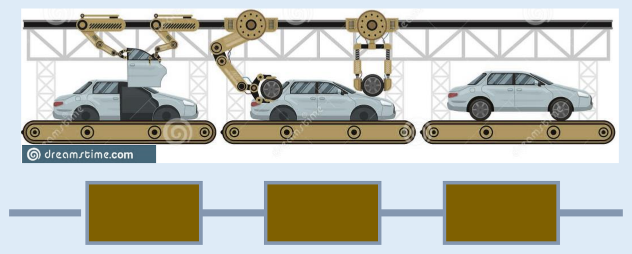
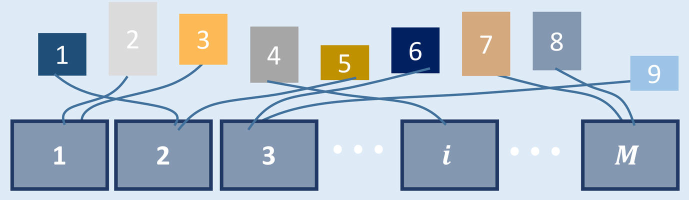
BACKGROUND

Manufacturing Systems

- Manufacturing systems design begins with the solution of the assembly line balancing problem
- The simple assembly line balancing problem (SALBP) is used to determine the assignment of tasks to workstations
- The Type I simple assembly line balancing problem (SALBP-1) minimizes the number of workstations for a given cycle time, and the Type II does the converse
- SALBP-1 and SALBP-2 are NP-hard

(Becker, C. and Scholl, A. 2006)

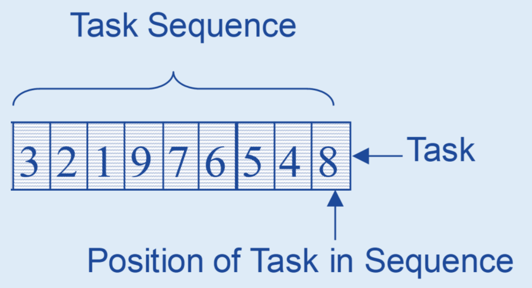


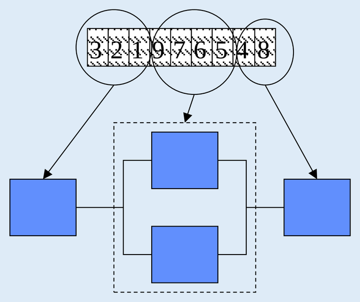


Genetic Algorithms

- Genetic algorithms (GAs) are evolutionary algorithms based on natural selection
- The performance of GA populations improve as generations evolve through the use of genetic operators

(Holland, J. 1975)



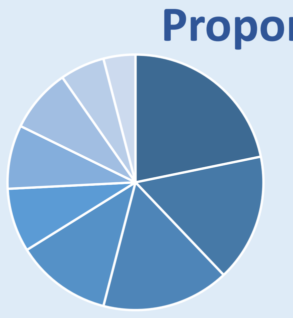


GA Selection Methods

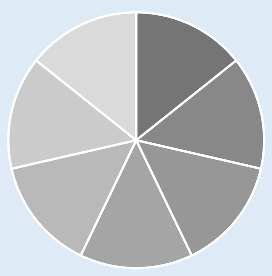
- Selection methods are used to select members of the population for mating
- A selection method that is too aggressive causes early convergence of a GA, and one that is not sufficiently aggressive converges too slowly
- There are two main types of Selection Methods
  - Proportionate Selection
  - Ordinal Selection

(Sastry, K., Goldberg, D. and Kendall, G., 2005)

Proportionate Selection

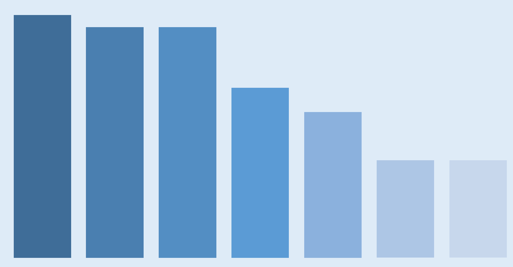


Roulette Wheel Selection (RWS)

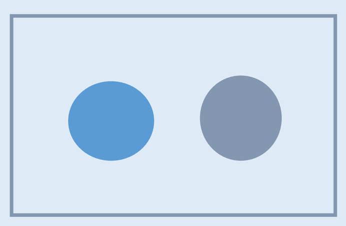


Stochastic Universal Sampling (SUS)

Ordinal Selection



Elitist Selection (ES)



Tournament Selection (TS)

AIM & OBJECTIVES

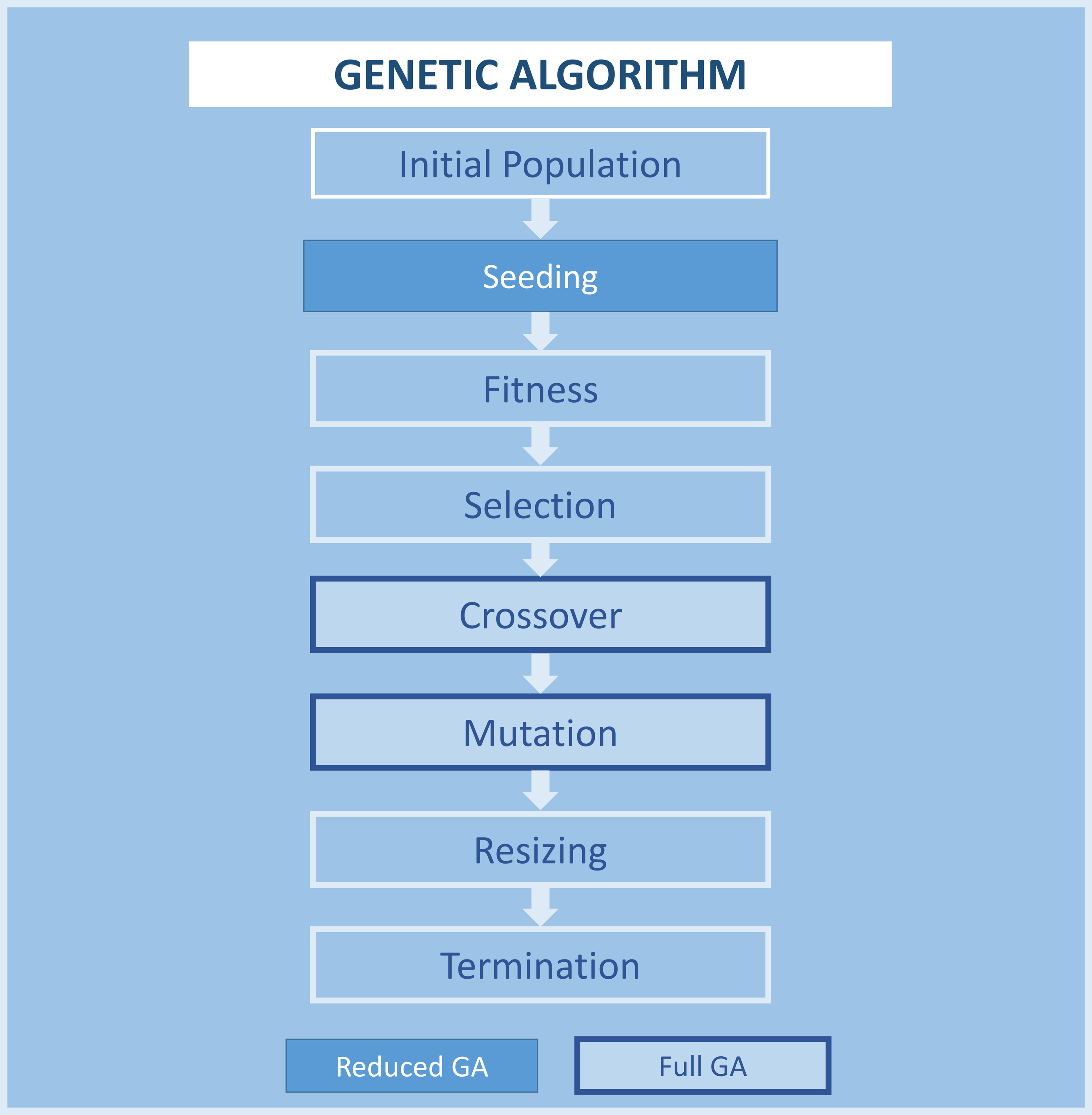
To investigate the influence that GA selection methods have on the solution of the SALBP

Objectives

- To compare the performances of ES, RWS, TS, and SUS in the solution of the SALBP-1 and SALBP-2
- To determine the effects that other GA parameters, viz. population size, selection rate, and penalty have on the performance of GAs for SALBP

METHODOLOGY

1. Develop Algorithm



2. Develop Test Parameters

No. of Generations to Convergence

Elitist Selection

$$G = \lceil 1 - \log_2 r_{s1} \rceil + \left\lceil \frac{1}{p_s} - r_{s1} 2^{\lceil 1-\log_2 r_{s1} \rceil - 1} \right\rceil \quad 0 < r_{s1} \le 1$$

$$G = \lceil 1 + p_s^{-1} - r_{s1} \rceil \qquad r_{s1} \ge 1$$

Tournament Selection

$$\bar{G} = \left\lceil \frac{\ln(1/p_1^* + 1/r_{s1})}{\ln(1+p_s)} \right\rceil$$

$$G^L = \lceil 1 + p_s^{-1} - r_{s1} \rceil \qquad G^U = 1 + N(1 - p_1^*)$$

Roulette Wheel Selection

$$G^L = \lceil 1 + p_s^{-1} - r_{s1} \rceil \qquad G^U = 1 + N(1 - p_1^*)$$

Stochastic Universal Sampling

$$\bar{G} = \lceil 1 - \log_2 2p_1^* \rceil + 2\left\lceil 1 - {p_1^*}^{\lceil 1 - \log_2 2p_1^* \rceil} \right\rceil \quad 0 < 2p_1^* < 1$$

$$\bar{G} = 1 + \lceil 2(1 - p_1^*) \rceil 2p_1^* \ge 1$$

Other Performance Parameters

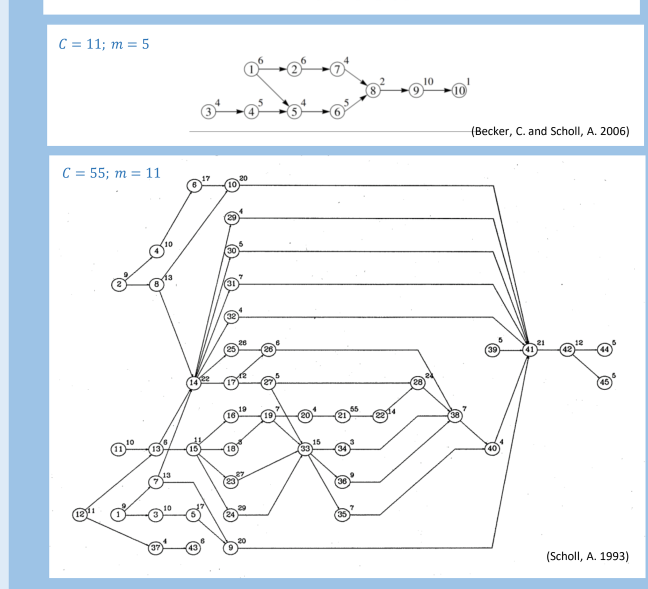
Fitness Correlation $d_\rho = \sum_{g=1}^{G-2} \left| \rho_{g+1}^2 - \rho_g^2 \right|^{1/2}$

Generational Growth Rate $\bar{\phi}_g = {}^{p_{g+1}^*}/_{p_g^*} \qquad g = 1, \cdots, G-1$

Generational Diversity $\Delta_g = \frac{u_g - 1}{N} g = 1, \cdots, G$

3. Design Experiments

Data Sets



Tests

ANOVA Parameters

N	p_s	λ
[100,500]	[0.25,1.0]	{1,10,100,1000}

- 80 combinations of experimental levels
- 10 replicates per combination
- $\alpha = 0.001$

Examples

	SALBP-1	SALBP-2
B&S	Example 1	Example 3
K&W	Example 2	Example 4

- All experiments not run for SUS
- Total of 25,600 experiments

GA Parameters

$p_1^* = 0.1; \varepsilon = 0.000\,1; p_{\bar{m}} = 0.1; p_m = 0.5; G = 500$

RESULTS

Reduced GA

Convergence Times

- The experimental results were in close agreement with the analytical solutions for the Reduced GA
- Maximum convergence times were closer to the predicted average convergence times
- RWS performed the best and SUS the worst

p_s	Predicted G^L	Predicted G^U	Predicted $\bar{G}$	Example 1 G^L	Example 1 G^U	Example 1 $\bar{G}$	Example 2 G^L	Example 2 G^U	Example 2 $\bar{G}$	Example 3 G^L	Example 3 G^U	Example 3 $\bar{G}$	Example 4 G^L	Example 4 G^U	Example 4 $\bar{G}$
	ES														
0.25	6.0	6.0	6.0	6.0	6.0	6.0	6.0	6.0	6.0	6.0	6.0	6.0	6.0	6.0	6.0
0.50	5.0	5.0	5.0	5.0	5.0	5.0	5.0	5.0	5.0	5.0	5.0	5.0	5.0	5.0	5.0
0.75	5.0	5.0	5.0	5.0	5.0	5.0	5.0	5.0	5.0	5.0	5.0	5.0	5.0	5.0	5.0
1.00	5.0	5.0	5.0	5.0	5.0	5.0	5.0	5.0	5.0	5.0	5.0	5.0	5.0	5.0	5.0
	RWS														
0.25	-	-	-	5.0	9.0	5.7	5.0	6.0	5.2	5.0	10.0	6.0	5.0	7.0	5.5
0.50	-	-	-	3.0	5.0	3.7	3.0	4.0	3.3	3.0	6.0	3.8	3.0	5.0	3.5
0.75	-	-	-	3.0	4.0	3.3	3.0	3.0	3.0	3.0	4.0	3.3	3.0	4.0	3.2
1.00	-	-	-	2.0	4.0	2.5	2.0	3.0	2.3	2.0	4.0	2.7	2.0	3.0	2.5
	SUS														
-	5.0	451.0	5.0	5.0	8.0	5.5	5.0	8.0	5.5	5.0	9.0	5.5	5.0	9.0	5.5
	TS														
0.25	5.0	451.0	12.0	7.0	10.0	8.2	7.0	10.0	8.3	7.0	10.0	8.2	7.0	10.0	8.3
0.50	3.0	451.0	7.0	5.0	6.0	5.1	5.0	6.0	5.1	5.0	6.0	5.1	5.0	6.0	5.1
0.75	3.0	451.0	6.0	4.0	5.0	4.1	4.0	5.0	4.0	4.0	5.0	4.1	4.0	5.0	4.1
1.00	2.0	451.0	5.0	3.0	4.0	4.0	3.0	4.0	4.0	3.0	4.0	4.0	3.0	4.0	4.0

Other Parameters

- Trends in the results were consistent across the correlation parameter, d_ρ, the generational growth rate, $\bar{\phi}$, and generational diversity, β_Δ
- The ranking of Selection Methods across all parameters was as follows

1	2	3	4
RWS	TS	ES	SUS

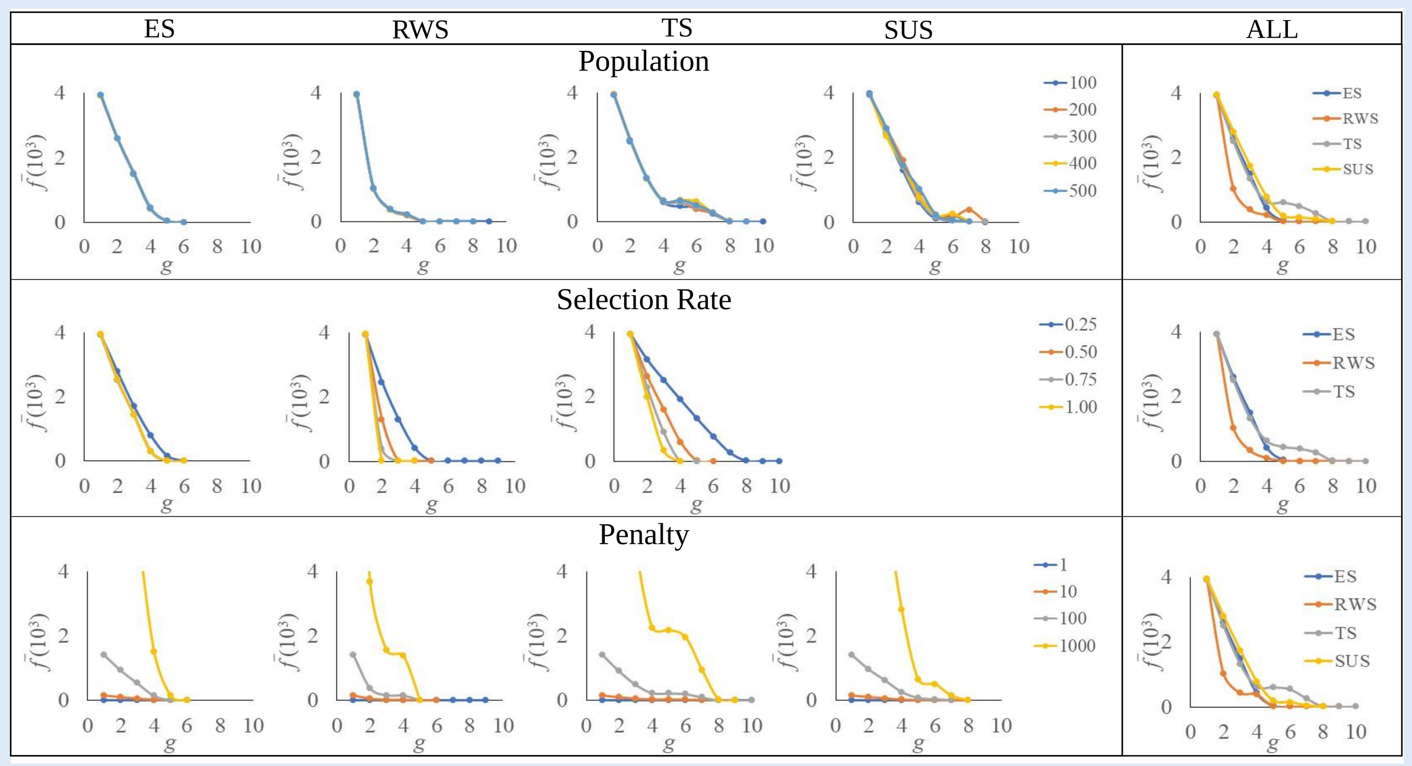
Full GA

Test Parameters

- The results of the Full GA were not consistent with those of the reduced GA
- Convergence times varied between SALBP-1 and SALBP-2, and also with the size of the problem
- The observation for convergence times was consistent across all parameters

GA Parameters

- Selection Methods were unaffected by population size
- The magnitude of penalty in the fitness function had the largest effect on Selection Methods



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