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ANT COLONY OPTIMIZATION (ACO) IN SCHEDULING OVERLAPPING ARCHITECTURAL DESIGN ACTIVITIES

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Abstract. The increasing complexity of architectural design works refers to the need for high quality design solutions for overlapping activities through a shorter time period. Conventional network analysis techniques such as CPM could only represent sequential processes yet it is unable to handle a process which contains iterations so that it leads to the occurrence of unwanted omission of logic or information links between design activities. Ant Colony Optimization emerged as an efficient metaheuristic technique for solving computational problems in finding good paths through graphs. This research aims to develop an ACO based Design Activity Scheduling model (ACO-DAS) for the scheduling of overlapping architectural design activities and to test the workability of ACO-DAS through a hypothetical run. From the computational results of both CPM and ACO methods, the determination of critical path using ACO-DAS model resulted in a design duration at 50 while that for CPM was as long as 78. The durations of architectural design activities have been significantly shortened by ACO-DAS. ACO-DAS results in shorter design completion time thus it deems more advanced than CPM.

Keywords: ant colony optimization, design activity scheduling, CPM, overlapping architectural design activities, metaheuristic technique.

Introduction

Recently, the pressures to improve the design performance have increased due to the increasing complexity of projects and the competitive market. Such improvements refer to the need for high quality design solutions for overlapping activities through a shorter time period (Hoseini, Shayesteh 2013; Tzortzopoulos, Cooper 2007). There lacks of a formal procedure or computerized tools to guide the architects in considering overlapping decisions and most architects do not have a good mathematics background (Srour *et al.* 2013). Fast-tracking in the construction industry is becoming more popular due to the growing industry demands (Srour *et al.* 2013). Construction delays are commonly occurred due to the lateness of design deliverables such as drawings, calculations and reports. Scheduling of building design activities includes assessing the status on the activities' readiness to be performed, assigning resources and determining the start time, duration, and completion time for each activity (Bożejko *et al.* 2012). Construction practitioners normally rely on experience and standard scheduling methods such as bar charts or Critical Path Method (CPM) of network analysis for design activities scheduling. CPM was developed in 1950s with concepts of identifying activities, determining logical order of activities and estimating the duration of each activity (Kloppenborg 2009). CPM in design and planning has been in existence for many years but it was initially developed only for construction scheduling because design activities normally have information dependencies between each other and this makes the application of CPM imperfect for architectural design. Hence, a more efficient alternative to the traditional CPM technique is needed for the architectural design with overlapping design activities.

In 1992, Ant Colony Optimization (ACO) was first introduced by Dorigo who was inspired from the foraging behavior of real ant colonies (Mateos *et al.* 2013). Duan and Liao (2010) found ACO an efficient metaheuristic technique for solving computational problems in finding good paths through graphs. In recent times, ACO has been applied in the construction management such as resource-constrained project scheduling (Zhang, Ng 2012), construction site layout planning (Ning, Lam 2013; Lam *et al.* 2007), optimizing construction time and cost (Ng, Zhang 2008), resource-unconstrained scheduling (Thiruvady *et al.* 2013), determining project critical paths (Duan, Liao 2010) and so forth. This research aims

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to develop an ACO based Design Activity Scheduling model (ACO-DAS) for the scheduling of overlapping architectural design activities and to test the workability of the developed ACO-DAS model through a hypothetical run.

1. Ant Colony Optimization (ACO)

Ant Colony Optimization (ACO) is categorized as a part of swarm intelligence (SI) inspired by the social behavior of swarms (Junior *et al.* 2013). Swarm Intelligence is related to the transformation of knowledge about the ability of insects to solve problems cooperatively into artificial problem solving methods (Bonabeau *et al.* 2000). There are many techniques inspired by the ants' behavior and ACO is the most successful example of ant algorithms (Dorigo *et al.* 2006). ACO was first introduced by Marco Dorigo in year 1992 where the idea came from the foraging behavior of some ant species, particularly on the ability of ants to discover the shortest route between their nest and food sources. As described by Dorigo and Socha (2007), when ants are walking around searching for food, they will deposit an odorous chemical substance which is known as pheromone on the path, forming a pheromone trail. When the ants are choosing their way to the food sources, they able to smell the pheromone and they are more likely to follow the route that have stronger concentration of pheromone. This pheromone trail enables the ant to reach good sources of food which have been previously explored by the other ants. In 1992, the first ACO system, known as Ant System (AS) was proposed by Marco Dorigo in his PhD thesis. Since then, ACO started to attract the attention of many researchers and broad fields of ACO applications are now available.

1.1. Foraging behavior of real ant colonies

Ants can be classified as social insects which live together in colonies. Normally their behavior is influenced by the goals of their colony survival but not concentrated on the individual survival (Blum 2005). A research has been done by Deborah Gordon to observe the ant colony behavior, who clarified that ants are not smart but ant colonies are (Miller 2010). Ant is a simple creature but an ant colony was able to complete some complex activities which in certain circumstance far beyond the ability of individual ant (Dorigo *et al.* 2000). One of the amazing abilities of ant colony is that they are able to discover the shortest path from their nest to the food source through stigmergy. This ant behavior is especially remarkable as we know ant is almost blind. Hence, it is impossible for the ant colonies to find out the shortest path by the employment of visual clues. Dorigo and Blum (2005) described the concept of ACO algorithms from the sourcing of food in ant colonies. Many ant species had a depositing-trial following behavior when they are searching for food (Dorigo *et al.* 2000). While the ants are foraging, they will first explore the area surrounding their nest and randomly moving around. Once a forager found an important food source, it will evaluate the food quality and quantity and transport it back to its nest. When the forager is heading back to its nest, it will lay an odorous chemical substance which is known as pheromones along their travelled path (Blum, Dorigo 2004). Other foragers might then follow such pheromone trails with some probability to reach the food source. The ants can communicate indirectly between each other to exchange information through depositing a chemical substance which is called pheromone (Duan, Liao 2010). In practice, choices between different paths occur when several intersect. Then, ants choose the path to follow by a probabilistic decision biased by the amount of pheromone: the stronger the pheromone trail, the higher its desirability. The level of tendency, equivalently, the quantity of pheromone deposited, is dependent upon the quality of food. A high level of pheromone concentration attracts ants to follow it with high probability thus reinforcing he trail with its own pheromone. The more ants follow a trail, the more attractive it become to other ants. On the other hand, the pheromones will evaporate over some time due to natural environment (Duan, Liao 2010). In those less-travelled paths, the concentration of pheromones will varnish with time and thus become weaker and weaker. This whole process can be characterized by a positive feedback loop where the probability of each ant chooses to follow the path increases with the numbers of ants that have previously chosen to travel the same path. As a result, the ant population and path-traversing process converge to the shortest path from the nest to the food source in a relatively short period of time (Duan, Liao 2010).

1.2. Ant Colony Optimization (ACO) variants and applications

Variants of ACO algorithms are basically differing from each other in the aspect of the pheromone update rule that have been employed (Dorigo, Blum 2005). After the Ant System (AS) has been introduced, many researchers and practitioners have made extension and improvement on the original AS algorithm to discover the further application of ACO. A selection of some successful ACO variants applications are listed in Table 1.

The first ACO algorithm example is Ant System (AS) which was introduced by Marco Dorigo in 1992 to solve the travelling salesman problem (TSP). The next two applications of ACO after the travelling salesman problem (TSP) were the quadratic assignment problem (QAP) and the job-shop scheduling problem (JSP) that have been introduced in year 1994 and followed by the first network routing applications in 1996. The number of ACO applications started to increase and these include the classical vehicle routing problems, sequential ordering, flow shop scheduling and also graph coloring problems. Since then, ACO has been applied to solve

Table 1. Various applications of ACO algorithms according to problem type

Problem	Authors	Year	Algorithms
Travelling Salesman	Dorigo *et al.*	1991	AS
	Gambardella and Dorigo	1995	Ant-Q
	Dorigo and Gambardella	1996	ACS-3-opt
	Stutzle and Hoos	2000	MaxMin-AS
	Bullnheimer *et al.*	1997	Rank AS
Quadratic Assignment	Maniezzo *et al.*	1994	AS-QAP
	Gambardella *et al.*	1997	HAS-QAP
	Stutzle and Hoos	2000	MMAS-QAP
	Maniezzo and Colorni	1998	AS-QAP
	Maniezzo	1998	ANTS-QAP
Vehicle Routing	Bullnheimer *et al.*	1997	AS-VRP
	Gambardella *et al.*	1999	HAS-VRP
Scheduling problems	Colorni *et al.*	1994	AS-JSP
	Stutzle	1997	AS-FSP
	Merkle *et al.*	1997	ACO-RCPS
	Bauer *et al.*	1999	ACS-SMTTP
	den Besten *et al.*	1999	ACS-SMTWTP
	Blum *et al.*	2004	HCF
	Blum	2005	PACO
Connection-oriented network routing	Schooderwoerd *et al.*	1996	ABC
	White *et al.*	1998	ASGA
	Di Caro and Dorigo	1998	AntNet-FS
	Bonabeau *et al.*	2000	ABC-smart ants
Connection-less network routing	Di Caro and Dorigo	1997	Ant Net-FA
	Subramanian *et al.*	1997	Regular ants
	Heusse *et al.*	1998	CAF
	Van der Put and Rothkrantz	1998	ABC-backward
Multiple knapsack	Leguizamon and Michalewicz	1999	AS-MKP
Generalized assignment	Ramalhinho *et al.*	1998	MMAS-GAP
Optical networks routing	Navarro Varela and Sinclair	1999	ACO-VWP
Sequential Ordering	Gambardella and Dorigo	1997	HAS-SOP
Graph Coloring	Costa and Hertz	1997	ANTCOL
Shortest Common Supersequence	Michel and Middendorf	1998	AS-SCS
Frequency assignment	Maniezzo and Carbonaro	2000	ANTS-FAP
Travelling Salesman Problem (TSP)	Blum and Lopez-Ibanez	2010	Beam-ACO

the combinatorial optimization problems such as shortest common super sequence, generalized assignment, set covering, multiple knapsack and constraint satisfaction problems. Recently, the application of ACO has been further expanded by several other researchers for machine learning purposes, concretely to the design of learning algorithms for knowledge representation structures such as classical logic rules (Parpinelli *et al.* 2002), and fuzzy logic rules (Cordon *et al.* 2002) showing very promising results. Christodoulou (2009) presents a methodology for the critical path calculation from network diagram by imitating the behavior of real ants in finding the shortest route from their nest to the food source. Duan and Liao (2010) pointed out the number and allocation of logical dummy activities associated with AoA Network can affect the performance of the two existing ACO algorithms. Shankar *et al.* (2011) discussed an approach to apply ACO for solving CPM Network. Abdallah *et al.* (2009) has proposed the application of ACO to look into and solve the problems of PERT network in project management. As described by Christodoulou (2009), ACO algorithms exhibit many similarities in construction scheduling, especially in the characteristic of underlying network topology and path searching approach to compute longest or shortest path. The application of ACO in defining the longest path in acyclic graph is actually the same as the determination of critical path in construction activities network. The ACO ants, state, connection and cost functions could represent the CPM's resources, activity, relationship and durations respectively.

2. Research procedures and model development

The planning and control of design work is considered the fundamental activity in a design project. Time aspect is always the most important consideration to make sure the project is completed within budget. A development team was formed among experts from various fields such as architects, building consultants, IT professionals, and Mathematicians, whose profiles are presented in Table 2. A qualitative technique enables misunderstanding or intangible issues to be avoided so that the model development process can be rectified immediately (Hennink *et al.* 2010). Owing to the nature of the research where people's experiences, perceptions, opinions and knowledge are necessities to the development of the

Table 2. Profiles of the ACO-DAS Developing Team

Topology parameters	Description
β	Parameter that determine the relative influence of the heuristic information
ρ	Parameter that determine the level of pheromone concentration evaporation in local pheromone update
α	Parameter that determine the level of pheromone concentration evaporation in global pheromone update
q_0	Assist the selection of path based on the probability or random selection

model, qualitative approach was employed in this study, which consists of the following four main stages. A hypothetical run of the ACO-DAS was conducted to test how it works in a building design project. The first stage worked out the ACO algorithm processes used for the development of ACO-DAS. Secondly, each step of the final model was developed and outlined. The complete ACO-DAS associated with its main components was finalized on the third stage. The final but significant stage is the hypothetical run of the developed ACO-DAS. The ACO algorithm processes for the ACO-DAS development consists of 9 steps as follows.

Step 1: Categorization of design activities

Design activities can be categorized into conceptual design, electrical design, HVAC design and structural design. By categorizing the design activities, the developing team listed down all the detailed design activities under each category to find the sequence. The durations and relationship between the activities were clearly stated. For example, conceptual design consists of floor plan design, exterior elevations design, wall section design, ceiling design and so forth. Structural design is comprised of structural calculations, foundation design, floor framing design, etc. All the detailed activities were tabulated with respective durations.

Step 2: Construction of network topology

Network topology was formed by circles and paths linked by arrows. The circle, which is known as node is the intersection point of two or more arrows. This network topology technique can meet the requirements of different functions and purposes. The network model graphically represents the order of events or sequence of design activities. There are two types of network diagram which are AON and AOA. AOA diagram is a graphic technique in which the arrows represent activities and nodes represent the start and finish of those activities. On the other hand, AON diagram represent activities as nodes and activity sequences as arrows. The network topology provides a comprehensive layout for project schedule with a set of activities that have relations with each other. In this research, the design network topology was defined by an AON graph G = (V, E) in which V represents the design activities and E represents the relationships connected to the nodes. The established network topology which represents the design schedule should be analyzed to initialize topology parameter in Step 3.

Step 3: Initialization of topology parameters

The setting of topology parameters (β, ρ, α, q_0) actually depends on a sensitivity analysis for other randomized topologies and the observed rate and accuracy of convergence to an optimal solution (Christodoulou 2009). Evaluation of the accuracy and rate of convergence for the examined solution methodology in relation with the examined parameters are allowed by the sensitivity analysis. The base value combinations for the examined parameters can be obtained through the examination of various network topologies. After constructing the network topology, the topology parameters were initialized before the generation of solution through ACO algorithms. The values of each parameter are the results of sensitivity analysis. The performance of all the topology parameter was verified against other network characteristics such as the number of nodes and arcs in the network topology and also the number of possible starting nodes (ant nest) found in the network. The 4 common parameters that associated with the ACO technique is shown in Table 3.

Step 4: Setting of initial pheromone level

In this step, the artificial ants were expected to randomly walk and search the path because there was no previously visited path with higher pheromone concentration which the ants could sense. Therefore, the initial pheromone level was set at an equal value at each edge. The initialized pheromone level of the path was updated after it had been travelled by the ants. The pheromone levels at all arcs were initialized with a small amount of pheromone, τ_0. The values of this initial pheromone level of the path was either the inverse line-distance between two nodes or the inverse line-distance of the arc between the nodes, which referred to the durations of activity found in the network.

Step 5: Allocation of ants to initial node

After initializing the pheromone level, all ants were allocated.

The ants were allocated from the initial node pseudo-randomly walking via the connecting edges until it reached the end node.

Step 6: Generation of best paths

When the ants were randomly walking from the initial node, they will come across the node where they need to select which path to follow. The path selection process depended on Eqn (1):

$$\rho_i = \tau_i \eta_i^{\beta} / \sum_i \tau_i \eta_i^{\beta}, \quad (1)$$

Table 3. The network topology parameters

No	Specialty	Gender	Age	Working experience	Qualification		Roles in model development
A	Architect	Male	57	25 years	Bachelor	*Stage 1 and 4*	Collaborating with Developer B to determine the sequence of design activities and their nodes. Working with Developer D to determine the critical path of design activities.
B	Building Consultant	Male	52	28 years	Master	*Stage 1 and 4*	Expertise in electrical design, HVAC design. Working with Developer A, C, D, L to determine the sequence of design activities and their nodes.
C	Architect	Male	48	15 years	Bachelor	*Stage 1 and 4*	He is the project manager of the ACO-DAS hypothetical run. All the design activities and nodes were finalized by him. He supervised the hypothetical run.
D	Architect	Male	45	18 years	PHD	*Stage 1 and 4*	Assisting Developer C. He was in charge of finding critical path from design activities.
E	Cartographer and ACO algorithms	Male	50	20 years	PHD	*Stage 3 and 4*	Worked out the ACO algorithm processes for the development of the final ACO-DAS. He was in charge of establishing network topology, initializing topology parameters, setting initial pheromone level, and constructing best solution.
F	Computer-aided Scheduling	Male	47	25 years	PHD	*Stage 2 and 4*	Reasoning the selection of ACO algorithms in design activities. Developer F was in charge of finding the critical path by calculating the total float. He was also the main programmer of the hypothetical run.
G	Mathematician	Female	51	27 years	PHD	*Stage 2 and 3*	She was in charge of local pheromone update rule, global pheromone update, and reach number of iterations and termination.
H	ACO algorithms	Male	56	31 years	PHD	*Stage 3*	All the design activities and nodes finalized by the Developer C were translated and inputted by Developer H into the ACO-DAS. He is the cartographer of the iteration diagrams.
I	Architect	Male	44	19 years	Master	*Stage 2 and 4*	Expertise in structural design. Collaborating with Developer B to determine the sequence of design activities and their nodes.
J	Mathematician	Female	33	8 years	PHD	*Stage 3*	The complete ACO-DAS associated with its main components was graphed and calculated by her.
K	Project Scheduling and CPM	Male	42	16 years	Master	*Stage 3 and 4*	Reasoning the selection of ACO algorithms in schedule acceleration. Developer D 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 hypothetical run. The critical path of the design process was identified by both the traditional CPM and the new ACO approach to verify the application of ACO in finding the critical path.
L	Architect	Male	39	17 years	Bachelor	*Stage 2 and 4*	Collaborating with Developer B to determine the sequence of design activities and their nodes.

where: τ_i – pheromone concentration on the i^{th} arc; η_i – priori available heuristic value for the i^{th} arc, can be the inverse of the arc length or the inverse of the arc length plus the line-distance between the nodes; and β_i – parameter determining the relative influence of the heuristic information.

Step 7: Apply local pheromone update

After passing each arc in the network during the construction of solutions, the local pheromone update rule was applied to update the level of pheromone at the given arc. Local pheromone updating is to allow more paths or routes to be explored and chosen by lowering the chance where the previously travelled paths to be chosen again when the ants are randomly selecting the arc. The pheromone evaporation was updated by means of local pheromone update to all paths. The local pheromone update was computed by Eqn (2):

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

where: ρ – network topology parameter, $0 \le \rho \le 1$; τ_0 = initial pheromone level.

Step 8: Apply global pheromone update

Global pheromone update was applied to the best path of the iteration. The ant that made the longest path in the particular iteration was the best path adding an amount of pheromone concentration on the travelled arc in which the line distance of that path was increasing. The amount of pheromone concentration depends on how frequent the path is being chosen, which means that the more frequently selected best path of the iterations, the higher is the pheromone concentration. The global pheromone update was calculated using Eqn (3).

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

where: α – network topology parameter, $0 \le \alpha \le 1$, which determines the pheromone concentration evaporation level; τ_L – inversely proportional to the path length of the best solution, zero for all other solution.

Step 9: Reach number of iteration

The whole ACO process ended when a fixed number of iterations were reached after repeating Step 6 to Step 8. The best solution was determined from the final pheromone level and the chosen probability of the nodes. The longest path was finally obtained. The above mentioned 9 steps could be run in accordance with the sequence shown in the developed ACO-DAS model as illustrated in Figure 1.

3. Hypothetical run of ACO-DAS

A hypothetical run of the ACO-DAS model was conducted to test its workability. The critical path was calculated by both the CPM and the ACO-DAS model, thus a comparison could be made between these two methods based on the computation results. A design case was created for the hypothetical run, in which all the detailed design activities were coded to construct the network topology. The detailed information on each activity in the hypothesized project including the nodes, immediate predecessors, and durations are tabulated in Table 4.

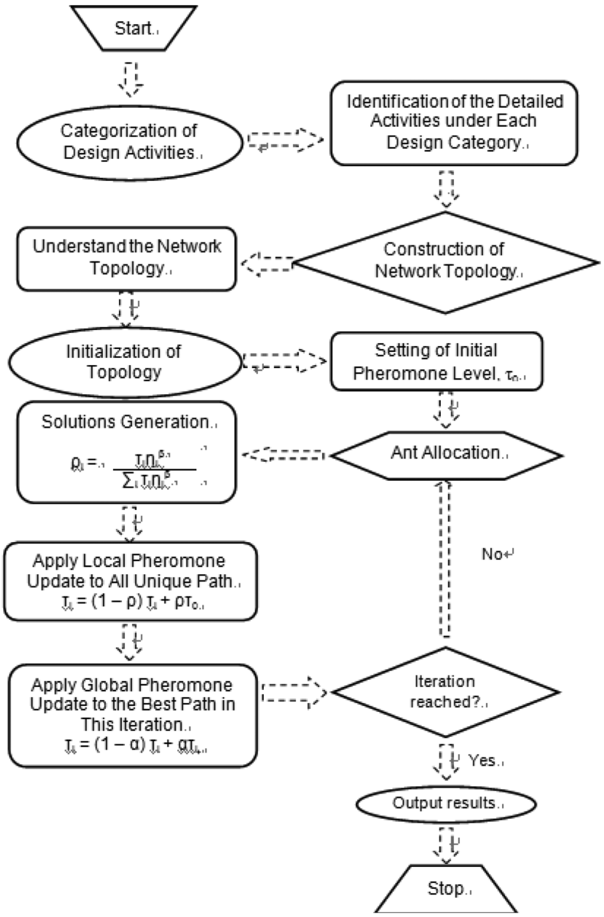

Fig. 1. The developed ACO-DAS model for overlapping architectural design activities

3.1. Network diagram in hypothesized design case

A network diagram as shown in Figure 3 was created based on the detailed architectural design activities listed in Table 4. The hypothesized design case has a topology with 12 nodes and 20 node connections. The 12 nodes of the simulation network topology consists of an ant nest, a food source, and regular nodes. The node without predecessors represents the ant nest and the one without any successor is the food source.

3.2. Calculating critical path by CPM

As the most conventional method for design activity scheduling, CPM was conducted in this hypothetical run in order to compare with the developed ACO-DAS. CPM involved the computation of forward pass and backward pass for the determination of critical path in the network. The computation of forward pass involved the earliest

Table 4. Description and predecessors of each activity in the hypothesized design project

Activity			Immediate predecessor	Durations (days)
Code	Name	Node		
A	Floor Plan Design	(0,1)	–	7
B	Exterior Elevations Design	(1,2)	A	8
C	Wall Sections Design	(1,3)	A	10
D	Ceiling Plan Design	(2,3)	B	9
E	Restroom Details Design	(2,5)	B	12
F	Door and Window Details Design	(3,5)	C, D	13
G	Cafeteria Furniture Design	(3,4)	C, D	5
H	Interior Elevation Design	(4,5)	G	15
I	Construction Details Design	(5,8)	E, F, H	16
J	Architectural Design Review	(4,8)	G	1
K	HVAC Calculations	(4,7)	G	4
L	AHU Equipment Design	(4,6)	G	10
M	Piping System Design	(6,7)	L	9
N	Air Duct Plan Design	(7,8)	K, M	8
O	Electrical Switchgear Calculations	(8,10)	I, J, M	7
P	Electrical Switchgear Design	(7,10)	K, M	6
Q	Light Fixture and Wiring Design	(6,9)	L	8
R	Emergency Light Design	(9,10)	G	2
S	Smoke Detector Design	(9,11)	Q	3
T	Emergency Exhaust Duct Design	(10,11)	O, P, R	11

start (ES) and earliest finish (LS), whereas the computation of backward pass involved the calculation of latest finish (EF) and the latest start (LS). The critical path was then selected with critical activities of zero float.

3.2.1. Calculation of forward pass

The starting point of a forward pass was the very first activity in the network diagram shown in Figure 2. The ES of this very first activity equals to zero. The FS of this activity was then calculated by adding its durations to the ES.

3.2.2. Calculating backward pass

The starting point for a backward pass was the last activity in the network diagram shown in Figure 3. LS was calculated from the longest duration of the activity path and taken into consideration the smallest value for more than one activity for the subsequent activities.

3.2.3. Calculation of total float (TF)

After computing all the values of ES, EF, LS and LF for each activity, the total float was then determined. The total float was the amount of time that an activity could be delayed without delaying the project's estimated completion period. For activity A, TF = LF – EF/ LS – ES = 7 – 7/ 0 – 0 = 0. For activity C, TF = LF – ES – Duration of activity C = 24 – 7 – 10 = 7. The same computation method was used to calculate the TF of all other activities in the network.

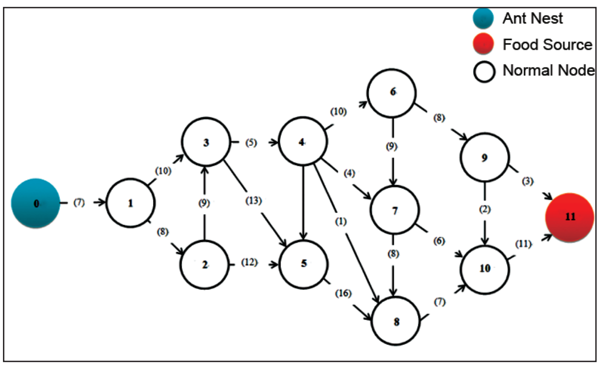

Fig. 2. Network topology for hypothesized design case

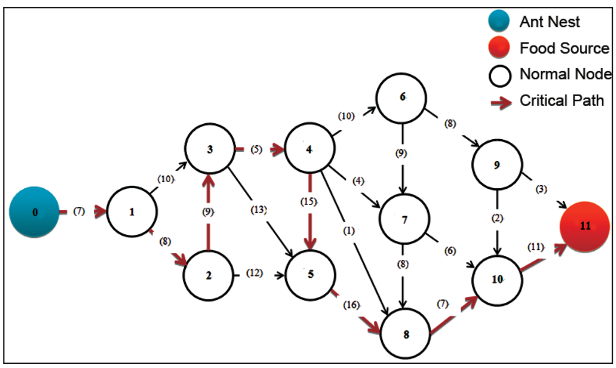

Fig. 3. Network Diagram for Final Solution of CPM

Table 5. Solution of critical path by applying CPM

Activity code	(i,j)	Duration	Immediate predecessor	ES	EF	LS	LF	TF	Critical activity
A	(0,1)	7	–	0	7	0	7	0	**Yes**
B	(1,2)	8	A	7	15	7	15	0	**Yes**
C	(1,3)	10	A	7	17	14	24	7	No
D	(2,3)	9	B	15	24	15	24	0	**Yes**
E	(2,5)	12	B	15	27	32	44	17	No
F	(3,5)	13	C,D	24	37	31	44	7	No
G	(3,4)	5	C,D	24	29	24	29	0	**Yes**
H	(4,5)	15	G	29	44	29	44	0	**Yes**
I	(5,8)	16	E,F,H	44	60	44	60	0	**Yes**
J	(4,8)	1	G	29	30	59	60	30	No
K	(4,7)	4	G	29	33	48	52	19	No
L	(4,6)	10	G	29	39	33	43	4	No
M	(6,7)	9	L	39	48	43	52	4	No
N	(7,8)	8	K,M	48	56	52	60	4	No
O	(8,10)	7	I,J,M	60	67	60	67	0	**Yes**
P	(7,10)	6	K,M	48	54	61	67	13	No
Q	(6,9)	8	L	39	47	57	65	18	No
R	(9,10)	2	G	29	31	65	67	36	No
S	(9,11)	3	Q	47	50	75	78	28	No
T	(10,11)	11	O,P,R	67	78	67	78	0	**Yes**

3.2.4. Determination of critical path

The critical activity, if delayed by any amount of time, will delay the completion of entire project by the same amount of time. Any node not in the critical path will have float, which means that critical activities have zero float. In this network, the activity A was one of the critical activities as it had zero float. On the other hand, activity B contained the total float of 7, which indicated that activity B was not a critical activity. The results of the forward pass (ES and LS), the backward pass (LS and LF) and also the total float computation are tabulated in Table 5. The critical path was then identified in Figure 3. The critical path in this network was formed by the critical activities 0–1–2–3–4–5–8–10–11 which had zero float. Hence, the longest project total durations were 7 + 8 + 9 + 5 + 15 + 16 + 7 + 11 = 78. This is the shortest durations to finish the entire design project using CPM scheduling.

3.3. Calculating critical path using ACO-DAS

The ACO-DAS was used to identify the critical path to compare the result with CPM. The same network topology was used as shown in Figure 3. The assumption of topology parameters is tabulated in Table 6. After initializing the topology parameters, the initial pheromone level was set. In the beginning, the pheromone levels of all arcs were the same because there was no path travelled by the ant. Nevertheless, each arc had a small value of pheromone concentration to initialize the selection process in which the ant moved randomly to choose which path to travel. The values of the pheromone concentration were set according to the line distance between the nodes. It could be the inverse line distance between two nodes or the inverse line distance of the arc between the nodes. The line distances in the network topology represented the durations of each activity. The probability where the path to be chosen was computed by Eqn (1). The selection of path was made between the arcs according to the probability stochastic process. The number of iteration was fixed to 5 by the researcher. The probability calculation process for the given arcs in Figure 3 with different initial pheromone level are presented in detail below. The probability was computed for each path from the left to the right of the

Table 6. Assumption of topology parameter

Topology parameters	Description
$\alpha = 1.0$	Determine the level of evaporation of pheromone concentration for global update
$\beta = 1.0$	Determine the relative influence of the heuristic information
q0 = 0.3	Assist in the path selection based on the probability or random selection
p = 0.5	Determine the level of evaporation of pheromone concentration for local update

network topology. When the ant reached a node without any branch, the possibility for the ant to travel to it always equaled to 1.

3.3.1. Probability and pheromone level for arc 0 – 1

Iteration 1: P_{01} = 1, the local pheromone update was then applied to all travelled paths. The chosen arc was updated to enable other arcs to have the higher probability to be chosen, the initial pheromone level τ_0 was set to 1. The computation was based on Eqn (2), thus the local pheromone level updated as: $\tau_{01} = (1 - 0.5)(1) + (0.5)(1/7) = 0.5714$. The global update was applied to the chosen best path to update the pheromone level because the frequently travelled path by the ant would have higher pheromone concentration. However, the previously chosen arc would not be considered as part of the possible trails. The computation was based on Eqn (3), thus the global pheromone level updated as: $\tau_{01} = (1 - 0.5)(0.5714) + (0.5)(1/7) = 0.3571$. Likewise, the global pheromone level updated in Iteration 2, 3, 4, and 5 are:

Iteration 2: P_{01} = 1, thus $\tau_{01} = (1 - 0.5)(0.3571) + (0.5)(1/7) = 0.2500$;

Iteration 3: P_{01} = 1, thus $\tau_{01} = (1 - 0.5)(0.2500) + (0.5)(1/7) = 0.1964$;

Iteration 4: P_{01} = 1, thus $\tau_{01} = (1 - 0.5)(0.1964) + (0.5)(1/7) = 0.1696$;

Iteration 5: P_{01} = 1, thus $\tau_{01} = (1 - 0.5)(0.1696) + (0.5)(1/7) = 0.1562$.

Five iterations were completed and the final pheromone levels were established. The highest probability revealed that the longest path of the network was the critical activity and the highest pheromone concentration was the shortest travelled distance. The results were tabulated in Table 7.

3.3.2. Probability and pheromone level for arcs 1–2 and 1–3

Next, the ant reached the node 2 with two branches, namely: 1–2 and 1–3. The results are tabulated in Table 8. The global pheromone level updated: $\tau_{12} = (1 - 0.5)(0.4747) + (0.5)(1/8) = 0.2999$; and $\tau_{13} = (1 - 0.5)(0.5253) + (0.5)(1/10) = 0.3127$.

Table 7. Probability and pheromone level for arc 0–1

No of iteration	0–1
	Global pheromone update, τ_{01}
1	0.3571
2	0.2500
3	0.1964
4	0.1696
5	0.1562

Table 8. Probability and pheromone level for arcs 1–2 and 1–3

No of iteration	1–2		1–3	
	Probability, P_{12}	Global pheromone update, τ_{12}	Probability, P_{13}	Global pheromone update, τ_{13}
1	0.5014	0.3438	0.4986	0.3250
2	0.4747	0.2999	0.5253	0.3127
3	0.5191	0.3221	0.4809	0.2905
4	0.4529	0.2890	0.5471	0.3236
5	0.5515	0.3383	0.4485	0.2743

3.3.3. Probability and pheromone level for arcs 2–3 and 2–5

The next selection is between the arcs 2–3 and 2–5. The calculated values for 5 iterations were tabulated in Table 9.

3.3.4. Probability and pheromone level for the rest notes and arcs

Next, the ant was facing new braches which are arcs 3–4 and 3–5. After that, the ant arrived the arcs 4–5, 4–6, 4–7 and 4–8. Then, the ant arrived at the node with no branch through the arc 5–8. As the ant travelled on, the probability and pheromone level for arcs 6–7 and 6–9 is in Table 10. Further, the ant was facing new braches arcs 7–8 and 7–10. Next, the ant reached the node with no branch through arc 8–10. Then, the ant was facing braches 9–10 and 9–11. Finally, the ant arrived again at the node without branch through arc 10–11. The critical path in this network was formed by the critical activities 0–1, 1–2, 2–3, 3 –4, 4–6, 6–9 and 9–11 which have zero float. Hence, the longest project total durations are 7 + 8 + 9 + 5 + 10 + 8 + 3 = 50. This equals to the shortest durations to finish the entire project.

3.4. Computational results

The network topology for final solution using ACO-DAS is presented in Figure 4 and the computational result by ACO-DAS is tabulated in Table 10, which indicates that the determined critical path is much more efficient than that by CPM.

The critical path determined by CPM was formed by the critical activities 0–1, 1–2, 2–3, 3–4, 4–5, 5–8,

Table 9. Probability and pheromone level for arcs 2–3 and 2–5

No of iteration	2 – 3		2–5	
	Probability, P_{23}	Global pheromone update, τ_{23}	Probability, P_{25}	Global pheromone update, τ_{25}
1	0.5013	0.3334	0.4987	0.3209
2	0.4827	0.2969	0.5173	0.3003
3	0.5052	0.3082	0.4948	0.2891
4	0.4707	0.2909	0.5293	0.3063
5	0.5237	0.3174	0.4763	0.2798

Table 10. Solution of network using the ACO algorithm

Network				Pheromone level		Result	
Activity node	Start node	End node	Duration	Original	After 5 iterations	Probability	Critical activity
A	0	1	7	0.1429	0.1562	**1.0000**	**YES**
B	1	2	8	0.1250	0.3383	**0.5515**	**YES**
C	1	3	10	0.1000	0.2743	0.4485	NO
D	2	3	9	0.1111	0.3174	**0.5237**	**YES**
E	2	5	12	0.0833	0.2798	0.4763	NO
F	3	5	13	0.0769	0.2011	0.3252	NO
G	3	4	5	0.2000	0.4374	**0.6748**	**YES**
H	4	5	15	0.0667	0.1626	0.2585	NO
I	5	8	16	0.0625	0.0772	1.0000	NO
J	4	8	1	1.0000	0.5338	0.0676	NO
K	4	7	4	0.2500	0.2854	0.3208	NO
L	4	6	10	0.1000	0.2266	**0.3531**	**YES**
M	6	7	9	0.1111	0.2921	0.4730	NO
N	7	8	8	0.1250	0.2868	0.4485	NO
O	8	10	7	0.1429	0.1562	1.0000	NO
P	7	10	6	0.1667	0.3591	0.5515	NO
Q	6	9	8	0.1250	0.3260	**0.5270**	**YES**
R	9	10	2	0.5000	0.4964	0.4921	NO
S	9	11	3	0.3333	0.4203	**0.5073**	**YES**
T	10	11	11	0.0909	0.1052	1.0000	NO

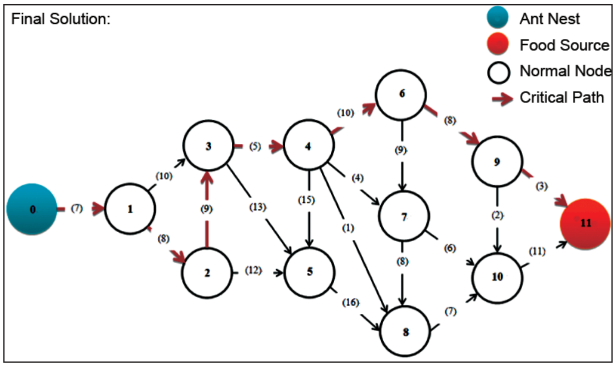

Fig. 4. Network topology for final solution using ACO-DAS

8–10 and 10–11 with the total critical path duration of 78. Whereas, the critical path determined by ACO-DAS is formed by the critical activities 0–1, 1–2, 2–3, 3–4, 4–6, 6–9 and 9–11 with critical path duration of 50. It justified that ACO-DAS could significantly further shorten the design duration determined by CPM. ACO-DAS could therefore be used to create a compressed design schedule for a fast-tracked project.

3.5. Discussion on results

The developed ACO-DAS was proved more efficient in scheduling overlapping architectural design activities compared with CPM. ACO-DAS resulted in shorter design completion time thus it is more advanced than CPM. From the computational results of both CPM and ACO methods, the determination of critical path using ACO-DAS model resulted in a design duration at 50 while that for CPM was as long as 78. The durations of architectural design activities have been significantly shortened by ACO-DAS. Even though the CPM approach is an effective planning tool for scheduling construction projects, it does not make use of opportunities for optimization during the design phase (Oloufa 2003). Many researchers have pointed out the limitations of CPM in design scheduling. Srour *et al.* (2013) stressed that currently there is no computerized tools to guide architects in making overlapping decisions. CPM is unable to schedule design overlapping especially in a fast-tracked project. Network analysis techniques and tools such as CPM could only represent sequential processes yet it is unable to handle a process which contains iterations so that it leads to the occurrence of unwanted omission of logic or information links between design activities. ACO-DAS has remedied those limitations in CPM and provided a more efficient computational algorithm comparing to CPM. The benefits of the developed ACO-DAS are simplified as a) it provides a formalized scheduling approach to guide the design mangers, architects, and project managers in making overlapping decisions in design works; b) the breaking down of every category of design activities provides a clear image of the flows of design phase; c) more careful attention is paid to the critical activities being determined; and d) it leads to more effective fast-tracking in construction.

Conclusion and recommendations

ACO algorithms have not been used by architects or other building designers world widely due to their unawareness of this kind of powerful tool in the overlapped architectural design activities. The workability of the developed ACO-DAS model was verified by a hypothetical run in the design work of fast-track construction and the comparative results with CPM demonstrated a significantly shorter design completion time thus it deemed more advanced than CPM in overlapping design activities. Future work can elaborate on the factors ensuring a successful fast-track strategy due to high demand of faster completion of designing work. Besides, the ACO-DAS has not been fun tune for Industrialized Building System (IBS). By taking into consideration that IBS is highly implemented in the construction sector, which is for the same purpose of time saving, a tailored ACO-DAS is highly recommended to be developed and tested for IBS design purposes.

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