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MULTI-CRITERIA OPTIMIZATION OF CONSTRUCTION MACHINERY SELECTION USING A HYBRID AHP-GA MODEL

Abstract:

This paper presents a hybrid model integrating the Analytic Hierarchy Process (AHP) and Genetic Algorithms (GA) to optimize construction machinery selection based on cost, CO_2 emissions, maintenance, and age. AHP was used to determine precise weighting criteria, while a Python-based GA explored the solution space using technical penalty functions. Results demonstrate the model's efficiency in balancing fleet performance and costs. The proposed model enables unbiased decision-making, systematizing subjectivity in engineering judgment and providing an objective framework for sustainable resource management.

Keywords: AHP, Genetic Algorithms, construction machinery, optimization, sustainability, CO_2

ВИШЕКРИТЕРИЈУМСКА ОПТИМИЗАЦИЈА ИЗБОРА ГРАЂЕВИНСКЕ МЕХАНИЗАЦИЈЕ ПРИМЕНОМ ХИБРИДНОГ AHP-GA

Abstract:

Овај рад представља хибридни модел који интегрише Аналитички хијерархијски процес (АНП) и генетичке алгоритме (ГА) ради оптимизације избора грађевинске механизације према критеријумима цене, емисије CO_2, одржавања и старости. АНП је коришћен за прецизно одређивање тежинских коефицијената, док је ГА, имплементиран у Python окружењу, претраживао простор решења уз примену техничких казнених функција. Резултати демонстрирају ефикасност модела у постизању баланса између трошкова и перформанси флоте. Предложени модел омогућава непристрасно доношење одлука, систематизујући субјективност инжењерске процене и пружајући објективан оквир за управљање ресурсима.

Keywords: AHP, Генетски алгоритми, грађевинска механизација, оптимизација, одрживост

1. INTRODUCTION

The construction industry in the contemporary environment faces increasing challenges regarding efficiency, economic sustainability, and environmental protection. Selecting adequate construction machinery is one of the most critical tasks in the project planning phase, as it directly impacts costs, work duration, and execution quality [1]. Traditional equipment selection approaches often rely on the empirical estimates of engineers or partial economic analyses, which are insufficient for achieving optimal performance under complex site conditions[2].

In the last decade, the global focus has shifted significantly toward sustainable construction and reducing the environmental footprint. It is estimated that the carbon footprint of the construction sector will double globally by 2050 unless urgent optimization measures in resource management are undertaken [3]. Heavy machinery, through direct carbon dioxide (CO_2) emissions during operation, constitutes a significant portion of a construction project's total emissions, necessitating the introduction of environmental criteria as equal factors in the decision-making process[4], [5].

Given the non-linear nature of the problem and the presence of conflicting objectives, such as cost minimization while maximizing reliability and environmental acceptability, the application of advanced optimization algorithms is essential[2]. This paper presents a hybrid model integrating the Analytic Hierarchy Process (AHP) for structural priority determination[6] and Genetic Algorithms (GA) for efficient solution space searching and defining the optimal machine fleet[7], [8]. Through performance and cost analysis, the study highlights key trade-offs between machinery age and operational stability, providing a model applicable to real-world engineering practice.

2. METHODOLOGY

A hybrid model integrating AHP and GA was applied in this study to solve the complex problem of optimal construction machinery fleet selection. The application of multi-criteria optimization in civil engineering is necessary because traditional methods often fail to simultaneously balance conflicting factors, such as minimum cost and maximum operational reliability[1], [2].

To navigate the vast combinatorial complexity of machinery selection, we used a GA as the primary optimization engine and integrated weights derived by using AHP. Unlike traditional search methods that can become trapped in local optima, GA mimics natural evolutionary processes, selection, crossover, and mutation, to rapidly explore the immense solution space. This computational speed allows the model to evaluate thousands of fleet configurations in seconds, a feat that is simply not feasible through manual calculation or empirical guesswork. By iteratively evolving "chromosomes" of machine data, the GA efficiently converges toward an optimal, or near-optimal, fleet combination that strictly adheres to set criteria.

The real power of this hybrid approach lies in the synergy between the two methods, AHP provides the intelligence by translating subjective engineering expertise into precise weights, while GA provides the best possible match for those weights. Without the weights derived from the AHP process, the optimization would lack the necessary context to balance conflicting goals like minimizing cost while maximizing maintenance support. Ultimately, this hybrid model ensures that the final selection is specifically tailored to the defined criteria.

2.1. AHP METHOD

We opted for the AHP for this study because traditional machinery selection often relies on empirical estimates that lack a structured mathematical basis. By implementing AHP, we can decompose the complex goal of fleet optimization into the four distinct, manageable criteria.

To bridge the gap between qualitative engineering experience and numerical data, Saaty's 1–9 scale is applied [6]. This effectively translated expertise, such as the operational risks associated with older equipment or the importance of service availability, into the precise weighting coefficients (w_1 to w_4). To verify that criteria weights were logically sound and not a result of random choice, the Consistency Ratio (CR) was calculated. If the calculated CR is below the recommended 0.10 threshold, the weights are considered acceptable.

The selection of machinery is based on four key criteria reflecting modern engineering and environmental standards:

- Cost (C): Includes unit operating costs per working hour (€/m^3)[9]
- Machine Age (A): An indicator of reliability and the risk of downtime on-site.
- Maintenance Support (M): The quality and availability of service, which is crucial for maintaining work dynamics[10], [11]

- CO_2 Emission (*E*): The environmental footprint, aligned with global construction sector decarbonization goals by 2050 [3], [4]

2.2. GENETIC ALGORITHM WITH MULTI-CRITERIA ANALYSIS

Following the determination of criteria weights, a Genetic Algorithm (GA) was implemented using the Python programming language [7]. The algorithm simulates an evolutionary process through specialized operators, selection, crossover, and mutation, to identify the optimal combination of variables that minimizes the fitness function (f_{fit}) within an expansive solution space:

$$\text{Lower limit} \leq \{\text{productivity of machine group 1}\} \leq \text{Upper limit} \tag{1}$$
$$\text{Lower limit} \leq \{\text{productivity of machine group 2}\} \leq \text{Upper limit} \tag{2}$$
$$\text{Lower limit} \leq \{\text{productivity of machine group 3}\} \leq \text{Upper limit} \tag{3}$$
$$1 \leq \text{number of selected machines from group 1} < \text{Available slots} \tag{4}$$
$$1 \leq \text{number of selected machines from group 2} < \text{Available slots} \tag{5}$$
$$1 \leq \text{number of selected machines from group 3} < \text{Available slots} \tag{6}$$
$$f_{fit} = 1 - \left(w1 * \frac{Cmin}{Ccur} + w2 * \frac{Amin}{Acur} + w3 * \frac{Mcur}{Mmax} + w4 * \frac{Emin}{Ecur}\right) + penalty \tag{7}$$
$$\text{Final value} = 1 - f_{fit} \tag{8}$$

The algorithm is configured to optimize three distinct groups of machinery simultaneously, following the principles of a continuous production line. During the selection process, the redundant acquisition of the same machine is prohibited. To address the challenge of an unknown number of required machines, the chromosome structure includes "slots" that can either be assigned a specific machine or remain vacant (Eq. 4, Eq. 5, Eq. 6). To ensure that the entire search space has been explored effectively, the algorithm is monitored to ensure that several slots remain empty upon convergence; this serves as a verification that the solution was not constrained by an insufficient number of available machine positions.

The primary operational constraint is defined by the required output capacity, established through designated lower limit and upper limit parameters.

To ensure the algorithm accurately evaluates the quality of a solution, the reference values (C_{min}, E_{min}, M_{max}, A_{min}) must remain static during the main execution. Dynamically updating these values during runtime leads to premature convergence on initial values and suboptimal results. To overcome this, a two-stage approach was adopted: for a given set of lower limit and upper limit constraints, the algorithm is first executed with individual objective functions to determine the reference values for each criterion independently ($f_{(Cmin)}$=cost+penalty, $f_{(Amin)}$= age+penalty,...). Once these benchmarks are established, the final objective function (Eq. 7) is executed, and final value calculated (Eq. 8) .

The normalization of Cost, Emission, and Age was designed to favor lower values (minimization) by using the ratio of the minimum benchmark to the current value. In contrast Maintenance was processed to favor higher values (maximization) by using the ratio of the current value to the maximum benchmark. This ensures that the algorithm prioritizes lower costs, emissions, and age, while seeking high maintenance rating."

The optimization used the geneticalgorithm2 library with a population of 1000 over 100 generations, ensuring extensive solution space exploration. The selection strategy employs a 10% parents' portion with elitism enabled to preserve top-performing configurations across iterations. With a 0.8 crossover and 0.1 mutation rate, the model effectively balances global exploration and local exploitation to identify the optimal machinery fleet.

A specific contribution of this model is the introduction of a penalty function for solutions that do not meet the required productivity range (Eq. 1, Eq. 2, Eq. 3), constraint violations are handled through a linear penalty approach, where the magnitude of the penalty is directly proportional to the distance from the required productivity boundaries effectively eliminating technically inadequate fleet configurations from the selection process [8], [12]. Furthermore, a redundancy penalty is enforced to ensure that each asset within a group remains unique.

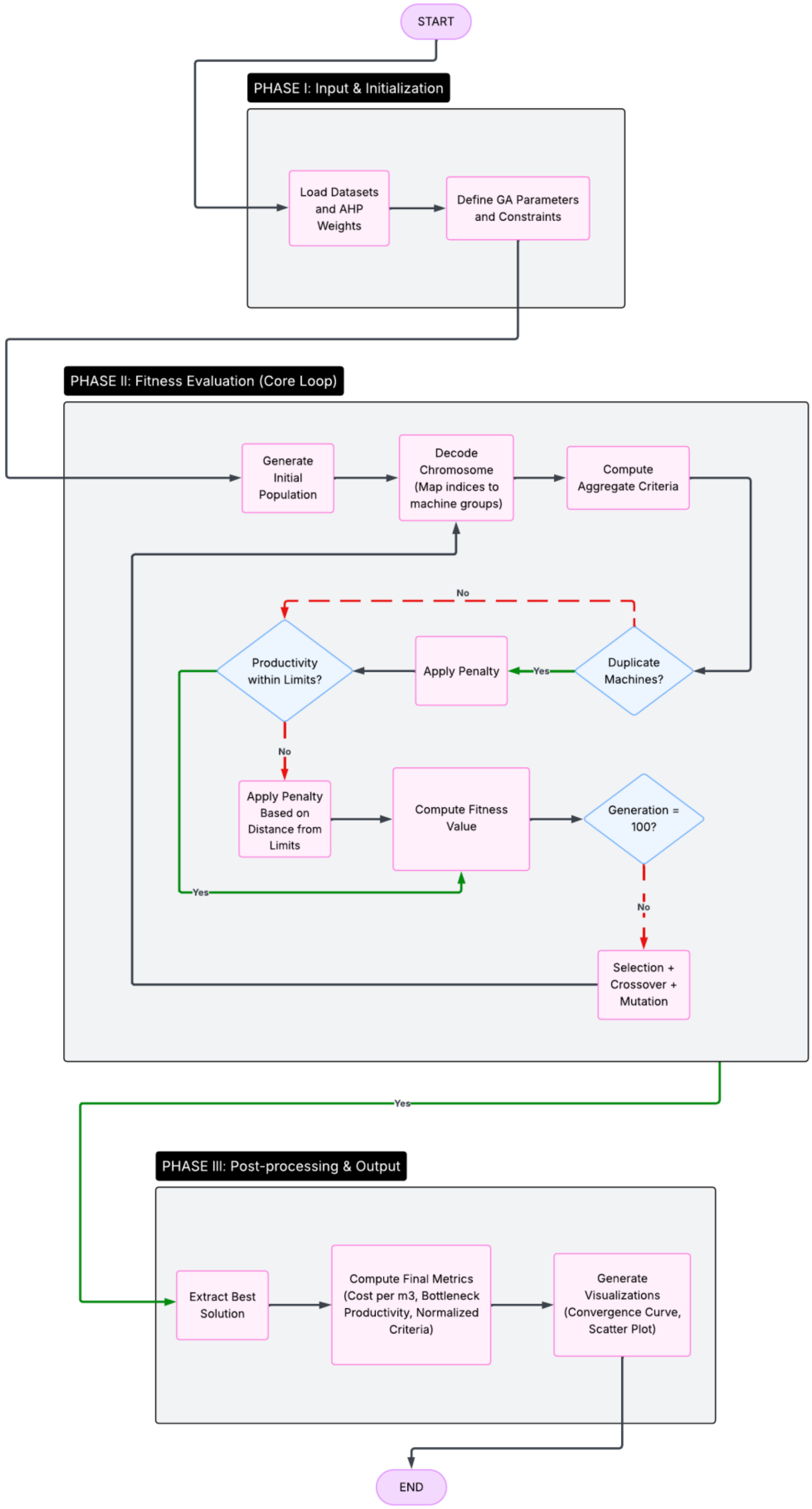

Figure 1. Flow chart of applied algorithm

3. CASE STUDY

This chapter presents the results of the optimization performed on a test model consisting of three databases, each containing 50 different construction machines, including excavators, dump trucks, and additional equipment. The simulation aimed to form an optimal fleet that meets the required productivity where lower limit is 70 and upper limit 80 m^3/h, number of available "slots" for group one was 4, for group two was 10, and for group three was 4.
Expert assessment was translated into a comparison matrix, resulting in the following weighting coefficients (w_i):

- Cost: $w_1 = 0.558$
- Age: $w_2 = 0.122$
- Maintenance: $w_3 = 0.263$
- CO_2 Emission: $w_4 = 0.057$

Matrix consistency was confirmed by a Consistency Ratio $CR = 0.044$, which is significantly below the 0.10 threshold, thus confirming the logical validity of the priority decisions [6].

3.1. PRESENTATION OF RESULTS

After 100 generations, the genetic algorithm identified a solution with a total fitness function value of 0.834, where 1.0 represents a theoretical ideal solution. The selected combination of machines achieved a projected productivity of 74.71 m^3/h, which is in the center of the specified range, confirming the efficiency of the penalty function in eliminating inadequate solutions [8], [12].
The normalized criteria values for the optimal group are presented in Table 1.

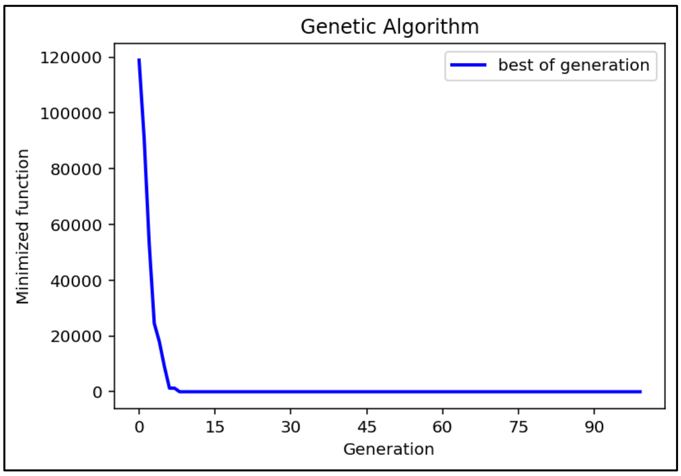

Figure 2. Fitness function convergence across generations

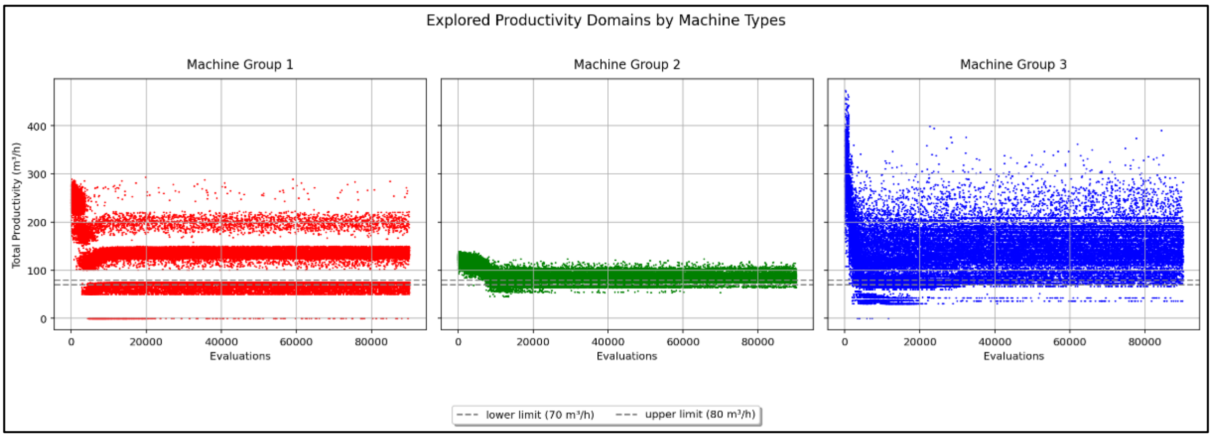

Figure 3. *Explored productivity domains by machine types*

The results are shown in the the table below:

Table 1. Algorithm output

Group:	Chosen machinery:	Group productivity:
Selected Machines 1	[0 0 43 0]	74.71 m^3/h
Selected Machines 2	[8 10 1 4 0 0 20 17 0 6]	76.1 m^3/h
Selected Machines 3	[7 9 0 0]	79.86 m^3/h

Productivity: 74.71 [m^3/h]
Cost (Normalized value): 0.944
CO_2 (Normalized value): 0.926
Maintenance (Normalized value): 0.938
Age (Normalized value): 0.061
Fitness Function: 0.834

The results displayed in Table 1 illustrate the output of the optimization algorithm for machinery selection. For the chosen group, the analysis reveals high normalized scores for cost (0.944), CO_2 emissions (0.926), and maintenance (0.938), all of which serve as critical inputs for the AHP model. Despite a relatively low score for the age of the machinery (0.061), the final Fitness Function value of 0.834 demonstrates that the algorithm successfully optimizes construction resources by reconciling high productivity with stringent economic and environmental constraints.

3.2. ENGINEERING DISCUSSION AND “TRADE-OFF” ANALYSIS

A detailed analysis of the optimization results indicates a high degree of mathematical convergence; however, the distribution of values across specific criteria reveals an important trade-off. While the overall fitness score is optimized, the Machine Age criterion achieved a normalized value of 0.061, which is significantly lower than the other three criteria.

This outcome is not an algorithmic inconsistency but rather a transparent reflection of the defined objective function. Given that the economic criterion (Cost) was assigned a dominant weight of 55.8%, the Genetic Algorithm prioritized solutions with lower hourly rates. From a strictly optimization-oriented perspective, the model performed correctly by identifying that the financial gains from older machinery outweigh the marginal penalties in other areas within the current weighted sum.

However, from an on-site engineering and supervision standpoint, this result highlights the inherent sensitivity of the model to weight distribution:

- Reliability vs. Economy: The selection of older machinery, while economically efficient in the model, introduces a higher probability of unscheduled downtime, which can impact the stability of the entire production line. [13]
- Operational Sensitivity: In a linear production chain, even minor performance deviations in one unit can propagate, potentially affecting the overall project deadline.

These results align with real-world industry trends where decision-making is frequently driven by the lowest bid price, sometimes at the expense of long-term operational reliability [1]. The analysis suggests that the current model effectively explores the solution space, but also indicates that the "ideal" fleet configuration is highly dependent on the initial weight calibration. Therefore, rather than changing the algorithm, future practical applications should focus on fine-tuning the weight ratios or introducing stricter boundary conditions for age-sensitive projects to ensure a more balanced distribution across all performance indicators.

4. CONCLUSION

This study successfully demonstrated the application of a hybrid AHP-GA model for optimizing the selection of construction machinery. By integrating the Analytic Hierarchy Process for weight determination with Genetic Algorithms for combinatorial optimization, the model provides a robust decision-making framework that transcends subjective assessment in favor of exact mathematical evaluation [2],[6].

The main findings of the research indicate the following:

- Algorithmic Efficiency in Large Solution Spaces: The implemented Genetic Algorithm proved to be an exceptionally effective tool for navigating complex environments with a vast number of potential machine combinations. It allows for the rapid identification of optimal fleet configurations that would be statistically impossible to derive through manual calculation.

- Multi-Criteria Synergy: The model successfully balanced four conflicting criteria while strictly adhering to the required productivity threshold. This demonstrates the algorithm's capability to maintain operational requirements while simultaneously optimizing for cost, environmental impact, and service ratings [12].
- Operational Flexibility and Data Processing: A key strength of the model is its ability to process large machine databases and extract solutions that align precisely with the user's defined priorities. The results highlight that the GA can effectively identify trade-offs within the search space, providing engineers with a transparent overview of how different criteria weights influence the final fleet composition.

The primary contribution of this work is the development of a tool that allows engineers to eliminate technically inadequate solutions through integrated "penalty functions." This makes the model directly applicable for large-scale project bidding and site planning where precision and speed are paramount [7],[8]. Future research could focus on further refining the decision-making balance by introducing multi-criteria ranking methods, such as TOPSIS, to harmonize the distribution across all criteria and ensure that no single parameter disproportionately influences the final selection.

While the results confirm the theoretical validity of the model, the next essential step is its application to a concrete case study under real market conditions. Further empirical testing on a live project will be necessary to fully quantify the system's benefits and validate its practical applicability within the dynamic environment of the construction industry.

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