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Research Article

Selection and Optimization of Heavy Earth Moving Equipment for Improved Mine Productivity

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Abstract

Equipment selection remains one of the most critical decision problems in earthmoving construction projects, with equipment-related expenditure accounting for more than 30% of total project cost and equipment emissions contributing substantially to the sector's environmental footprint. Choosing the right mix of trucks and excavators is driven by a tangled set of competing factors — unit work capacity, fleet size, travel speed, fuel consumption, and project deadlines — that make purely experience-based or manufacturer-chart selection methods unreliable at scale.

This review provides a comprehensive optimization model for earthmoving equipment selection, structured around three sequential stages: (1) data definition, which organizes fixed costs, variable costs, contract specifications, and equipment specifications; (2) mathematical model formulation, which defines the relevant decision variables and constraints governing equipment choice; and (3) application of a genetic algorithm (GA) to solve the resulting multi-objective, multi-variable problem. Unlike prior equipment-selection models, truck travel speed is embedded as a primary decision variable, allowing the model to capture more realistic time-cost trade-offs than models that treat speed as fixed. (Halpin et al. (2017))

The model was tested and validated using data from a real-world earthmoving project, evaluating how total project cost varies with the time allowed for completion while simultaneously tracking fuel consumption and carbon emissions. Results show that the optimization approach can achieve average savings of 14.35% in project time and 9.5% in project cost, alongside meaningful reductions in fuel use and CO_2 output. (Sherafat et al. (2020))

By combining rigorous mathematical formulation with GA-based multi-objective optimization, this study offers contractors and construction managers a practical decision-support tool to balance time, cost, and environmental performance when planning earthmoving fleets. (Hummer et al. (2017))

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1. INTRODUCTION

Earthmoving activity is one of the most resource-intensive elements of civil construction projects, frequently accounting for over 30% of total project cost. Despite its central role in project economics, equipment selection for earthmoving is still often handled through informal, experience-based judgment rather than systematic, research-backed methods. Construction sites are typically populated with a wide range of trucks, excavators, and support equipment, yet many firms lack a structured approach to select, schedule, and monitor this fleet effectively.

Poor equipment selection is not a minor inefficiency — it is a business risk. Construction firms have been driven to bankruptcy after relying on judgment-based equipment choices instead of validated planning tools. Because the earthmoving equipment fleet can represent the single largest cost category on a project, delays or misallocation in this area propagate directly into missed deadlines, contractual penalties, and eroded profit margins. (Halpin et al. (2017))

Unlike simpler, linear cost-estimation problems, earthmoving equipment selection is a high-dimensional, non-linear, multi-objective problem: minimizing project time and minimizing project cost are frequently competing goals, and a shorter schedule often forces higher expenditure. Traditional linear optimization techniques struggle to handle this complexity, and most existing models have treated equipment travel speed as a fixed input rather than a variable that can itself be optimized — leaving a meaningful gap in how realistically these models represent field conditions. (Marzouk & Moselhi (2002))

Recent advances in evolutionary and metaheuristic optimization including genetic algorithms, memetic algorithms, and multi-objective search techniques — have opened new opportunities to solve exactly this class of problem. Genetic algorithms in particular, built on the principle of natural selection, have proven well suited to multi-objective, multi-variable construction problems such as scheduling, resource allocation, and site layout, and are a natural fit for the combined time-cost-environmental trade-offs inherent in earthmoving equipment selection. (Gransberg (1996))

This research addresses that gap by developing a novel GA-based multi-objective optimization model for earthmoving equipment selection, in which truck speed is embedded as a primary decision variable alongside equipment type, capacity, and fleet size. The model is designed to help contractors and project managers identify optimal trade-offs between project time, project cost, fuel consumption, and carbon emissions, using real project data for validation. Accordingly, this study poses the following research question: How can a genetic algorithm be used to perform multi-objective optimization for selecting heavy equipment in earthmoving construction projects?

2. Cost Structure and Decision Variables in Earthmoving Operations

Before an effective optimization model can be formulated, it is essential to understand the cost architecture underlying earthmoving operations. Input data for the model is organized into four interacting categories: fixed costs, variable costs, contract specifications, and equipment specifications. Each category contributes differently to the total ownership and operating cost of the fleet and, ultimately, to the time and cost objectives the model seeks to optimize.

2.1 Fixed Costs

Fixed costs are incurred regardless of ongoing project activity and must be paid in all cases.

- **Equipment Cost:** Based on the delivered price of the machine (including transportation and taxes) less its residual or trade-in value at replacement.
- **Interest, Insurance, and Tax Costs:** Calculated from simple interest rates, insurance rates, and tax rates applied to the machine's net value; these are treated as part of the hourly owning cost.
- **Additional Costs:** Mobilization, demobilization, supervision, and any owner-caused delay costs.
- **Operator Wages:** The per-hour cost of labor, affected by local wage scales, legislation, and benefits.

2.2 Variable Costs

Variable costs change as the project progresses and are the primary driver of net project profit.

- **Fuel Consumption:** approximated from manufacturer data and rises in proportion to machine speed; operating more slowly saves fuel but extends activity time and can idle other equipment in the fleet. (Liu et al. (2020))
- **Service Cost:** covers oil, grease, hydraulic fluids, filters, and labor, computed as a percentage of fuel cost that reflects the severity of operating conditions (favorable, average, or severe). (Akhavian & Behzadan (2013))
- **Repair Cost:** depends on machine age, usage pattern, and preventive maintenance, and is a significant component of total operating cost.

2.3 Contract and Equipment Specifications

Contract specifications capture the project-level constraints that frame the optimization problem: total project quantity (converted from bank cubic meters to lose cubic meters via a swell factor), and the project time and cost allowed for completion — competing objectives that are difficult to balance without a formal planning tool.

Equipment specifications capture machine-level constraints drawn from manufacturer handbooks: truck safety (Kishore et al., 2026) speed (a hard constraint, since higher speeds increase the risk of operator falls and collisions), basic excavator cycle time, bucket fill factor, efficiency factor, truck dump time, undercarriage cost, and the original tire life cycle — which itself shortens as truck speed increases.

3. Key Parameters Influencing Time and Cost Objectives

Earthmoving cost and duration rarely hinge on a single input. Instead, they emerge from the interaction of decision variables the planner controls (equipment type, number, capacity, and speed) and operational or contractual variables fixed by site conditions. Table 1 summarizes the parameters most influential to the model's time and cost objectives.

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Table 1. Key parameters influencing time and cost objectives in earthmoving equipment selection.

Category	Parameter	Influence on Time and Cost Objectives
Decision Variable	Number of Excavators (NOE)	Increases excavation capacity and shortens loading time, but raises fixed ownership cost roughly linearly; beyond about four units, additional excavators no longer reduce activity time.
Decision Variable	Number of Trucks (NTP)	More trucks reduce queuing delay and activity time up to a saturation point (around eight units), beyond which trucks idle and cost rises without further time benefit.
Decision Variable	Excavator Capacity (EC)	Larger bucket capacity increases material moved per cycle, directly affecting excavator productivity and loading time for trucks.
Decision Variable	Truck Capacity (TC)	Determines the number of loads required to move the total project quantity; larger capacity reduces trips but may increase per-hour ownership cost.
Decision Variable	Truck Speed (Es)	The primary driver of the time-cost-emission trade-off: higher speed cuts travel time but increases fuel consumption, tire wear, and, past an optimal point, causes truck queuing that erases further time savings.
Operational	Loading and Cycle Time	Governed by excavator capacity, bucket fill factor, and efficiency factor; shorter cycle times increase overall equipment productivity. (Gransberg (1996))
Contract/Site	Moving Distance (Md) and Total Project Quantity (TPQ)	Fixed by site conditions; longer haul distances amplify the sensitivity of both time and cost to truck speed.
Environmental	Load Factor and Engine Power	Determine CO2 emissions per hour of operation together with activity time; equipment operated nearer to rated load and optimal speed produces lower total emissions.

4. Optimization Modelling Approaches

Selecting and scheduling earthmoving equipment has historically relied on a mix of contractor experience and simplified analytical tools. Over time, these approaches have evolved toward increasingly capable optimization techniques able to handle the multi-variable, non-linear nature of the problem.

4.1 Conventional Equipment Selection Approaches

Early approaches relied on contractor experience, historical project databases, and manufacturer performance charts to select fleet equipment based on tradeoffs between budget and schedule. A cost index number (CIN) has been used to quantify the optimum haul-unit size and number for a given loading configuration, and hybrid approaches combining discrete event simulation with genetic algorithms have been applied to optimize truck dispatch schedules and filter out inefficient routing options. Linear integer programming models have also been used to constrain multi-pollutant equipment emissions alongside total cost. (Hummer et al. (2017))

4.2 Limitations of Conventional Approaches

- **Experience Dependence:** historical-data and judgment-based approaches do not generalize well across projects with different site conditions, contract terms, or equipment fleets. (Marzouk & Moselhi (2002))
- **Fixed-Speed Assumption:** most prior models treat truck travel speed as a constant input rather than a variable that can itself be optimized, understating its effect on time, cost, fuel use, and emissions.
- **Linear, Single-Objective Framing:** traditional linear optimization techniques struggle with the non-linear, non-convex, multi-objective nature of simultaneously minimizing time, cost, and environmental impact. (Whitley (1994))

5. GA-Based Multi-Objective Optimization Framework

To address these limitations, the proposed model formulates earthmoving equipment selection as a multi-objective optimization problem and solves it using a genetic algorithm, with truck speed embedded as a primary decision variable alongside equipment type, number, and capacity.

5.1 Objective Function Formulation

The total direct cost of each piece of equipment is built from an owning-cost component (equipment cost, interest, insurance, and tax) and an operating-cost component (repair, operator wage, additional costs, undercarriage, fuel, service, and tire replacement). Excavator cost is treated purely as a fixed cost, since excavator speed has a negligible effect on fuel use over short in-pit distances. Truck cost, by contrast, is split into a fixed component and a speed-dependent variable component, because truck travel over haul distances makes fuel consumption, service cost, and tire wear all functions of speed. (Hummer et al. (2017))

Excavator productivity is derived from the number of excavators, excavator capacity, bucket fill factor, efficiency factor, and cycle time. Truck cycle time is built from dump time, travel time (a function of haul distance and truck speed), and loading time (a function of truck and excavator capacity). Combining these relationships yields the two central objective functions of the model: total activity time and total activity cost, both expressed as functions of the number of excavators and truck speed, subject to the equipment availability and speed constraints defined by the manufacturer's handbook and applicable regulations.

5.2 Model Implementation

The genetic algorithm proceeds through four linked phases:

- **Data Input and Initial Population:** all constants, parameters, and constraints are entered, and an initial population of randomly generated variable sets (equipment numbers, capacities, and truck speed) is created. (Senouci & Eldin (2004))
- **Time and Cost Evaluation:** the activity time and activity cost objective functions are computed for every candidate set in the population.

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- **Fitness Assessment:** each candidate is evaluated against the objective functions to determine its relative fitness.
- **Crossover and Mutation:** genetic operators generate new candidate solutions from fit parents; this cycle repeats until an optimal set of variables is found within the applied constraints.

5.3 Case Study Validation

The model was tested on a real earthmoving project for a public-school construction, sponsored by USAID, involving excavation of 9,730.45 loose cubic meters of sand and gravel and haulage 5.5 km to a dumping site. The contractor fielded two CAT 320D2 excavators and a mixed fleet of CAT 725C and CAT 735C trucks. Baseline (as-built) performance, with trucks run at their maximum allowable speed, totaled 90 hours and 29,000 USD.

The optimization model generated a full set of Pareto-optimal time-cost trade-offs for each equipment combination rather than a single answer, letting the contractor choose based on project priorities. Table 2 summarizes representative optimal solutions alongside the field baseline.

Table 2. Representative GA-optimized time-cost solutions compared with the field baseline.

Solution	Excavators	Trucks	Truck Speed (km/h)	Time (hr)	Cost (USD)	Notes
A	3 × CAT 320D2	4 × CAT 725C	38	51.74	32,678.0	Minimum time; 42.5% time saving, 12.7% higher cost
B	2 × CAT 320D2	3 × CAT 725C	42	77.16	28,439.0	Balanced: 14.3% time saving, 2% cost saving
C	1 × CAT 320D2	2 × CAT 725C	45	152.19	26,416.4	Minimum cost; 8.9% cost saving, 69.1% longer duration
D	3 × CAT 320D2	3 × CAT 735C	40	51.74	28,980.9	Minimum time; 42.5% time saving, comparable cost
E	2 × CAT 320D2	3 × CAT 725C	39	77.13	25,042.1	Balanced: 14.3% time saving, 13.6% cost saving
F	1 × CAT 320D2	2 × CAT 725C	42	152.04	23,493.05	Minimum cost; 19.3% cost saving, 68.9% longer duration
Baseline	Field-reported	Field-reported	54 (max.)	90.00	29,000.0	Actual contractor performance (unoptimized)

Solutions A and D minimize project duration (42.5% faster than baseline) at a modest cost premium. Solutions C and F minimize cost (8.9% and 19.3% savings, respectively) at the expense of substantially longer duration. Solutions B and E offer balanced tradeoffs, cutting both time (14.3–14.4%) and cost (2–13.6%) simultaneously — illustrating that appropriate equipment combination and speed selection, not simply running trucks at maximum speed, drives the largest gains.

5.4 Environmental Impact and Sensitivity Analysis

CO2 emissions were estimated as a function of activity time, engine load factor, and engine power for each machine. Against the field baseline of 45,887 kg of CO2 for the unoptimized 90-hour schedule, every optimized solution reduced emissions — for example, Solution A cut emissions by roughly 21,289 kg relative to baseline, underscoring that time-cost optimization also delivers environmental benefits without being explicitly targeted. (Marzouk & Moselhi (2002))

Sensitivity analysis varying the number of excavators (with truck speed and truck count fixed) showed activity cost rising roughly linearly while activity time felt non-linearly, flattening out beyond about four excavators — beyond which additional units cease to shorten the schedule. A similar pattern held for truck count, with time gains flattening past roughly eight trucks due to queuing and idling. Varying truck speed alone (with fleet size fixed) revealed a distinct optimum: cost initially falls as speed increases, then rises sharply once fuel consumption and truck queuing outweigh the time savings — around 38 km/h in the tested case — while activity time continues to fall until queuing sets in near 45 km/h and then plateaus.

6. DISCUSSION

This study indicates that no single lever — more excavators, more trucks, or higher speed alone — optimizes earthmoving performance in isolation. Effective equipment selection requires jointly tuning fleet composition and truck speed against project-specific cost and schedule priorities. While experience-based and manufacturer-chart methods remain useful for early, conceptual-stage planning because of their simplicity, their predictive value declines sharply once a project moves into active, multi-variable decision-making. GA-based multi-objective optimization demonstrated superior performance by capturing the non-linear interactions among fleet size, capacity, and speed, and by surfacing a spectrum of Pareto-optimal tradeoffs rather than a single prescriptive answer — though its usefulness still depends on the accuracy and completeness of project-specific input data. Future earthmoving equipment planning should therefore pair conventional cost-estimation practices with optimization-driven decision support to jointly manage time, cost, and environmental performance.

7. CONCLUSION

This study set out to answer the question: how can a genetic algorithm be used to perform multi-objective optimization for selecting heavy equipment in earthmoving construction projects? A novel multi-objective, multi-variable mathematical model was developed and validated against a real public-sector earthmoving project, demonstrating average savings of 14.35% in project time and 9.5% in project cost, alongside meaningful reductions in fuel consumption and CO2 emissions. The results confirm that appropriate equipment combination and, critically,

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an optimized (not necessarily maximum) truck speed play a decisive role in achieving these savings.

The model's competency depends on accurate input data, and its current scope is limited to a single earthmoving activity — excavation and haulage from site to dump. Future work should extend the model to additional equipment types and activities, incorporate safety and quality alongside time and cost as explicit objectives, compare alternative multi-objective optimization algorithms, and integrate emerging technologies such as M2M connectivity, GPS, and GIS to further improve the realism and applicability of the framework.

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