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Programming Model for Enterprise Multi-Process Decision Optimization

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Abstract: This paper addresses critical decision-making challenges faced by enterprises during the production process, particularly focusing on efficient quality inspection, inspection and disassembly decisions, defective rate control, and cost minimization. In the current dynamic market environment, existing algorithms demonstrate insufficient adaptability, hindering their effectiveness in addressing complex production scenarios. To overcome these limitations, we propose a novel genetic algorithm that incorporates dynamic change adjustment through a 0-1 programming model. This approach enhances the algorithm's flexibility, enabling enterprises to develop scientifically sound and rational production decision schemes tailored to varying market conditions. Our empirical analysis reveals that the average production cost for enterprises utilizing this method is 32.7, indicating significant potential for cost reduction while maintaining product quality. The findings contribute to the existing literature by providing a robust theoretical framework that underscores the importance of adaptive algorithms in improving production efficiency and decision-making processes in an ever-evolving market landscape.

Keywords: 0-1 Planning Model, Genetic Algorithm, Optimal Strategy.

1. Introduction

Enterprise production resource scheduling and allocation is a variant of project scheduling problem under resource constraints (RCPSP). Under the premise of scarce production resources, how to optimize the allocation of production resources and scheduling schemes under various production tasks to ensure full capacity to complete various production tasks is the main content of this optimization problem [1]. At the same time, the production scheduling of enterprises is constrained by many conditions, such as whether parts are checked, whether finished products are tested, and whether unqualified finished products are disassembled. Due to the above constraints, it is difficult to solve the production scheduling problem of enterprises, which belongs to the Non-deterministic Polynomial hardproblem (NP) [2]. The traditional genetic algorithm has some shortcomings, such as poor adaptability to dynamic environment and lack of real-time adjustment. During real-time decision making, the production environment changes rapidly. Traditional genetic algorithms are usually based on static constraint solving and lack the ability of real-time adjustment, which is insufficient to cope with the variability and uncertainty in production decision-making. Therefore, based on the defects of traditional genetic algorithms, many scholars at home and abroad put forward optimization strategies: In literature [3], the author proposed the genetic algorithm using the full crossover operator, selecting and, or one of the three types of crossover between chromosomes, and comparing single-point crossover and multi-point crossover to obtain the optimization effect of full crossover. In literature [4], due to the defect of local optimization of genetic algorithm, the author introduced population variance factor and population entropy factor as decision variables and dynamically adjusted the parameters of genetic algorithm to optimize population diversity and search efficiency. In addition to adjusting the crossover operator and mutation operator to optimize the genetic algorithm, it can also improve the solution effect, robustness and adaptability of the algorithm by combining a variety of heuristic algorithms. In literature [5], Diana S et al. proposed to represent chromosomes in the form of binary strings, decode SSGS, and obtain the optimal solution by disk selection. In reference [6], the authors combined genetic algorithm (RCGA) and self-organizing migration algorithm (SOM) to propose a hybrid algorithm to solve the boundary constrained nonlinear optimization problem with multimodal continuous functions. However, the existing theories are based on various decision-making scenarios [7-9], and few of them [10, 11] are applied to the actual production decision-making problems. Therefore, this paper applies the optimization algorithm to a simple production decision case, compares the actual result with the predicted result, and analyzes the performance of the optimization algorithm.

2. The Basic Fundamental of Genetic Algorithm

2.1. The Structure of Genetic Algor

Genetic algorithms are stochastic optimization techniques based on probability theory, widely applied to address complex optimization challenges. In the context of multi-process production decision-making in enterprises, the search process primarily relies on random strategies, meaning that each step of selection and evolution occurs within a probabilistic framework. This approach allows genetic algorithms to explore vast solution spaces and seek potential global optima, thereby providing robust support for production decisions.

In this study, we represent the production decisions using a four-bit binary character encoding for chromosomes. The first two bits indicate whether to inspect components 1 and 2, the third bit specifies whether to inspect the finished product, and the fourth bit determines whether to disassemble the finished product. This encoding effectively captures critical information relevant to production decision-making, enabling the algorithm to search more efficiently. The search process begins with an initial set of random solutions, each referred to as a "chromosome." These chromosomes evolve through genetic operations such as selection, crossover, and mutation, continually enhancing their fitness. The selection operation ensures the retention of superior solutions, while crossover and mutation introduce new solutions, promoting diversity. This adaptive mechanism allows genetic algorithms to flexibly adjust and optimize decision strategies in response to complex and dynamic production environments.

In summary, genetic algorithms, with their inherent randomness and adaptability, offer effective support for production decision-making in enterprises and hold the potential to discover global optimal solutions, providing innovative approaches to tackling multi-process production decision problems.

2.2. The Main Logic and Framework of The Algorithm

The suboptimal solutions generated through the operations of the genetic algorithm exhibit a degree of randomness, which necessitates the implementation of multiple iterations to achieve a relatively stable decision-making framework. To attain this stability, the genetic algorithm is executed repeatedly, with each simulation carefully recording the total cost associated with the respective solution. Subsequently, the average cost across all simulation results is calculated, allowing for the determination of the expected total cost under various strategic configurations. This averaging process is crucial, as it provides a more reliable estimate of performance, mitigating the effects of random fluctuations inherent in individual runs. Upon the completion of the evolutionary process, the individual with the highest fitness score is selected and outputted. This individual represents the optimal strategy combination identified by the genetic algorithm. Additionally, the total cost associated with this optimal strategy, along with the previously calculated expected total cost, is presented. This comprehensive approach not only highlights the effectiveness of the genetic algorithm in producing viable decision-making strategies but also underscores the importance of rigorous evaluation methods in ensuring that the derived solutions are both robust and reliable within the context of production decision-making.

2.3. The Determination of The Genetic Parameter

In the experimental setup of this study, the population size is set to 100 to ensure sufficient genetic diversity within the population, which is crucial for exploring a wide solution space. The objective of the defined fitness function is to minimize costs; thus, lower costs correspond to higher fitness levels. A roulette wheel selection method is employed, allowing for the selection of superior individuals based on their fitness scores. This mechanism ensures the preservation and transmission of advantageous genes, facilitating the population's evolution toward optimal solutions and, consequently, the identification of more effective decision-making strategies. The crossover rate is established at 0.7, utilizing single-point crossover to maintain population stability while promoting genetic recombination. Additionally, the mutation rate is set within the typical range of 1% to 5%. For this study, a mutation rate of 2% is chosen to effectively sustain solution diversity while mitigating the risk of excessive randomness. This strategic balance helps avoid local optima, thereby enhancing the overall robustness and reliability of the algorithm's performance in dynamic production environments.

3. The Establishment of Simulation Model

The text build a model based on the problems in CUMCM Question B in 2024:

The inspection of parts 1 or 2 can reduce the number of unqualified parts entering the assembly process, thereby reducing the rate of defective finished products.

In the production process, there are only two options for parts 1: detection and non-detection. When 0-1 variable L_i is introduced, there is the detection behavior of parts1 L_i:

$$L_i = \begin{cases} i = 0, & \text{No test the parts 1} \\ i = 1, & \text{Test the parts 1} \end{cases} \tag{1}$$

Similarly, part 2 also has only two options of detection and non-detection, and the introduction of 0-1 variable L_i' will have the detection behavior of part 2 L_i':

$$L_i' = \begin{cases} i = 0, & \text{No test the parts 2} \\ i = 1, & \text{Test the parts 2} \end{cases} \tag{2}$$

After the parts are tested, the untested parts and the finished products assembled with qualified parts are selected. For the finished products, there are also two choices: test and no test. When 0-1 variable h_i :is introduced, the behavior of the products tested is h_i:

$$h_i = \begin{cases} i = 0, & \text{No test the product} \\ i = 1, & \text{Test the product} \end{cases} \tag{3}$$

The unqualified products obtained after the inspection of the finished products are treated by disassembly and non-disassembly means. The 0-1 variable B_i is introduced, then there is product treatment behavior B_i:

$$B_i = \begin{cases} i = 0, \text{Disassemble nonconforming products} \\ i = 1, Do\ no \text{ disassemble nonconforming products} \end{cases} \tag{4}$$

The goal of this article is to minimize the total cost C_z. According to the question, the total cost is composed of three parts: the inspection cost of spare parts C_L, the inspection cost of finished products C_h, the processing cost of unqualified products C_B, the assembly cost C_p and the replacement cost C_d.

Assume that the purchase quantity of parts 1 is m_1, the purchase quantity of parts 2 is m_2, the production quantity of finished products is m_3, the number of unqualified products is m_4, the defective rate is p_m, the loss of single finished product replacement is C_{d0}, and the single assembly cost is C_{p0}.

The inspection cost of spare parts C_L is:

$$C_L = L_i \times C_1 \times m_1 + L_i' \times C_2 \times m_2 \tag{5}$$

The inspection cost of the finished product C_h is:

$$C_h = h_i \times m_3 \times C_{h0} \tag{6}$$

The processing cost C_B of nonconforming products is:

$$C_D = B_i \times m_4 \times C_n \tag{7}$$

Assuming that the unqualified products bought by the customer are from the products that have not been tested for finished products (that is, the products that have passed the product test must be qualified), the cost C_d generated by the replacement is:

$$C_d = p_m \times m_3 \times (1 - h_i) \tag{8}$$

Assembly cost C_p is:

$$C_p = m_3 \times C_{p0} \tag{9}$$

The whole decision-making process is carried out, and the assembly cost that is not affected by the inspection decision has no impact on the minimization of the total cost, then the part of production cost C_t that is affected by the inspection decision and thus affects the total cost is as follows:

$$C_t = \{C_L + C_h + C_B + C_d\} \tag{10}$$

Therefore, to sum up, a single objective programming model which is influenced by the test decision and thus affects the total cost minimization C_z is established as follows:

The decision variables are:

$$L_i,\ L_i',\ h_i,\ B_i \tag{11}$$

The objective function is:

$$C_z = min\{C_L + C_h + C_B + C_d + C_p\} \tag{12}$$

4. Results

4.1. Analysis of Experimental Results

The optimal decision-making solutions Table 1 Optimal decision scheme obtained through multiple genetic iterations align closely with actual decision-making outcomes; however, some discrepancies remain, primarily due to the inherent randomness associated with genetic algorithms.

Table 1. Optimal decision scheme

conditions	strategies	average cost (RMB)
1	[1 0 1 1]	33.2
2	[1 0 1 0]	34.8
3	[0 0 1 1]	33.2
4	[1 1 0 0]	31.8
5	[0 0 0 1]	31.4
6	[0 0 1 0]	32.16

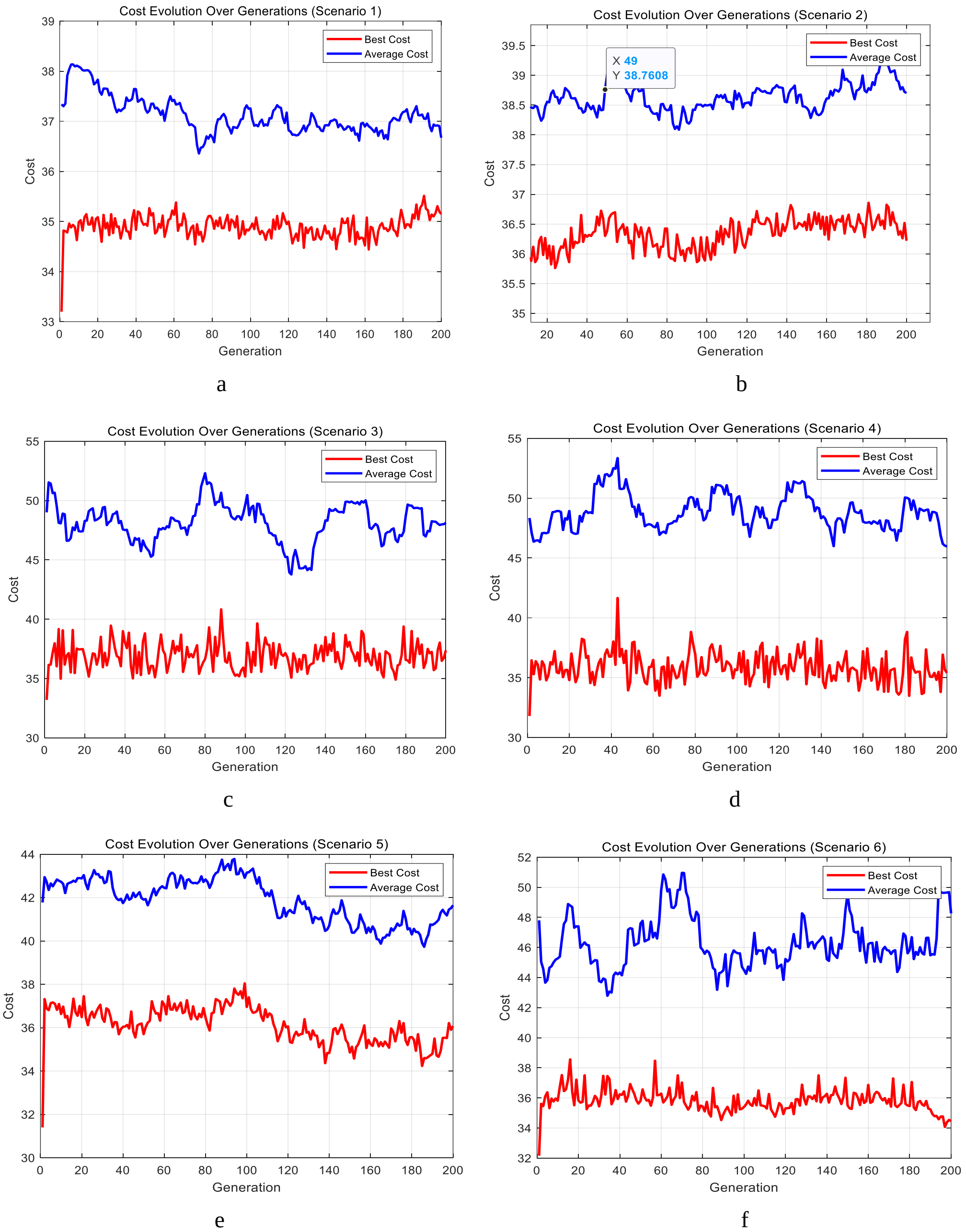

Figure 1. The average and minimum cost of the decision solution under 6 scenarios

A comparative analysis between the predicted solutions Figure 1 The average and minimum cost of the decision solution under 6 scenarios. and the actual implementations reveals that genetic algorithms exhibit robust predictive performance, demonstrating relatively small errors. Nevertheless, the efficacy of the genetic algorithm is significantly dependent on the tuning of its parameters. Therefore, future experiments should focus on refining these algorithmic parameters to enhance solution quality further, potentially leading to more optimal strategies. This ongoing optimization process is essential to fully leverage the capabilities of genetic algorithms in dynamic production environments and to minimize the impact of their stochastic nature.

(In the chart below, the vertical coordinates cost/ yuan and the horizontal coordinates child/generation are shown)

5. Conclusion

In this paper, we tackle the shortcomings of traditional genetic algorithms by proposing a dynamic genetic algorithm that supports real-time parameter adjustments. This advancement enables the development of decision-making solutions that are specifically tailored to the unique demands of various production environments. Our experimental results reveal that the dynamic parameter-tuning genetic algorithm significantly outperforms conventional methods when applied to Resource-Constrained Project Scheduling Problems (RCPSP). By improving decision-making efficiency, this algorithm enhances the system's ability to adapt to changing environmental conditions. Moreover, this research provides valuable insights into production decision-making, illustrating the transformative potential of genetic algorithms in complex, dynamic contexts. Our findings not only advance the theoretical understanding of genetic algorithms but also highlight their practical applicability in optimizing production processes. Ultimately, by demonstrating the advantages of dynamic adjustments, we emphasize the importance of adaptive algorithms in contemporary industry, encouraging further exploration and development in this critical area. This work lays the groundwork for future research, aiming to refine the capabilities of genetic algorithms and broaden their implementation across diverse industrial applications, ultimately contributing to more efficient and responsive production systems.

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