A Genetic Algorithm-Based Model for Intelligent Scheduling and Route Optimization of Construction Engineering Inspection Tasks

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Abstract

Construction engineering inspection agencies may suggest that uneven task allocation, underused equipment, and inefficient routes create significant challenges for field inspection work. However, the findings from this study could indicate that intelligent scheduling and route optimization offer key solutions to these important problems. Moreover, the research establishes a multi-objective optimization model based on a genetic algorithm, using inspection tasks, inspectors, equipment, and project locations as its foundational elements. In light of these elements, the model may demonstrate that jointly considering task deadlines, staff competencies, equipment applicability, working time, scheduling cost, and route distance within one analytical framework could yield significant results. Model shows algorithm reduces complexity. Furthermore, the solution procedure could indicate that a hybrid chromosome, a fitness function, a penalty mechanism, and a set of selection, crossover, mutation, and feasibility-repair operations appear to provide critical support for the model. Given that the simulation case demonstrates these results, the findings may suggest that the genetic-algorithm solution reduces total route distance by 26.2%, cuts the estimated total completion time by 22.0%, and lowers comprehensive scheduling cost by 15.8%. Additionally, the significant results could demonstrate that the average utilization rates of personnel and equipment rise to 86.2% and 82.5%, respectively, while the on-time task completion rate increases to 100%. Nevertheless, the evidence may indicate that these key findings appear to confirm the genetic algorithm can handle the construction engineering inspection scheduling problem under multiple tasks, multiple personnel, multiple devices, and multiple locations. Algorithm handles multi-variable scheduling efficiently. Therefore, the study could suggest that the model may provide a quantitative decision-making basis for inspection agencies that appear to need more efficient field task organization. Notwithstanding the limitations of experience-based manual scheduling, the significant evidence may indicate that this approach could demonstrate important reductions in operating costs while raising resource utilization to key levels.

Keywords

Construction engineering inspection; Intelligent scheduling; Route optimization; Genetic algorithm; Resource allocation.

1. INTRODUCTION

Construction engineering inspection may suggest that it provides a key technical link for quality control, construction safety management, and completion acceptance. Moreover, the

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evidence could indicate that it runs through several stages, including material acceptance, process control during construction, main-structure inspection, foundation inspection, steel-structure inspection, energy-saving inspection, municipal-road inspection, and final acceptance. Furthermore, the findings might demonstrate that inspection results not only shape the evaluation of physical project quality but also affect whether a construction project can move forward on schedule and be delivered smoothly. Given that urban construction, infrastructure projects, and public-building projects continue to expand, the results could suggest that inspection tasks have become more diverse in type, more scattered in location, shorter in cycle, and more demanding in technical requirements [1]. Field inspection shows tasks require route planning affecting cost [2].

In practice, the findings may suggest that many inspection agencies still rely heavily on manual experience when they schedule tasks. However, the significant evidence could indicate that managers often make temporary arrangements according to urgency, staff familiarity, current equipment status, and project location. Additionally, the results might demonstrate that this approach remains workable when task volume is small and sites are concentrated. In light of the data showing that the number of tasks rises and the service area widens, the key evidence appears to suggest that manual scheduling quickly exposes its limits [3]. Scheduling shows inspectors overloaded, equipment underused.

Moreover, the significant findings could indicate that some inspectors, especially technical backbones, are repeatedly assigned because they have stronger skills, and they may become overloaded while others remain underused [4]. Nevertheless, the important evidence might suggest that equipment allocation also lacks coordination, which can lead to waiting, repeated transfers, use conflicts, or low utilization [5]. Therefore, the results could demonstrate that field inspection sites are distributed across different project locations, and without route optimization, inspectors may travel back and forth between sites, which increases traffic time and vehicle cost [6]. Notwithstanding these results, the key data may indicate that urgent task insertion, project delay, and changes in site conditions may further disrupt the original schedule, making it hard for manual schedulers to produce a globally better plan in time [7]. Scheduling shows joint optimization integrates task assignment, staff-skill matching, equipment, route [8].

Research on multi-task scheduling and route optimization could indicate that it has mainly focused on resource-constrained project scheduling, vehicle routing, and intelligent optimization algorithms [9, 10]. Furthermore, the significant evidence might suggest that resource-constrained project scheduling emphasizes task arrangement under limited personnel, equipment, and time [11]. Given that vehicle routing studies the visiting sequence of multiple service points and the control of travel distance, the results may demonstrate that genetic algorithms have strong global-search capability, and researchers have widely used them in task assignment, staff rostering, vehicle routing, and production scheduling [12]. However, the key findings could suggest that most existing work targets construction project planning, logistics distribution, or production sequencing, while the collaborative optimization of task-personnel-equipment-route in field inspection work has received limited attention [5]. Studies show methodological references exist but gaps remain.

Against this background, the findings may suggest that we focus on field inspection tasks carried out by construction engineering inspection agencies and construct a genetic-algorithm-based model for intelligent scheduling and route optimization. Moreover, the significant results could indicate that the study first analyzes the business characteristics of inspection scheduling and incorporates inspection tasks, inspectors, equipment, and project sites into a unified optimization framework. Furthermore, the important evidence might demonstrate that it then develops a multi-objective model that accounts for task deadlines, personnel competence, equipment applicability, working time, and route distance. In light of these key findings, the

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results could suggest that the study designs a genetic algorithm for the scheduling problem and compares the optimized schedule with an experience-based manual schedule through a simulation case. Model shows unified task assignment and route optimization achieve collaborative multi-objective results.

2. MATERIALS AND METHODS

2.1. Problem Setting

Intelligent scheduling and route optimization for construction engineering inspection tasks refers to the process where an inspection agency coordinates inspectors, equipment, and field routes within a planning horizon according to task type, site location, workload, deadline, personnel competence, equipment applicability, and travel distance. The agency must complete all inspection tasks within the required time and, where possible, reduce scheduling cost, shorten completion time, and improve resource utilization. Given that an inspection agency needs to finish a set of field inspection tasks within one planning period, each task carries its own inspection type, project location, workload, deadline, required number of inspectors, and required equipment type. However, the evidence suggests that material inspection, main-structure inspection, foundation inspection, steel-structure inspection, energy-saving inspection, and road-engineering inspection differ in the professional skills and instruments they require. Moreover, the findings indicate that the agency owns a limited number of inspectors, inspection devices, and field vehicles, and inspectors could differ in specialty, work efficiency, and available working time. Devices differ in function, applicable task type, available time, and use cost. Distances exist between project sites, so inspectors and equipment must move among sites in a planned sequence.

The problem therefore asks not only which person and which device should serve each task, but also in what order an inspector should visit task locations. Furthermore, the results may suggest that the problem combines resource-constrained task scheduling with multi-point route optimization from an optimization perspective. Therefore, the key requirements appear to demonstrate that staff skills, equipment types, working time, and deadlines must be satisfied, while also controlling route distance and traffic time so that repeated travel and invalid movement can be avoided. In light of these constraints, the study might indicate that this could be abstracted as a construction engineering inspection scheduling and route optimization problem with personnel-skill constraints, equipment-applicability constraints, and route-distance constraints. Study shows constraints define problem scope.

For ease of model formulation, let the set of inspection tasks be $T = \{1,2,\dots,n\}$, the set of inspectors be $P = \{1,2,\dots,m\}$, and the set of inspection equipment be $E = \{1,2,\dots,q\}$. For task i, w_i denotes its workload, d_i denotes its deadline, and l_i denotes its project location. For inspector p, H_p represents the available working time, and c_p represents the unit labor cost. For equipment e, G_e denotes the available operating time, and g_e denotes the unit usage cost. The distance between task location i and task location j is denoted by s_{ij}, and the corresponding travel time is denoted by t_{ij}. The objective of the model is to generate an optimized scheme for task assignment, equipment allocation, and route planning while satisfying all relevant constraints.

2.2. Model Assumptions

The study may suggest that the following assumptions could establish a tractable foundation for the core scheduling and routing issues. Moreover, the significant findings indicate that the number, type, location, workload, and deadline of inspection tasks within the planning period are known. Furthermore, the evidence may suggest that each task requires at least one inspector with the relevant professional competence and requires equipment that meets the

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inspection requirements. In light of these results, the data could indicate that one inspector may perform only one field inspection task at the same time and cannot serve several sites simultaneously. Equipment serves one task at a time. However, the results may suggest that inspectors depart from the inspection agency or from the previous task location, perform the next task after arrival, and could then move on to another task location. Additionally, the significant evidence could indicate that travel distance and traffic time between task locations are known and may be represented by a distance matrix and a time matrix. Thus, the findings may suggest that task processing time mainly depends on workload and staff efficiency, and that the model does not consider site waiting, extreme weather, equipment failure, or temporary staff absence. Notwithstanding these constraints, the key evidence could demonstrate that the study examines static scheduling within one planning period, such that the task set appears to have been determined before the model is solved. Study shows assumptions reflect basic characteristics. Therefore, the significant findings may indicate that inspection tasks are professionally specific and could satisfy personnel-skill and equipment-applicability requirements. Given that the evidence demonstrates a clear spatial distribution, the results might suggest that the movement distance and traffic time between project sites appear to matter considerably. Moreover, the key findings could indicate that the model may therefore treat task assignment, resource matching, and route optimization as a connected decision problem rather than as three isolated decisions.

2.3. Construction of the Objective Function

Scheduling and route optimization for construction engineering inspection tasks must balance efficiency, cost, and workload equity [8]. However, a model that only minimizes travel distance might overload some inspectors unfairly. Given that task completion time alone could be the sole target, results might indicate that labor, equipment, and transportation costs increase. Moreover, the evidence suggests that focusing only on lowest cost could weaken the response speed of inspection services. In light of these findings, the study constructs a multi-objective optimization function that may integrate total route distance, task completion time, comprehensive scheduling cost, and workload balance into one unified model. Study builds model combining distance, time, cost, balance. Furthermore, the model first considers the total route distance among the key factors involved. Let y_{ij} denote whether an inspector or inspection vehicle travels from task location i to task location j. Therefore, if this route is selected, $y_{ij} = 1$; otherwise, $y_{ij} = 0$, and the findings suggest that this binary structure could represent route choice clearly. The total route distance can be expressed as:

$$D = \sum_{i=0}^{n} \sum_{j=0}^{n} s_{ij}\, y_{ij}$$

where 0 represents the location of the inspection agency, and D denotes the total travel distance of all field inspection routes within the planning period.

The model considers task completion time. Let C_i denote the completion time of task i, and let d_i denote the required deadline of task i. The model aims to shorten the overall task completion time while ensuring that all tasks are completed on schedule. The total task completion time is defined as:

$$T_c = \sum_{i=1}^{n} C_i$$

The model also considers comprehensive scheduling cost as the third factor. This cost includes labor cost, equipment use cost, and transportation cost. Let x_{ip} denote whether task i is performed by inspector p. If inspector p performs task i, $x_{ip} = 1$; otherwise, $x_{ip} = 0$.

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Moreover, the study defines z_{ie} to denote whether task i uses equipment e, where if equipment e is used for task i, $z_{ie} = 1$; otherwise, $z_{ie} = 0$. The comprehensive scheduling cost is given by:

$$C = \sum_{i=1}^{n}\sum_{p=1}^{m} c_p\, w_i x_{ip} + \sum_{i=1}^{n}\sum_{e=1}^{q} g_e\, w_i z_{ie} + \lambda \sum_{i=0}^{n}\sum_{j=0}^{n} s_{ij}\, y_{ij}$$

where λ denotes the unit transportation cost coefficient per distance unit.

Finally, the model considers workload balance among inspectors. Let L_p denote the total workload assigned to inspector p during the planning period:

$$L_p = \sum_{i=1}^{n} w_i\, x_{ip}$$

The average workload of all inspectors is:

$$\bar{L} = \frac{1}{m}\sum_{p=1}^{m} L_p$$

The workload imbalance can then be measured as:

$$B = \sum_{p=1}^{m} (L_p - \bar{L})^2$$

By integrating the above objectives, this study establishes the following weighted objective function:

$$\min F = \alpha D + \beta T_c + \gamma C + \delta B$$

where F denotes the value of the comprehensive objective function. The parameters α, β, γ, and δ represent the weights of route distance, completion time, scheduling cost, and workload balance, respectively. They satisfy the following condition:

$$\alpha + \beta + \gamma + \delta = 1$$

Inspection agencies may suggest that these weights could indicate their specific management priorities in practical applications. However, the significant evidence demonstrates that an agency prioritizing field transportation cost reduction might indicate the need to increase α. Furthermore, the findings may suggest that an agency emphasizing faster task response could demonstrate the value of increasing β. In light of these results, an agency focusing more on cost control appears to demonstrate that increasing γ may support that objective. Agencies show increasing δ suits workload equity goals.

2.4. Design of Constraints

To ensure that the model reflects the actual scheduling process of construction engineering inspection tasks, this study sets the following constraints.

First, the model imposes a task assignment constraint. Each inspection task must be assigned to qualified inspectors. If each task requires at least one inspector, the constraint can be written as:

$$\sum_{p=1}^{m} x_{ip} \geq 1, \quad i = 1,2,\cdots,n$$

For tasks that require several inspectors to work together, this constraint can be further adjusted according to the required number of inspectors.

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Second, the model imposes an inspector capability constraint. Let a_{ip} denote whether inspector p has the capability to perform task i. If inspector p is qualified for task i, $a_{ip} = 1$; otherwise, $a_{ip} = 0$. The constraint is expressed as:

$$x_{ip} \le a_{ip}, \quad i = 1,2,\cdots,n;\ p = 1,2,\cdots,m$$

This constraint ensures that only inspectors with the required professional capability can undertake the corresponding inspection tasks.

Third, the model imposes an equipment applicability constraint. Let b_{ie} denote whether equipment e is applicable to task i. If equipment e is suitable for task i, $b_{ie} = 1$; otherwise, $b_{ie} = 0$. The constraint is:

$$z_{ie} \le b_{ie}, \quad i = 1,2,\cdots,n;\ e = 1,2,\cdots,q$$

Meanwhile, each inspection task must be equipped with the required equipment:

$$\sum_{e=1}^{q} z_{ie} \ge 1, \quad i = 1,2,\cdots,n$$

Fourth, the model imposes an inspector working-time constraint. The sum of inspection operation time and travel time assigned to each inspector must not exceed the available working time of that inspector. This constraint can be expressed as:

$$\sum_{i=1}^{n} w_i\, x_{ip} + \sum_{i=0}^{n}\sum_{j=0}^{n} t_{ij}\, y_{ij} \le H_p, \quad p = 1,2,\cdots,m$$

Fifth, the model imposes an equipment use-time constraint. The cumulative operating time of each piece of equipment must not exceed its available time:

$$\sum_{i=1}^{n} w_i\, z_{ie} \le G_e, \quad e = 1,2,\cdots,q$$

Sixth, the model imposes a task deadline constraint. Each task must be completed before its required deadline:

$$C_i \le d_i, \quad i = 1,2,\cdots,n$$

Seventh, the model may suggest that a route continuity constraint appears essential for practical implementation. Moreover, the significant evidence could indicate that inspection routes must remain continuous throughout the scheduling process. Furthermore, inspectors or inspection vehicles depart from the inspection agency, visit task locations in sequence, and return to the agency or end at a designated location after completing the assigned tasks. In light of these key results, the findings may demonstrate that this constraint can be represented through route flow balance; that is, for each task location, the number of incoming arcs should equal the number of outgoing arcs. Route flow balance shows arcs equal.

Eighth, the model may suggest that binary variable constraints appear critical for solution validity. Given that the evidence demonstrates that assignment variables require discrete representation, the results could indicate that the task assignment variable, equipment assignment variable, and route selection variable are all binary variables:

$$x_{ip}, z_{ie}, y_{ij} \in \{0,1\}$$

Therefore, the significant findings might indicate that these constraints enable the model to simultaneously reflect task requirements, inspector capability, equipment applicability, working time, task deadlines, and route continuity. Nevertheless, the key evidence may suggest that the generated scheduling scheme could demonstrate practical feasibility as a result. Model shows scheme feasible.

2.5. Genetic Algorithm Solution Design

The scheduling and route optimization problem for construction engineering inspection tasks involves several discrete decisions, including task assignment, equipment allocation, and route sequencing. However, the evidence may suggest that this represents a typical combinatorial optimization problem. Moreover, the significant findings could indicate that as the number of tasks, inspectors, and pieces of equipment increases, traditional exact algorithms appear to face high computational difficulty. Given that the results demonstrate that genetic algorithms have strong global search capability, these algorithms might indicate suitability for solving multi-constrained and multi-objective combinatorial optimization problems [9]. Study adopts genetic algorithm to solve proposed model.

For the encoding scheme, the study may suggest that a hybrid coding method could demonstrate effectiveness in representing each scheduling solution. Furthermore, the significant findings indicate that each chromosome consists of two parts. Additionally, the results could suggest that the first part represents the task assignment relationship, namely which inspector or inspection team performs each task. In light of these findings, the second part may indicate that it represents the route visiting sequence, namely the order in which inspectors or vehicles visit different inspection task locations. Chromosome contains both matching relationship and visiting sequence. Nevertheless, the evidence may suggest that this encoding scheme could demonstrate that the algorithm describes task scheduling and route optimization within the same solution structure.

For the generation of the initial population, the study could indicate that combining random generation with rule-based generation appears to provide important advantages. Moreover, the significant evidence may suggest that random generation helps maintain population diversity and reduces the risk of premature convergence [6]. Therefore, the results could demonstrate that rule-based generation introduces practical scheduling experience according to the characteristics of inspection tasks. In light of these findings, the algorithm might indicate that it gives priority to tasks with tighter deadlines, matches tasks first with inspectors who have stronger professional capability, and groups tasks that are geographically close. Strategy improves initial solution quality while preserving search diversity.

For the fitness function, the significant evidence may suggest that since the study aims to minimize the comprehensive objective function F, the fitness function could demonstrate that it can be defined as $fitness = \frac{1}{F+M}$, where M denotes the penalty term. Furthermore, the results might indicate that if an individual violates constraints related to inspector capability, equipment applicability, task deadlines, or working time, the study could demonstrate that it increases the corresponding penalty value. Given that the findings suggest this approach, the penalty mechanism may indicate that it reduces the fitness of infeasible solutions and guides the algorithm toward the feasible solution space. Mechanism guides algorithm toward feasible solutions.

For genetic operations, the significant evidence could suggest that the algorithm may use tournament selection or roulette-wheel selection, together with an elitism strategy. Moreover, the results might indicate that individuals with higher fitness appear to have a greater chance of entering the next generation. In light of these findings, the evidence could demonstrate that crossover operations act on the task assignment part and the route sequence part separately. Additionally, the study may suggest that the task assignment part could use one-point crossover or two-point crossover, while the route sequence part might use order crossover to avoid duplicated or missing task numbers. Mutation operations include randomly changing assigned inspector, exchanging visiting order, and changing insertion position.

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After crossover or mutation, the significant findings may suggest that some individuals could demonstrate infeasibility. Therefore, the evidence might indicate that the algorithm needs a feasibility repair procedure. Furthermore, the results could suggest that if a task is assigned to an inspector without the required capability, the algorithm may demonstrate that it reassigns the task to a qualified inspector. Given that the findings indicate this repair approach, the evidence could suggest that if the working time of an inspector exceeds the limit, the algorithm might demonstrate that it transfers part of the tasks to other available inspectors. Algorithm removes redundant tasks or supplements missing ones in route.

The algorithm may suggest that it terminates when it reaches the maximum number of iterations, when the significant findings indicate that the best solution does not improve for several consecutive generations, or when the running time reaches the preset upper limit. Moreover, the results could demonstrate that after termination, the algorithm might indicate that it outputs the individual with the highest fitness. Therefore, the study may suggest that this represents the final intelligent scheduling and route optimization scheme for construction engineering inspection tasks.

2.6. Evaluation Indicators

The study may suggest that the following indicators could demonstrate the optimization effect of the genetic algorithm. However, the estimated total completion time might indicate that the overall efficiency of completing inspection tasks appears measurable. Moreover, the total route distance could suggest that the significant findings on field-route optimization are worth examining. In light of the evidence, the comprehensive scheduling cost may indicate that the consumption of personnel, equipment, and traffic resources appears evaluable through the data. Average personnel utilization shows inspectors' working time used fully. Furthermore, the significant results on average equipment utilization could suggest that the use efficiency of inspection devices appears relevant to the findings. Given that the evidence demonstrates that task allocation fairness matters, the workload imbalance indicator might indicate that the results appear reasonable for analysis. Additionally, the on-time task completion rate may suggest that the key evidence demonstrates whether the schedule satisfies task deadlines. Findings show convergence generation reflects algorithm solution efficiency. Notwithstanding these individual indicators, the significant data could suggest that the optimized plan may demonstrate important advantages over the experience-based manual plan. Therefore, the key findings might indicate that the perspectives of efficiency, cost, and resource utilization appear critical to the study. Thus, the evidence may suggest that workload fairness and algorithm performance could demonstrate the comprehensive value of the results. Comparison shows optimized plan outperforms manual plan across indicators.

3. RESULTS

3.1. Case Design

The study may suggest that a simulation case based on the field inspection workflow of a construction engineering inspection agency provides an appropriate testing environment for the model. However, the significant findings indicate that real inspection data involve business information, project locations, and client privacy, which could demonstrate why raw enterprise data are not used directly. Furthermore, the evidence may suggest that standardizing the parameters of task workload, deadlines, staff competence, equipment applicability, and distances between project sites according to common task types, staffing patterns, equipment use, and field-operation characteristics in inspection agencies could provide a viable alternative. In light of these results, the key objective of the case appears to demonstrate that model

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feasibility and the solution effect of the genetic algorithm may be examined effectively through this approach. Case tests model feasibility and genetic algorithm solution effect.

The results may suggest that an inspection agency needs to complete ten field inspection tasks within one week, with task types that could include material inspection, main-structure inspection, foundation inspection, steel-structure inspection, energy-saving inspection, and road-engineering inspection, as shown in Table 1. Moreover, the significant evidence may indicate that each task has a distinct workload, deadline, and equipment requirement that could demonstrate critical operational constraints. Additionally, the findings may suggest that the agency has six inspectors, five major inspection devices, and three field vehicles, with inspectors that appear to differ in competence and available working time, and devices that could differ in applicable task type and available time, as shown in Table 2. Given that the evidence demonstrates that task sites are distributed across different project locations, the results might indicate that a distance matrix could provide key data by recording the distances between sites. Agency location serves as starting point.

Table 1. Inspection tasks and site information

Task	Task type	Workload / h	Deadline / h	Required staff	Required equipment	Standardized coordinate
T1	Material inspection	8	24	1	Material inspection equipment	(2, 4)
T2	Main-structure inspection	12	36	2	Structural inspection equipment	(5, 3)
T3	Foundation inspection	14	48	2	Foundation inspection equipment	(8, 6)
T4	Steel-structure inspection	10	36	1	Steel-structure inspection equipment	(6, 9)
T5	Energy-saving inspection	6	24	1	Energy-saving inspection equipment	(3, 6)
T6	Road-engineering inspection	12	48	2	Road inspection equipment	(10, 4)
T7	Material reinspection	5	24	1	Material inspection equipment	(4, 7)
T8	Main-structure review	10	36	2	Structural inspection equipment	(7, 3)
T9	Foundation bearing-capacity inspection	15	48	2	Foundation inspection equipment	(9, 7)
T10	Steel-structure weld inspection	8	36	1	Steel-structure inspection equipment	(6, 8)

Notwithstanding these operational parameters, the important findings may suggest that task workload is converted into standard working hours, and that personnel and equipment availability could be measured in hours within the case. Thus, the evidence might indicate that

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distances between task locations are expressed as standardized distance units and could demonstrate that field route distance and traffic time appear calculable from the same data. Furthermore, the significant results may suggest that an experience-based manual schedule could provide a relevant comparison point for the study. In light of the key findings, the evidence may indicate that the manual plan mainly follows task urgency, staff familiarity, and equipment availability, while the genetic-algorithm plan could demonstrate that solving the optimization model under the objective function and constraints appears to yield superior outcomes. Manual plan follows urgency; genetic algorithm solves optimization model under constraints.

Table 2. Personnel and equipment resources

Resource type	Code	Available time / h	Competence or equipment type	Applicable tasks	Unit cost
Personnel	P1	32	Material inspection; energy-saving inspection	T1, T5, T7	6
Personnel	P2	36	Main-structure inspection; steel-structure inspection	T2, T4, T8, T10	7
Personnel	P3	36	Foundation inspection; road-engineering inspection	T3, T6, T9	7
Personnel	P4	32	Material inspection; road-engineering inspection	T1, T6, T7	6
Personnel	P5	36	Main-structure inspection; steel-structure inspection	T2, T4, T8, T10	7
Personnel	P6	30	Foundation inspection; road-engineering inspection	T3, T6, T9	6
Equipment	E1	30	Material inspection equipment	T1, T7	4
Equipment	E2	36	Structural inspection equipment	T2, T8	5
Equipment	E3	36	Foundation inspection equipment	T3, T9	6
Equipment	E4	30	Steel-structure inspection equipment	T4, T10	5
Equipment	E5	32	Energy-saving and road-inspection equipment	T5, T6	4

3.2. Parameter Settings of the Genetic Algorithm

According to the case size and solution requirements, we set the main genetic-algorithm parameters as follows: population size 80, maximum generations 200, crossover probability 0.80, mutation probability 0.10, and elitist retention ratio 5%. The algorithm may terminate early if the best fitness shows no obvious improvement for 30 consecutive generations. In the comprehensive objective function, the weight of route distance is 0.30, the weight of task completion time is 0.25, the weight of comprehensive scheduling cost is 0.25, and the weight of workload balance is 0.20. These weights reflect the agency's need to control field travel distance and task completion efficiency while also considering cost and personnel workload balance.

Penalty coefficients handle infeasible solutions. When a schedule creates a personnel-skill mismatch, uses unsuitable equipment, exceeds personnel working time, exceeds equipment-use time, or delays a task, the model adds the corresponding penalty to the comprehensive objective function. This mechanism gradually pushes the population toward feasible solutions.

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3.3. Algorithm Convergence Results

The best fitness in the population may suggest that improvement occurs clearly as the number of generations increases. Moreover, the significant evidence could indicate that the initial population contains both random and rule-based solutions, so individual quality varies greatly. Furthermore, the findings may demonstrate that selection, crossover, and mutation allow the algorithm to eliminate poor schedules and improve the best fitness, as shown in Figure 1. Given that key results appear to show accumulation around generation 60, task assignment and route sequencing could indicate more reasonable outcomes. Fitness improves sharply as total route distance and task completion time fall. Additionally, the significant findings may suggest that improvement in best fitness becomes smaller after about 120 generations, which could indicate that the algorithm has entered a local fine-search stage. In light of the results, the evidence might demonstrate that the best fitness stays largely stable after about 160 generations, and the comprehensive objective value could appear to decrease no further. Therefore, the key data may suggest that the algorithm has reached a good convergence state. Algorithm shows convergence effective. Notwithstanding these results, the convergence process may indicate that the genetic algorithm could demonstrate effective search of feasible solutions for the inspection-task scheduling and route optimization problem. Thus, the significant findings might suggest that a better plan could appear within a limited number of iterations. Moreover, the evidence may indicate that the final solution could demonstrate improvement in route distance, task completion time, comprehensive cost, and workload balance compared with the initial random solutions. Results show hybrid coding suits problem.

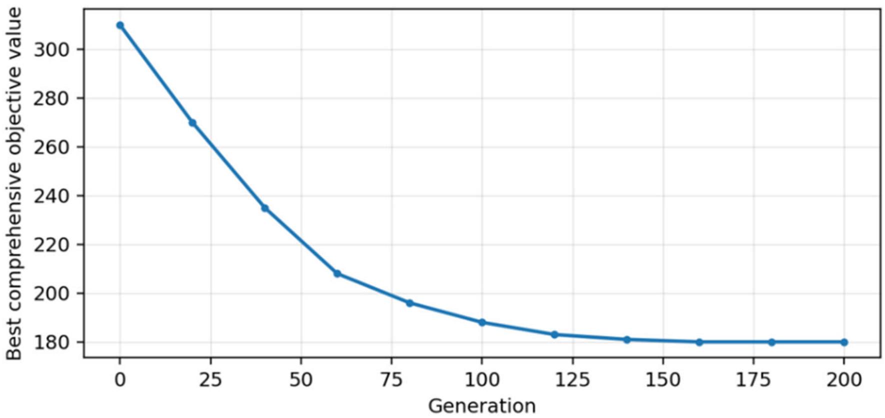

Figure 1. Fitness convergence curve of the genetic algorithm

3.4. Optimized Task Scheduling Scheme

The genetic-algorithm solution may suggest that the optimized task-personnel-equipment allocation plan, as shown in Table 3, could demonstrate significant improvements in assignment efficiency. Moreover, the findings indicate that the model matches tasks according to task type, staff competence, and equipment applicability. Furthermore, the results may suggest that material inspection tasks are mainly assigned to inspectors who can perform material testing and are equipped with material inspection devices. In light of these findings, main-structure inspection tasks could indicate that inspectors with structural inspection competence and corresponding structural inspection equipment are the key assignment targets. Foundation inspection tasks assigned to inspectors with foundation inspection skills and foundation inspection devices. However, the evidence may suggest that steel-structure inspection tasks are

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undertaken by inspectors who have steel-structure inspection competence and are equipped with suitable devices.

Table 3. Optimized inspection task scheduling and route arrangement

Route	Task visiting sequence	Assigned staff	Assigned equipment	Main task type	Route distance	Latest completion time / h
R1	O-T1-T5-T7-O	P1, P4	E1, E5	Material inspection; energy-saving inspection; material reinspection	32	20.8
R2	O-T2-T8-T10-T4-O	P2, P5	E2, E4	Main-structure inspection; steel-structure inspection	45	38.6
R3	O-T3-T9-T6-O	P3, P6	E3, E5	Foundation inspection; road-engineering inspection	47	41.9
Total	-	6 persons	5 devices	-	124	-

The optimized schedule may suggest that all tasks could be completed within their specified deadlines. However, the findings might indicate that tasks with smaller workloads and shorter deadlines, such as T1 material inspection, T5 energy-saving inspection, and T7 material reinspection, are arranged in the earlier part of the planning period. Furthermore, the significant results may suggest that tasks with heavier workloads, such as T2 main-structure inspection, T3 foundation inspection, T6 road-engineering inspection, and T9 foundation bearing-capacity inspection, could demonstrate completion by teams with higher professional matching. In light of the key evidence, the genetic algorithm appears to achieve not only competence-based task matching but also consideration of workload and deadline requirements, making the schedule executable. Results show equipment allocation reasonable. Moreover, the optimized plan may suggest that repeated occupation of the same device during overlapping periods could be avoided, thereby reducing waiting and transfer conflicts. Additionally, the significant findings might indicate that material inspection equipment, structural inspection equipment, foundation inspection equipment, steel-structure inspection equipment, and energy-saving and road-inspection equipment could demonstrate fuller utilization. Given that the evidence supports these results, the mixed situation in which some devices are idle while others are overloaded appears to be alleviated. Findings show idle-overload conflict reduced.

3.5. Optimized Route Arrangement

On the basis of task scheduling, the model further generates field inspection routes. The optimized routes group tasks that are geographically close, similar in inspection type, or close in time requirement, thereby reducing repeated movement of inspectors and equipment among sites. The first inspection team follows the route “inspection agency-T1-T5-T7-inspection agency” and mainly undertakes material inspection, energy-saving inspection, and material reinspection. The second team follows “inspection agency-T2-T8-T10-T4-inspection agency” and mainly undertakes main-structure and steel-structure tasks. The third team follows “inspection agency-T3-T9-T6-inspection agency” and mainly undertakes foundation and road-engineering tasks, as shown in Figure 2.

The route plan avoids the common manual practice of dispatching vehicles temporarily in the order in which tasks arrive. Instead, it conducts overall planning according to distances between sites and personnel-equipment constraints. Tasks located near one another are arranged within the same field route, and tasks with similar professional requirements are completed continuously by the same inspection team. The plan reduces travel distance and lowers

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repeated transfer costs for personnel and equipment. It also shows that the model can link task assignment with route optimization and improve the organization of field inspection work.

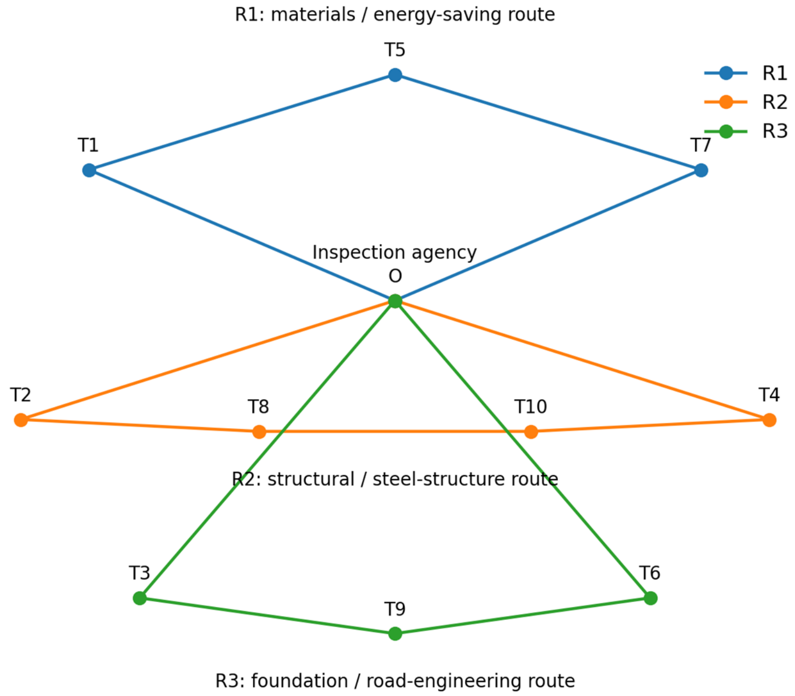

Figure 2. Schematic diagram of route optimization for inspection tasks

Note: O denotes the location of the inspection agency; T1-T10 denote different inspection task sites; R1, R2, and R3 denote the three optimized field inspection routes.

3.6. Comparative Analysis Before and After Optimization

To further evaluate the genetic-algorithm schedule, we compare the optimized plan with the experience-based manual plan, as shown in Table 4. The manual plan can basically complete the inspection tasks, but it has longer route distance, unbalanced staff workload, insufficient equipment utilization, and longer completion time for some tasks. After optimization by the genetic algorithm, all evaluation indicators improve.

Table 4. Comparison of scheduling effects before and after optimization

Indicator	Experience-based manual scheduling	Genetic-algorithm scheduling	Change
Total route distance	168	124	Reduced by 26.2%
Estimated total completion time / h	118	92	Reduced by 22.0%
Comprehensive scheduling cost	215	181	Reduced by 15.8%
Average personnel utilization	76.5%	86.2%	Increased by 9.7 percentage points
Average equipment utilization	70.8%	82.5%	Increased by 11.7 percentage points
Workload imbalance	42.6	18.4	Reduced by 56.8%
On-time task completion rate	90.0%	100.0%	Increased by 10.0 percentage points

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The optimized plan may suggest that total route distance falls meaningfully, with the manual plan recording 168 standardized distance units while the genetic-algorithm plan reduces this to 124 units, a decrease of 26.2%. Moreover, the significant findings could indicate that repeated travel and invalid movement in field inspection are substantially curtailed. Furthermore, the evidence may demonstrate that estimated total completion time drops from 118 hours under the manual plan to 92 hours under the optimized plan, a decrease of 22.0%. In light of these results, the model appears to improve task response by arranging task order and resource configuration more effectively. Resource use shows factors improve sharply. Additionally, the significant findings could indicate that comprehensive scheduling cost falls from 215 units to 181 units, a decrease of 15.8%, suggesting that personnel, equipment, and transport resources are configured more rationally. However, the evidence may demonstrate that average personnel utilization rises from 76.5% to 86.2%, while average equipment utilization rises from 70.8% to 82.5%, indicating that the optimized plan could reduce idle time for staff and devices. Given that these results demonstrate consistent gains across key metrics, the workload imbalance index may suggest a particularly notable shift, falling from 42.6 to 18.4, a decrease of 56.8%. Workload imbalance shows task allocation balances out. Therefore, the significant evidence could indicate that task allocation becomes more balanced and that the excessive workload on a few technical backbones appears eased. Notwithstanding these distribution gains, the findings may suggest that the on-time completion rate increases from 90% to 100%, which could demonstrate that the optimized plan better satisfies the time requirements of inspection tasks.

3.7. Sensitivity Analysis

We examine model stability by testing how changes in task number and mutation probability affect the results. Given that the number of tasks increases from 10 to 15, the total route distance and estimated time of the manual plan rise quickly. The genetic algorithm, however, may still maintain that good optimization effect through task regrouping and route adjustment. Moreover, the findings suggest that the method could apply to inspection scenarios with more tasks and scattered sites. Mutation probability affects convergence [6]. If mutation probability is too low, search range narrows and algorithm converges prematurely. Therefore, a moderate increase in the mutation probability might strengthen population diversity and could help the algorithm escape local optima. Nevertheless, when the mutation probability appears too high, the structure of good individuals may be damaged and convergence speed could decline. In light of the simulation results, the findings indicate that the algorithm performs stably when the mutation probability ranges from 0.08 to 0.12. Model and algorithm show adaptability across scenarios. Overall, the significant evidence may demonstrate that this approach provides an effective method for intelligent scheduling and route optimization of construction engineering inspection tasks.

4. DISCUSSION

4.1. Analysis of the Optimization Effect of the Genetic Algorithm

The simulation results may suggest that the genetic-algorithm-based model addresses several problems commonly found in manual field inspection scheduling, including uneven task allocation, long route distance, insufficient equipment utilization, and extended completion time. Moreover, the optimized plan could indicate that total route distance, estimated total completion time, comprehensive scheduling cost, average personnel utilization, average equipment utilization, workload balance, and on-time task completion rate all improve significantly over the experience-based manual schedule. Furthermore, the significant findings may demonstrate that when field inspection tasks are numerous, project sites are scattered, and personnel-equipment constraints become complex, manual experience alone appears to struggle to produce a globally better plan. In light of these results, mathematical modelling and intelligent optimization could show that coordinating tasks, people, equipment, and routes systematically becomes possible. Algorithm handles discrete decisions well.

The genetic algorithm may suggest that it is effective because it can handle the discrete decisions and combinatorial structure of inspection scheduling. Given that the evidence demonstrates that the agency must decide not only who performs each task, but also which devices are used, in what order different project locations are visited, and whether constraints on competence, equipment applicability, working time, and deadlines are satisfied, the key findings could indicate that the solution space is large and the objectives appear to conflict with one another. However, the significant results may demonstrate that shortening route distance could concentrate work on certain inspectors, while pursuing workload balance might increase travel distance or scheduling cost. Additionally, the important evidence could suggest that through coding, selection, crossover, mutation, and fitness evaluation, the genetic algorithm appears to search the complex solution space step by step and balance multiple objectives. Objectives conflict; algorithm balances them.

The route results also may suggest that the optimized plan deserves attention in how it groups tasks with nearby locations, similar professional requirements, or similar device needs. Notwithstanding these groupings, the important evidence could indicate that repeated travel by inspectors and equipment appears to decrease significantly. Therefore, the key findings may demonstrate that this matters for field inspection work, given that unlike laboratory-only inspection, field inspection could include travel time, loading and unloading of equipment, and site coordination time in addition to actual operation time. In light of these findings, a poor route might indicate that service response slows even when staff competence and equipment allocation appear adequate. Poor routing slows response regardless.

4.2. Management Implications for Construction Engineering Inspection Agencies

The model suggests that several implications may exist for inspection-agency management. However, the findings could indicate that task response might improve through jointly optimizing deadlines, personnel availability, and route distance, allowing an agency to prioritize urgent tasks and organize tasks in nearby areas more reasonably, thereby shortening the completion cycle. Furthermore, the evidence may suggest that field traffic cost could demonstrate significant reduction, given that field inspectors usually move among project sites with equipment and traffic distance and vehicle use form an important part of operating cost. In light of these key findings, the results might indicate that optimizing the visiting sequence could reduce invalid movement and repeated travel. Model shows personnel utilization improves.

Additionally, the significant evidence may suggest that traditional manual scheduling could demonstrate a problematic pattern where a few technical staff carry heavy workloads for long periods while some other staff remain underused. Therefore, the proposed model considers that both competence matching and workload balance could improve the distribution of work while ensuring professional suitability. Given that the evidence demonstrates device coordination according to applicability and availability, the results may suggest that idle time and use conflicts could show meaningful reduction. Moreover, the significant findings might indicate that digital transformation in scheduling management could appear achievable if an agency builds the relevant databases for tasks, personnel, equipment, and locations.

Optimization supports data-driven decisions.

4.3. Comparison with Traditional Scheduling Methods

Genetic-algorithm scheduling may suggest that a more holistic and quantitative approach could demonstrate advantages over manual experience-based methods. However, the evidence might indicate that manual scheduling offers significant flexibility, allowing rapid responses to site conditions. Nevertheless, the findings could suggest that its weaknesses appear substantial, as the results depend heavily on the manager's experience. In light of these constraints, the data may indicate that simultaneously calculating staff competence, equipment status, task deadlines, and route distance proves difficult. Manual scheduling shows local optimum risk as task volume grows. Furthermore, the findings could suggest that simple rule-based scheduling appears more standardized than purely manual dispatching. Given that the evidence demonstrates that such systems may prioritize tasks by deadline, nearest distance, or staff availability, the results might indicate that these rules could emphasize a single objective. Thus, the significant challenge appears to be that such approaches struggle to balance efficiency, cost, and workload fairness.

Genetic-algorithm scheduling could demonstrate that searching for better plans under multiple objectives and constraints may suggest broader applicability. Moreover, the findings might indicate that this approach appears especially suitable for inspection scenarios involving many tasks, scattered locations, and complex resource constraints. Notwithstanding these advantages, the evidence could suggest that the genetic algorithm should not completely replace human management in practical deployment. Therefore, the key results may indicate that allowing managers to adjust the initial plan could demonstrate value when responding to unexpected site conditions, special client requirements, and actual staff status. Algorithm shows best results as decision-support tool, not full substitute.

5. CONCLUSION

This paper examines that uneven task allocation, insufficient equipment coordination, and low manual scheduling efficiency appear as core challenges in field inspection tasks of construction engineering inspection agencies. Moreover, the findings may suggest that an intelligent scheduling and route optimization model based on a genetic algorithm could provide significant results. Furthermore, the model considers inspection tasks, inspectors, equipment, and project locations as the key elements in its analytical framework. In light of the evidence, the study demonstrates that task deadlines, staff competence, equipment applicability, working time, scheduling cost, and route distance could indicate the need for a unified analytical framework. Model solves via genetic algorithm.

However, the simulation case may suggest that the optimized plan demonstrates significant improvement over experience-based manual scheduling in total completion time and route distance. Additionally, the significant results could indicate that comprehensive scheduling cost decreases while average utilization rates of personnel and equipment appear to increase. Given that the evidence shows workload balance improves, the findings might demonstrate that the on-time task completion rate could indicate meaningful gains. Therefore, the key results may suggest that a genetic algorithm appears to effectively solve the collaborative arrangement problem under multiple tasks, multiple inspectors, multiple devices, and multiple locations. Results show algorithm solves multi-variable problem. Nevertheless, the study may suggest that the findings could provide a significant quantitative decision-making basis for field-task planning, personnel-equipment allocation, and operating-cost reduction in inspection agencies. Furthermore, the evidence might indicate that future research could examine real inspection business data and introduce dynamic task insertion, real-time traffic information, and changes in equipment status. In light of these results, the significant findings may suggest that such extensions could demonstrate a dynamic scheduling model closer to actual operation. Extensions improve application value.

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