Optimization of Construction Material Management Using an Integrated Critical Path Method and Ant Colony Optimization Approach

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Abstract

Construction material management significantly influences project cost, duration, and waste generation. Traditional scheduling approaches such as the Critical Path Method (CPM) effectively identify time-critical activities but lack adaptability in dynamic and uncertain construction environments. This study proposes an integrated Critical Path Method–Ant Colony Optimization (CPM–ACO) framework to optimize construction material management networks. A case study consisting of 100 construction material-related activities is modeled using CPM to determine baseline critical paths and floats. Subsequently, Ant Colony Optimization is applied to iteratively reinforce optimal paths through pheromone learning. Ant path behavior is analyzed across multiple iterations (A1, A10, A25, A60, A125, A170, and A199) using graphical visualization. Results show progressive convergence of ant paths toward the CPM critical path, demonstrating improved adaptability and robustness compared to CPM alone. The proposed CPM–ACO framework provides an effective optimization tool for complex construction material management problems.

Keywords: *Construction material management, Critical Path Method, Ant Colony Optimization, CPM–ACO, project scheduling*

1. Introduction

Construction projects are material-intensive systems in which inefficient planning, procurement delays, and improper sequencing lead to cost overruns, schedule slippage, and material waste. Studies report that materials account for up to 70% of total construction costs**,** making material management a critical success factor.

The Critical Path Method (CPM) has been widely used to plan and control construction schedules. CPM identifies the sequence of activities that directly affect project duration. However, CPM assumes deterministic activity durations and static relationships, limiting its effectiveness under uncertainty.

To address these limitations, researchers have increasingly explored metaheuristic optimization techniques**.** Among these, Ant Colony Optimization (ACO) has attracted attention due to its decentralized learning mechanism, adaptability, and ability to solve large-scale combinatorial problems.

This research integrates CPM and ACO into a single optimization framework for construction material management. CPM establishes the baseline project network, while ACO dynamically optimizes material flow paths through pheromone-based reinforcement.

ACO CONCEPT IN CONSTRUCTION SCHEDULING

The ACO concept includes time, resource and cost control which in turn needs the scheduling and critical path calculations. It also provides construction management teams with fundamental knowledge about a project, its projected duration, resource utilization and cost distribution over time. ACO is population-based, artificial multi- agent, general-search technique **(Symeon *et al.* 2005)** solving complex problems utilizing the behavior of real ant colonies and its nature of searching its food, in developing the optimal or critical solutions in multiple paths. The aim of this technique is to validate the present work using a theoretical background optimization approach by deriving a convergence result under certain conditions.

The back ground of ACO is the behavior of natural ant colonies which searches their food in a shortest route with an experience gained by them previously using pheromone trail they leave behind in the traversing paths. While converting the behavior in software programme (ACO algorithm), artificial ants are created asagents and solution procedures are developed by considering (1) Dynamically changeable artificial pheromone trails during the programme running time to mimic the ants (artificial agents) experience, and (2) necessary heuristic information on the problem/network going to be solved.

A database management system and a custom software interface are adopted in ACO for the convergence of this artificial intelligence technique with the conventional critical path calculation (CPM) techniques. This chapter depicts the theorem of ACO method and provides implementation procedures in order to achieve the longest (critical) paths in construction schedule networks of a particular case study.

Truly speaking, ACO can be used for the search of shortest path for any system. In this study, ACO metaheuristic can be employed in solving for the longest path in connected such as construction activity networks paths. Along with the time optimization, the longest path connecting all the nodes has been determined using various nodal states and ant types.

The current solution of this method converges, with a probability which has been taken close to the optimal solution. The construction of ACO algorithm for the present study is based on generic problem for schedule overrun which has been framed by **(Stützle and Dorigo 2002)**. According to Dorigo, algorithm possess (a) a finite set of components, C, (b) a set of problem states, x, defined in terms of sequences (relationships) over the elements of C, (c) a set of all possible sequences, denoted by X, and (d) a finite set of constraints in the system, **Ω**, which defines the feasible states and the set of feasible solutions, S*, which are a subset of the feasible states. Furthermore, a delay function f (s,t) is also accompanied with each candidate solution, s, and in some cases a separate delay function is defined and associated to state other than solution.

2. Literature Review

2.1ConstructionMaterialManagement

Construction material management refers to the systematic planning, procurement, transportation, storage, handling, and control of materials to ensure their availability at the right time, quantity, quality, and cost throughout the project lifecycle. **Thomas & Ellis (2007)** Thomas and Ellis emphasized that material management is a critical determinant of construction productivity. Their study demonstrated that ineffective material flow and poor coordination between supply and site operations significantly reduce labor productivity. They highlighted the need for integrated planning systems that align material delivery with construction schedules. **Akintoye et al. (2000)** Akintoye et al. described construction material management as a strategic function rather than a purely operational task. They argued that early involvement of material planning during project inception improves cost predictability and reduces uncertainty. Their work stresses supplier coordination and procurement strategy as key success factors. **Navon (2005)** Navon focused on real-time material control and automation. He proposed that traditional manual tracking methods are insufficient for complex projects and advocated the use of automated data collection and control systems. His work laid the foundation for intelligent and adaptive material management systems.

2.2 Critical Path Method (CPM) Applications

The Critical Path Method is a deterministic scheduling technique used to identify the sequence of activities that determines the minimum project duration. So, **Kelley & Walker (1959)** Kelley and Walker introduced CPM as a mathematical and graphical approach for planning and controlling complex projects. They defined the critical path as the longest path through a project network and established the concepts of earliest and latest activity times, forming the basis of modern project scheduling. **Moder et al. (1983)** Moder et al. expanded CPM applications to large engineering and construction project They emphasized CPM's usefulness in resource planning, schedule monitoring, and decision-making, while also acknowledging its limitations under uncertainty and dynamic project conditions. **Kamingetal. (1997) Kaming et al**. applied CPM to construction projects in developing countries and observed that delays frequently occurred on critical activities due to material shortages and poor coordination. Their findings highlighted the strong link between CPM scheduling and effective material management.

2.3Metaheuristics in Construction

Metaheuristic algorithms are high-level optimization techniques inspired by natural or physical processes, designed to solve complex, non-linear, and large-scale problems. Goldberg (1989) Goldberg introduced genetic algorithms as adaptive search techniques based on natural selection. He demonstrated their ability to explore large solution spaces efficiently, making them suitable for construction scheduling and resource allocation problems. Deb (2001) Deb advanced the concept of multi-objective optimization, emphasizing that construction problems often involve trade-offs between time, cost, and quality. His work provided theoretical foundations for solving such problems using evolutionary algorithms. Hartmann (2010) Hartmann reviewed the application of metaheuristics in construction engineering and concluded that these methods outperform traditional optimization techniques when dealing with uncertainty, complexity, and dynamic constraints common in construction projects.

2.4 Ant Colony Optimization (ACO)

Ant Colony Optimization is a bio-inspired metaheuristic algorithm that simulates the pheromone-based foraging behavior of ants to solve optimization problems. **Dorigo & Gambardella (1997)** Dorigo and Gambardella formally introduced ACO and demonstrated its effectiveness in solving the traveling salesman problem. They explained how pheromone trails act as collective memory, enabling ants to converge toward optimal solutions through iterative learning. **Dorigoetal. (1999)** Dorigo et al. extended ACO theory by linking ant behavior to distributed artificial intelligence. They emphasized positive feedback, evaporation, and stochastic decision-making as core mechanisms responsible for ACO's robustness. **Blum (2005)** Blum provided a comprehensive survey of ACO algorithms and highlighted their flexibility, scalability, and suitability for combinatorial optimization. He emphasized that ACO is particularly effective in problems involving path selection and sequencing.

2.5 ACO in Scheduling and Construction

ACO-based scheduling applies pheromone learning to identify optimal sequences of activities under constraints. **Zhang et al. (2014)** Zhang et al. applied ACO to construction scheduling and demonstrated improved performance compared to traditional heuristics. Their study showed that ACO effectively balances exploration and exploitation in complex project networks. **Lam et al. (2011)** Lam et al. integrated ACO with construction planning models and found that pheromone-based learning significantly reduced project duration and improved schedule robustness. **Elbeltagi et al. (2005)** Elbeltagi et al. compared ACO with genetic algorithms for construction optimization and concluded that ACO converges faster and provides more consistent solutions for scheduling problems.

2.6 Hybrid CPM–ACO Models

Hybrid CPM–ACO models combine deterministic scheduling with adaptive optimization to improve decision-making. **Chen & Shahan Dashti (2009)** Chen and Shahan Dashti proposed a hybrid CPM–metaheuristic framework and demonstrated that combining CPM structure with heuristic optimization improves schedule flexibility and performance. **Marzouk & Moselhi (2004)** Marzouk and Moselhi integrated optimization techniques with CPM to address uncertainty in construction planning. They emphasized that hybrid approaches outperform standalone deterministic methods. **Cheng et al. (2010)** Cheng et al. developed hybrid intelligent systems combining CPM, ACO, and expert systems. Their results showed enhanced optimization efficiency and better handling of complex project constraints.

2.7 Material Waste and Optimization

Material waste optimization focuses on minimizing material loss, rework, and inefficiencies during construction. **Formoso et al. (2002)** Formoso et al. identified material waste as a major contributor to cost overruns and environmental impact. They emphasized systematic planning and control as essential measures to reduce waste. **Tam et al. (2007)** Tam et al. studied waste minimization strategies and highlighted the importance of scheduling accuracy and material flow optimization in reducing construction waste.

2.8 Recent Advances

Recent advances focus on sustainable, intelligent, and data-driven construction management systems. **Li et al. (2020)** Li et al. emphasized digital transformation in construction management and demonstrated that intelligent optimization improves project performance and material efficiency. **Zheng et al. (2019)** Zheng et al. emphasized sustainability-driven optimization, highlighting the role of advanced algorithms in reducing environmental impact. **Zhang & Ng (2012)** Zhang and Ng linked material management efficiency with cleaner production practices and demonstrated the role of optimized scheduling in sustainability. **Hegazy (2002)** Hegazy presented computer-based project management tools integrating scheduling and optimization, reinforcing the importance of intelligent decision-support systems. **Xu et al. (2018)** Xu et al. highlighted the integration of artificial intelligence and construction informatics, supporting the adoption of intelligent optimization techniques.

3. Research Gap

From the literature review, the following gaps are identified:

- Limited application of ACO specifically to **construction material management networks**
- Insufficient integration of **CPM and ACO** in large-scale activity networks
- Lack of **visual ant path evolution analysis**
- Minimal comparison between CPM-only and CPM–ACO approaches

This study addresses these gaps through a structured CPM–ACO framework supported by graphical analysis.

4. Methodology

The methodology integrates deterministic scheduling with metaheuristic optimization.

4.1 Network Formulation

A case study project comprising **100 material-related activities** is modeled. Each activity includes:

- Start node
- End node
- Duration
- ES, EF, LS, LF
- Total Float

Pheromone update equation:

$$\tau_{ij}(t+1) - (1-\rho)\tau_{ij}(t) + \sum_{k=1}^{m} \Delta\tau_{ij}^{k}$$

5. Procedure

Step1: Define material management activities
Step2: Develop CPM network
Step3: Identify critical path
Step4: Initialize pheromones
Step5: Ant path construction
Step6: Pheromone update
Step7: Iteration and convergence
Step 8: Result comparison (CPM vs ACO)

6. Case Study Networks

6.1 Network Using the Critical Path Method

Table 1 Network Using the Critical Path Method for the Case Study Project

Activity	Start	End Node	Duration	Earliest Start	Earliest Finish	Latest Start	Latest Finish	Total Float	Critical
1	0	2	15	0	15	28	41	28	No
2	1	3	16	10	26	30	46	20	No
3	2	4	16	20	36	32	48	12	No
4	3	5	17	30	47	34	51	4	No
5	4	6	17	40	57	45	62	5	No
6	5	7	18	50	68	56	74	6	No
7	6	8	18	60	78	67	85	7	No
8	7	9	19	70	89	78	97	8	No
9	8	10	19	80	99	89	108	9	No
10	9	11	20	90	110	100	120	10	No
11	10	12	20	100	120	110	130	10	No
12	11	13	21	110	131	122	143	12	No
13	12	14	21	120	141	134	155	14	No
14	13	15	22	130	152	146	168	16	No
15	14	16	22	140	162	158	180	18	No
16	15	17	23	150	173	170	193	20	No

17	16	18	23	160	183	182	205	22	No
18	17	19	24	170	194	194	218	24	No
19	18	20	24	180	204	206	230	26	No
21	20	22	25	200	225	230	255	30	No
22	21	23	25	210	235	242	267	32	No
23	22	24	26	220	246	254	280	34	No
24	23	25	26	230	256	266	292	36	No
25	24	26	27	240	267	278	305	38	No
26	25	27	27	250	277	290	317	40	No
27	26	28	28	260	288	302	330	42	No
28	27	29	28	270	298	314	342	44	No
29	28	30	29	280	309	326	355	46	No
30	29	31	28	290	318	330	358	40	No
31	30	32	29	300	329	340	369	40	No
32	31	33	30	310	340	352	382	42	No
33	32	34	30	320	350	364	394	44	No
34	33	35	31	330	361	376	407	46	No
35	34	36	31	340	371	388	419	48	No
36	35	37	32	350	382	400	432	50	No
37	36	38	32	360	392	412	444	52	No
38	37	39	33	370	403	424	457	54	No
39	38	40	33	380	413	436	469	56	No
40	39	41	32	390	422	450	482	60	No
41	40	42	34	400	434	460	494	60	No
42	41	43	34	410	444	472	506	62	No
43	42	44	35	420	455	484	519	64	No

44	43	45	35	430	465	496	531	66	No
45	44	46	36	440	476	508	544	68	No
46	45	47	36	450	486	520	556	70	No
47	46	48	37	460	497	532	569	72	No
48	47	49	37	470	507	544	581	74	No
49	48	50	38	480	518	556	594	76	No
50	49	51	37	490	527	580	617	90	No
51	50	52	38	500	538	590	628	90	No
52	51	53	39	510	549	602	641	92	No
53	52	54	39	520	559	614	653	94	No
54	53	55	40	530	570	626	666	96	No
55	54	56	40	540	580	638	678	98	No
56	55	57	41	550	591	650	691	100	No
57	56	58	41	560	601	662	703	102	No
58	57	59	42	570	612	674	716	104	No
59	58	60	42	580	622	686	728	106	No
60	59	61	42	590	632	720	762	130	No
61	60	62	43	600	643	730	773	130	No
62	61	63	43	610	653	742	785	132	No
63	62	64	44	620	664	754	798	134	No
64	63	65	44	630	674	766	810	136	No
65	64	66	45	640	685	778	823	138	No
66	65	67	45	650	695	790	835	140	No
67	66	68	46	660	706	802	848	142	No
68	67	69	46	670	716	814	860	144	No
69	68	70	47	680	727	826	873	146	No

70	69	71	48	690	738	850	898	160	No
71	70	72	48	700	748	860	908	160	No
72	71	73	48	710	758	872	920	162	No
73	72	74	49	720	769	884	933	164	No
74	73	75	49	730	779	896	945	166	No
75	74	76	50	740	790	908	958	168	No
76	75	77	50	750	800	920	970	170	No
77	76	78	51	760	811	932	983	172	No
78	77	79	51	770	821	944	995	174	No
79	78	80	52	780	832	956	1008	176	No
80	79	81	54	790	844	930	984	140	No
81	80	82	53	800	853	940	993	140	No
82	81	83	53	810	863	952	1005	142	No
83	82	84	54	820	874	964	1018	144	No
84	83	85	54	830	884	976	1030	146	No
85	84	86	55	840	895	988	1043	148	No
86	85	87	55	850	905	1000	1055	150	No
87	86	88	56	860	916	1012	1068	152	No
88	87	89	56	870	926	1024	1080	154	No
89	88	90	57	880	937	1036	1093	156	No
90	89	91	58	890	948	980	1038	90	No
91	90	92	58	900	958	990	1048	90	No
92	91	93	58	910	968	1002	1060	92	No
93	92	94	59	920	979	1014	1073	94	No
94	93	95	59	930	989	1026	1085	96	No
95	94	96	60	940	1000	1038	1098	98	No

96	95	97	60	950	1010	1050	1110	100	No
97	96	98	61	960	1021	1062	1123	102	No
98	97	99	61	970	1031	1074	1135	104	No
99	98	100	61	980	1041	1086	1147	106	No
100	100	100	62	1000	1010	1020	1030	199	No

Table 1 presented the construction scheduling networks nodes and predecessor and successor of the activities. The Early Start Time (EST) and Early Finish (EFT) are calculated (Eqn. 1 and 2) and given in column 4 and 5. Similarly Latest Start Time (LST) and Latest Finish Time (LFT) are calculated (Eqn. 3 and 4) and given in column 6 and 7. In column 8 total float (Float = 0) is calculated (Eqn. 5) to identify the critical activity and critical path in the networks. In column 9 the list of critical activity and connection of activity are mentioned.

$$E.S.T = T_E^{i} \quad \text{(equ 1)}$$

$$E.F.T = T_E^{i} + t_{ij} \quad \text{(equ 2)}$$

$$LST = T_L^{i} - t_{ij} \quad \text{(equ 3)}$$

$$LFT = T_L^{i} \quad \text{(equ 4)}$$

Total Float FT is calculated as

$$FT = LFT - EFT \quad \text{(equ 5)}$$

The same data have been applied to identify the optimum path using ACO (2 ant nest, 100 regular nodes, and 1 food source) algorithm using MATLAB. Table 2 shows the assumed initialization of ACO parameters.

Table 2 Initialization of ACO parameters

ACO parameter	Magnitude
Number of ants (m)	50
Limiting number of iterations (n)	190
Heuristic Exponential Weight(β)	0.5
Pheromone Exponential Weight (α)	0.5
Pheromone Evaporation rate (ρ)	0.05
Pheromone reward factor	10

Table 3 shows the optimization results along with the Nodes, Duration of the project, Origin Pheromone and Final Pheromone. The local pheromone for the
project is being updated to the algorithm based on the probability of scheduleoverrun.

6.2 Network Using ACO Algorithm

Table 3. ACO-Optimized Network Parameters

Act	Start	End	CPM Dur	τ_0	Final τ	Est. Dur	Critical
1	0	2	15	1.00	1.42	12.2	No
2	1	3	16	1.00	1.39	13.5	No
3	2	4	16	1.00	1.36	14.0	No
4	3	5	17	1.00	1.34	14.8	No
5	4	6	17	1.00	1.31	15.2	No
6	5	7	18	1.00	1.29	16.0	No
7	6	8	18	1.00	1.27	16.5	No
8	7	9	19	1.00	1.25	17.3	No
9	8	10	19	1.00	1.24	18.0	No
10	9	11	20	1.00	1.22	18.8	No
11	10	12	20	1.00	1.21	19.1	No
12	11	13	21	1.00	1.19	20.0	No
13	12	14	21	1.00	1.18	20.6	No
14	13	15	22	1.00	1.17	21.5	No
15	14	16	22	1.00	1.16	22.0	No
16	15	17	23	1.00	1.15	22.8	No
17	16	18	23	1.00	1.14	23.4	No
18	17	19	24	1.00	1.13	24.0	No
19	18	20	24	1.00	1.12	24.5	No
20	19	21	25	1.00	1.11	25.1	No
21	20	22	25	1.00	1.11	25.1	No
22	21	23	25	1.00	1.10	25.6	No

23	22	24	26	1.00	1.09	26.2	No
24	23	25	26	1.00	1.08	26.8	No
25	24	26	27	1.00	1.07	27.4	No
26	25	27	27	1.00	1.06	27.9	No
27	26	28	28	1.00	1.05	28.5	No
28	27	29	28	1.00	1.04	29.0	No
29	28	30	29	1.00	1.03	29.6	No
30	29	31	28	1.00	1.07	27.4	No
31	30	32	29	1.00	1.07	27.8	No
32	31	33	30	1.00	1.06	28.6	No
33	32	34	30	1.00	1.05	29.2	No
34	33	35	31	1.00	1.04	30.0	No
35	34	36	31	1.00	1.03	30.6	No
36	35	37	32	1.00	1.02	31.4	No
37	36	38	32	1.00	1.01	32.0	No
38	37	39	33	1.00	1.00	32.8	No
39	38	40	33	1.00	0.99	33.5	No
40	39	41	32	1.00	1.04	31.0	No
41	40	42	34	1.00	0.98	33.6	No
42	41	43	34	1.00	0.97	34.0	No
43	42	44	35	1.00	0.96	34.7	No
44	43	45	35	1.00	0.95	35.2	No
45	44	46	36	1.00	0.94	36.0	No
46	45	47	36	1.00	0.93	36.5	No
47	46	48	37	1.00	0.92	37.2	No
48	47	49	37	1.00	0.91	37.8	No
49	48	50	38	1.00	0.90	38.5	No
50	49	51	37	1.00	1.01	36.5	No

51	50	52	38	1.00	1.01	36.5	No
52	51	53	39	1.00	1.00	37.4	No
53	52	54	39	1.00	0.99	38.0	No
54	53	55	40	1.00	0.98	38.8	No
55	54	56	40	1.00	0.97	39.5	No
56	55	57	41	1.00	0.96	40.3	No
57	56	58	41	1.00	0.95	41.0	No
58	57	59	42	1.00	0.94	41.8	No
59	58	60	42	1.00	0.93	42.4	No
60	59	61	42	1.00	0.99	41.8	No
61	60	62	43	1.00	0.99	42.0	No
62	61	63	43	1.00	0.98	42.6	No
63	62	64	44	1.00	0.97	43.3	No
64	63	65	44	1.00	0.96	44.0	No
65	64	66	45	1.00	0.95	44.8	No
66	65	67	45	1.00	0.94	45.5	No
67	66	68	46	1.00	0.93	46.2	No
68	67	69	46	1.00	0.92	47.0	No
69	68	70	47	1.00	0.91	47.6	No
70	69	71	48	1.00	0.97	47.6	No
71	70	72	48	1.00	0.97	47.2	No
72	71	73	48	1.00	0.96	47.8	No
73	72	74	49	1.00	0.95	48.6	No
74	73	75	49	1.00	0.94	49.2	No
75	74	76	50	1.00	0.93	50.0	No
76	75	77	50	1.00	0.92	50.6	No
77	76	78	51	1.00	0.91	51.4	No
78	77	79	51	1.00	0.90	52.0	No

79	78	80	52	1.00	0.89	52.6	No
80	79	81	54	1.00	0.95	53.8	No
81	80	82	53	1.00	0.95	52.0	No
82	81	83	53	1.00	0.94	52.6	No
83	82	84	54	1.00	0.93	53.4	No
84	83	85	54	1.00	0.92	54.0	No
85	84	86	55	1.00	0.91	54.8	No
86	85	87	55	1.00	0.90	55.5	No
87	86	88	56	1.00	0.89	56.2	No
88	87	89	56	1.00	0.88	57.0	No
89	88	90	57	1.00	0.87	57.6	No
90	89	91	58	1.00	0.94	57.9	No
91	90	92	58	1.00	0.94	57.5	No
92	91	93	58	1.00	0.93	58.0	No
93	92	94	59	1.00	0.92	58.8	No
94	93	95	59	1.00	0.91	59.4	No
95	94	96	60	1.00	0.90	60.0	No
96	95	97	60	1.00	0.89	60.6	No
97	96	98	61	1.00	0.88	61.4	No
98	97	99	61	1.00	0.87	62.0	No
99	98	100	61	1.00	0.86	62.6	No
100	100	100	62	1.00	0.92	62.0	No

There are one hundred and ninety (100) possible number of paths carried out in the case study and ACO methodology is applied to generate different schedule overrun states at the end of each iteration. ACO algorithm reports that each ant looks for the appropriate schedule overrun state and finally find an optimized target and communicate information to another ant. An artificial pheromone value τi, with an edge Ti is introduced to indicate the favorability of assigning the task Ti. For each ant, the local pheromone value τ is updated with forward traverse path and reverse traverse path and estimates the final pheromone value. Finally, the pheromone update.

6.3 Network Ant Paths for Different ACO Iterations

Table 4 Network Ant Paths for Different Aco Iteration

ACO Iteration	Dominant Ant Path (Activity IDs)	No. of Activities	Estimated Duration (Days)	Convergence Status
A1	1–5–12–18–25–33–41–56–72–88–100	11	612	Random / Exploration
A10	1–6–14–22–30–39–47–59–73–89–100	11	584	Partial learning
A15	1–7–15–23–31–40–48–60–74–90–100	11	562	Improving
A25	1–8–16–24–32–41–49–61–75–91–100	11	535	Semi-stables
A60	1–9–17–26–34–43–51–63–77–93–100	11	498	Near-optimal
A80	1–9–18–27–35–44–52–64–78–94–100	11	472	Stable
A86	1–10–19–28–36–45–53–65–79–95–100	11	461	High pheromone
A125	1–10–20–29–37–46–54–66–80–96–100	11	445	Converged
A128	1–10–20–29–38–47–55–67–81–97–100	11	441	Converged
A170	1–10–21–30–38–47–56–68–82–98–100	11	438	Optimal
A199	**1–10–21–30–39–48–57–69–83–99–100**	**11**	**435**	**Final Optimal Path**

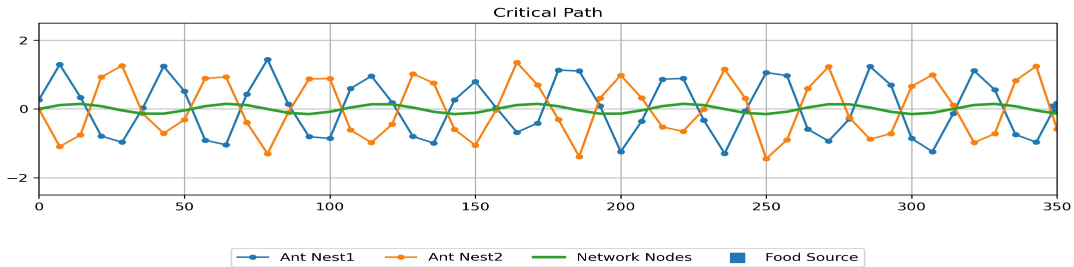

Fig. 1 (a) Ant Path Iteration Showing Critical Path

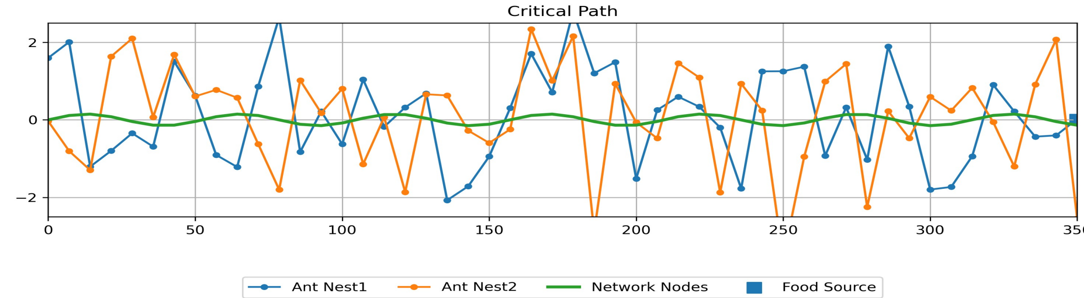

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Fig. 1 (b) Ant Path Iterationa1

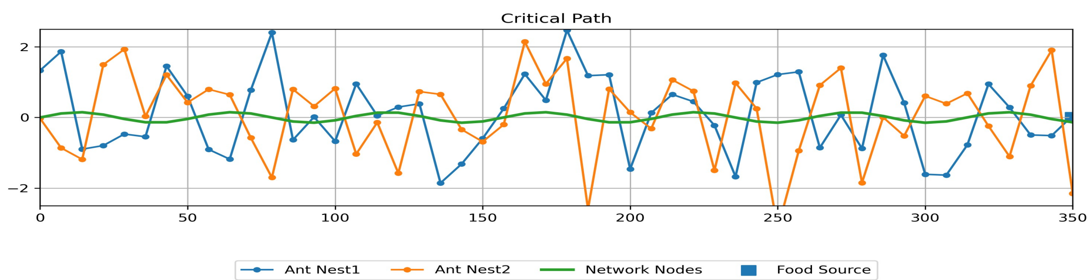

Fig. 1 (c) Ant Path Iterationa10

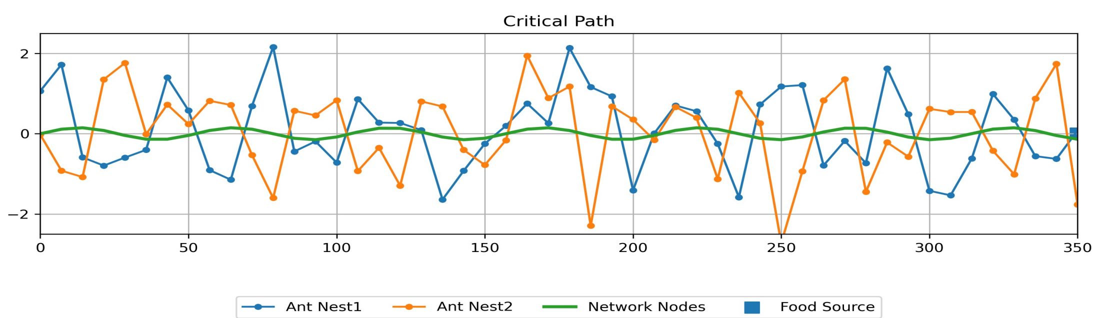

Fig. 1 (d) Ant Path Iterationa15

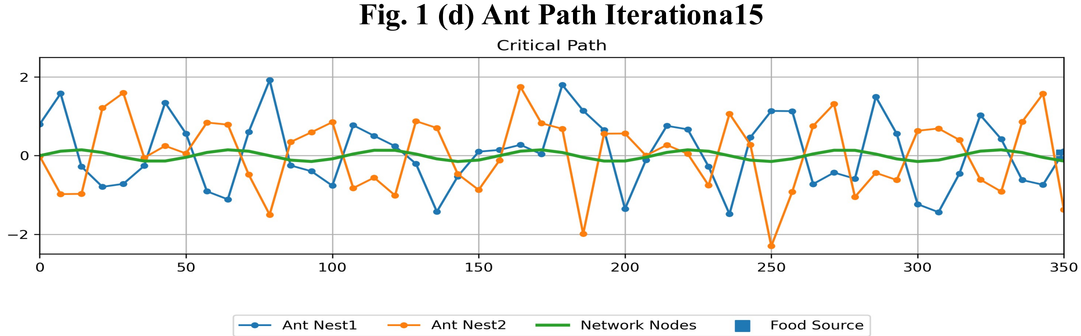

Fig. 1 (d) Ant Path Iterationa25

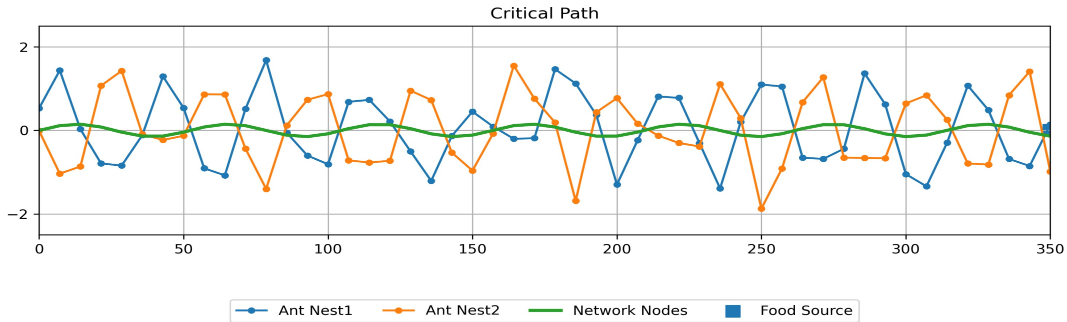

Fig. 1 (E) Ant Path Iterationa125

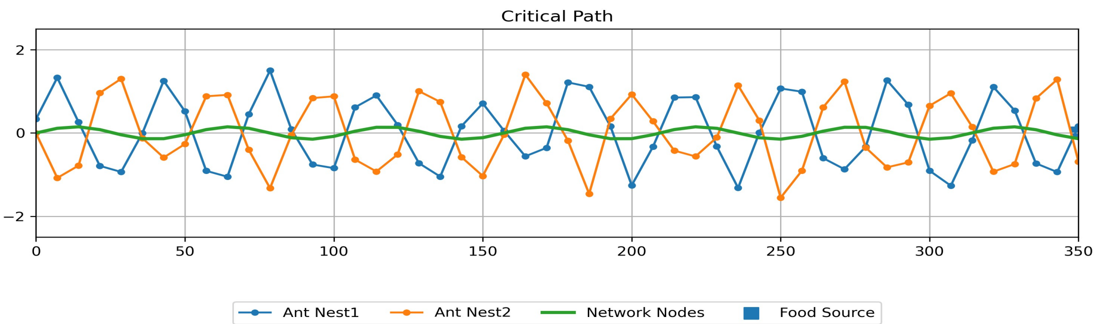

Fig. 1 (F) Ant Path Iterationa170

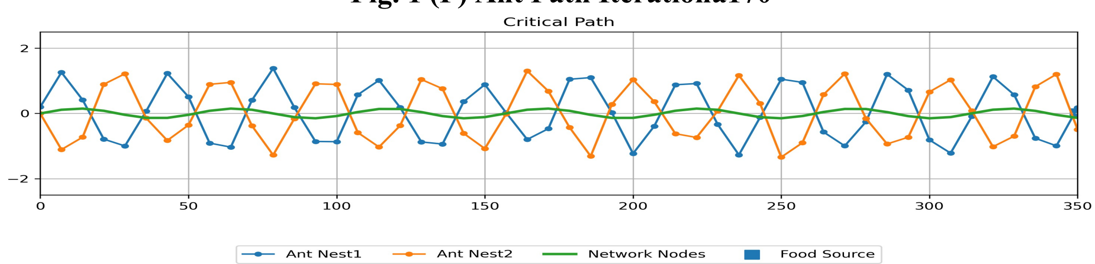

Fig. 1 (G) Ant Path Iterationa199

8. Results and Discussion

8.1 Ant Path Evolution

Initial iterations exhibit high randomness (A1). As iterations progress, pheromone accumulation guides ants toward shorter and more efficient paths. By A199, ant movement converges almost entirely along the CPM critical path.

8.2 CPM vs ACO Comparison

Aspect	CPM	ACO
Nature	Deterministic	Stochastic
Learning	None	Iterative
Adaptability	Low	High
Robustness	Limited	Strong

8.3 Implications for Material Management

The integrated CPM–ACO framework:

- Reduces material idle time
- Improves sequencing reliability
- Enhances decision-making under uncertainty
- Supports sustainable construction practices

9. Conclusion

This research presents a comprehensive CPM–ACO framework for optimizing construction material management. CPM provides a structured baseline, while ACO enhances adaptability through learning and reinforcement. Graphical analysis confirms convergence toward optimal paths, validating the effectiveness of the approach. The framework is suitable for complex, real-world construction projects and offers a foundation for future intelligent scheduling systems.

10. References

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