Genetical algorithms

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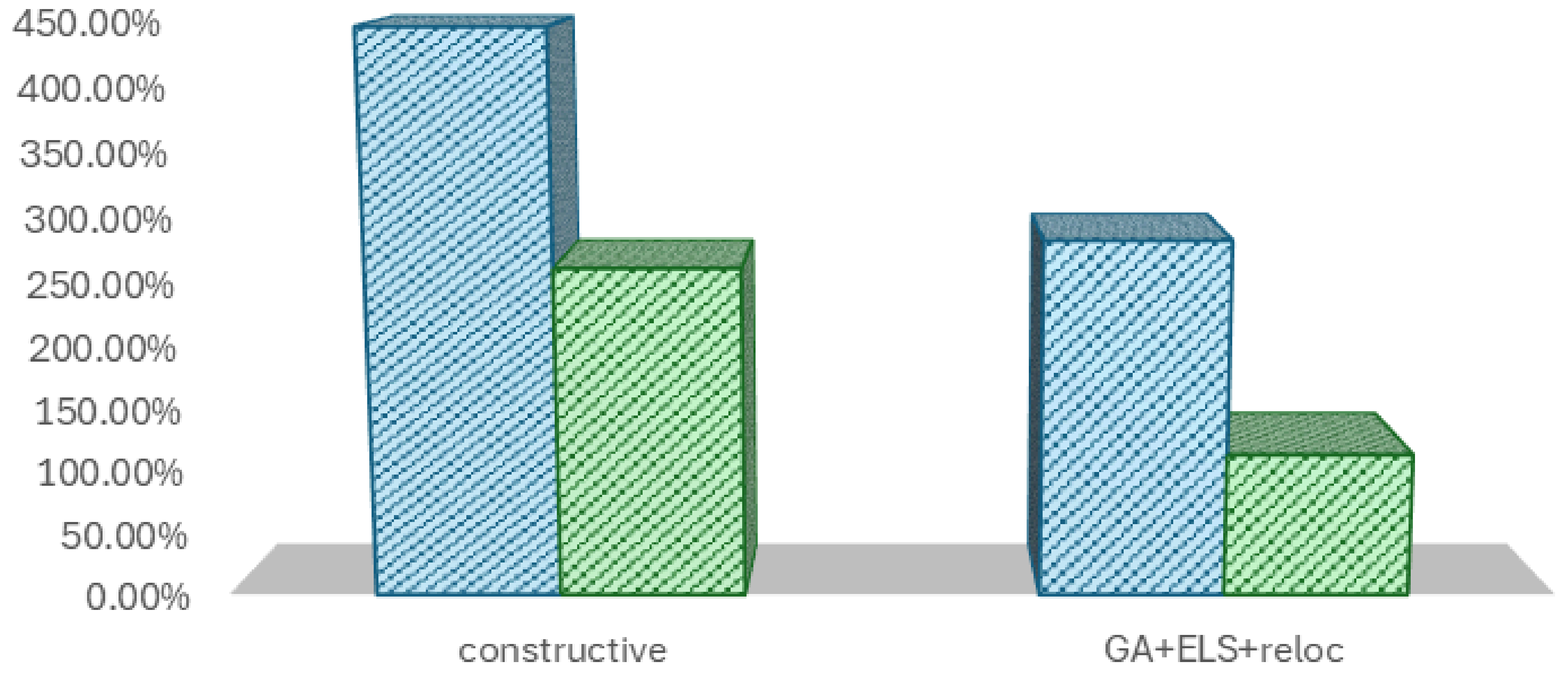
Hybrid Genetic Algorithm

ELS+GA+Relocation best improvement

This hybrid approach combines a Genetic Algorithm (GA) with Evolutionary Local Search (ELS) and a Relocation Best Improvement technique. It is designed to enhance the standard GA by integrating local search for more effective exploration and exploitation of the solution space.

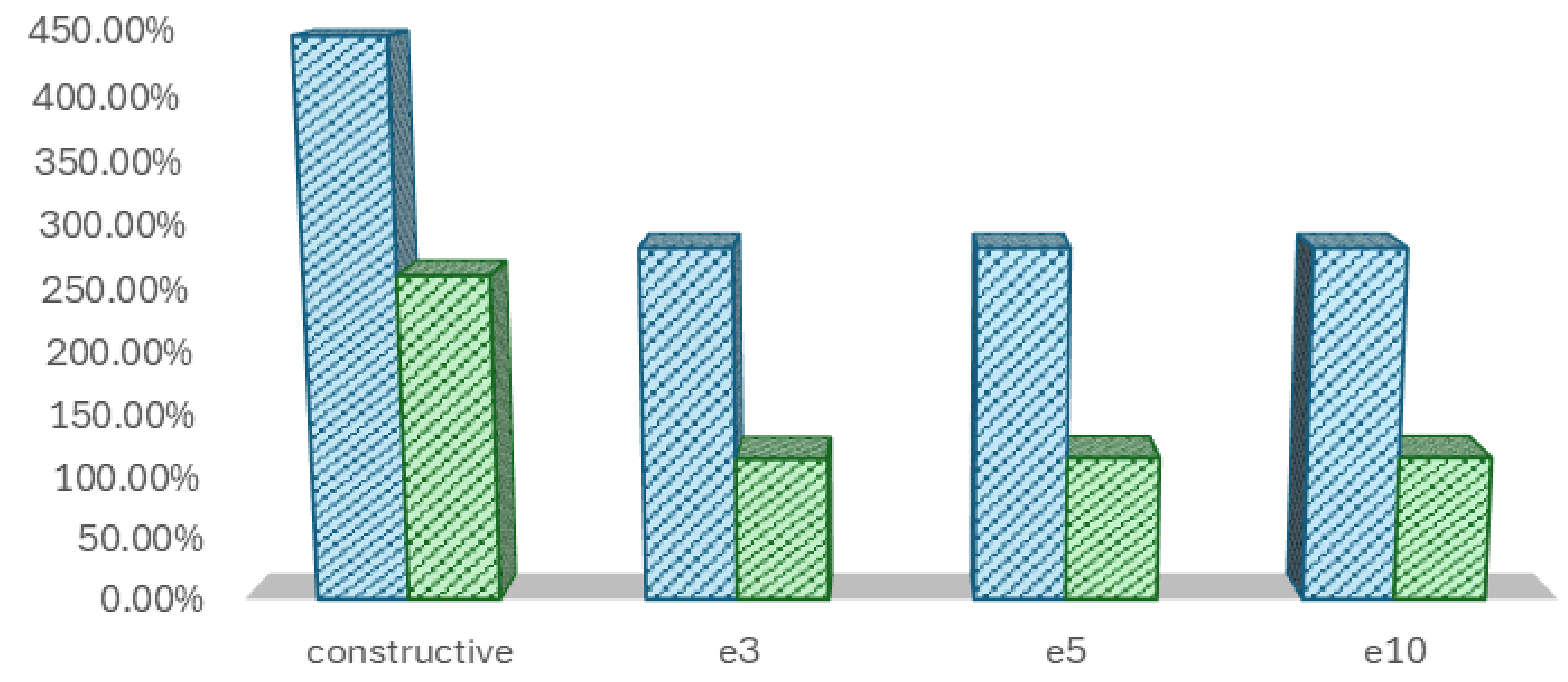
- Genetic Algorithm (GA): Generates initial population, crossover, mutation, and selection operators to explore global solution space.
- Evolutionary Local Search (ELS): Applies local search on selected solutions to intensify search in promising areas.
- Relocation Best Improvement: Evaluates all possible relocations for nodes within routes and selects the one that provides the best improvement to the objective.

Solution



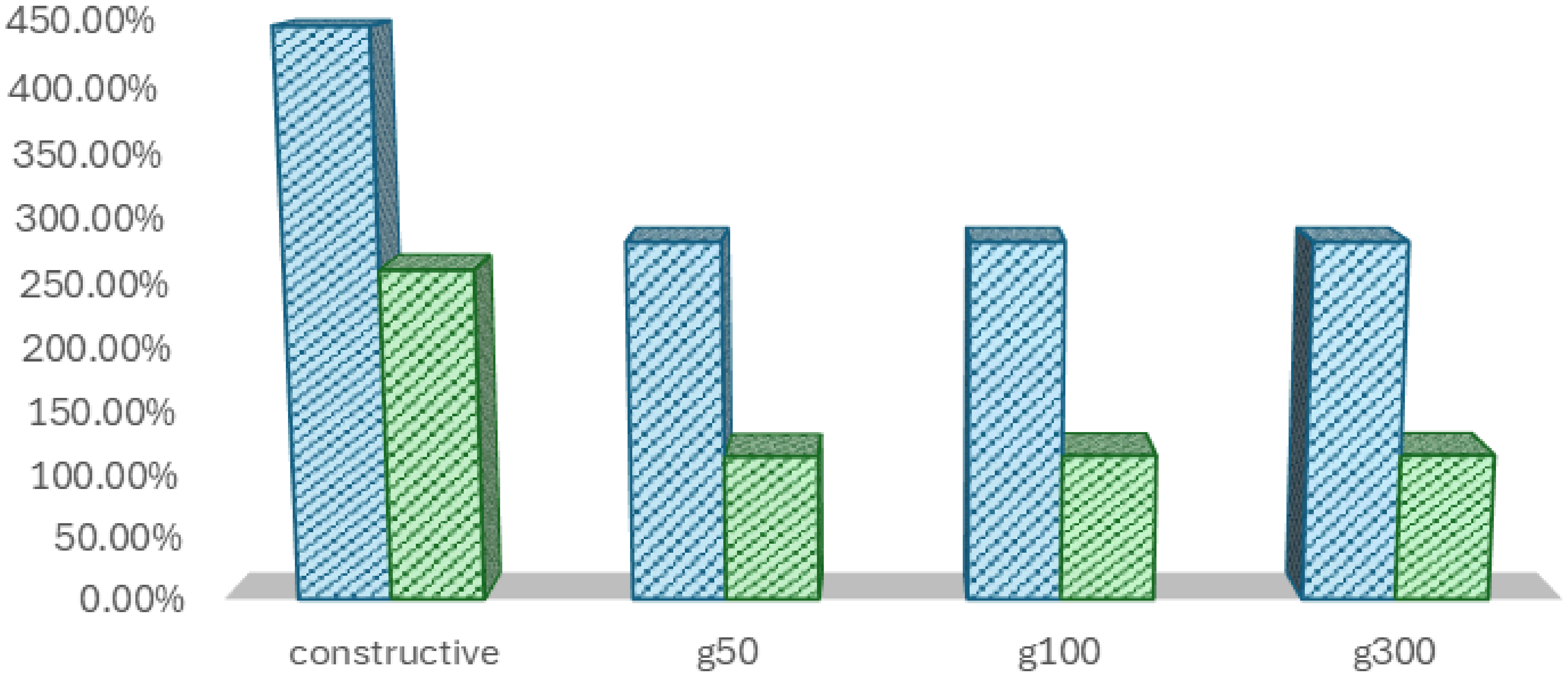
	constructive	GA+ELS+reloc
Vehicle GAP	444.86%	281.84%
Distance GAP	260.08%	113.04%

Elite modifications



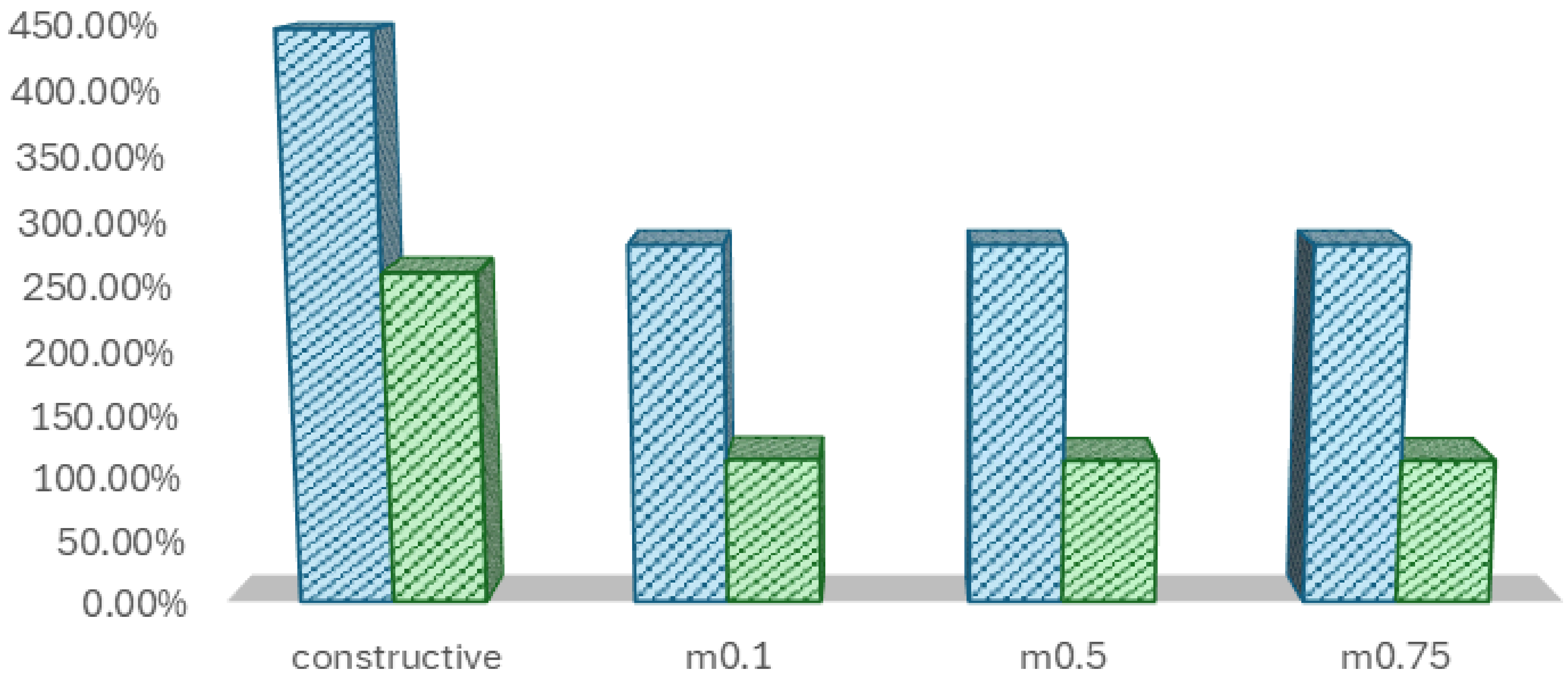
	constructive	e3	e5	e10
vehicle gap	444.86%	281.84%	281.84%	281.84%
distance gap	260.08%	114.38%	115.12%	115.34%

Generations modification



	constructive	g50	g100	g300
vehicle gap	444.86%	281.84%	281.84%	281.84%
Distance GAP	260.08%	114.38%	115.12%	115.34%

Mutation modification



	constructive	m0.1	m0.5	m0.75
Vehicle GAP	444.86%	281.84%	281.84%	281.84%
Distance GAP	260.08%	114.15%	113.32%	113.37%

Conclusions

- The combination of the genetic algorithm with ELS and Relocation Best Improvement has proven highly effective, achieving a notable performance improvement over the initial constructive algorithm. Both the Vehicle Gap and Distance Gap were significantly reduced from 444.86% and 260.08% to 281.84% and 113.04%, respectively, highlighting the potential of this approach for optimization.
- While changing the elite parameters (e3, e5, e10) and the number of generations (g50, g100, g300) did not show large variations in the gaps, the results remained positive, staying around 281.84% and 113.04%. This suggests that a more stable configuration, less dependent on these parameters, can still be effective in optimization.
- Despite modifying the mutation rates (m0.1, m0.5, m0.75), the results remained consistently favorable, with stable gap values. This suggests that the algorithm is robust and adapts well to different mutation settings without compromising overall performance.

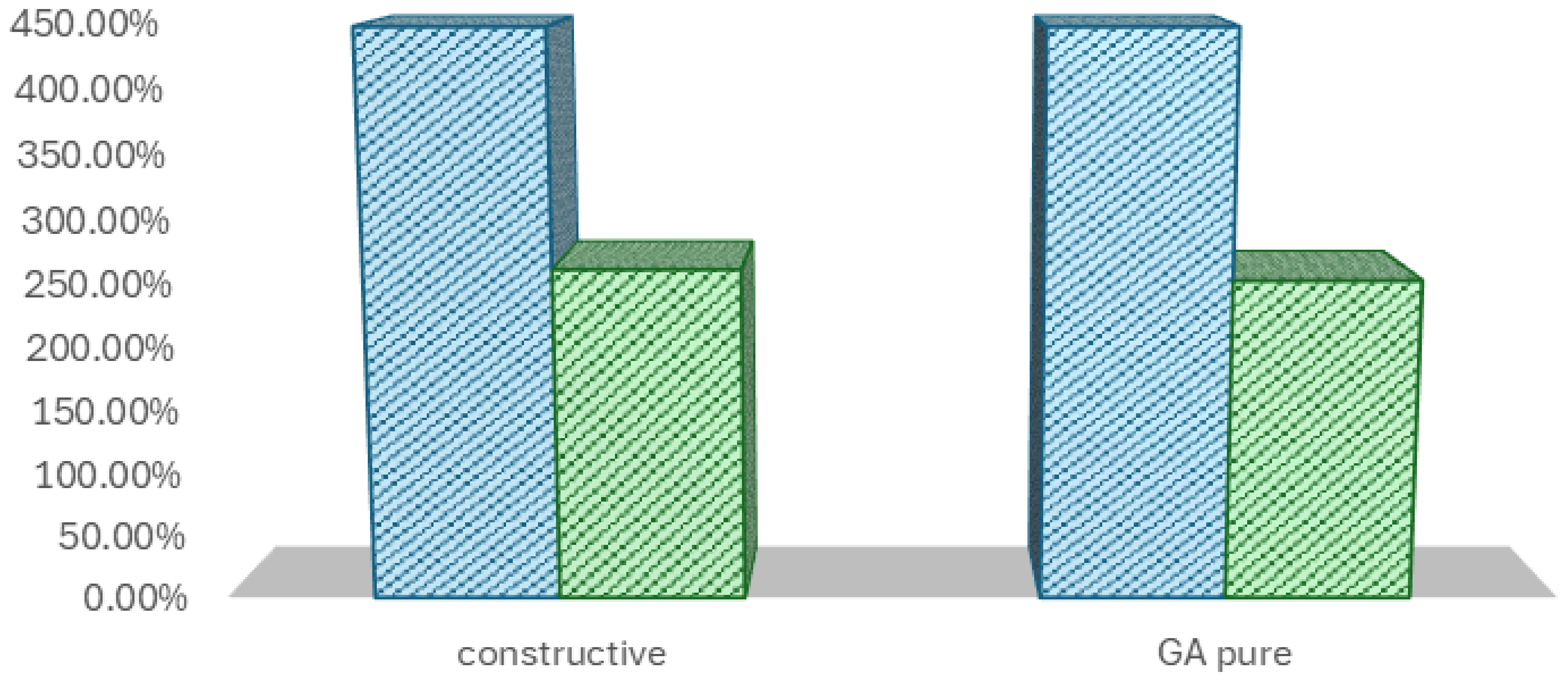
GA pure algorithm

This approach utilizes a Genetic Algorithm (GA) to solve the optimization problem. The GA is designed to efficiently explore the solution space and find high-quality solutions through evolutionary processes.

- Genetic Algorithm (GA): The GA starts by generating an initial population of candidate solutions. Through operators like crossover, mutation, and selection, it iteratively explores the global solution space, aiming to find better solutions in each generation. The algorithm balances exploration (searching broadly) and exploitation (refining promising solutions) to converge towards an optimal or near-optimal solution.

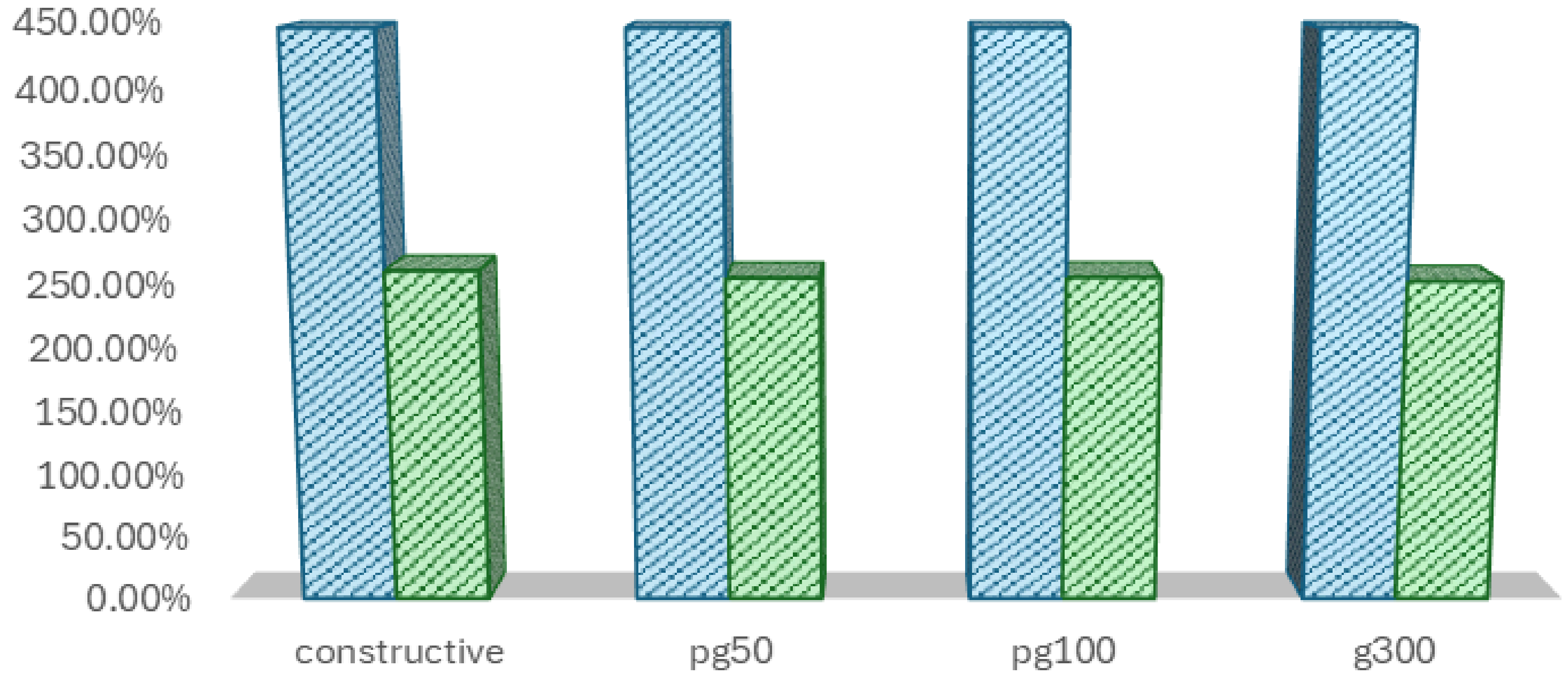
By applying these genetic operations, the algorithm is capable of adapting to complex problem landscapes, offering a flexible and robust solution method for optimization tasks.

GA pure



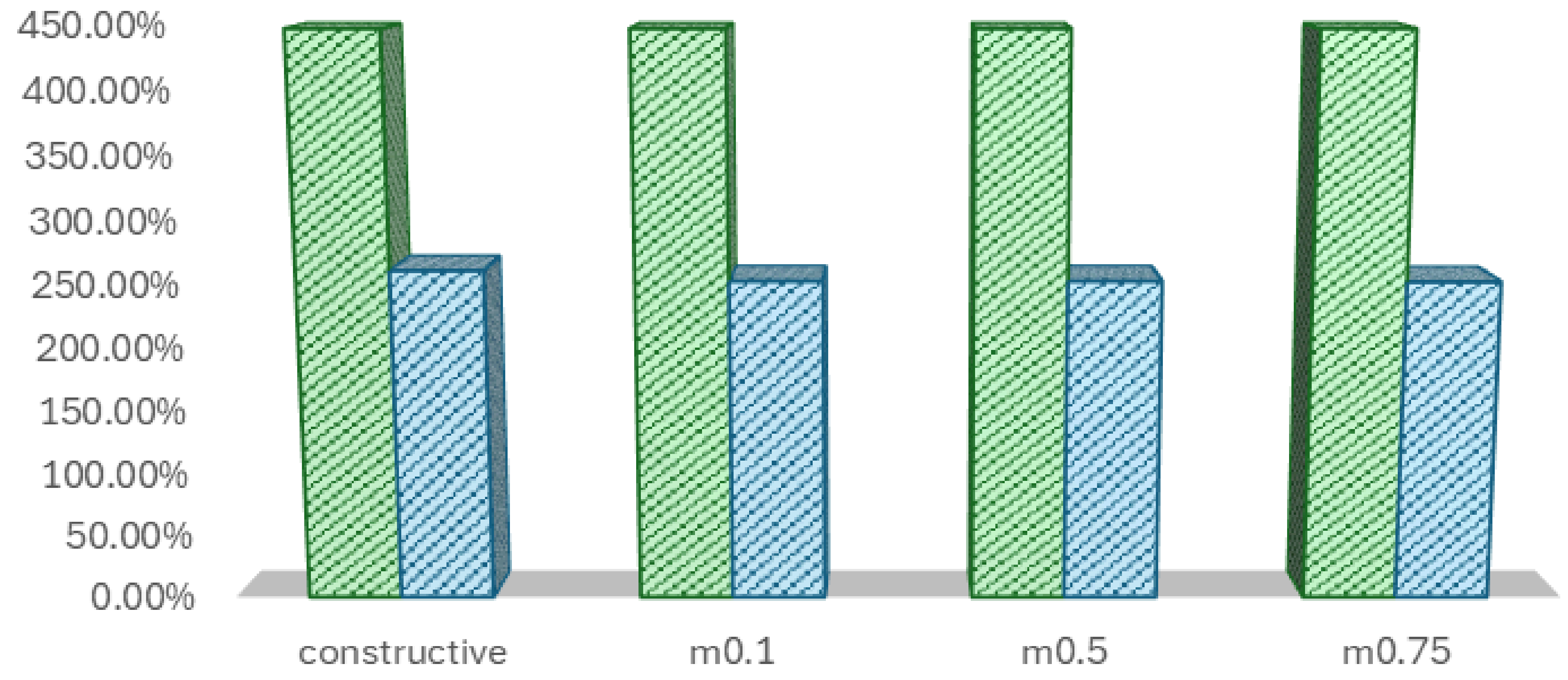
	constructive	GA pure
Vehicle GAP	444.86%	444.86%
Distance GAP	260.08%	251.86%

Generations variation



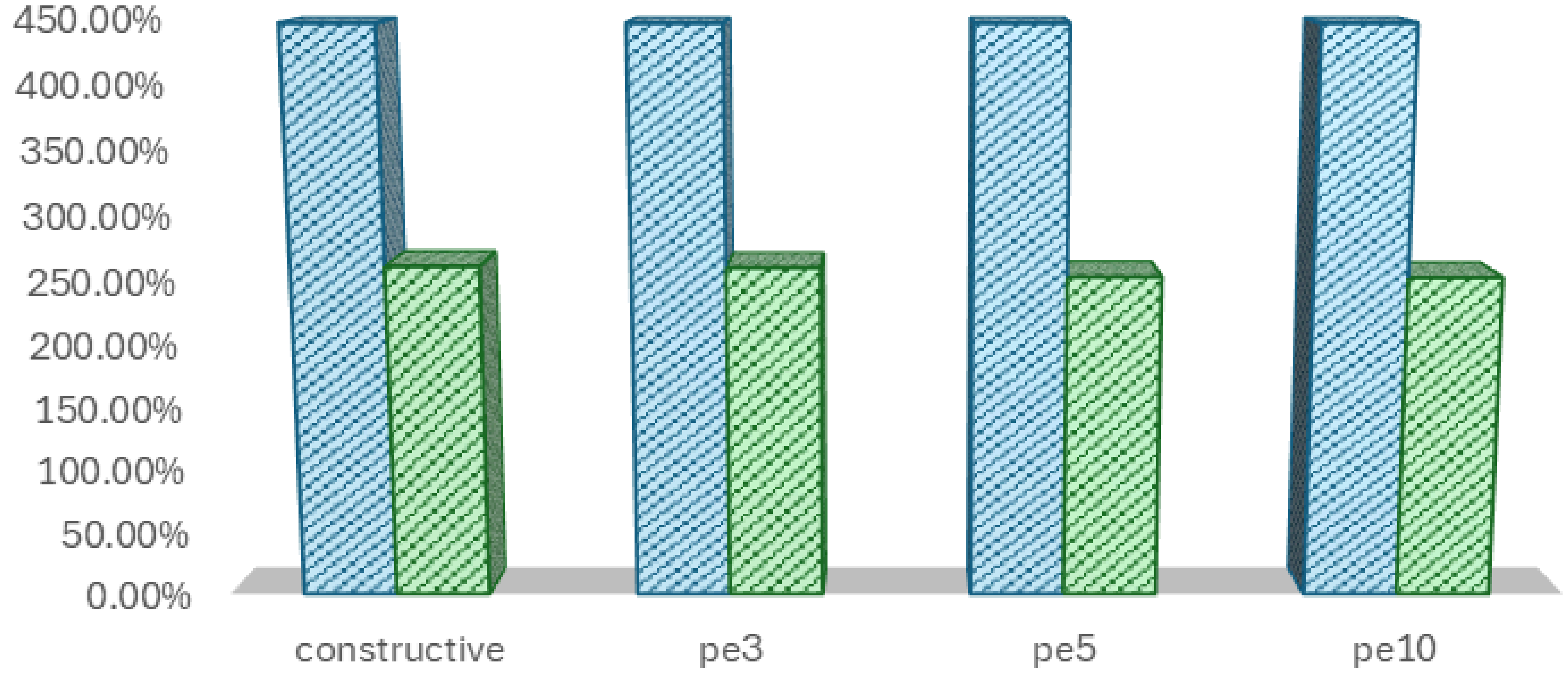
	constructive	pg50	pg100	g300
vehicle gap	444.86%	444.86%	444.86%	444.86%
distance gap	260.08%	254.59%	254.92%	251.86%

Mutation variation



	constructive	m0.1	m0.5	m0.75
vehicle gap	444.86%	444.86%	444.86%	444.86%
distance gap	260.08%	251.88%	251.86%	251.36%

Elite variation



	constructive	pe3	pe5	pe10
vehicle gap	444.86%	444.86%	444.86%	444.86%
distance gap	260.08%	258.89%	251.86%	251.21%

Conclusions

- The variation in the number of generations (pg50, pg100, g300) showed a consistent improvement in the Distance Gap, with values decreasing from 260.08% (constructive) to around 251.86% for the higher-generation settings. However, the Vehicle Gap remained unchanged at 444.86%, indicating that increasing generations primarily impacts the Distance Gap without significantly affecting the overall vehicle optimization.
- Changing the mutation rate (m0.1, m0.5, m0.75) also resulted in a reduction of the Distance Gap, which decreased from 260.08% (constructive) to values between 251.36% and 251.88%. The Vehicle Gap remained stable at 444.86% across all mutation rates, suggesting that mutation primarily influences the Distance Gap, enhancing solution refinement without altering the global vehicle optimization significantly.
- The variations in the elite strategy (pe3, pe5, pe10) also led to improvements in the Distance Gap, with values dropping from 260.08% (constructive) to between 251.21% and 258.89%. Like the other parameters, the Vehicle Gap remained unchanged, confirming that modifying the elite strategy helps to refine the solutions but does not significantly impact the overall vehicle allocation.