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# Contractor Selection Criteria for Building Refurbishment Projects through Genetic Algorithm (GA)

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**Abstract**
The objective of this study is to determine the most ideal composition of criteria to be considered by project owners in selecting specialized contractors for architectural and MEP (Mechanical, Electrical, and Plumbing) renovation works in existing buildings. This research also aims to explore the structure and stages of implementing the Genetic Algorithm (GA) method in the context of optimizing contractor selection criteria, specifically for architectural and MEP repair works. The study was conducted through GA-based analysis utilizing both secondary data (literature review) and primary data (respondent questionnaires). The results of GA for evaluating Architectural criteria indicate that Work Quality and Project Comprehension emerged as the dominant criteria from both the historical (secondary) perspective and the viewpoint of field stakeholders (primary). Meanwhile, the GA result for MEP criteria evaluation revealed that Work Quality and Personnel Competencies were consistently identified as key criteria across both data perspectives. The application of the Genetic Algorithm (GA) in this study has proven effective in evaluating and determining the optimal weights for each contractor selection criterion in building refurbishment projects. The GA parameters used in this study included an initial population of 150 individuals, 5000 generations, a crossover rate of 0.5 using the arithmetic crossover method, and an adaptive mutation rate set at 0.8 in the early generations, 0.5 in the mid generations, and 0.05 in the final generations—using random mutation. The selection process employed the Stochastic Universal Sampling (SUS) method.

**Keywords:** Genetic Algorithm (GA), Contractor Selection, Renovation Works, Building Refurbishment Project

## Introduction

The building refurbishment sector is one of the most critical sectors in many developed countries. The European standard defines refurbishment as the modification and improvement of existing buildings to bring them into an acceptable condition. The building refurbishment encompasses a wide range of activities, including improvement, renovation, alteration, conversion, extension, and modernization of existing buildings, but excludes routine maintenance and cleaning works. This activity includes extending, adding to, repairing, enhancing, or upgrading the structure and form of a building, thereby maintaining its aesthetic appeal, increasing its value, and improving its functionality. The process not only restores the physical condition of a building to make it more visually appealing and clean but also enhances its commercial value, improves user comfort, and ensures compliance with current regulatory standards.

Refurbishment projects are generally more complex and unpredictable than new construction projects. Additionally, they often require a higher demand for specialized labor. Other challenges include limited space, higher occupational risks, and the frequent presence of the project owner during the construction process.

In terms of task specification, refurbishment projects are typically unique, tailored to the specific needs of the end user, and differ significantly from new building projects. Their implementation demands greater attention and care, as such projects often take place in operational buildings where daily business activities must continue uninterrupted. Consequently, the refurbishment process must be carefully managed to ensure that ongoing operations are not disrupted by construction activities, and in many cases, it is the project that must adapt to the operational requirements—not the other way around.

The quality performance of a building refurbishment project refers to how well the project meets the established quality standards. This encompasses several aspects, including specification compliance, process efficiency, customer satisfaction, and adherence to relevant regulations. In practice, although technical specifications are typically well-defined, quality deviations frequently occur during project execution, resulting in buildings that do not fully meet the required quality standards.

Quality is commonly defined as the degree of customer satisfaction and the extent to which project outcomes fulfill the prescribed standards. It is also characterized by meeting client requirements, minimizing defects, and reducing the need for rework. Defects hinder the functional performance of buildings and negatively impact client satisfaction.

Several studies have been conducted to identify the causes of quality failures in building refurbishment projects. Hughes (2014) [24] investigated that poor supervisory competence and incomplete design drawings were major contributing factors. Love (2017) identified quality failures as being associated with the inefficient use of technology, excessive client involvement in renovation activities, the absence of clear work procedures, and insufficient change management. Aiyetan (2013) [2] highlighted causes such as inadequate communication, incomplete construction planning, ineffective management, lack of personnel experience, and poor concrete quality.

A significant number of quality-related issues arise from poor workmanship. For example, walls may be installed unevenly, with visible undulations, large gaps, and rough finishes, not only the building's functionality and aesthetics but also requiring additional corrective work, which results in increased time and cost. Other issues include the use of low- quality paint or roofing materials, leading to roof leaks or peeling paint shortly after project completion. Furthermore, discrepancies between the outcome and the design expectations of the project owner are frequently reported, such as changes in flooring materials, wall or ceiling finishes, lighting fixtures, and other architectural details. These discrepancies often stem from material limitations or variations in installation techniques, ultimately leading to owner dissatisfaction and additional costs.

In apartment renovations, particularly in MEP-HVAC (Mechanical, Electrical, Air Conditioning, and Plumbing) systems, problems such as poorly functioning air conditioning units have been reported, resulting in uncomfortable indoor temperatures and disruption of building operations. Inaccurate or untidy installation of piping systems may also lead to leaks and structural damage. These examples indicate that project-related quality problems frequently occur in both architectural and MEP works. However, a comprehensive review shows that architectural works tend to generate a greater number of issues compared to MEP-related tasks.

**Urgency of Contractor Evaluation**

Refurbishment projects are more challenging to manage compared to new construction. Subcontractors play a critical role in the successful execution of such projects. However, current knowledge regarding effective subcontractor selection techniques for building refurbishment remains limited. There is a clear need for a more comprehensive set of selection criteria beyond cost alone. Marzouk (2013) emphasized that improper selection of contractors and subcontractors can lead to numerous issues throughout the course of the project.

The selection process of contractors for refurbishment projects in existing buildings requires special attention, as all project activities must be carried out without disrupting daily operations. Buildings that require development, renovation, or replacement often possess complex structural and system conditions, such as aging electrical, plumbing, and HVAC systems, which demand a high level of caution. Contractors must have prior experience working with existing conditions that are not always ideal. They must also be capable of operating within existing constraints without damaging the current structural integrity.

Moreover, to minimize operational disruptions, contractors should be equipped with the ability to control noise levels and other disturbances, such as unpleasant odors, dust, and emissions resulting from chemicals or construction equipment, to ensure the comfort of building occupants. Work hours must also be managed effectively to avoid interference with ongoing business activities. Risk management and occupant safety must be prioritized to protect both the building users and construction workers throughout the renovation process. Therefore, selecting contractors with relevant experience, proven risk management skills, and the ability to coordinate with various stakeholders is essential to the success of building refurbishment projects.

**Genetic Algorithm (GA) Method**

The Genetic Algorithm (GA) method is employed to determine the optimal weights of contractor selection criteria. This approach is aligned with the study conducted by Banwet (2014) [4], which compared the Analytical Hierarchy Process (AHP) and Genetic Algorithm for raw material selection in the textile industry in India. The study concluded that experienced decision-makers play a significant role in determining criterion weights within the AHP method. However, GA can be utilized as an optimization tool to derive the most optimal combination of weights to maximize the correlation coefficient between cotton quality and yarn strength. The conclusion indicated that GA was the most effective and validated method, especially when applied across various yarn quantity scenarios.

In a comparative study of constraint programming and genetic algorithm conducted by Nafis (2020), it was found that GA outperformed constraint programming in terms of cost scope and the time required to obtain optimal percentage outcomes. According to Krisnandi (2017), GA is highly suitable for solving complex problems that are difficult to address using conventional methods. Sitompul (2014) further emphasized that GA excels in finding optimal solutions for nonlinear problems, both constrained and unconstrained, and is considerably less complex than gradient-based methods.

In a course scheduling case study by Mone (2021), GA was demonstrated to be robust and highly applicable across a variety of problem domains. Similarly, in a study on inventory prediction of gas cylinders, Sulistiani (2017) concluded that GA achieved an average error percentage of 4.1%, indicating an accuracy level of approximately 95.4%.

Contractor Selection Criteria Several studies have indicated that the selection criteria for architectural contractors tend to be more diverse compared to those for MEP (Mechanical, Electrical, and Plumbing) contractors. Factors influencing contractor selection included current workload, experience, managerial capability, and project duration. These factors suggest that the selection of architectural contractors involves a broad range of managerial and operational considerations. In contrast, in the context of MEP works, contractor selection criteria tend to focus more narrowly on technical and specific aspects, such as technical capability, contractor experience, management skills, financial capacity, past project performance, previous client and supplier relationships, reputation, and occupational health and safety (OHS) compliance.

This distinction highlights that architectural contractor selection typically involves broader and more diverse criteria encompassing managerial and operational aspects, while MEP contractor selection emphasizes technical and system-specific qualifications related to mechanical, electrical, and plumbing systems.

In building refurbishment projects related to architecture, contractor selection criteria often include completeness of bidding documents, company legality, partnership status, tax compliance, financial balance sheet, understanding of project characteristics, technical analysis, construction method, specification details, quantity of rented and owned equipment, availability of skilled and technical personnel, company experience, client satisfaction, cost alignment, and schedule compatibility. According to Hartono *et al.* (2016) [19] and Suwandari (2021), the contractor's experience—particularly in similar types of projects—holds the highest weight, followed by the availability of skilled and technical personnel. Meanwhile, Hasanti and Rochman (2023) [21] found that schedule compatibility ranks second in importance after experience in similar projects. Khoso and Yusof (2019) argued that there is no specific decision-making technique for contractor selection, but appropriate selection and a clear understanding of the problems at hand are crucial. The application of a specific technique depends on the number of criteria, the nature of the information involved, and the accuracy of the data.

In MEP works, contractor selection indicators include company financial status, work quality, company experience, availability of equipment, company legality, maintenance planning, human resource management, and understanding of OHS and environmental requirements. According to Roundini (2015), understanding of occupational health, safety, and environmental concerns carries the highest weight, followed by human resource management, which includes the availability of skilled and technical personnel. In contrast, Supriyono (2020) emphasized that the most critical factor is the availability of MEP- specific equipment, followed by HR management aspects. On the other hand, Zubair (2024) [28] concluded that the most significant factor is company legal compliance, followed by the quality of MEP work.

**Contractor Selection Process**

In the contractor selection process in Libya, tender submissions are required to account for all associated costs, including tender documentation fees, delivery transportation, procurement, insurance, and applicable taxes. The tender price must be quoted in Libyan currency and written both in numerals and in words. Predefined technical specifications may be submitted in a separate document, provided they are attached along with the technical proposal. Furthermore, priority is given to bidders who fulfill requirements related to the use of local labor, equipment, machinery, and materials. Finally, to prepare a realistic bid, contractors are expected to visit the project site, investigate the actual on-site conditions, and consider all relevant data (Elsayah, 2016).

The contractor selection process begins with a pre-qualification stage involving the collection of documentation from prospective contractors, such as company legality, financial statements, human resource readiness, and equipment preparedness plans. In addition, contractors are required to complete a pre-qualification form to assess their suitability for the specific project type, in accordance with its respective occupational health and safety (OHS) risk level. The subsequent phase is the evaluation stage, which entails a comprehensive assessment and scoring of both technical and non- technical aspects. The evaluation of technical aspects should be conducted first, followed by the evaluation of non-technical factors.

**Contractor Classification**

Based on business qualifications as regulated in detail by Government Regulation No. 5 of 2021, contractor classifications include small-scale contractors (K1, K2, K3), intended for firms with limited capacity and typically designated for local enterprises; medium-scale contractors (M1, M2), which are capable of handling medium-scale construction projects; and large-scale contractors (B1, B2), which have the capacity to execute large- scale and high-technology projects, including government infrastructure projects.

In this study, the author evaluates the selection criteria for contractors providing integrated services (both design and execution) for building construction and MEP (Mechanical, Electrical, and Plumbing) installation works. Based on business classifications, the research focuses on contractors categorized as small and medium enterprises (K1, K2, K3, M1, and M2). This focus is because quality performance issues are more frequently observed in renovation projects involving small and medium-scale contractors. Large- scale contractors are generally involved in high-risk projects and are typically appointed through direct selection.

**Research Variables**

Research variables are measurable and observable factors within a study. These variables are used to describe the elements that are intended to be analyzed or tested in the research. In a study, variables play a crucial role as they help the researcher understand the relationships among various factors involved. This study involves several research variables, as presented in Table 1.

**Table 1:** Research Variables and Indicators

| | Variables & Indicators | Source |
|---|---|---|
| X | Independent Variables | |
| X1 | Architectural Contractor Selection Criteria | |
| X1.1 | Company legality | (Gunawan, 2019; Fauzan, 2020) [15, 13] |
| X1.2 | Client satisfaction / work quality | (Lestari, 2018; Lubis, 2020) |
| X1.3 | Tax compliance | (Torgler, 2006) |
| X1.4 | Cost suitability | (Mahamid, 2013) |
| X1.5 | Technical specification | (Moseley, 2014; Caldas, 2008 [7]; Yuan, 2011, Sullivan, 2003) |
| X1.6 | Number of rented equipment | (Doloi, 2010; Zhang, 2007; Bassioni, 2008 [5]) |
| X1.7 | Schedule adherence | (Cohen, 2009 [9]; Kerzner, 2013; Mousavi, 2014) |
| X1.8 | Company balance sheet | (Chang, 2004 [8]; Ogunlana, 2008; Hwang, 2013) |
| X1.9 | Corporate partnerships | (Zaheer, 2005; Kotabe, 2004) |
| X1.10 | Number of owned equipment | (Davis, 2011 [10]; Doloi, 2010; Laryea, 2010; Hwang, 2013) |
| X1.11 | Project comprehension | (Turner, 2009; Kerzner, 2013; Beringer, 2013) |
| | **Variables & Indicators** | **Source** |
| X1.12 | Administrative compliance (bid documents) | (Mollah, 2012; Gunduz, 2012 [16]; Hwang, 2013) |
| X1.13 | Personnel competencies | (Kerzner, 2013; Hwang, 2013; Muller, 2010) |
| X1.14 | Previous work experiences | (Muller, 2010; Hwang, 2013; Mollah, 2012) |
| X1.15 | Execution method | (Kerzner, 2013; Edwards, 2005 [12]) |
| X1.16 | Technical analysis | (Hwang, 2013; Cao, 2014) |
| X2 | MEP Contractor Selection Criteria | |
| X2.1 | HSE awareness | (Zhang, 2011 [26]; Jarkas, 2015; Cohen, 2009 [9]) |
| X2.2 | HR Management / personnel competencies | (Becker, 2006 [6]; Kaufman, 2010; Noe, 2017) |
| X2.3 | Company legality | (Siahaan, 2016; Sudiana, 2017; Fitriani, 2014 [14]; Haryanto, 2018 [20]; Wahyuni, 2015) |
| X2.4 | Maintenance commitment (warranty) | (Sita, 2016; Zebua, 2016) |
| X2.5 | Client satisfaction / work quality | (Davis, 2012; Agarwal, 2012 [1]; Javadian, 2013) |
| X2.6 | Company balance sheet | (Harris, 2013 [17]; Harrison, 2011 [18]; Shen, 2014) |
| X2.7 | Equipment availability | (Harris, 2013; Alwi, 2003) [17, 3] |
| X2.8 | Previous experiences | (Mahamid, 2013; Zhang, 2011 [26]) |
| Y | Dependent Variable | |
| Y1 | Quality Performance | (Jarkas, 2015; Hwang, 2013; Shen, 2014; Mahamid, 2013) |

**Method**

The research approach was conducted by developing a structured Python-based Genetic Algorithm (GA) experiment in a step-by-step manner. Each experiment was designed to represent the core components of the GA in the context of optimizing the weight composition of contractor selection criteria in relation to improving project quality performance. The key GA parameters employed as research instruments include population size, selection method, crossover method, crossover rate, mutation method, mutation rate, number of generations, and termination criteria.

The population size was set at 150 individuals for both the secondary data (RQ3) and the primary data (RQ4). This value was chosen based on the best practices in the literature, which suggest that a population size of 150 provides a balance between solution diversity (exploration) and computational efficiency (exploitation) in multi-criteria problems. The data processing was carried out using Python software and the following computations were obtained:

```
# Fungsi GA
def initialize_population(n, size):
return [np.random.dirichlet(np.ones(n)) for _ in range(size)]
```

The selection method employed was Stochastic Universal Sampling (SUS), due to its advantages in maintaining proportional distribution based on fitness values and ensuring that each individual has a fair chance of being selected. SUS is also effective in preserving population diversity and preventing the dominance of certain individuals. The data processing was carried out using Python software and the following computations were obtained:

```
# Fungsi GA
def stochastic_universal_sampling(pop, fits):
total_fit = sum(fits)
pointer_distance = total_fit / len(pop)
start_point = random.uniform(0, pointer_distance)
pointers = [start_point + i * pointer_distance for i in range(len(pop))] selected = []
cumulative_fitness = 0
i = 0
for pointer in pointers:
while cumulative_fitness < pointer: cumulative_fitness += fits[i] i += 1
selected.append(pop[i - 1]) return selected
```

The type of crossover used was Arithmetic Crossover, which produces offspring as linear combinations of two parents. This method was selected because it aligns with the real-valued representation of weight criteria and maintains stability across generations. The offspring generated remain within a controlled and realistic solution space. The experiments were conducted using a crossover rate of 0.5, a commonly adopted value in many GA studies. The data processing was carried out using Python software and the following computations were obtained:

```
# Fungsi GA
def arithmetic_crossover(parent1, parent2):
```

```
alpha = random.random()
child1 = alpha * np.array(parent1) + (1 - alpha) * np.array(parent2) child2 = (1 - alpha) * np.array(parent1) + alpha * np.array(parent2) return child1, child2
```

Mutation was performed using a random mutation approach, where specific genes (weights) are randomly replaced with new values within the [0, 1] range. This process is followed by normalization to ensure the total sum of weight remains equal to 1. Random mutation was chosen for its flexibility, ease of implementation, and effectiveness in maintaining solution diversity.

An adaptive mutation strategy was implemented based on the evolutionary phase of the generation. This approach promotes aggressive exploration at the beginning with a mutation rate of 0.8, followed by directed exploitation at 0.5, and stabilizing the best solutions during the final phase with a mutation rate of

0.05. The data processing was carried out using Python software and the following computations were obtained:

```
# Fungsi GA
def adaptive_mutation_rate(gen):
if gen <= 1500:
return 0.8
elif gen <= 3500:
return 0.5 else:
return 0.05

def mutate(weights, rate):
for i in range(len(weights)):
if random.random() < rate:
weights[i] = random.random() return weights / np.sum(weights)
```

The number of generations in this experiment was set at 5000, based on literature suggesting that such a number is sufficient to achieve convergence for complex multi-criteria problems like contractor evaluation, without compromising computational efficiency.

In addition to the maximum number of generations (5000), the following early stopping criteria were also applied: If the best fitness value does not change significantly over 100 consecutive generations, the GA process is terminated early. Fitness convergence is evaluated based on the difference in average fitness between generations being less than ε (e.g., 0.0001). The data processing was carried out using Python software and the following computations were obtained:

```
def run_ga(data, constraint=False):
n_criteria = data.shape[1] - 1
population= initialize_population(n_criteria, POPULATION_SIZE) best_fitness = []
best_weights = None best_score = -np.inf

for gen in range(GENERATIONS):
fitnesses = [fitness_function(ind, data) for ind in population] new_population = []
if max(fitnesses) > best_score:
best_score = max(fitnesses)
best_weights = population[np.argmax(fitnesses)] best_fitness.append(best_score)
selected=stochastic_universal_sampling(population, fitnesses) mutation_rate = adaptive_mutation_rate(gen)
while len(new_population) < POPULATION_SIZE: p1, p2 = random.sample(selected, 2)
if random.random() < CROSSOVER_RATE:

c1, c2 = arithmetic_crossover(p1, p2) else:
c1, c2 = p1, p2

if constraint:
c1 = mutate(apply_constraints(c1), mutation_rate) c2 = mutate(apply_constraints(c2), mutation_rate)
else:
c1 = mutate(c1, mutation_rate) c2 = mutate(c2, mutation_rate)

new_population.extend([c1, c2])
population = new_population[:POPULATION_SIZE]
return best_weights, best_fitness

# --- Load data dari file Excel ---
file_path = "Data Untuk Olah GA 11 May.xlsx"
ars_data = pd.read_excel(file_path, sheet_name="Arsitektur") mep_data = pd.read_excel(file_path, sheet_name="MEP")

# --- Jalankan GA ---
best_weights_ars_uncon, fit_ars_uncon =
        run_ga(ars_data, constraint=False)
best_weights_ars_con, fit_ars_con =
        run_ga(ars_data, constraint=True)
best_weights_mep_uncon, fit_mep_uncon = run_ga(mep_data, constraint=False)
best_weights_mep_con, fit_mep_con =
        run_ga(mep_data, constraint=True)

# --- Tampilkan Hasil Bobot ---
def print_best_result(title, weights, prefix): print(f"\n{title}:")
for i, w in enumerate(weights):
print(f" {prefix}{i+1}: {w:.4f}") max_idx = np.argmax(weights)
print(f"➡ Kriteria {prefix}{max_idx+1} paling berpengaruh terhadap
mutu proyek.")

print_best_result("Bobot Arsitektur (Tanpa
        Kendala)", best_weights_ars_uncon, "X1.")
print_best_result("Bobot Arsitektur (Dengan
        Kendala)", best_weights_ars_con, "X1.")
print_best_result("Bobot MEP (Tanpa Kendala)", best_weights_mep_uncon, "X2.")
print_best_result("Bobot MEP (DenganKendala)", best_weights_mep_con, "X2.")

plot_weights(best_weights_ars_uncon, "Arsitektur
        (Tanpa Kendala)", "X1.")
plot_weights(best_weights_ars_con, "Arsitektur (Dengan Kendala)", "X1.")
plot_weights(best_weights_mep_uncon, "MEP (Tanpa Kendala)", "X2.")
plot_weights(best_weights_mep_con, "MEP (Dengan Kendala)", "X2.")
```

The initial data collection phase was based on secondary data obtained from a literature review. This study focused on the criteria for selecting contractors in building renovation projects. The contractor selection criteria and their corresponding weights were derived through a classification and categorization process conducted by the author, which referred to the PMBOK Guide Sixth Edition and was aligned with the criteria identified in six relevant studies, respectively, for architectural and MEP works.

The second stage of data collection was based on primary data obtained through the distribution of questionnaires to 100 respondents. This study focused on the criteria for selecting contractors in building renovation projects. The weighting of contractor selection criteria was derived by converting the ranking data provided by respondents (ranks 1–16 for architectural works and 1–8 for MEP works) into percentage values, ensuring that the total weight for each set of criteria (architectural and MEP) summed to 100%.

The respondents consisted of practitioners involved in building refurbishment projects, serving in various professional roles. These included procurement project personnel responsible for the overall procurement scope, and project engineers overseeing renovation needs in civil works, mechanical, electrical, plumbing, HVAC (Heating, Ventilation, and Air Conditioning), waste treatment, power supply, and fire safety systems. The projects handled by the respondents involved activities such as pipe rerouting, chiller line additions or replacements, and other infrastructure improvements.

Additional data was collected from respondents working in project development, whose responsibilities included enhancing building facilities such as installing canopies, gates, and landscaping elements. Other respondents were from the fitting-out division, responsible for replacing tenants or shops within shopping centers and renovating rooms for new occupants in office or apartment settings. Respondents in project operations were responsible for areas such as building signage, door function modifications, and LED screen installations on structural columns. Meanwhile, those in parking security projects were involved in procuring basement signage, directional indicators, parking guidance lights, and security detectors.

The secondary data was subsequently analyzed using the Genetic Algorithm (GA) based on the predetermined parameters. Meanwhile, the primary data was first subjected to a normality test before proceeding to the GA analysis using the same parameters as applied to the secondary data.

## Results and Discussion

From secondary data of architecture criteria, GA processing was carried out using the Python software and the following results were obtained:

**Table 2:** Results of Architectural Contractor Selection Criteria (secondary: Literature review)

| | Criteria | GA Constraint | Rank | Final Weights |
|---|---|---|---|---|
| X1.2 | Client satisfaction / work quality | 0.6288 | 1 | 62.88% |
| X1.4 | Cost suitability | 0.1575 | 2 | 15.75% |
| X1.11 | Project comprehension | 0.0862 | 3 | 8.62% |
| X1.14 | Previous work experiences | 0.0281 | 4 | 2.81% |
| X1.9 | Corporate partnerships | 0.0252 | 5 | 2.52% |
| X1.5 | Technical specification | 0.0179 | 6 | 1.79% |
| X1.8 | Company balance sheet | 0.0174 | 7 | 1.74% |
| X1.7 | Schedule adherence | 0.0079 | 8 | 0.79% |
| X1.13 | Personnel competencies | 0.0072 | 9 | 0.72% |
| X1.12 | Administrative compliance (bid documents) | 0.0066 | 10 | 0.66% |
| X1.16 | Technical analysis | 0.0046 | 11 | 0.46% |
| X1.6 | Number of rented equipment | 0.004 | 12 | 0.40% |
| X1.15 | Execution method | 0.0031 | 13 | 0.31% |
| X1.10 | Number of owned equipment | 0.0025 | 14 | 0.25% |
| X1.1 | Company legality | 0.0017 | 15 | 0.17% |
| X1.3 | Tax compliance | 0.0013 | 16 | 0.13% |

From primary data of architecture criteria, GA processing was carried out using the Python software and the following results were obtained:

**Table 3:** Results of Architectural Contractor Selection Criteria (primary: Stakeholders' viewpoint)

| | Criteria | GA Constraint | Rank | Final Weights |
|---|---|---|---|---|
| X1.2 | Client satisfaction / work quality | 0.4966 | 1 | 49.66% |
| X1.16 | Technical analysis | 0.2309 | 2 | 23.09% |
| X1.11 | Project comprehension | 0.1216 | 3 | 12.16% |
| X1.1 | Company legality | 0.0787 | 4 | 7.87% |
| X1.15 | Execution method | 0.0387 | 5 | 3.87% |
| X1.13 | Personnel competencies | 0.0159 | 6 | 1.59% |
| X1.10 | Number of owned equipment | 0.0049 | 7 | 0.49% |
| X1.14 | Previous work experiences | 0.0022 | 8 | 0.22% |
| X1.4 | Cost suitability | 0.0017 | 9 | 0.17% |
| X1.9 | Corporate partnerships | 0.0017 | 10 | 0.17% |
| X1.5 | Technical specification | 0.0015 | 11 | 0.15% |
| X1.12 | Administrative compliance (bid documents) | 0.0015 | 12 | 0.15% |
| X1.8 | Company balance sheet | 0.0014 | 13 | 0.14% |
| X1.7 | Schedule adherence | 0.0012 | 14 | 0.12% |
| | **Criteria** | **GA Constraint** | **Rank** | **Final Weights** |
| X1.3 | Tax compliance | 0.0008 | 15 | 0.08% |
| X1.6 | Number of rented equipment | 0.0007 | 16 | 0.07% |

In the secondary data analysis, the Genetic Algorithm (GA) results indicated that the most dominant criterion was "Client satisfaction / quality of work" (X1.2) with a weight of 0.6288, followed by "Cost suitability" and "Project comprehension." Meanwhile, in the primary data, the highest weight was also assigned to "Client satisfaction / quality of work" (X1.2) at 0.4966, followed by "Technical analysis" and "Project comprehension." These findings demonstrate that the aspect of client satisfaction and the quality of project outcomes (X1.2) is consistently viewed as the most crucial criterion in contractor selection, both from the perspective of literature or historical data and from the viewpoint of respondents actively involved in real- world renovation projects. The contractor's reputation in meeting quality expectations serves as a key indicator reflecting their performance in enhancing the quality outcomes of building refurbishment projects. Moreover, the consistent ranking of the "Project comprehension" criterion (X1.11) among the top three across both data sources highlights the importance of a comprehensive technical understanding of the project.
From secondary data of MEP criteria, GA processing was carried out using Python software and the following results were obtained:

**Table 4:** Results of MEP Contractor Selection Criteria (secondary: Literature review)

| | Criteria | GA Constraint | Rank | Final Weights |
|---|---|---|---|---|
| X2.6 | Company balance sheet | 0.6606 | 1 | 66.06% |
| X2.5 | Client satisfaction / work quality | 0.1263 | 2 | 12.63% |
| X2.2 | HR Management / personnel competencies | 0.1217 | 3 | 12.17% |
| X2.7 | Equipment availability | 0.0440 | 4 | 4.40% |
| X2.8 | Previous experiences | 0.0237 | 5 | 2.37% |
| X2.4 | Maintenance commitment (warranty) | 0.0174 | 6 | 1.74% |
| X2.3 | Company legality | 0.0050 | 7 | 0.50% |
| X2.1 | HSE awareness | 0.0013 | 8 | 0.13% |

From primary data of MEP criteria, GA processing was carried out using the Python software and the following results were obtained:

**Table 5:** Results of MEP Contractor Selection Criteria (primary: Stakeholders' viewpoint)

| | Criteria | GA Constraint | Rank | Final Weights |
|---|---|---|---|---|
| X2.5 | Client satisfaction / work quality | 0.4928 | 1 | 49.28% |
| X2.2 | HR Management / personnel competencies | 0.3927 | 2 | 39.27% |
| X2.3 | Company legality | 0.0505 | 3 | 5.05% |
| X2.8 | Previous experiences | 0.0256 | 4 | 2.56% |
| X2.4 | Maintenance commitment (warranty) | 0.0187 | 5 | 1.87% |
| X2.7 | Equipment availability | 0.0082 | 6 | 0.82% |
| X2.1 | HSE awareness | 0.0066 | 7 | 0.66% |
| X2.6 | Company balance sheet | 0.0049 | 8 | 0.49% |

In MEP (Mechanical, Electrical, and Plumbing) works, the results from the secondary data indicate the dominance of "Financial stability / company balance sheet" (X2.6) with a weight of 0.6606, followed by "Client satisfaction / quality of work" and "Human resource management." Meanwhile, the primary data shows that "Client satisfaction / quality of work" (X2.5) is the most dominant criterion, with a weight of 0.4928, followed by "Human resource management" and "Company legality." These findings reaffirm that client satisfaction and the quality of work remain key indicators in the selection of MEP contractors, especially from the perspective of on-site practitioners (primary data). On the other hand, from a historical data standpoint, the contractor's financial stability is considered the most critical aspect, reflecting the importance of financial capability in ensuring the smooth execution of technically complex and high-cost projects such as MEP-HVAC systems. Furthermore, the consistent presence of human resource management among the top three criteria in both perspectives highlights that the success of MEP projects is highly dependent on the contractor's ability to manage skilled personnel, given the technical expertise and interdisciplinary coordination required in such works.
Based on this study, it can be concluded that all Genetic Algorithm (GA) parameters employed are ideal and appropriate for both secondary data (small-scale) and primary data (large-scale). The adopted approach effectively accommodates the need for exploration and exploitation of the solution space in a computationally efficient manner. The selection of these parameters aligns with best practices in GA literature and has demonstrated the ability to produce optimal and stable solutions in the context of contractor selection criteria evaluation for building renovation projects. This finding is consistent with the study by Rashidi *et al*. (2017), which emphasized that the use of an adequate population size, sufficiently long generations, and the application of adaptive selection and mutation methods play a crucial role in enhancing GA performance in multi-criteria contractor selection modeling. Furthermore, Zavadskas *et al*. (2012) highlighted that the implementation of GA in data processing—both small- and large-scale—is highly effective when the algorithm is structured with flexible and adaptive parameters tailored to data complexity. Therefore, the parameter configuration applied in this research reflects a population-based optimization strategy that is both theoretically grounded and empirically validated.

## Conclusion

The implementation of the Genetic Algorithm (GA) method for evaluating architectural criteria revealed that Client Satisfaction / Work Quality and Project Comprehension emerged as the dominant criteria, both from the perspective of historical studies (secondary data) and actual stakeholders in the field (primary data). Meanwhile, the GA implementation for evaluating MEP (Mechanical, Electrical, and Plumbing) criteria identified Client Satisfaction / Work Quality and Human Resource Management, including the availability of skilled personnel, as the most dominant criteria from both historical (secondary) and practical (primary) viewpoints. The GA process was conducted iteratively and terminated upon reaching the 5000th generation. The application of constraint handling on the weights ensured that the total sum of weights remained equal to 1 ($\sum wi = 1$), in accordance with the principles of weighting criteria. This approach guarantees that the output weights remain proportional and consistent, making the results valid and applicable for both secondary (literature-based) and primary (respondent-based) data.

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