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Title:
Comparison Study of Different Genetic Algorithms for Assembly Sequence Planning

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Introduction:
Assembly planning (AP) is a critical process in the product manufacturing. As the assembly process accounts for approximately 20-30% of the manufacturing cost and 50% of the total production time, it is essential to reduce the assembly time and cost through assembly planning. AP includes assembly sequence planning (ASP), assembly line balancing (ALB), and assembly path planning (APP) as shown in Fig.1 [2].

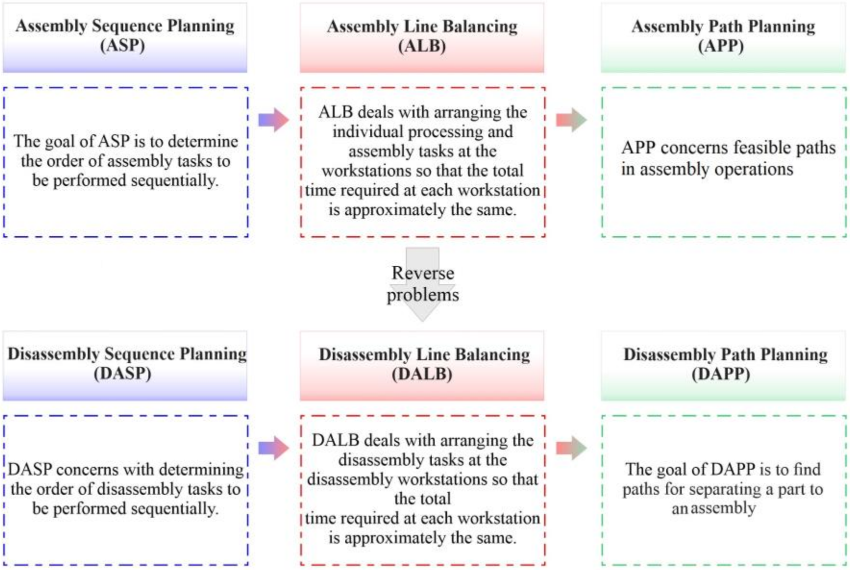

Fig. 1: Assembly planning.

ASP searches an optimal sequence of the product assembly, which deals with different components and relations in product structures and operations. Metaheuristics methods such as the genetic algorithm (GA), particle swarm optimization (PSO), and ant colony optimization (ACO) have been used in ASP. GA is a most commonly used algorithm in ASP. However, there is a lack of research on the GA

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performance for ASP. This research investigates crossover operators and selection mechanics of GA for ASP [4].

Main Idea:

Problem statement

Different measures can be used in searching optimal sequences to reduce the assembly time and cost for ASP. In this study, the minimum changes of assembly orientations, tools, and operation types are considered to achieve the objective. Matrices are used to represent product details in the computer, including the precedence matrix, fastener-part connectivity matrix, fastener accessibility matrix, and part accessibility matrix. The optimization search has to meet given constraints. In ASP, constraints will limit feasible assembly sequences. Feasible assembly sequences require that components are assembled without interfering with other parts. Therefore, a fitness function is used as follows.

$$F_1 = -(2n - w_1 f_1 - w_2 f_2 - w_3 f_3) \tag{1}$$

where f_1 represents assembly orientation changes in the assembly operations, f_2 indicates the number of assembly tool changes in the operation and f_3 is the number of assembly operation type changes. n represents the number of parts to be assembled in the product. w_1, w_2 , and w_3 are weights of f_1, f_2, and f_3, respectively. A constant weight distribution is used in this research as $w_1 = 0.4$, $w_2 = 0.3$, and $w_3 = 0.3$.

Four types of Genetic Algorithms (GAs)

Four GAs are examined with four different types of crossover operators. The crossover represents one of the three main operations in GA. The other two GA operations are mutation operation and selection mechanism. The pseudo-code of GAs used in this research is shown in Fig. 2.

```
Randomly initializing the chromosomes
Fitness value calculation
while NFE ≤ MaxNFE:
    for Number of chromosomes/2:
        Choosing parents using selection mechanism
        Applying one of the four crossover types
        Mutation operation
        Calculate the fitness values using Equations 1 based to the value of m
        NFE ← NFE + 2
    end for
    Combining the lately generated chromosomes with the previous ones
    Sort chromosomes from the best to the worst based on their fitness values
    Save the best half and discard the remaining
end while
```

Fig. 2: Pseudo-code of GAs for different types of crossovers.

An array of non-repeating numbers is generated by a specific crossover operator to implement GA for ASP. We examine four well-known crossover operators, namely Cycle crossover (CX), Position-based crossover (PBX), Order crossover (OX), and Partially-mapped crossover (PMX) [5] to evaluate performance of GAs for ASP. There are two common GA mechanisms to select parents and survivors, the roulette wheel and tournament selection. This study uses the roulette wheel selection method.

Cycle Crossover (CX): The cycle crossover aims to conserve as much information as possible regarding the absolute positions of elements. CX operators divide elements into cycles. When parents of entities are in alignment with one another, elements form a cycle. In order to create the offspring, alternative cycles are chosen from each parent's permutation as shown in Fig. 3. In order to construct

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cycles, it is necessary to identify cyclical elements of the offspring and copy each one into the offspring.

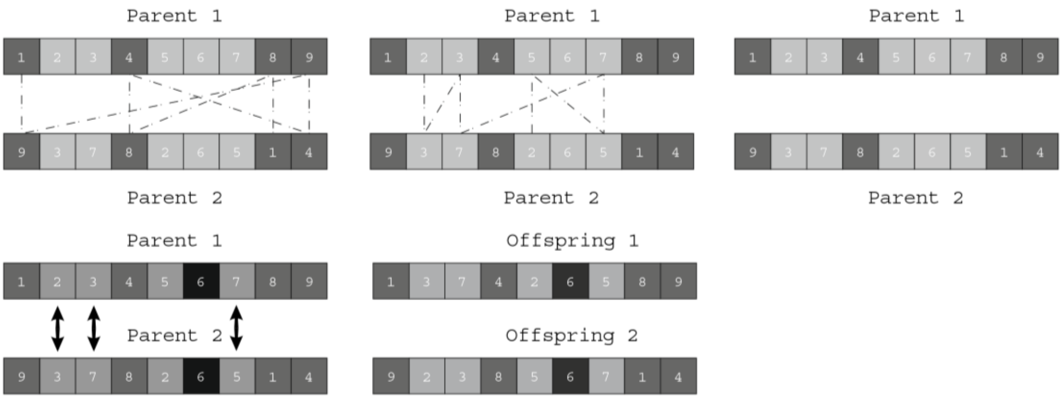

Fig. 3: Operations of CX crossover.

Position-based crossover (PBX): Position information is maintained throughout recombination by this operator. A sequence is constructed by selecting several random locations and one parent as shown in Fig. 4. Those elements have the same parent as those in those positions. The remaining elements are inherited in the order they appear in the second parent after removing elements of the second parent in those random locations of the first parent. Its elements are chosen at random, not based on their locations within a parent.

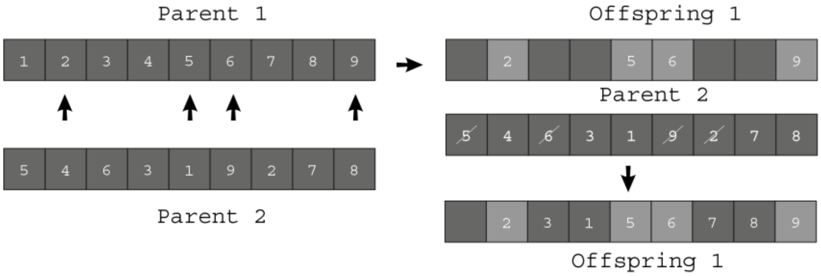

Fig. 4: PBX crossover procedure.

Order crossover (OX): This type of operator is useful for solving order-based permutation problems. It involves copying the first portion of the first parent into an empty offspring at random. From the first element of the second parent, the remaining numbers are copied to the new child, and unused numbers are removed from the subsequent offspring as shown in Fig. 5. A second offspring can be created by switching the functions of the parents.

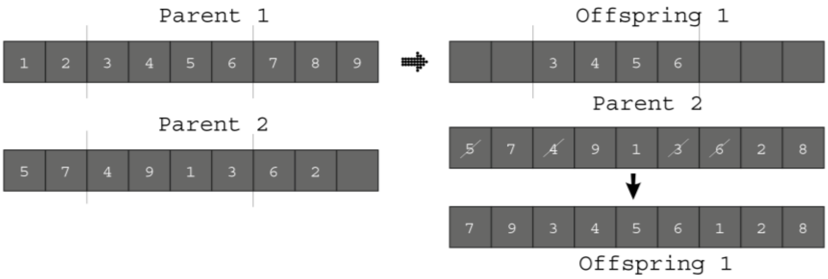

Fig. 5: Operations of OX crossover.

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Partially Mapped Crossover (PMX): Two points are selected in this crossover operator. From one parent to the other, elements are replaced between these two points as shown in Fig. 6. It is necessary to find and replace the corresponding element from the other parent if it is already present between two crossover points of the offspring. The second parent must also contain a corresponding element if it is also present between the crossover points of the first chromosome. This process may be continued until there is no corresponding number between the crossover points.

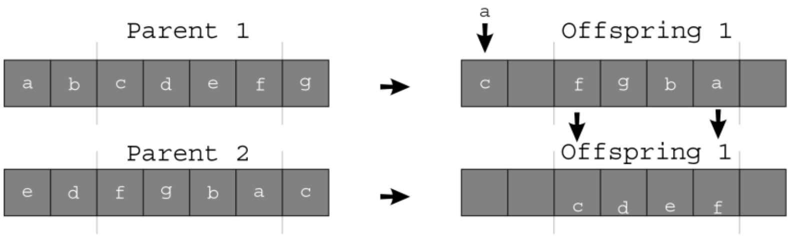

Fig. 6: Representation of PMX crossover.

Case study:
Fig. 7 shows a product used in the case study. It is comprised of 22 components. The six principal directions, namely ±x, ±y, and ±z, are considered as the assembly directions of the components. The fitness function Eqn. (1) is used to search optimal solutions of different GAs through the check of precedence feasibility and geometrical feasibility of assembly sequences. The precedence feasibility addresses the correct order of the assembly process. The geometrical feasibility evaluates the interference of parts in the assembly for a collision-free operation.

Each GA is examined by running 30 times for the statistical analysis. An algorithm is considered as more robust when it shows larger values for best, mean, and worst fitness values while having the least standard deviation. Tab. 1 lists statistical data based on 30 independent runs.

Fig. 8 shows the average convergence curves of the different GAs. It shows that the OX-GA algorithm converges to the optimal solution faster than other algorithms. According to the statistical data in Tab. 1, the CX-GA algorithm couldn't find the optimal solution. Also, the OX-GA algorithm shows the best statistical result by having the maximum values of best, mean, and worst values while having the minimum standard deviation. This result indicates that among four crossover operators of the GAs, OX would be the best candidate for ASP, since this approach can obtain the most robust result for different runs.

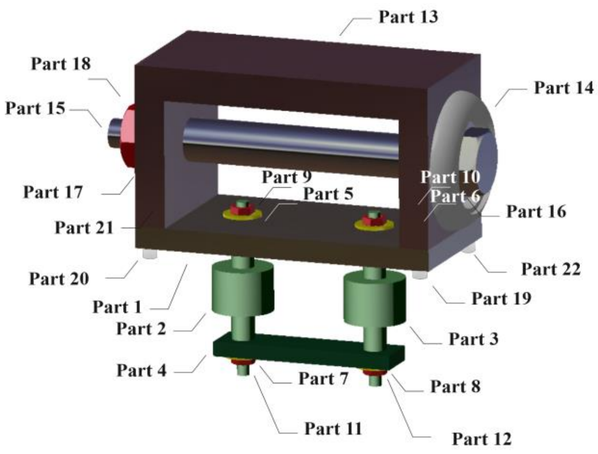

Fig. 7: Case study product.

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Algorithm	Best	Mean	STD	Worst
CX-GA	38.2	37.867	0.409	36.9
OX-GA	**38.3**	**38.237**	**0.049**	**38.2**
PBX-GA	**38.3**	38.197	0.085	37.8
PMX-GA	**38.3**	38.117	0.164	37.6

Tab. 1: Statistical data of Gas.

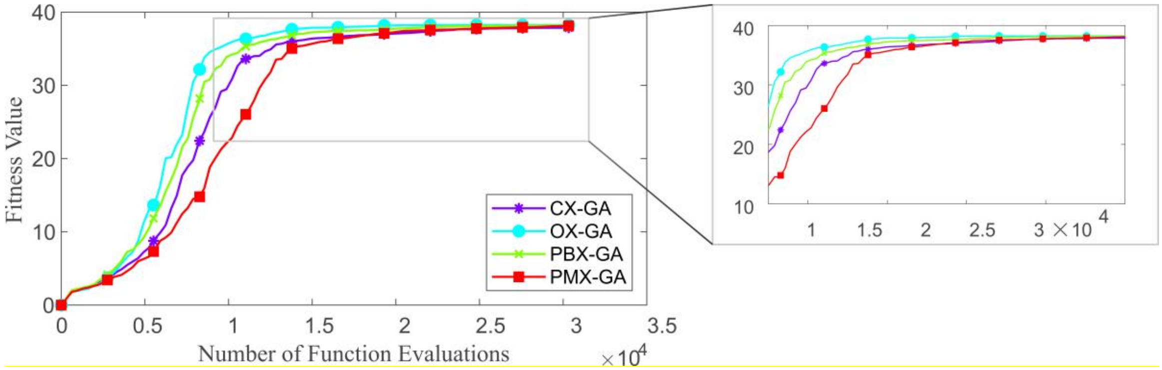

Fig. 8: Average convergence curves of GAs with different crossover operators.

Conclusion:
This paper conducts a comparison study on different crossover operators of GAs. CX, OX, PMX, and PBX of GAs are implemented to examine their performance in ASP. A fitness function is proposed for minimum changes of assembly orientations, tools, and operation types in searching for the optimal assembly sequence. In the case study, mean convergence curves of the four examined algorithms show that OX-GA outperforms other crossover operators in terms of the initial speed of convergence, and maximum values of the best, mean, worst fitness, and the least standard deviation.

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