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DEVELOPMENT AND TEST RUN OF CIVIL ENGINEERING SCHEDULE ACCELERATION MODEL THROUGH ANT COLONY OPTIMIZATION

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Abstract. The traditional scheduling tool Critical Path Method (CPM) exhibits limitations in computational insufficiency due to exhaustive enumeration. Ant Colony Optimization (ACO) was therefore applied as a metaheuristic inspired by the ants behavior in foraging activities. A model development team was formed among construction engineers, IT professionals, and Mathematicians to develop a schedule acceleration model by integrating ACO into CPM to ensure proper resources allocated on critical path. The developed model CSAM-ACO targets on schedule acceleration by allocating resources on the newly found critical path after two stages of computation. The trial run proved CSAM-ACO model more favorable compared with CPM.

Keywords: Ant Colony Optimization (ACO), Critical Path Method (CPM), construction schedule acceleration, ACO algorithm, exhaustive enumeration.

Introduction

In 1992, Marco Dorigo proposed an efficient metaheuristic technique for solving computational problems to find good paths through graphs, which is called Ant Colony Optimization (ACO) inspired by the foraging behavior of real ant colonies (Duan, Liao 2010; Zundel 2013; Al Salami 2009). Due to its benefit in solving difficult combinatorial problems, many researchers have presented the application of ACO in management of construction projects especially in large and complex projects (Srour *et al.* 2013; Lopez-Ibanez, Blum 2010). ACO could be applied in resources management (Christodoulou 2009), determining project critical paths (Duan, Liao 2010), construction site layout planning (Lam *et al.* 2007), optimizing construction time and cost (Ng, Zhang 2008), and management of time-cost-risk trade off (Lakshminarayanan *et al.* 2011). ACO is also proposed in construction project scheduling owing to the fact that the real ant colonies exhibit a behavior that is suitable to optimal network traversing and to find the longest path in scheduling (Mateos *et al.* 2013). Recently, the formulation of ACO algorithms in solving the resource-unconstrained schedule and determining of project critical paths have great contributions to the scheduling technique (Hani *et al.* 2007; Mubarak 2010; Kloppenborg 2009). The ACO alternative provides powerful way in construction scheduling with quick convergence to the final solution so that it can be applied to deal with more realistic project scheduling problems to take into account the inevitable situation to make the construction works in faster track (Sauter 2011; Naylor 1995).

Therefore, this research is focused on rescheduling critical tasks by integrating ACO into CPM in construction schedule acceleration. The aim of this study is to develop a schedule acceleration model, based on ACO and CPM, to assist construction practitioner in schedule acceleration to ensure proper resources allocated on critical path. Eventually, the developed model deems to increase the probability to complete a delayed project within the stipulated time and to satisfy the request of an earlier completion of project.

1. Ant Colony Optimization (ACO) and application in construction

Ants are undoubtedly one of the most successful species on the earth today and they have been so 100 million years (Dorigo, Stutzle 2004). It is not surprising that the increasing design of algorithms inspired from the behavior of ants. The first ACO system was introduced by Marco Dorigo from Italy in his PhD dissertation in 1992 and it is also called as Ant System (AS) (Dorigo 1992). ACO transforms the model of collective intelligence of ants into optimization algorithms (Dorigo, Blum 2005). ACO has been applied in solving many combinatorial op-

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timization problems such as travelling salesman (Dorigo, Gambardella 1997), graph coloring (Costa, Hertz 1997), vehicle routing (Dorigo *et al.* 2000), feature selection (Duan, Liao 2010), and quadratic assignment problem (Wiesemann, Stutzle 2006).

In ACO, a colony of biological ants is typically modeled by a society of artificial agents and those agents build solutions by making path traversing on the directed acyclic network. Dorigo *et al.* (1999) defined ACO as a population-based general search technique for the solution of difficult combinatorial problems. This metaheuristic technique is inspired by the behavior exhibited by real ant colonies proposed by Dorigo with the concept of pheromone trail laying (Dorigo, Stutzle 2004). The main idea of ACO is the cooperation of a number of artificial ants via pheromone laid on path where each ant contributes a little effort to the solution construction, while the final result is an emergence of the ants' interaction (Hoseini, Shayesteh 2013; Kong, Tian 2006). This method is inspired by the foraging behavior of ants so that it presents a highly structured organization, which is able to accomplish complex tasks that is far exceed compared with the individual capabilities of a single ant.

1.1. Variations of ACO algorithms

In general, the variants of the ACO algorithm are differed from each other in the pheromone update rule applied (Dorigo, Blum 2005). There are several extensions and improvements of the original algorithm introduced over the years for the adoption to more combinatorial optimization, namely: Elitist Ant System (EAS) (Dorigo *et al.* 1996), Rank-based Ant System (RAS) (Bullnheimer *et al.* 1997), MAX-MIN Ant System (MMAS) (Stutzle, Hoos 2000), Ant Colony System (ACS) (Dorigo, Gambardella 1997), Hyper-Cube Framework (FCF) (Blum, Dorigo 2004), Ant System (AS) (Dorigo *et al.* 1996), and Best-Worst Ant System (BWAS) (Cordon *et al.* 2002).

1.2. Application of ACO Algorithms

The ACO metaheuristic introduced by Dorigo has been successfully applied to a large number of combinatorial optimization problems. The travelling salesman problem (TSP) was the first problem tackled by the ACO algorithm because this problem is suitable to adopt a real ant's behavior to solve it with the constraint shortest path (Dorigo *et al.* 1999). ACO was also used for machine learning purposes, concretely to the design of learning algorithms for knowledge representation structures such as classical logic rules (Parpinelli *et al.* 2002), fuzzy logic rules (Alcala *et al.* 2001), and Bayesian networks (Campos *et al.* 2002). Table 1 shows a summary of various ACO applications.

Table 1. Various applications of ACO algorithms

Applications	Authors	Algorithm S
Travelling Salesman Problem (TSP)	Dorigo *et al.* (1996) Gambardella and Dorigo (1996) Dorigo and Gambardella (1997) Stutzle and Hoos (2000) Bullnheimer *et al.* (1997) Blum and Lopez-Ibanez (2010)	AS Ant-Q ACS & ACS-3-opt MMAS RAS Beam-ACO
Quadratic Assignment Problem (QAP)	Maniezzo and Colorni (1999) Gambardella and Dorigo (1996) Stutzle and Hoos (2000) Maniezzo and Colorni (1999) Wiesemann and Stutzle (2006)	AS-QAP HAS-QAP MMAS-QAP ANTS-QAP & AS-QAP MMAS-QAP
Vehicle Routing Problem (VRP)	Bullnheimer *et al.* (1997) Li and Tian (2006)	AS-VRP ACS-OVRP
Connection-oriented network routing	Schoonderwoerd *et al.* (1996) Caro and Dorigo (1998)	ABC AntNet-FS
Graph coloring	Costa and Hertz (1997)	ANTCOL

1.3. Ant Colony Optimization in construction scheduling

Christodoulou (2009) outlined the steps in finding the critical path by using ACO algorithms. Firstly, all the arcs or connectors in the network are initialized with pheromone, τ_0 which is the value of the inverse line-distance between the nodes or the inverse line-distance of the particular arc. After that, an artificial ant is launched from a start node and pseudo-randomly walking from a node to a successor node passed through the connecting arcs until it reaches the end-node or dead end. However, the previously selected arcs are excluded from the selection for "tree spanning" and avoid memorization. The artificial ant's selection for the successor node to follow is probabilistic which is based on the stochastic assignment of each arc's selection defined by Eqn (1):

$$P_i = \frac{\tau_i \eta_i^{\beta}}{\Sigma \tau_i \eta_i^{\beta}}, \qquad (1)$$

where τ_i is the pheromone concentration on the i^{th} arc, η_i is a priori available heuristic value which allows incorporation of problem specific information for the i^{th} arc, defined as the length of the inverse arc or the length of the inverse arc plus the line-distance between the nodes. β_i is a parameter determining the relative influence of the heuristic information. Moreover, the selection is also assisted by the consideration of a randomly generated number $q (0 \le q \le 1)$ to compare with a predefined value which is specific to the network topology q_0. By using this network topology, if $q \le q_0$, the arc with the highest probability will be selected. Otherwise, the arc is selected randomly based on the distribution defined by Eqn (1). A local pheromone update rule is applied to update the pheromone concentration level of a given arc, when the ants crossing each of the arcs during the construct solution phase. The purpose of this update rule is to enable exploration of more paths or routes to give the already visited arcs less chance to be selected during the randomization of the arc selection process. The local update pheromone is defined by Eqn (2):

$$\tau_i = (1-\rho)\tau_i + \rho\tau_0, \quad (2)$$

where ρ is another network topology parameter $(0 \le \rho \le 1)$. In this procedure, stochastic decision process and local pheromone update rule will be repeated for all ants in the colony and the most successful ant is used in global pheromone update to update the pheromone level of the network defined by Eqn (3):

$$\tau_i = (1-\alpha)\tau_i + \alpha\tau_L, \quad (3)$$

where α is used to determine the level of evaporation of pheromone concentration and τ_L is a value that inversely proportional to the path length of the best solution in case of an arc visited by the best ant or zero for other ants $(0 \le \alpha \le 1)$. Here, the global pheromone update rule can be applied by using either "global-best" or "iteration-best" ant. In "global-best" ant, the ant that obtained the best solution which is the longest path in the network during optimization process is the one who perform the update. In the other hand, the "iteration-best" is performed by the ant who reaching the best solution during each iteration. All the steps from the probabilistic rule to pheromone update rule that include the local pheromone update and global pheromone update are repeated until a fixed number of iteration or a predefined conditions is met, and upon the termination of the algorithm the pheromone trail is used to determine the solution where the arc with the highest pheromone concentration level is defined as the longest path in the network.

2. Research procedures and model development

Owing to the nature of the research where people's experiences, perceptions, opinions and knowledge are necessities to the development of the model, qualitative approach is employed in this study, which consists of the following five stages. The first stage reasoned the selection of ACO algorithms in schedule acceleration. The second stage worked out the ACO algorithm processes used for the development of the final CSAM-ACO acceleration model. In the third stage, each step of the final model was developed and outlined. The complete CSAM-ACO acceleration model associated with its main components was finalized on the fourth stage. The final but significant stage is the trial run of the developed CSAM-ACO model using a real high rise building project. This qualitative technique enables any misunderstanding or intangible issues to be avoided so that the model development process can be rectified immediately. A development team was formed among experts from various fields such as construction engineers, IT professionals, and Mathematicians, whose profiles are presented in Table 2. Extensive data are collected through the development process. A trial run of the CSAM-ACO model was conducted to test how it works in a real situation. Prior to the commencement of trial run, a pilot study was carried out to identify the most commonly delay activity for high rise buildings. The ACO algorithm processes for the final CSAM-ACO acceleration model consists of 7 steps as follows.

Step 1: Establish network topology

Network topology is used in presenting the precedence relationship of the construction activities. In a construction project, the network topology provides a comprehensive layout for project schedule with a set of activities related to one another. There are two types of network diagrams, namely: activity-on-node (AON) and activity-on-arrow (AOA). For an AON network, the node represents the activity and the arc represents the precedence relationship among the activities. On the other hand, the node in an AOA network represents the event and the arc represents the activity. In this study, the activities in a real construction are represented by letters in the network diagram and the purpose of using different letters to represent the activities is to show a real scenario of various activities in the construction process. The project network topology in this study is defined by an AON graph $G = (N, A)$ where a finite set of components is given, where $N = \{1, 2, 3, ..., n\}$ is the set of nodes representing the activities, and A is a set of arcs representing the relationship among the nodes. The established network topology is analyzed to initialize the topology parameters in the next step.

Step 2: Initialize topology parameters

The choice of topology parameters is based on a sensitivity analysis on other randomized topologies and the observed accuracy of convergence to an optimal solution. There are four common parameters for ACO algorithm in finding the critical path, namely: i) q_0, which assists the selection of path based on probability or random selection; ii) ρ, which determines the level of evaporation of pheromone concentration for local update; iii) α, which determines the level of evaporation of pheromone concentration for global update, and iv) β, which determines the relative influence of the heuristic information. The established network diagram shows the complexity of the project by sequencing out the activities.

Step 3: Set initial pheromone level

At this step, the artificial ants are expected to search the path randomly because no previously visited arc with higher pheromone concentration can be detected by them. Hence, the initial levels of pheromone concentration of all arcs are set to an equal small constant value as the

Table 2. Profiles of CSAM-ACO development team

No	Age	Gender	Specialty/area	Roles in model development	
i	34	Male	Project Monitoring	Stage 1 & 5	Reasoning the selection of ACO algorithms in schedule acceleration. Developer i examined the limitation of traditional CPM a) CPM is unable to calculate the longest or shortest paths from a node to any node; b) CPM does not take into consideration the resource-driven relationships for the activities; and c) The computational insufficiency of CPM due to exhaustive enumeration. He was also in charge of the CPM calculation part in the trial run. The critical path of the project was identified by both the traditional CPM and the new ACO approach to verify the application of ACO in finding the critical path.
ii	46	Male	Construction IT Application	Stage 1 & 5	Reasoning the selection of ACO algorithms in schedule acceleration. Developer ii was in charge of finding the critical path of the project by calculating the total float.
iii	31	Female	Mathematician	Stage 2	Worked out the ACO algorithm processes for the development of the final CSAM-ACO acceleration model. She was in charge of establishing network topology, initializing topology parameters, setting initial pheromone level, and constructing best solution.
iv	57	Male	ACO algorithms	Stage 2 & 5	He was in charge of local pheromone update rule, global pheromone update, and reach number of iterations and termination.
v	42	Male	Mathematician	Stage 3	Each step of the final CSAM-ACO acceleration model was developed. He was in charge of selecting critical activities and splitting critical activities.
vi	29	Female	Mathematician	Stage 3 & 5	She was in charge of finding critical path from critical tasks. He was also the main programmer of the model trial run.
vii	35	Male	Modelling	Stage 4	The complete CSAM-ACO acceleration model associated with its main components was graphed and finalized by him.
viii	38	Male	Project Manager	Stage 5	He is the project manager of the high rise building project used for CSAM-ACO trial run. All the on-site data were provided by him. He supervised the trial run of the developed CSAM-ACO model on a high rise building project.
ix	43	Male	Cartographer & ACO algorithms	Stage 4 & 5	All the on-site data provided by the Developer viii were translated and inputted by Developer ix into the CSAM-ACO. He is the cartographer of the iteration diagrams.

initial pheromones laid on the connections. The pheromone level of all arcs in the network topology is initialized with small amounts of pheromone τ_0.

Step 4: Construct best solution

After the initial pheromone level is set, an ant population is allocated. The ant population starts to walk randomly from the initial node to the end node or dead end via the connecting arcs. The artificial ants moving on the directed cyclic graph will build either feasible or infeasible solutions but in general, the feasible solutions will try to be built. At each node, the artificial ants will select the edge to move from one node to any other nodes following the probability defined by Eqn (1).

Step 5: Local pheromone update rule

After crossing each arc of the network, the local pheromone update rule is applied to update the level of pheromone at the given arc. The evaporation of pheromone is updated by the means of local pheromone update applied to all paths. The local pheromone update rule is defined by Eqn (2).

Step 6: Global pheromone update

Global pheromone update applies to the best path of the iteration. The longest path made by an ant in the particular iteration is the best path plus an amount of pheromone concentration on the travelled path where the line-distance of that path is increasing. The most frequently chosen path of the iterations has the highest pheromone concentration. Therefore, the longest path can be found when reaching the fixed number of iterations after the global pheromone update rule is applied. The global pheromone update is defined by Eqn (3).

Step 7: Reach number of iterations and termination

The ACO algorithm process comes to the end when a fixed number of iterations are reached after repeating step 4 to step 6. The best solution is found from the final pheromone level and the chosen probability of the nodes. The ACO algorithm processes for the development of the final CSAM-ACO acceleration model is summarized in Figure 1.

3. Appearance of developed CSAM-ACO acceleration model

Step 1: Finding critical path of project

The critical path of a project is identified through the calculation of total float. CPM is performed to calculate the forward pass and the backward pass. Eqn (4) to Eqn (7) are applied in the computational process of CPM:

$$EF_i = ES_i + \text{duration of activity}; \quad (4)$$

$$LS_i = LF_i - \text{duration of activity}; \quad (5)$$

$$TF = LF - EF/LS - ES; \quad (6)$$

$$TF = LF - ES - \text{duration}. \quad (7)$$

In the developed model, ACO algorithm was applied to tackle the computational problem of CPM. The first step of the developed CSAM-ACO acceleration model is to find the critical path using ACO algorithm process and to compare the computational time and result with that of using CPM.

Step 2: Selection of critical activities

The duration of the critical path equals to the duration of the entire project, hence shortening of project duration can be achieved by shortening the duration of the critical path. To shorten the duration of the longest path, the duration of the critical activities can be reduced by using the method of crashing or splitting of task. If a project is delayed, more additional works need to be completed within the stipulated time, or same amount of works need to be performed in a shorter duration.

Step 3: Splitting of critical activities

This step is to rearrange activities by splitting or crashing them into smaller tasks. The smaller tasks are presented in a new network topology which represents the relationship of the tasks and the durations, respectively. The crashing of critical activities has an advantage in reducing the total completion period by rescheduling all the possible tasks that can be completed concurrently. By doing this, more successor tasks can be completed without waiting for the completion of predecessor task if it is an independent task.

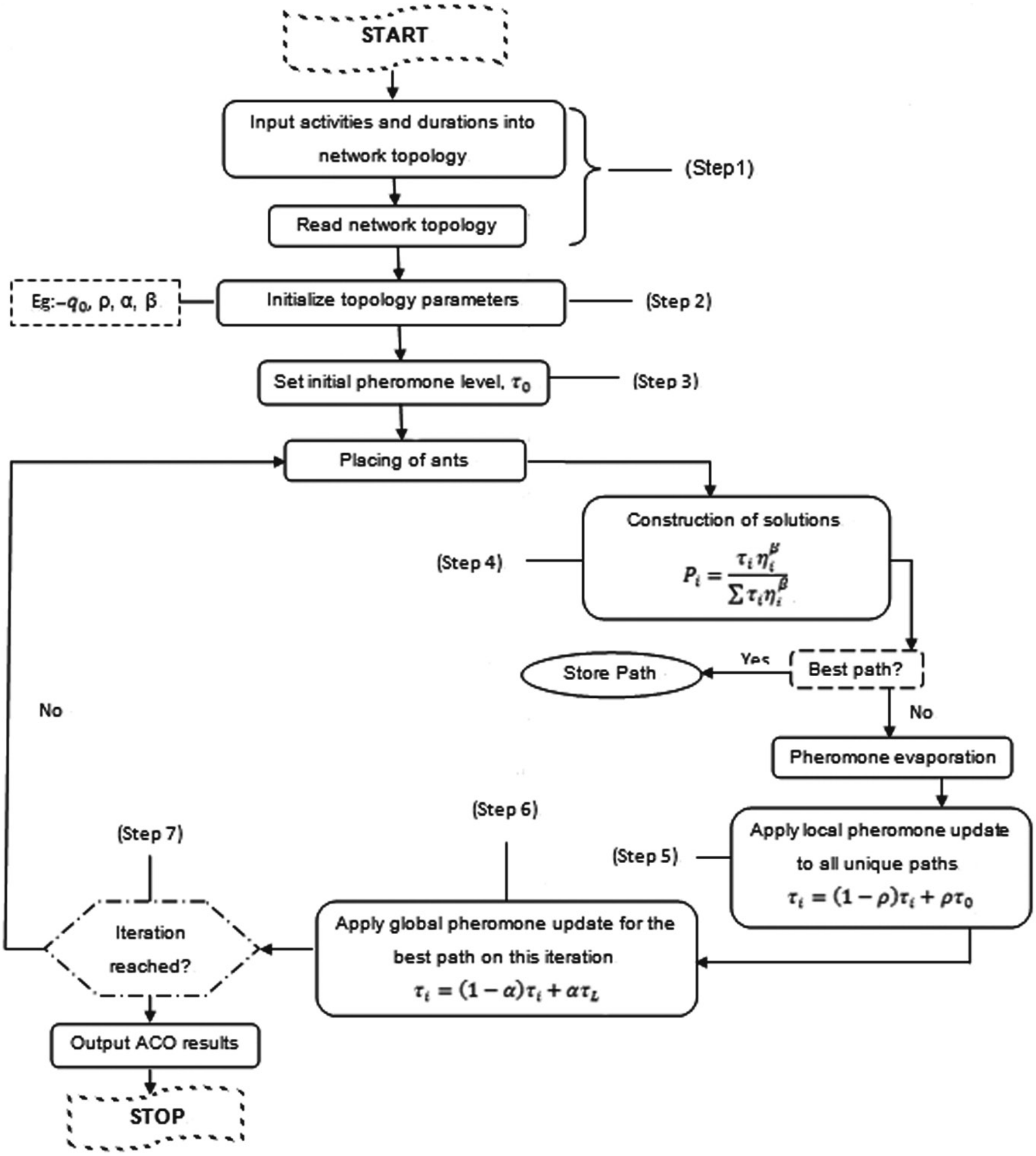

Fig. 1. ACO algorithm processes for the development of CSAM-ACO acceleration model

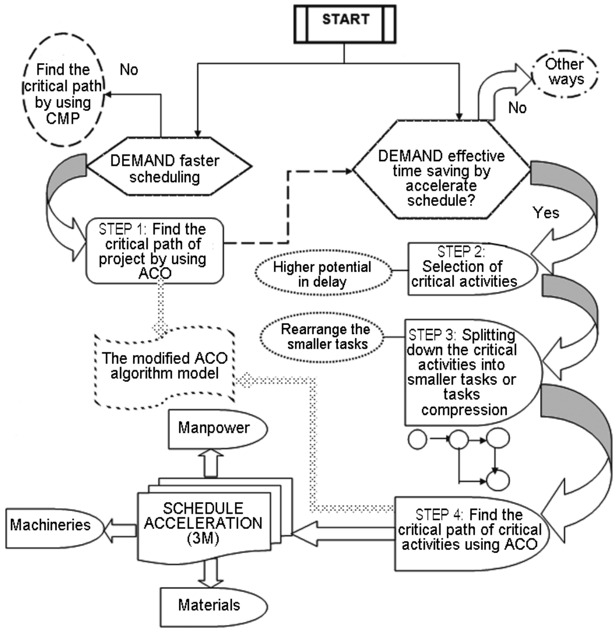

Fig. 2. Appearance of Final CSAM-ACO

Step 4: Find critical path from critical tasks

The critical path of a project is determined in Step 1 and is splitting into smaller tasks or is compressed in Step 3. A new critical path is then determined from the smaller tasks that indicate the shortest duration of its particular critical activity. The project managers would pay more attention to the new critical path when conducting resource and cost allocation to ensure the tasks in the critical activity not to be delayed; otherwise it will lead to the delay of the whole activity and thus the entire project. The detailed activities help resources be allocated precisely. The final developed CSAM-ACO acceleration model is illustrated in Figure 2.

4. Trial run of developed CSAM-ACO model

A high rise construction project in the urban area was chosen for the trial run of the developed CSAM-ACO. The case is concerned with a top level construction company dealing with the client to construct an office building at Subang Jaya, Malaysia, and time is one of the main concerns. The goal is to find the critical path and to split down the critical activities into smaller tasks by taking into consideration the resource allocation to shorten the project duration.

Step 1: Find the critical path

In the trial run, the critical path of the project was identified by both the traditional CPM and the ACO approach. Activities are graphed in the network topology. Table 3 shows the activities in the high rise project and Figure 3 illustrates the network diagram. The trial run is based on the topology with 8 nodes and 12 nodal connections. Among the 8 nodes in the network topology, there are 2 ant nests, 1 food source and 5 regular nodes. The node with no predecessor node represents ant nest whereas food source with no successor node. A generated network is based on unidirectional nodal connections, which is an acyclic graph to imitate the real life of construction activity.

Table 3. Activities with precedence relationships and durations

Activity code	Activity name	Durations (days)	Predecessor	Successor
A: 0–2	Mobilize on site	10	–	F, G, H
B: 0–3	Factory fabrication	70	–	I
C: 0–4	Demolition and site clearing	33	–	J
D: 1–4	Earthworks	29	–	E, J
E:1–5	Install utilities	43	–	K
F: 2–3	Frame	70	A	I
G: 2–6	Foundation	67	A	L
H: 2–7	Doors and windows	78	A	–
I: 3–7	Roofing	67	B, F	–
J: 4–6	Excavation	37	C, D	L
K: 5–7	Plastering	11	E	–
L: 6–7	Piling	29	G, J	–

By Traditional Method: CPM

The earliest start (ES), earliest finish (EF), latest start (LS), and latest finish (LF) were calculated. All the possible paths were found along the way. The activity with zero total float is the critical activity. The calculation using traditional CPM is shown in Table 4. The results of calculated ES, EF, LS, LF and total float by using CPM method are tabulated in the Table 5. The critical path formed by the critical activities 0–2, 2–3, 3–7 with zero total float. Thus, the longest project total duration is 70 + 70 + 67 = 207 which equals to the shortest duration to complete the entire project.

By ACO Algorithm

Applying the developed ACO algorithm process, the network topology parameters are identified in Table 6.

The pheromone level of all the arcs are same at this stage since there is no path yet travelled by ants so far. However, each arc has a small value of pheromone concentration to initialize the selection process where the ant moves randomly to choose the path to travel. The value of the initial pheromone level was set according to the line-distance between the nodes. It is either the inverse line-distance between two nodes or the inverse line-distance of the arc between the nodes. The line-distance in the construction network topology represents the duration of the activity. The path chosen is based on the probability calculated by Eqn (1). Ten iterations were completed and the final pheromone level was established in Table 7. The highest probability indicates the longest path of the network which is the critical activity, and the highest

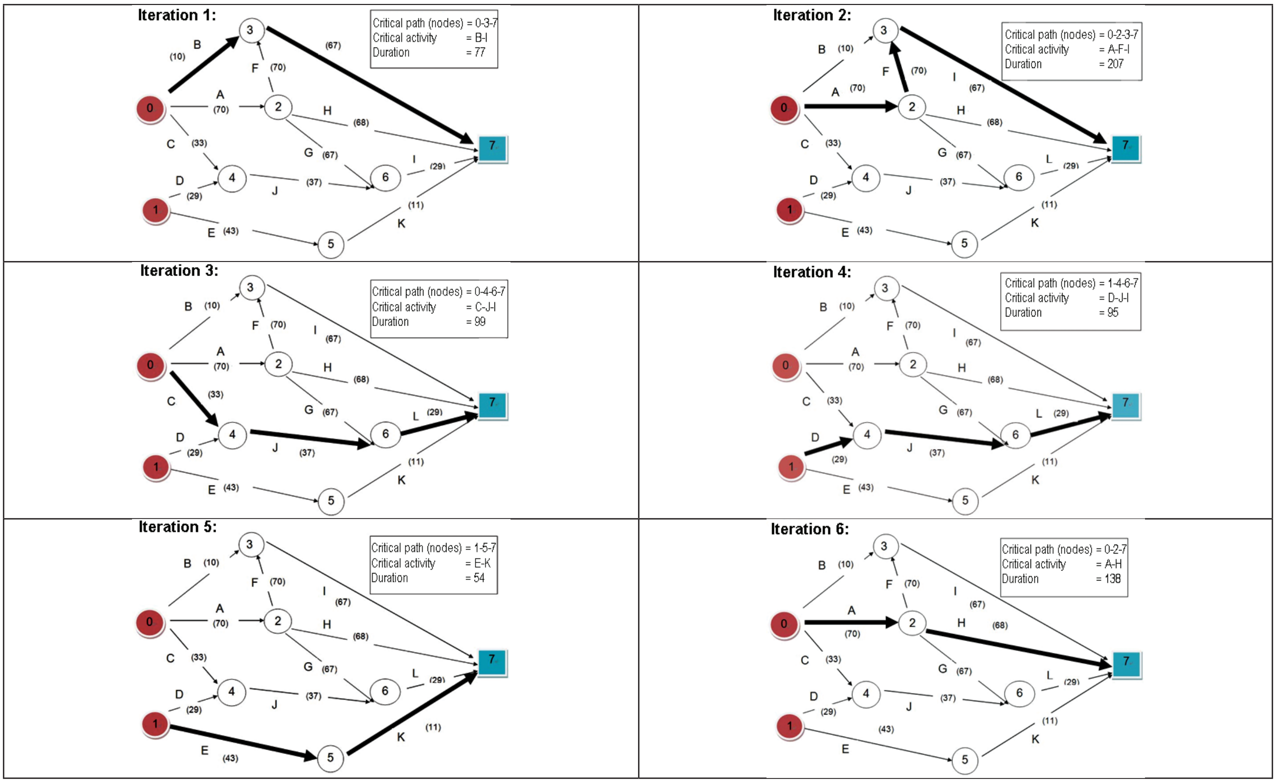

Fig. 3. Network topology for Iteration 1 to Iteration 6

Table 4. Calculation using traditional CPM for trial run

Calculation of forward pass	Calculation of backward pass:	Calculation of total float
$EF_i = ES_i$ + duration of activity	$LS_i = LF_i$ – duration of activity	TF = LF – EF/LS –ES or TF = LF – ES – duration
Activity A: The ES for activity A is zero because the node with no predecessor. Thus, $EF_A = ES_A$ + duration = 0 + 70 = 70	*Activity L:* LF of activity L is the largest value of the EF since activity L is one of the last activities that has the largest value of EF. Thus, $LS_L = LF_L$ – duration = 207 – 29 = 178	*Activity A:* TF = LF – EF/LS –ES = 70 – 70/0 – 0 = 0
Activity F: For the activity with only one predecessor, the ES of activity F is the EF of the predecessor. Thus, $EF_F = ES_F$ + duration = 70 + 70 = 140	*Activity J:* Activity J with only one successor, the LF of the activity J is the LS of the successor. Thus, $LS_j = LF_j$ – duration = 178 – 37 = 141	*Activity B:* TF = LF – ES – duration = 140 – 0 – 10 = 130
Activity J: For the activity with more than one or more predecessor, the smallest value was chosen. There are two choices of EF for activity J: 33 and 29, the smallest EF 29 was chosen as the ES of activity J. Thus, $EF_J = ES_J$ + duration = 29 + 37 = 66	*Activity A:* For the activity with more than one or more successor, the smallest value of the LS was chosen. There are three choices of EF for activity A: 10, 41 and 79, the smallest EF is chosen as the LF of activity A. Thus, $LS_A = LF_A$ – duration = 70 – 70 = 0	It shows that the activity B is not critical activity with total float of 130 whereas the activity A is the critical activity with zero value of the total float.

pheromone concentration is the shortest distance where the ant moves on.

The ACO algorithms generated different states of topology at the end of each iteration, because each successive iterative is selective based on the previously selected arc. Therefore, the critical path may change a few times before the last iteration. The network topologies for iteration 1 to iteration 6 are illustrated in Figure 3 and the final result is presented in Figure 4. The pheromone concentration is used to indicate the criticality of the activities as shown in Table 8. The "final pheromone level" or "probability" is the value to decide which activities are critical. The longest continuous path was identified and the activities of 0–2, 2–3, and 3–7 are the critical activities with the critical path duration at 207.

Table 5. Critical path using CPM

No	Start node	End node	Duration	Successor	ES	EF	LS	LF	TF	Critical activity
A	0	2	70	F, G, H	0	70	0	70	0	YES
B	0	3	10	I	0	10	130	140	10	No
C	0	4	33	J	0	33	108	141	48	No
D	1	4	29	E, J	0	29	112	141	52	No
E	1	5	43	K	0	43	153	196	93	No
F	2	3	70	I	70	140	70	140	0	YES
G	2	6	67	L	10	77	111	178	31	No
H	2	7	68	–	10	78	139	207	89	No
I	3	7	67	–	140	207	140	207	0	YES
J	4	6	37	L	29	66	141	178	52	No
K	5	7	11	–	43	54	196	207	93	No
L	6	7	29	–	66	95	178	207	52	No

Table 6. The identified network topology parameters

$q_0 = 0.3$	assist the selection of path based on the probability or random selection
$\rho = 0.5$	determine the level of evaporation of pheromone concentration for local update
$\alpha = 1.0$	determine the level of evaporation of pheromone concentration for global update
$\beta = 1.0$	determine the relative influence of the heuristic information

Table 7. Probability & pheromone level of 0–2, 0–3, 0–4

No. of iteration	0–2		0–3		0–4	
	Probability, P_{02}	Global pheromone update, τ_{02}	Probability, P_{03}	Global pheromone update, τ_{03}	Probability, P_{04}	Global pheromone update, τ_{04}
1	0.3322	0.5071	0.3354	0.5500	0.3324	0.5152
2	0.3868	0.1455	0.2577	0.2125	0.3555	0.1864
3	0.4768	0.0799	0.2288	0.1563	0.2944	0.1083
4	0.5516	0.0471	0.1468	0.1281	0.3016	0.0693
5	0.6252	0.0307	0.0856	0.1141	0.2892	0.0498
6	0.6881	0.0225	0.0504	0.1070	0.2615	0.0401
7	0.7352	0.0184	0.0328	0.1035	0.2319	0.0352
8	0.7661	0.0163	0.0244	0.1018	0.2094	0.0327
9	0.7842	0.0153	0.0204	0.1009	0.1954	0.0315

Table 8. Solution of Critical Path using ACO

NETWORK				RELATIONSHIP		RESULT	
No	Start node	End node	Duration	Original pheromone level	Final pheromone level (after iteration)	Probability	Critical activity
A	0	2	70	0.0143	0.0148	0.7941	YES
B	0	3	10	0.0100	0.1004	0.0185	No
C	0	4	33	0.0303	0.0309	0.1875	No
D	1	4	29	0.0345	0.3185	0.0350	No
E	1	5	43	0.0232	0.6815	0.0237	No
F	2	3	70	0.0143	0.0148	0.3486	YES
G	2	6	67	0.0149	0.0154	0.3211	No
H	2	7	68	0.0147	0.0152	0.3302	No
I	3	7	67	0.0149	0.0154	1	YES
J	4	6	37	0.0270	0.0275	1	No
K	5	7	11	0.0909	0.0914	1	No
L	6	7	29	0.0345	0.3495	1	No

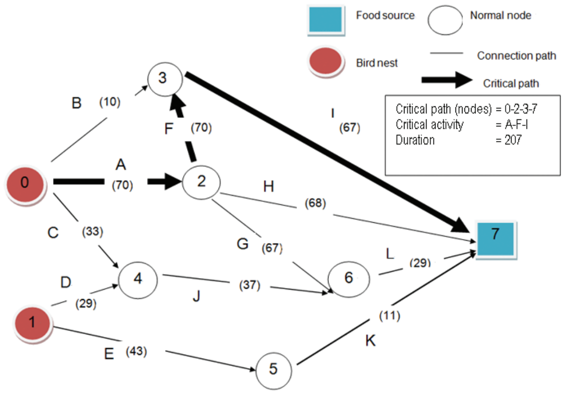

Fig. 4. Network topology result in Step 1 using CSAM-ACO acceleration model

Step 2: Selection of critical activities

After the critical path was found in Step 1, the 2nd step was to select the critical activity in the critical path. The critical activity is splitting down to be scheduled in a more detailed form. In order to accelerate the construction process, the duration of the critical activity has to be shortened. The selected critical activity was to be accelerated from the original duration at 70.

Step 3: Splitting down of selected critical activity

The list of splitting tasks is shown in Table 9.

Table 9. Activity table for splitting tasks

No	Activity	Durations (days)	Predecessor	Successor
A: 0–1	Stripping form	4	–	C, D
B: 0–2	Precast façade fixing	13	–	E
C: 1–5	Beam and slab steel fixing	21	A	I, J
D:1–4	Semi–precast slab fixing	28	A	H
E: 2–3	Wall steel fixing	12	B	F, G
F: 3–5	Wall form fixing	12	E	I, J
G: 3–7	Wall concreting	11	E	–
H: 4–7	Slab form fixing	15	D	–
I: 5–6	Electrical conduit installation phase 1	13	C, F	K
J: 5–7	Electrical conduit installation phase 2	10	C, F	–
K: 6–7	Beam and slab concreting	13	I	–

After splitting down the critical activity into smaller tasks, the original duration of the activity was shortened from 70 to 63. It was scheduled to repetitive tasks or separate tasks which could be conducted concurrently. Eventually, the duration was shortened with more detailed tasks, which provide a clearer picture of the tasks sequences. Same as the previous session, a network topology for these tasks was constructed. The topology was made up with 8 nodes and 11 nodal connections. In the 8 nodes, there are 1 ant nest, 1 food source and 6 regular nodes. The constructed new network topology for the detailed activity in the framing work is shown in Figure 5.

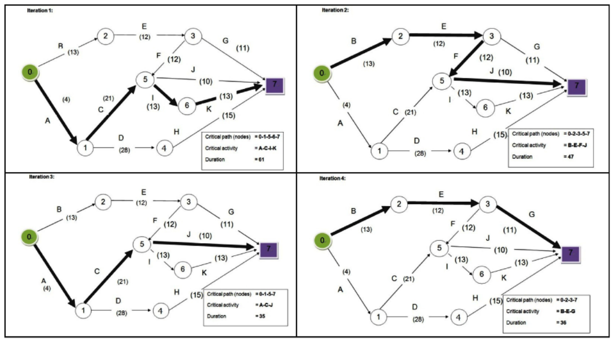

Fig. 5. New network topology for Iteration 1 to Iteration 4

Step 4: Finding new critical path

After the new network topology was constructed with the splitting tasks and durations, a new critical path was found requiring higher attention for resource allocation. The calculation in this step was similar as that in the Step 1.

By Traditional CPM

The calculated ES, EF, LS, LF, and total float were tabulated in Table 10. The critical path with zero total float is determined. The determined critical path identified by CPM was compared with the result of ACO. The critical path was formed by 0–2, 2–3, 3–5, 5–6 and 6–7. Thus, the longest duration of the task of the framing works is 13 + 12 + 12 + 13 + 13 = 63. It indicates that the original duration of 70 was reduced to 63, which is the longest duration of the activity.

By ACO Algorithm

The new network topology for Iteration 1 to Iteration 4 is shown in Figure 5. The new topology solution was calculated using the same equations as in Step 1. The computational result using ACO is tabulated in Table 11. The longest continuous path of these activities was identified and the activities of 0–2, 1–4, 3–5, 5–6 and 6–7 are the critical activities with the critical path duration at 63. The network topology of final solution was shown in Figure 6. It proved that the splitting down of framing works into smaller tasks reduced the duration by 7 days.

5. Discussion and comparison of CSAM-ACO with CPM and previous studies

Though Adeli and Karim (2001) believe, that the traditional CPM tool performs well in construction scheduling, the trial run conducted in this study proved that the developed CSAM-ACO model is more favorable compared with CPM. CSAM-ACO is able to calculate the longest node-to-node path, and the calculation can be done concurrently for different nodes and a big number of activities and resource allocation. In addition, the du-

Table 10. Solution of new critical path for splitting tasks using CPM

Code	Start node	End node	Duration	Successor	ED	EF	LS	LF	TF	CA
A	0	1	4	C, D	0	4	12	16	12	No
B	0	2	13	E	0	13	0	13	0	YES
C	1	5	21	I, J	4	25	16	37	12	No
D	1	4	28	H	4	32	20	48	16	No
E	2	3	12	F, G	13	25	13	25	0	YES
F	3	5	12	I, J	25	37	25	37	0	YES
G	3	7	11	–	25	36	52	63	27	No
H	4	7	15	–	32	47	48	63	16	No
I	5	6	13	K	37	50	37	50	0	YES
J	5	7	10	–	37	47	53	63	16	No

Table 11. Solution of splitting tasks using ACO

Network					Relationship		Result	
No	ID	Start node	End node	Duration	Original pheromone level	Final pheromone level	Probability	Critical activity
A	1	0	1	4	0.2500	0.2504	0.0924	No
B	2	0	2	13	0.0769	0.0774	0.9076	YES
C	3	1	5	21	0.0476	0.0481	0.3638	No
D	4	1	4	28	0.0357	0.0362	0.6362	No
E	5	2	3	12	0.0833	0.0838	1	YES
F	6	3	5	12	0.0909	0.0838	0.5426	YES
G	7	3	7	11	0.0833	0.0914	0.4574	No
H	8	4	7	15	0.0667	0.0671	1	No
I	9	5	6	13	0.1000	0.0774	0.6259	Yes
J	10	5	7	10	0.0769	0.1004	0.3741	No
K	11	6	7	13	0.0769	0.0774	1	YES

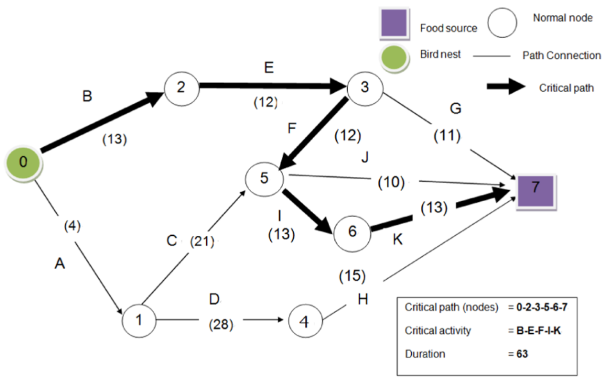

Fig. 6. New network topology for final solution

ration of the activity is shortened by splitting down the critical activity so that the resources allocated on the new found critical path could assist in accelerating the entire schedule. Besides, compared with the previous study conducted by Christodoulou (2009) who introduced ACO for project scheduling, this study developed a construction schedule acceleration model using the self-developed ACO algorithm processes. The concepts of both ACO and CPM in finding critical path were integrated in the schedule acceleration model for a more precise resource allocation. The uniqueness of this study was also incarnated by the trial run of CSAM-ACO under a real case. Besides its prominent advantages, the developed CSAM-ACO has yet some limitations, for instance the splitting down process of the critical activities is rather time-consuming. Furthermore, CSAM-ACO involves two stages of computation in finding the critical path which causes double calculation.

Conclusions and recommendations

The developed model CSAM-ACO targets on schedule acceleration by allocating resources on the newly found critical path after two stages of computation. The trial run proves CSAM-ACO is not only able to increase the probability of completing a delayed project within the stipulated time but also able to satisfy the request of earlier completion of a project. It accelerates the schedule and shortens the project duration where time is constraint. Breaking down of the critical activity provides a clear picture of the construction process so that it provides more precise resource allocation than CPM does by working on those smaller tasks in the critical activity. In further study, the splitting down process of critical activities in CSAM-ACO is to be optimized. Besides, by taking into consideration that the Industrialized Building System (IBS) is highly implemented in the construction sector, which is for the same purpose of time saving, a tailored CSAM-ACO is highly recommended to be developed for IBS projects.

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