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Construction Project Scheduling Optimization with Time-Cost Trade-Off Based on Genetic Algorithm in Python

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ABSTRACT

Construction project delays frequently occur due to discrepancies between planned and actual implementation schedules under field conditions, where time and cost factors represent two primary obstacles that must be optimally managed. This study aims to develop a construction project scheduling optimization model based on Genetic Algorithms using Python programming to provide effective, efficient, and measurable solutions that achieve a balance between implementation time and project costs. The research method involves developing a construction project scheduling optimization model that considers the time-cost trade-off using a Python-based genetic algorithm, with a case study of the *Sei Baru* 1 Water Bridge Replacement Project in *Belitung Regency*. Data were obtained from PT. *Billiton Hero Sukses Cemerlang* in the form of wage and material prices, *AHSP* (Unit Price Analysis), *RAB* (Budget Cost Plan), as well as information on[A1] duration and acceleration costs through interviews. The research results demonstrate that the implementation of the NetworkX-CPM and Genetic Algorithm hybrid effectively optimizes construction project scheduling, achieving a cost reduction of 3.49% and duration reduction of 34.82% compared to normal conditions. The optimal GA parameters for this case were: population 50, generation 100, tournament 5, crossover 0.7, and mutation 0.2. The resource leveling process successfully balanced the distribution of daily labor requirements. All optimization results were validated through manual CPM calculations, remained free from constraint violations, and were supported by data visualization and automation integrated with Excel and Microsoft Project.

Keywords: Genetic Algorithm, Optimization, Construction Project, Resource Leveling, Time-Cost Trade-Off

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INTRODUCTION

A construction project requires a plan and schedule to establish the completion timeframe of a project. However, it is not uncommon for plans and schedules to fail to align with field conditions, resulting in delays in project completion. There are two significant constraints on project implementation: time and cost, as noted by project managers (Garg, 2016; Mohanty et al., 2011; Namit et al., 2021).

According to Sadi Assaf et al., (1995), the causes of delays can be analyzed from various aspects including materials, workers, equipment, finance, situation, changes, relations with the government, contracts, time, and control. Meanwhile, according to Proboyo Budiman (1999), project delays generally occur due to changes in planning during the implementation process, poor management by contractor organizations, poorly managed and integrated work plans, incomplete drawings and specifications, or contractors' failure to carry out the work properly.

Problems related to the planning and implementation schedule of construction projects have been addressed in research by Chung-Wei Feng et al., (1997) entitled "Using Genetic Algorithms to Solve Construction Time-Cost Trade-Off Problems," which utilizes the Critical Path Method (CPM) with a Genetic Algorithm approach, since exact approaches are not efficient enough to handle complex CPM networks. This study discusses the principles of Genetic Algorithms to solve Time-Cost Trade-Off problems where the critical path costs will be reduced as optimally as possible without significantly impacting project completion time.

There are various methods for allocating resources to a project, including conventional, heuristic, and metaheuristic methods. Conventional methods are algorithms that use standard mathematical calculations. Several conventional methods are commonly used to find the shortest path, including the Dijkstra algorithm, the Floyd-Warshall algorithm, and the Bellman-Ford algorithm. Heuristic methods are a subfield of artificial intelligence used to find and determine the shortest path (Himawan et al., 2023; Muhammad et al., 2023; Siahaan, 2015; Slamet et al., 2014; Windya & Saptadi, 2019). The metaheuristic method is an approach that employs solution search schemes inspired by natural principles developed by living organisms, including evolution and natural selection adopted by Genetic Algorithms, social interactions of fish schools and birds imitated by Particle Swarm Optimization (PSO), and ant colony interactions in finding food sources that inspire Ant Colony Optimization (ACO) (D. et al., 2017; Sa'ad et al., 2022; Saha & Mukherjee, 2018; Zhou et al., 2019).

A genetic algorithm is a search algorithm that operates based on the mechanisms of natural selection and genetics. In genetics, chromosomes are composed of genes. Each gene has a specific trait (allele) and a specific position (locus). One or more chromosomes combine to form a genetic package called a genotype. The interaction of a genotype with its environment is called a phenotype. In genetic algorithms, chromosomes are comparable to strings and genes to characters. Each character has a specific position (locus) and meaning (allele).

In research conducted by Hoosyar et al., (2008) entitled "A Genetic Algorithm to Time-Cost Trade-off in Project Scheduling," a Genetic Algorithm approach is presented to solve the Time-Cost Trade-off Problem (TCTP). In this algorithm, a mutation operator is introduced based on the properties of each project, and two control variables are used. This study conducts an efficiency comparison between the algorithm and the Siemens algorithm. The research results show that although the Siemens algorithm can optimally solve small-sized examples, heuristic methods such as Genetic Algorithms are still needed to solve larger and more complex problems.

Based on the description above, this study aims to accelerate project completion by considering time and costs (crashing), particularly through the addition of overtime hours for workers using the Time Cost Trade-Off method based on Genetic Algorithms. This research was conducted on a completed bridge construction project, where the contractor hopes that this research will produce a program capable of accelerating project duration in the future without significantly increasing costs, thereby providing a basis for decision-making in subsequent project activities. In this study, the first important consideration is that workers must be paid daily for seven working hours. Second, the addition of overtime hours has the same duration of three hours per day, where overtime workers have the same coefficient as workers operating under normal duration. This means that the analysis of normal costs and costs due to overtime will use the coefficient contained in the contractor's *AHSP* (Unit Price Analysis). Additionally, in this study, direct costs will be derived from *AHSP* and indirect costs are calculated at 10% of the total direct costs.

METHOD

This research focuses on the development of a construction project scheduling optimization model by considering the time-cost trade-off using a genetic algorithm approach implemented in the Python programming language. The case study was conducted on the *Sei*

Baru 1 Water Bridge Replacement Project located on the Tanjung Kelayang–Tanjung Tinggi Sp. Section, *Belitung Regency*[A1], Bangka Belitung Islands Province, with a total replacement length of 35.8 meters. The construction of this bridge, scheduled for 2024, plays a strategic role as a link between villages, city centers, and tourism areas while supporting the smooth flow of goods and services to accelerate economic recovery and maintain environmental sustainability. The project, implemented by PT. *Billiton Hero Sukses Cemerlang* based on Contract No. HK.0201-PPK 2.1 Babel/390 dated March 4, 2024, is worth IDR 23,012,672,000 (including VAT) with an implementation period of 300 calendar days. The project requires professional supervision to ensure optimal, effective, and efficient results according to applicable quality standards.

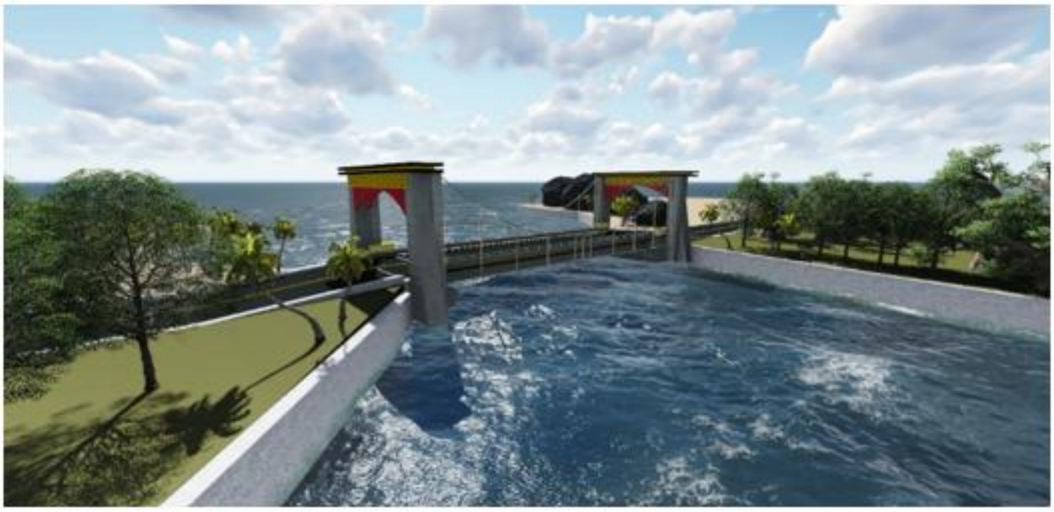


Figure 1. 3D landscape image of the Sei Baru Bridge Replacement 1
(Source: Project Archive Document)

The project scheme for the New Sei Air Bridge Replacement 1 can be seen in Figure 2

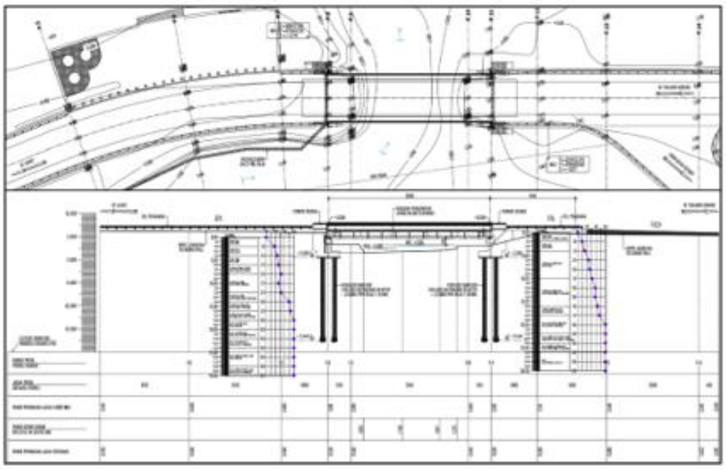


Figure 2. DED of the bridge plan
(Source: Project Archive Document)

The following is the location data for the Sei Baru 1 Water Bridge Replacement Project: The Air Sei Baru Bridge Replacement Project 1 Section Sp. Tg. Kelayang Tanjung Tinggi (Sijuk) is located in detail at KM. 28 + 480. The coordinate points are -2.5622, 107.6996" and are shown in figures 3 and 4 below.

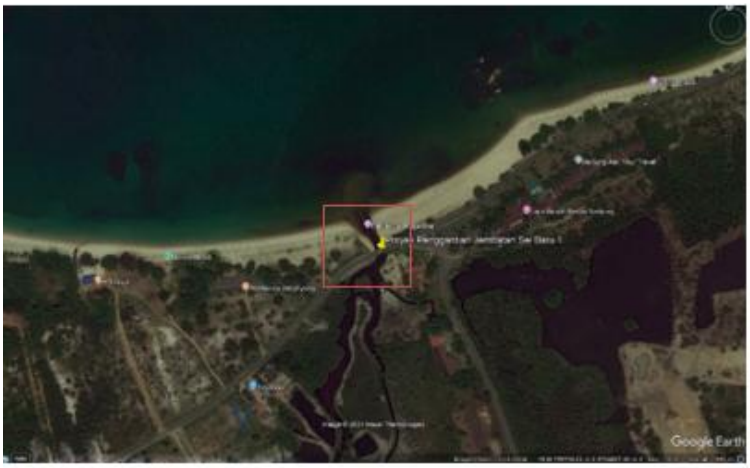


Figure 3. Location of the Air Sei Baru 1 bridge project
(Source: Google Earth Pro)

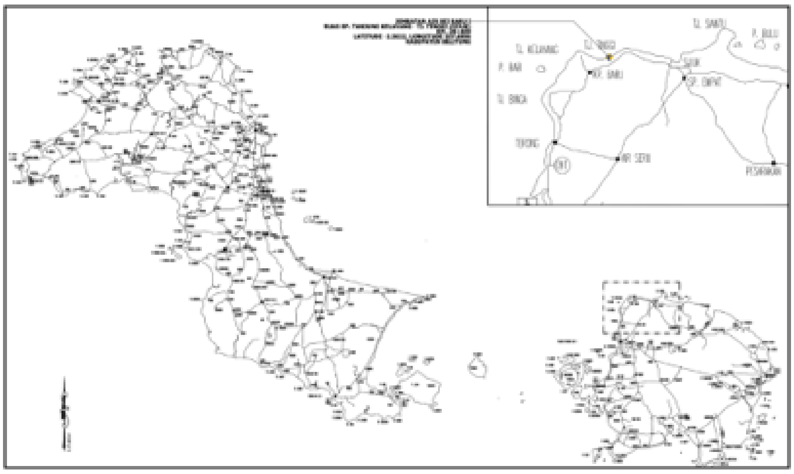


Figure Error! No text of specified style in document.. **Shop drawing of the Air Sei Baru 1 bridge project location**
(Source: Project Archive Document)

Data collection in this study was conducted using secondary data obtained from PT. *Billiton Hero Sukses Cemerlang*, including wage and material prices, work unit price analysis (*AHSP*), and cost budget plan (*RAB*). Additionally, data on initial duration, accelerated duration due to subcontractor utilization, and costs incurred by subcontractors were obtained through interviews with relevant parties. These data were processed to optimize the cost and time of project implementation under normal conditions. This study was supported by the use of several software programs: Microsoft Excel for processing initial data such as *AHSP*, *RAB*, and time schedules; Microsoft Project for validation and comparison of scheduling methods; and Visual Studio Code for developing optimization programs based on genetic algorithms. The integration of these three tools enables the analysis and optimization process to be conducted effectively, systematically, and in accordance with construction project management standards.

The analysis method in this study was conducted in two stages: initial data analysis and genetic algorithm (GA) analysis. Initial data analysis includes calculating normal implementation costs and time, indirect costs, and cost slopes. Subsequently, GA analysis begins with determining baseline parameters and research variables, probability calculations, and initialization of the initial population through encoding, population creation, mapping, and checking various constraints. These constraints include activity dependencies, float/criticality limits, subcontractor utilization, number of overtime days, weekly overtime, schedule feasibility, and the imposition of penalties on fitness values. The next stage includes cost and duration normalization, fitness function calculations, and the evolutionary process consisting of selection, crossover, mutation, and iteration across multiple generations, culminating in the development of a detailed GA scheme to produce an optimal solution.

RESULTS AND DISCUSSION

Network Development

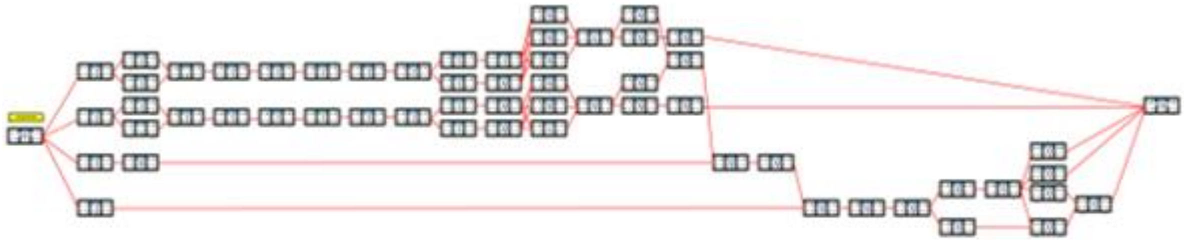


Figure 5. Project Network with Excel

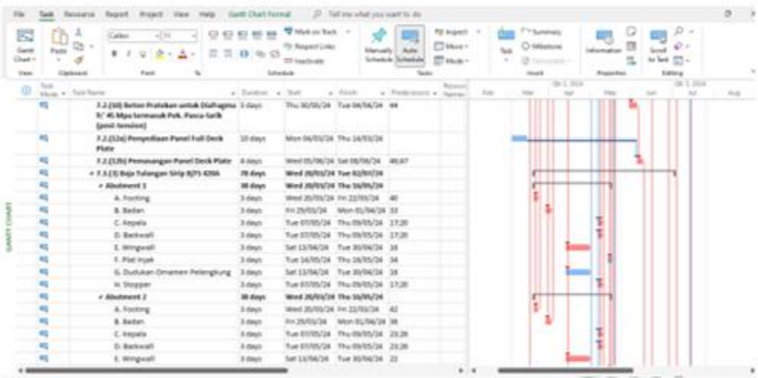


Figure 6. Project Networking with Microsoft Project

The project work network analysis conducted manually using Microsoft Excel and Microsoft Project resulted in a consistent total project duration of 112 days, with the sequence of activities, duration of work, and dependencies and relationships between activities valid on both platforms. The analysis results also show the similarity of the list of work on the critical path, where activities with total float = 0 are identified as the same, so that the risk of delays in critical work can be mapped consistently. This similarity proves that the basic project data and scheduling logic used are appropriate and accurate (Ndidiamaka et al., 2024; Kim, 2020).

Calculation of Project Components

After the scheduling process is complete, the project cost components are calculated, which include direct costs based on the analysis of work unit prices (AHSP), as well as indirect costs according to project management policies. In addition, the number of workers needed for each activity is calculated based on productivity standards and field estimates.

1. Analysis of unit price of work (AHSP)

   The AHSP value used in this study was taken directly from the executing contractor's AHSP document, with a focus on direct costs including labor, materials, and equipment, without an additional 10% overhead. This approach was chosen so that the results of the scheduling and optimization analysis better reflect the real cost requirements of each activity, while indirect costs such as overhead are calculated separately at a later stage. Thus, all normal costs in the CPM calculation and genetic algorithm optimization represent the cost of work according to the contractor's AHSP.

2. Calculation of Direct Cost (Normal Cost)

   After obtaining the AHSP value for each work item, where the cost components taken are direct costs without additional overhead, the next step is to calculate the direct cost for each activity. This cost is calculated by multiplying the direct cost value of the AHSP by the predetermined work volume. The total direct cost is Rp8,881,953,337.79.

3. Indirect Cost Calculation

   After all direct costs for each work item have been calculated, the next step is to determine indirect costs. In accordance with applicable rules and standards in Indonesia, especially in government project budgeting, indirect costs are set at 15% of total direct costs. This indirect cost component generally includes office overhead costs, project administration, supervision, and other costs that are not directly related to the implementation of physical activities in the field, but are still necessary for the smooth running of the project as a whole.

Thus, the value of indirect costs for this project is obtained by multiplying the total direct costs that have been calculated previously by a percentage of 15%. The results of this indirect cost calculation are then summed up with direct costs to obtain the total project cost requirements which form the basis for further scheduling and optimization analysis.

Indirect Cost Calculation:

Indirect Cost Total = 15% total direct cost

= 15% x Rp 8.881.953.337,79

= Rp 1.332.293.000,67

Indirect Per-day = Indirect Cost Total / Total Duration

= Rp 1.332.293.000,67 / 112 day

= Rp 11.895.473,22

4. ***Calculation of Number of Worker***

   After all resource requirements for each activity are detailed through the AHSP document and the recapitulation of work volume, the next step is to calculate the number of workers required for each project activity. This calculation is carried out based on the labor productivity data listed in the AHSP, which is the amount of output that can be produced by one worker in a certain unit of time. The number of workers in each activity is obtained by dividing the volume of work by the capacity or productivity per day that has been determined in the AHSP. Thus, an estimate of the number of workers that must be available so that the work can be completed in accordance with the planned duration is obtained. Example of calculation using the formula in equation (3.17):

Example: Abutment 1 Concrete Drill Work
Volume = 216 m3
Duration = 10 days
Working duration per day = 7 hours
Koef workers = 4.8193/hour
Koef fitters = 2.4096/hour
Koef foreman = 1.2048/hour
Number of Workers = (216 m3 x 4.8193/hour)/(10 days x 7 hours)
= 14.87091 (rounded)
= 15 people working 7 hours per day to complete 216 m3 5 days
Number of Fitters = (216 m3 x 2.4096/hour)/(10 days x 7 hours)
= 7, 435456 (rounded)
= 8 people work 7 hours per day to complete 216 m3 5 days
Number of Foremen = (216 m3 x 1.2048/hour) / (10 days x 7 hours) = 3,717728055 (rounded)
= 4 people work 7 hours per day to complete 216 m3 5 days
Total Number = 15 + 8 + 4
= 27 people work 7 hours per day to complete 216 m3 5 days

5. *Crash Cost Due to Overtime*

The calculation of crash costs is done by considering the overtime wages applicable to each worker. In general, the hourly overtime wage is higher than the regular working hour wage, following the applicable labor regulations, namely the first 1 hour the wage is 1.5 times the normal wage, while the next 2 hours the wage paid must be 2 times the normal wage.

Table 1. Sample List of Coefficients & Wages

Type of Worker	Coefficient (hour)	Wage per day	Wage per hour
Worker	4,8193	Rp 151.527,78	Rp 21.646,83
Handyman	2,4096	Rp 200.584,44	Rp 28.654,92
Foreman	1,2048	Rp 232.808,33	Rp 33.258,33

Prototype Model

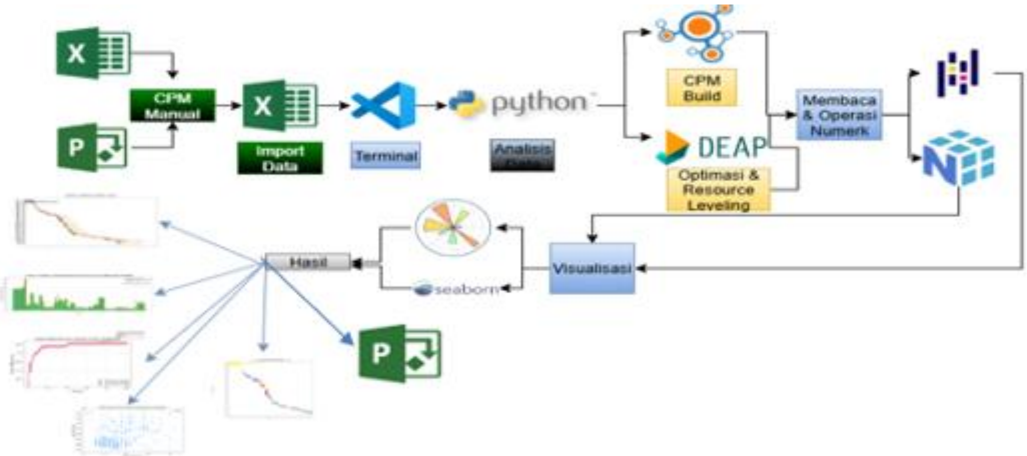


Figure 7. Prototype Model

The figure above shows the flow of the project scheduling optimization automation process with the CPM and genetic algorithm (GA) approach. The process starts from data input and manual validation of CPM, followed by data processing and network model building using Python and NetworkX. The optimization and resource leveling process is run with DEAP and NumPy, then the results are visualized comprehensively using Matplotlib and Seaborn to support project analysis and decision making.

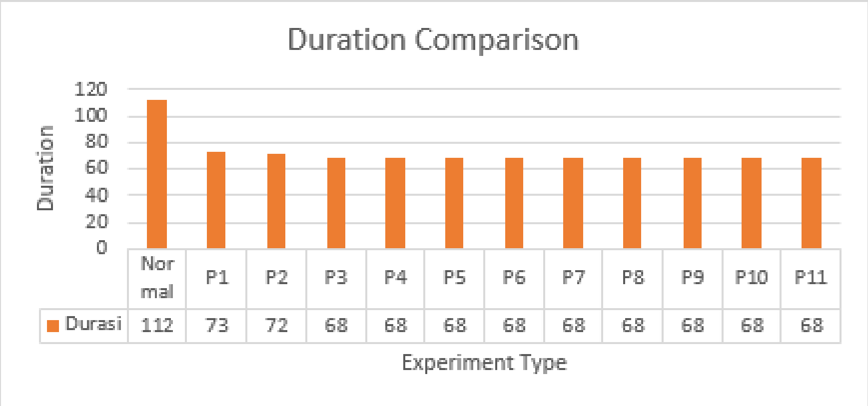
Optimization Results With Weight Variations

The table below shows the main results of optimization with the baseline, which is the main reference for all experiments, in this case the test is carried out by evaluating each weighting combination as follows.

Table 2. Weight Variation Optimization Results

Code	Pop	Gen	Tour	Cross	Mut	B:W	Day	Cost
Normal	-	-	-	-	-	-	112	Rp10.213.846.362,00
P1	**50**	100	3	0.7	0.2	1,0:0.0	73	Rp 9.862.815.135,00
P2	**50**	100	3	0.7	0.2	0.9:0.1	72	Rp 9.876.752.459,00
P3	**50**	100	3	0.7	0.2	0.8:0.2	68	Rp 9.950.911.915,00
P4	**50**	100	3	0.7	0.2	0.7:0.3	68	Rp 9.937.272.970,00
P5	**50**	100	3	0.7	0.2	0.6:0.4	68	Rp 9.937.272.970,00
P6	**50**	100	3	0.7	0.2	0.5:0.5	68	Rp 9.939.835.737,00
P7	**50**	100	3	0.7	0.2	0.4:0.6	68	Rp 9.937.272.970,00
P8	**50**	100	3	0.7	0.2	0.3:0.7	68	Rp 9.937.272.970,00
P9	**50**	100	3	0.7	0.2	0.2:0.8	68	Rp 9.937.272.970,00
P10	**50**	100	3	0.7	0.2	0.1:0.9	68	Rp 9.937.272.970,00
P11	**50**	100	3	0.7	0.2	0.0:1.0	68	Rp 9.982.074.578,00

Figure 8. Cost Comparison of Each Trial



	Normal	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P11
Durasi	112	73	72	68	68	68	68	68	68	68	68	68

Figure 9. Comparison of Duration of Each Trial

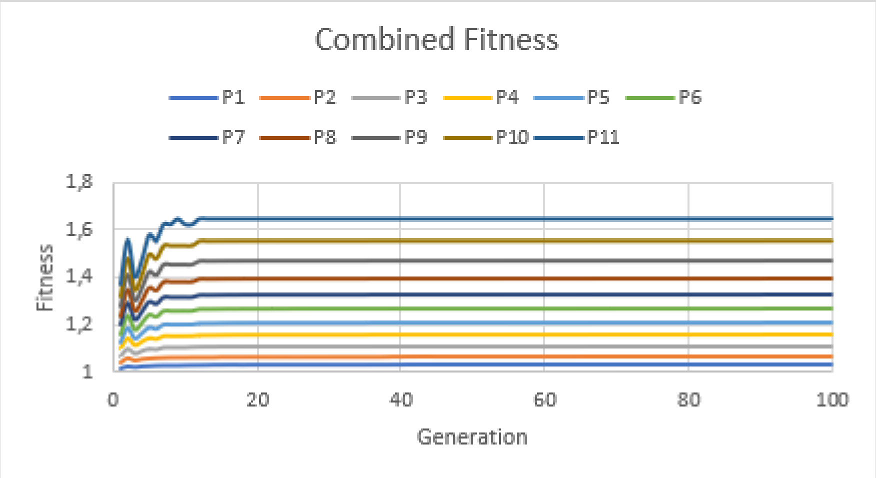


Figure 10. Combined Fitness

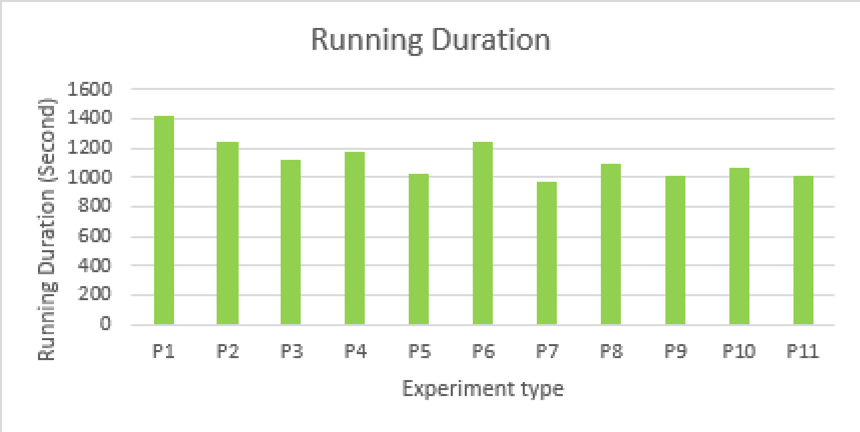


Figure 11. Runing duration

The optimization results using Genetic Algorithm (GA) produce various alternative solutions that can be selected according to project priorities. The "Combined Fitness" graph shows that all optimization scenarios (P1-P11) experienced a rapid increase in fitness at the beginning of the generation and stabilized in the final generation, indicating that the process of finding the optimal solution was effective. The variation in the final fitness value of each scenario confirms the influence of the given time-cost weights, so that the selection of the best scenario needs to be adjusted to the priority of the project needs. This variation shows the different complexity of the solution and search process for each parameter combination, but in general, the running time of all experiments is still within a reasonable and efficient range for GA-based optimization. Under normal conditions, the project implementation duration is 112 days with a total cost of IDR 10,213,846,362. After optimization, several alternatives were obtained as follows:

1. Lowest Cost Alternative (P1):
   With full optimization weight on cost (B:W = 1.0:0.0), the project duration can be shortened to 73 days and the total cost dropped to Rp 9,862,815,135. The cost reduction achieved was Rp 351,031,227 or about 3.44% of the initial cost.
2. Fastest Duration Alternative (P3-P11):
   With the variation of optimization weights focusing more on time, the fastest duration that can be achieved is 68 days, with costs ranging from Rp 9,937,272,970 to Rp 9,982,074,578. The cost reduction compared to the initial condition ranges from 2.27% to 2.71%, but the project duration is shorter (saving 44 days from the baseline).
3. Compromise Alternative (P2):
   In the cost-time weight combination (B:W = 0.9:0.1), the project duration is 72 days and the cost is Rp 9,876,752,459. A cost reduction of Rp 337,093,903 (3.30%), with a completion time almost as fast as the fastest duration alternative.

Evaluation of Preferred Alternative

Table 3. Preferred Alternative

Options	Duration (Days)	Cost (Rp)	Duration Decrease (Days)	Cost Decrease (Rp)	Cost Decrease (%)
Normal	112	Rp 10.213.846.362	-	-	-

Options	Duration (Days)	Cost (Rp)	Duration Decrease (Days)	Cost Decrease (Rp)	Cost Decrease (%)
P1	73	Rp 9.862.815.135	39	Rp 351.031.227	3,44%
P2	72	Rp 9.876.752.459	40	Rp 337.093.903	3,30%
P3–P11	68	Rp 9.937.272.970 s/d Rp 9.982.074.578	44	Rp 276.573.392 s/d Rp 231.771.784	2,71% s/d 2,27%

In this subchapter, The detailed evaluation of the selected alternative combinations. In this case, the result with the lowest cost value, namely experiment P1, here are the details.

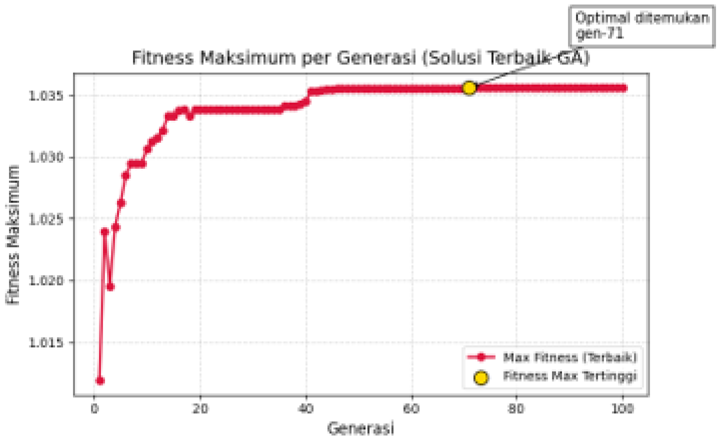


Figure 12. Fitness P1

This graph shows the development of the maximum fitness value at each generation during the Genetic Algorithm optimization process. It can be seen that the maximum fitness increases significantly in the early generations and then reaches the optimum value in the 71st generation. The yellow dot marks the best solution (highest fitness) that was achieved. This indicates that the algorithm quickly found the optimal and stable solution in a relatively short number of generations, showing the effectiveness of the optimization process carried out.

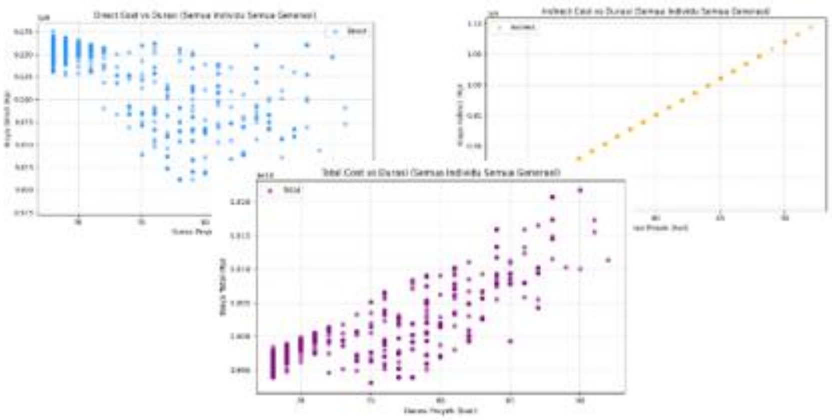


Figure 13. Universe of Solutions to Direct, Indirect, Total Costs

The graph above shows the relationship between project duration and the cost components (direct cost, indirect cost, and total cost) of all individuals across all optimization generations. The top left graph shows that direct costs tend to increase as the project duration gets shorter, because accelerated implementation generally requires additional labor, overtime, or more expensive special methods. The top right graph shows that indirect costs decrease linearly as the duration shortens, as accumulative overhead costs become smaller.

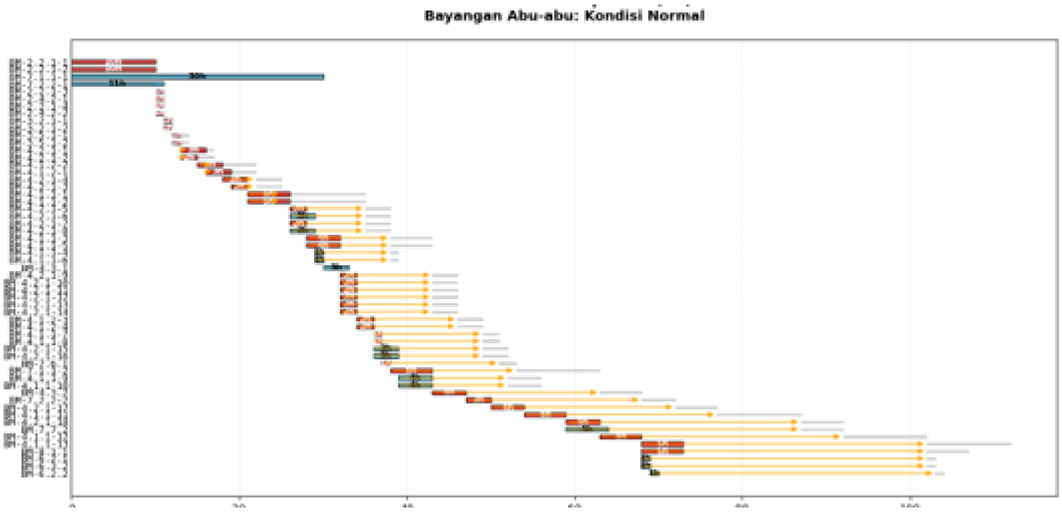


Figure 14. Optimization Gantt Chart

The Gantt chart above shows the optimized schedule of project scheduling under normal conditions. Each horizontal bar represents a project activity along with the start and finish times obtained from the optimization process. Different bar colors indicate the category or mode of implementation of certain activities according to the results of finding the best solution. The schedule distribution on this chart shows how activities can be arranged more efficiently so that the total project duration can be minimized. The gray shading shows the range of activity completion times before and after optimization, which confirms the positive impact of applying the optimization method on accelerating and rearranging the work sequence in the project.

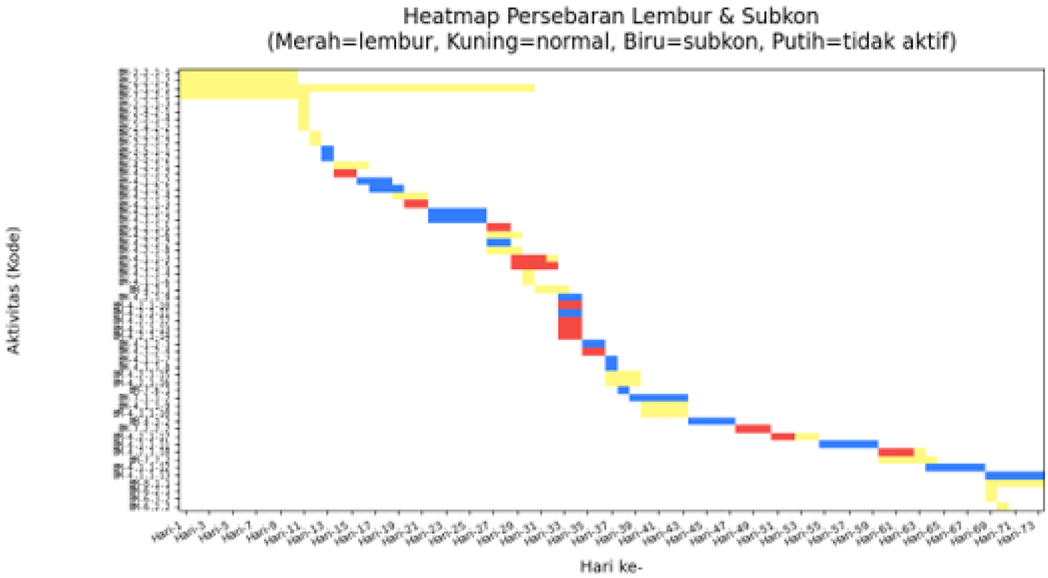


Figure 15. Distribution of Mode Details

The graph above is a heatmap of the distribution of project activity execution modes on each day of implementation, the result of the CPM-GA-resource leveling-based scheduling optimization process. The vertical axis shows all project activity codes, while the horizontal axis displays the project execution days (Day 1 to Day 73). Each cell on the heatmap represents the activity implementation status on a particular day, with the following color codes: red for overtime days, yellow for normal mode, blue for subcontractors, and white for inactive days (activities have not run on that day).

1. Yellow Color Domination (Normal):
   It can be seen that most activities are carried out in normal mode (yellow), especially at the beginning of the project and long-duration activities.
2. Spread of Red (Overtime):
   The red color appears spread over several activities in the middle and end of the project, indicating an acceleration strategy through overtime. This usually occurs on critical or near-critical activities to shorten the total project duration.
3. Blue Color Spread (Subcon):
   Blue signifies work that is outsourced to subcontractors. The distribution is relatively even on activities with a certain volume or level of complexity. The use of subcontractors is selected by the algorithm if it is considered advantageous in terms of duration and cost.

Mode Distribution Percentage

The percentage distribution of modes will be visualized with pie charts for more accurate analysis where each weight is detailed as showing the total percentage share of overtime, normal, or subcontract. Where several varied patterns are seen and there are similar patterns.

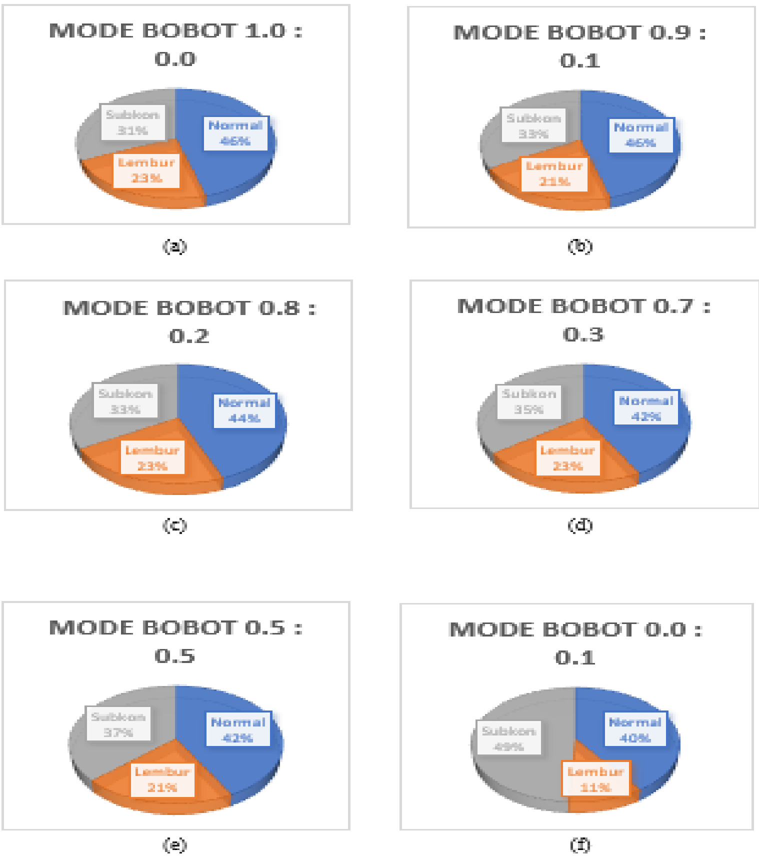


Figure 16. Mode Percentage

These diagrams show how the execution mode strategy is dynamically selected by the optimization algorithm according to the owner/project priorities. When cost orientation is very high, normal and overtime are more dominant; when time orientation is increased, the share of subcontractors rises significantly, and overtime tends to be reduced to avoid too high a cost premium. Understanding this pattern can be the basis for project execution strategy decisions, adjusting between cost, duration, and risk targets that are ready to be faced.

Table 5. Normal Vs Optimization Comparison

Description	Normal	Optimasi Gen 71
Duration	112	73
Direct Cost	Rp8.881.953.338	Rp8.994.706.289
Indirect Cost	Rp1.331.893.024	Rp868.108.846
Total cost	Rp10.213.846.362	Rp9.862.815.135

Based on the table of comparison results between normal conditions and optimization results in the 71st Generation, the project duration has significantly accelerated, which is reduced by about 39 days from 112 days to 73 days. This acceleration is achieved through the application of an appropriate activity mode strategy, where the combination of normal work, subcontractor usage, and overtime is optimally selected by the algorithm. Conversely, the drastic reduction in project duration caused indirect costs to drop significantly, so that the overall total project cost decreased by about 3.44% compared to normal conditions.

These results prove that the use of Genetic Algorithm in optimization can produce more effective project scheduling in terms of time and cost, in line with the findings of previous studies (Xie et al., 2021; Erdal & Kanit, 2021; Boukedroun et al., 2023; Alhamad & Alkhezi, 2024). The selection of priority weights between cost and time is proven to have a major effect on the distribution of work modes used, so that the acceleration strategy can be adjusted to the project target (Yu et al., 2023). This approach provides an optimal time-cost trade-off solution, minimizing the risk of cost overruns while ensuring the project can be completed faster. Thus, this method can be an effective decision-making tool for construction project managers in balancing duration, cost, and implementation risk (Bozejko dkk., 2011).

CONCLUSION

Based on the research results, the implementation of the hybrid NetworkX-CPM method and Genetic Algorithm proved effective in optimizing construction project scheduling in terms of both cost and duration. GA parameter testing demonstrates that the combination of population 50, generation 100, tournament size 5, crossover[A1] rate 0.7, and mutation rate 0.2 represents the optimal configuration for this case study. The optimization results successfully reduced the total project cost from IDR 10,213,846,362.00 to IDR 9,857,885,763.00 (a decrease of 3.49%) and accelerated the duration from 112 days to 73 days (a decrease of 34.82%). The implication of these findings is that this hybrid approach can serve as an effective time-cost trade-off solution, enabling project managers to make more rational and measurable decisions in managing project implementation time and cost.

For further development, it is recommended that the model consider additional variables such as work quality, risk factors, availability of equipment and materials, as well as external factors including weather conditions and design changes. Testing on different types and scales of projects is needed to achieve broader generalizability, while integration with *BIM* (Building Information Modeling) technology, interactive dashboards, and project management information systems will enhance the utilization of optimization results in the field. A multi-objective approach that includes worker comfort, optimal productivity, and safety factors also requires further exploration. Additionally, the developed Python-based program should be made open source so that it can be utilized by practitioners, researchers, and students in civil engineering.

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