

# A Case Study of Bee Algorithm for Ready Mixed Concrete Problem

W. Wongthatsanekorn, N. Matheekrieangkrai

**Abstract**—This research proposes Bee Algorithm (BA) to optimize Ready Mixed Concrete (RMC) truck scheduling problem from single batch plant to multiple construction sites. This problem is considered as an NP-hard constrained combinatorial optimization problem. This paper provides the details of the RMC dispatching process and its related constraints. BA was then developed to minimize total waiting time of RMC trucks while satisfying all constraints. The performance of BA is then evaluated on two benchmark problems (3 and 5 construction sites) according to previous researchers. The simulation results of BA are compared in term of efficiency and accuracy with Genetic Algorithm (GA) and all problems show that BA approach outperforms GA in term of efficiency and accuracy to obtain optimal solution. Hence, BA approach could be practically implemented to obtain the best schedule.

**Keywords**—Bee Colony Optimization, Ready Mixed Concrete Problem.

## I. INTRODUCTION

READY MIXED CONCRETE (RMC) is ready-to-use concrete that is produced in a batch plant according mixture recipe and then delivered to construction sites. Since RMC can solidify faster and has better quality than manual mixed concrete, its demand has been increasing over the years. To remain competitive, RMC suppliers need to improve their customer service level to meet customer requirement such as on-time delivery percentage without affecting the cost. One important aspect of RMC delivery is that RMC cannot be produced and stored as inventory at a batch plant because of its quick solidifying nature. Hence, RMC is delivered to the construction site within one to two hours after production. In the past, RMC problem has been solved and managed manually from the experience of the plant manager. This could make customer dissatisfied and increase delivery cost if the schedule is not efficiently planned. There are many researches study on RMC scheduling problem by using different techniques. Lu and Lam [1] optimized concrete delivery scheduling using simulation and genetic algorithm (GA) by mainly focusing on how to simultaneously optimize concrete delivery scheduling and resource provisions for RMC plants. Naso et al. [2] proposed a hybrid GA combined with

constructive heuristics for optimizing schedule for the just-in-time production and delivery RMC. Surico et al. [3] then proposed b-objective approach to solve the scheduling problem robustly. Graham [4] presented a neural network methodology to solve the problem. Yan and Lai [5], [6] developed a network flow model for an RMC carrier and employed a time-space network technique to formulate the production of RMC and the truck fleet flows in the dimensions of time and space. Schmid et al. [7], [8] used a hybrid solution approach by integrating an integer multi-commodity flow optimization component and a variable neighborhood search component. Feng et al [9]-[10] generated example problems and built a systematic model to solve RMC scheduling problem based on GA. The objective is to minimize the total waiting duration time of RMC trucks at construction sites and also develop a user-friendly computer program named RMC Dispatching Schedule Optimizer (RMC Diso) [11].

This research focuses on optimizing the schedule of RMC trucks with the same objective as Feng et al [10] by BA comparing to GA. Two benchmark problems with 3 and 5 construction sites are evaluated. BA is a typical meta-heuristic optimization approach which provides a search process based on intelligent behaviors of honey bees by Pham et al. [12], [13] in 2006. BA performs a kind of neighborhood search combined with random search which can efficiently explore and exploit information as mechanism itself. Therefore, BA can be used for both combinatorial and functional optimization. GA is a search approach based on natural selection and genetic recombination proposed by J. Holland [14] in 1975. The algorithm works by choosing solutions from the current population and then applying genetic operators such as mutation and crossover to improve random solution that can be changed to the worst solution or trapped in local loop. Hence, two case study problems would be solved by both BA and GA and the results are compared in term of quality solution, algorithm efficiency and accuracy.

## II. RMC DISPATCHING PROCESS

The RMC supply process consists of five sub processes as shown in Fig. 1. First process is a material preparation by mixing cement, aggregate and water loading and weighting material. Next process is quality inspection to ensure that RMC properties are qualified according to RMC specification before delivery to the construction sites. RMC Delivery process is for driver to deliver RMC to the construction site. RMC is then or poured at the construction site and the last process is for the driver to return the truck to the supplier site. These steps are repeated multiple times to fulfill customer's

Wuthichai Wongthatsanekorn is an associate professor, Industrial Engineering Department, Faculty of Engineering, Thammasat University, Rangsit campus, Klongluang, Pathum-thani, 12120, Thailand (e-mail: wuthichai@engr.tu.ac.th).

N.Matheekrieangkrai is a Ph.D. Student in Industrial Engineering Department, Faculty of Engineering, Thammasat University, Rangsit campus, Klongluang, Pathum-thani, 12120, Thailand.(corresponding author; e-mail:nunphysic@hotmail.com).

order quantity. In practice, RMC delivery and placement at multiple construction sites have limitation on the number of RMC trucks and the capacity of each RMC truck. Furthermore, RMC dispatching trucks need to be arranged continuously to avoid concrete setting problem. Hence, the traveling and casting time is limited as well.

If RMC truck delivery does not arrive on time, it could affect casting quality at construction site. This significantly affects to customer satisfaction. In addition, if RMC trucks are idle for a long period of time, this will lower RMC truck utilization and create discontinuity of RMC production flow at batch plant. The operation and delivery cost would not be optimized. Hence, truck delivery schedule is a vital process of the RMC business owner because improper RMC truck schedule would also affect the operating cost and quality.

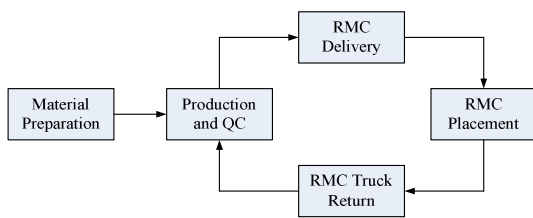


Fig. 1 RMC Dispatching Flow

Three assumptions for RMC truck scheduling problem are made in this study. First, the traveling time between the RMC batch plant and the construction sites is calculated based on the distance between two locations, speed of the RMC truck and traffic condition. In reality, the traveling time could be an average of the history data. Second, the time of casting RMC at the construction site depends on the types of the construction activities, which could affect the dispatching interval time between assigning RMC trucks to the same construction site. Third, the number of deliveries needed at a construction site depends on the quantity of RMC, loading capacity of the truck and the road bearing limit permitted by the regulation.

### III. SYSTEMATIC MODEL FOR RMC PROBLEM

Systematic model for RMC truck scheduling can be explained in four parts which are input parameters, decision variables, constraints and system output as shown in Fig. 2.

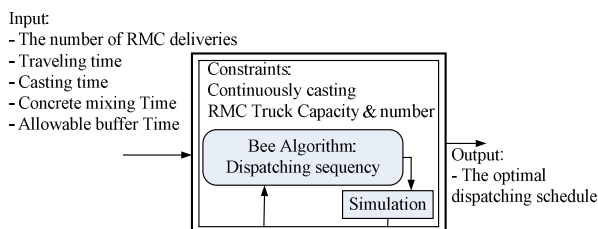


Fig. 2 Systematic Model of RMC Dispatching by BA

#### A. Input Parameters

The input parameters include the number of RMC deliveries, traveling time, casting time, mixing time, and

allowable buffer time. The allowable buffer time represents the maximum time that the construction site can wait for the arrival of RMC truck. The input varies depending on the construction type.

#### B. Decision Variables

The decision variables are the dispatching sequence of assigning each RMC truck to different construction sites. These will be used to determine the dispatching schedule in this model.

#### C. Constraints

The casting must be disrupted as little as possible. This requirement restricts the waiting time for the arrivals of the RMC truck at the construction sites. This time must be less than the allowable buffer time. This constraint helps eliminate any infeasible dispatching schedules. In addition, the RMC truck capacity and number of trucks are limited.

#### D. System Output

The objective of RMC truck scheduling problem is to minimize total waiting time of RMC trucks at construction sites without breaking off the casting concrete operation.

#### E. Total Solution Space

From the development of the RMC dispatching model above, it is clear that the performance of the RMC dispatching schedule depends on the dispatching sequence of the RMC trucks. The total possible dispatching sequence of the RMC trucks represents the permutation of all possible RMC delivery sequence required by different construction sites. Clearly, the solution space is exponentially large as the number of designated construction sites and the required RMC deliveries are increased. The total solution space of the dispatching schedules can be determined by (1). For example, if there are five construction sites and each site requires four deliveries, the total solution space of dispatching schedules is  $3.05 \times 10^{11}$   $((4+4+4+4+4)!/(4!4!4!4!4!))$ . The problem with this size cannot be efficiently solved by traditional optimization techniques. Therefore, BA is proposed to find the optimized RMC truck dispatching schedule because of its effectiveness in converging to the optimal or the sub-optimal solutions.

$$TS = \frac{\left( \sum_{j=1}^m k_j \right)!}{\prod_{j=1}^m (k_j!)} \quad (1)$$

where:

$TS$  = The total solution space

$k_j$  = The required number of RMC deliveries for construction site  $j$

$m$  = The number of construction sites that request RMC deliveries

## IV. BEE ALGORITHM FOR RMC PROBLEM

Bee algorithm was proposed by Pham et al. [12], [13] to optimize numerical problems. The procedure of BA for RMC truck scheduling problem is explained next.

## A. Procedures

BA is an optimization algorithm inspired by the natural foraging behavior of honey bees to find the optimal solution. Honey bees use several mechanisms like waggle dance to optimally locate food sources and to search new ones. This makes them a good candidate for developing new intelligent search algorithms. The colony of artificial bees contains two groups of bees, which are scout and employed bees. The scout bees have responsibility to find a new food source, while the task of employed bees is to determine a food source within the neighborhood of the food sources in their memory and share their information with other bees within the hive. The algorithm for BA can be described as follows:

$NC$  = Number of iteration.

$n_s$  = Number of scout bees which could be defined as initial feasible solution.

$m_B$  = Number of best selected sites out of  $n_s$  visited sites.

$e$  = Number of best sites out of  $m_B$  best selected sites.

$nep$  = Number of bees recruited for best  $e$  sites.

$nsp$  = Number of bees recruited for the other ( $m_B - e$ ) selected sites.

$ngh$  = Neighborhood search ratio which depends on neighborhood search space and decreases once search space is narrow down. It is computed as shown in (2). Since  $ngh$  is a swap time of solution, it is required to be integer. The "round" function in (2) converts real number to the nearest integer.

$$ngh = \text{round}\left(ngh_{\max} - \frac{ngh_{\max} - ngh_{\min}}{NC_{\max}} \times NC\right) \quad (2)$$

The solution representation for BA is RMC truck sequence and scheduling from single plant to different construction sites. The fitness function is obtained by interruption time and total waiting time. The procedure of BA as shown in Fig. 3 can be summarized as follows.

Step 1. Randomly generate initial populations of  $n$  scout bees.

These initial populations must be feasible so each solution must satisfy all constraints such as truck capacity of batch plant and continuity of casting at construction sites depending on the allowable buffer time. Then, set  $NC=0$

Step 2. Evaluate the fitness value of the initial populations which is defined by number of interruption and total waiting time based on (3) and (4). Number of interruption and waiting time for each RMC dispatch could be calculated per (5) – (16)

Step 3. Select  $m_B$  best solutions from step 2 for neighborhood search in the next step based on the visiting sites.

Step 4. Separated the  $m_B$  best solutions into two groups.

Group 1 has  $e$  best solutions and group 2 has  $m_B - e$  best solutions.

Step 5. Determine the scope of neighborhood search of each best solution ( $ngh$ ) as shown in (2) for group 1 and 2 of best solution.

Step 6. Generate new solutions randomly around  $m_B$  (group 1) and  $m_B - e$  best solution (group 2) within scope of neighborhood search per step 5.

Step 7. Evaluate the fitness value to get the total waiting time and interruption time of new solutions and select the fittest solution from each patch.

Step 8. Check the stopping condition. If satisfied, terminate the search, else  $NC = NC + 1$ .

Step 9. Assign the  $n - m_B$  population to generate new solutions. Go to step 2.

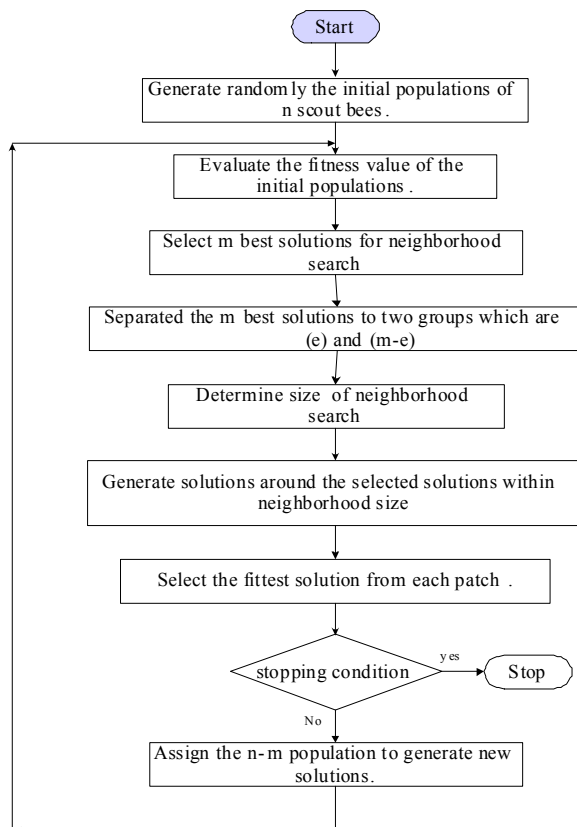


Fig. 3 BA process flow

In step 1 and 2, initial solutions or dispatching sequences (bees) are generated and they are checked for feasibility and computed for fitness value. In step 3 and 4, bees that have the highest fitness value are chosen as "selected bees" and the sites visited by them are chosen for neighborhood search. Then, in step 5 and 6, the searches are conducted in the neighborhood of the selected sites by assigning more bees to

search around the best  $e$  sites. The bees can be chosen directly according to the fitness values associated with the sites they are visiting. Alternatively, the fitness values are used to determine the probability of the bees being selected. Searching in the neighborhood of the best  $e$  sites for better solutions is performed by recruiting more bees to follow them rather than other selected bees. Together with scouting, this differential recruitment is a key operation of the BA. In step 7, only the bee with the highest fitness value will be selected to form next bee population. In nature, there is no such restriction. This restriction is introduced here to reduce the number of points to explore. In step 9, the remaining bees in the population are assigned randomly around the search space scouting for new potential solutions. These steps are repeated until a stopping criterion is met and the best schedule is obtained.

### B. Solution Structure

The solution structure used in this study is designed so that all permutations can be represented and evaluated. First, the length of the solution is defined as total number of RMC trucks that will be dispatched from RMC plant. For example, if there are three construction sites that require three, four and five RMC trucks in the same interval of time period, the length of the solution would be 12 or the summation of three, four and five. Secondly, an array of random number is used to avoid infeasible solutions generated within the evolution process. Fig. 4 shows the process of decoding a solution with random array. This solution represents the dispatching sequence involved with construction site number 1, 2 and 3, which requires three, four and five RMC trucks respectively. Here, "Site ID" denotes each bit, corresponding to each construction site. The dispatching sequence is then determined according to each bit's "Site ID" and its corresponding random number in ascending order. For example, the smallest random number of the bit is 0.03 and the corresponding "Site ID" is 2, which indicates the sequence starting with assigning the RMC truck to the construction site 2. Consequently, the dispatching sequence of the string is decoded to 2, 3, 2, 2, 1, 3, 3, 3, 1, 1, 2 and 3.

Site ID	1	1	1	2	2	2	2	3	3	3	3	3
Random values	0.67	0.75	0.39	0.17	0.03	0.26	0.82	0.95	0.44	0.58	0.11	0.50
Site ID	2	3	2	2	1	3	3	3	1	1	2	3
Decoded Sequence	0.03	0.11	0.17	0.26	0.39	0.44	0.50	0.58	0.67	0.75	0.82	0.95

Fig. 4 Example of the Solution Structure

### C. Fitness Value

The fitness value of a dispatching schedule is determined by summing the total waiting time ( $TWC$ ) that each truck must wait for placing concrete at the construction site. This could happen either when the previous RMC truck cannot finish the job before next truck arrives or when the next truck arrives later than it is supposed to.

The process of casting concrete at construction site could be

interrupted if the waiting time at the construction site for RMC truck to arrive is longer than the allowable buffer time. A penalty function,  $P$ , is used to represent the level of violation by assuming that one interruption can be converted as time in minutes of one day as defined in (3) and the interim fitness value,  $F$ , is a total waiting time at construction site (minute) including penalty of the interruption number.

$$P = (\text{the number of interruptions}) \times 60 \times 24 \quad (3)$$

The interim fitness value ( $F$ ) of a dispatched schedule is defined as shown in (4):

$$F = P + TWC \quad (4)$$

where  $TWC$  is the total time that RMC trucks wait for casting RMC at the construction sites.

## V. EXPERIMENTAL RESULTS

BA method has been applied to solve twelve RMC delivery problems from single batch plant to 3 and 5 construction sites in order to minimize the total waiting time of RMC trucks at construction site. The information for these two problems is described in Tables I and II. The results are compared with GA. All methods are performed with 30 trials, under the same evaluation function and individual definition, in order to compare the solution quality, convergence characteristic and computation efficiency. The feasible solution of each problem can be calculated according to (3). For 3-site and 5-site problem, the number of possible solutions is roughly  $18,918,900$  and  $2.09 \times 10^{16}$ . The software was implemented using MatLab® languages on Intel® Core2 Duo 1.66 GHz Laptop with 2 GB RAM under Windows XP.

TABLE I  
INFORMATION OF THE DISPATCHING OPERATION FOR 3-SITE PROBLEM

Site	SCT <sub>j</sub>	CD <sub>j</sub>	TDG <sub>j</sub>	TDB	ABD <sub>j</sub>	k <sub>j</sub>
1	08:00	20	30	25	30	3
2	08:00	30	25	20	20	4
3	08:30	25	40	30	15	5

Capacity of the batch plant: 5 trucks, Max load of trucks: 6 m<sup>3</sup>, Mixing Time: 3 minutes

TABLE II  
INFORMATION OF THE DISPATCHING OPERATION FOR 5-SITE PROBLEM

Site	SCT <sub>j</sub>	CD <sub>j</sub>	TDG <sub>j</sub>	TDB	ABD <sub>j</sub>	k <sub>j</sub>
1	08:00	20	30	25	5	2
2	08:00	30	25	20	15	4
3	08:30	25	40	30	15	4
4	08:00	10	15	15	5	4
5	08:00	35	35	30	5	2

Capacity of the batch plant: 5 trucks, Max load of trucks: 6 m<sup>3</sup>, Mixing Time: 3 minutes

$SCT_j$ : Started casting time of the construction site  $j$

$CD_j$ : Casting duration of the construction site  $j$

$ABD_j$ : Allowable buffer duration of construction site  $j$

$TDG_j$ : Traveling time from plant to construction site  $j$

$TBG_j$ : Traveling time from construction site  $j$  back to plant

$k_j$ : Required RMC truck deliveries for the construction site  $j$

The best parameter setting for BA using trial and error methods are performed for each problem and GA method has been implemented according to Feng et al. [10] by using the same crossover and mutation method. The selection is based on Roulette wheel selection methods. Crossover method is two points crossover and mutation method is self-mutation technique. The BA and GA parameter setting for each problem size is shown in Table III.

TABLE III  
BA AND GA PARAMETER SETTING

#Site	$n_s$	BA				Pop Size	GA		
		$m_B$	$e$	$nep$	$nsp$		Generation	Crossover rate	Mutation rate
2	20	5	3	10	5	200	100	0.3	0.1
4	250	120	20	50	20	200	100	0.3	0.1

TABLE IV  
OPTIMAL SOLUTION BY GA AND BA

# Site	Site ID (Dispatching Sequence) by BA and GA	Best Total Waiting Time (min)	Best Interruption Time (min)
3	[2, 3, 1, 2, 3, 1, 2, 3, 1, 2, 3, 3]	95	0
5	[4, 3, 4, 4, 4, 3, 2, 3, 2, 3, 5, 1, 1, 5]	150	0

For 3-site problem, the best solution is [2, 3, 1, 2, 3, 1, 2, 3, 1, 2, 3, 3] after 30 trials. The minimum total waiting time of the dispatching schedule that does not interrupt casting operation is 95 minutes as shown in Table IV. The details of RMC truck scheduling is shown in Figs. 5 and 6 shows GA and BA convergence curve of searching which converges to the optimal solution in 6.8 iterations. GA approach yielded the optimal solution within 31.41 iterations.

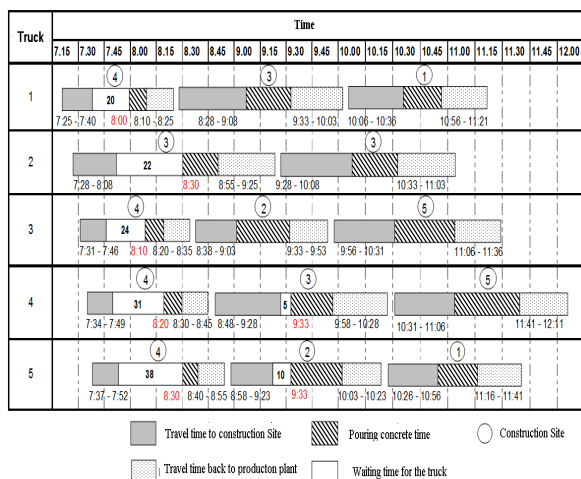


Fig. 5 Optimal schedule for 3-site problem

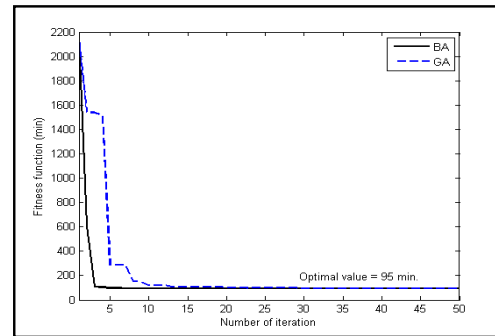


Fig. 6 Convergence of BA and GA for 3-site problem

For 5-site problem, the best solution is [4, 3, 4, 4, 4, 3, 2, 3, 2, 3, 5, 1, 1, 5] after 30 trials. The minimum total waiting time of the dispatching schedule that does not interrupt casting operation is 150 minutes as Table IV. RMC truck scheduling is shown in Fig. 7 and Fig. 8 shows GA and BA convergence curve of searching which BA converges to the optimal solution in 4.7 iterations. GA approach yield the optimal solution within 1163.07 iterations.

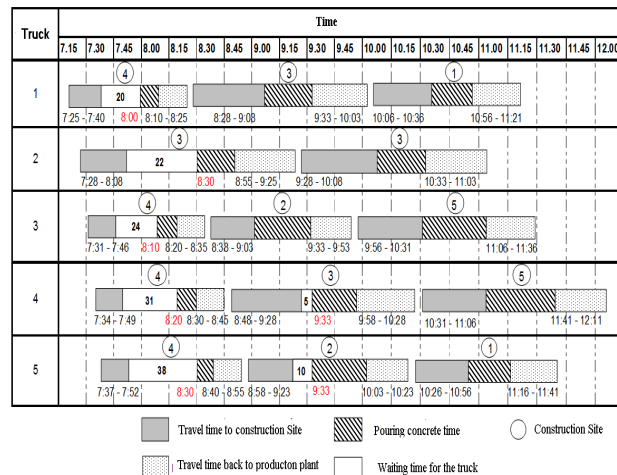


Fig. 7 Optimal schedule for 5-site problem

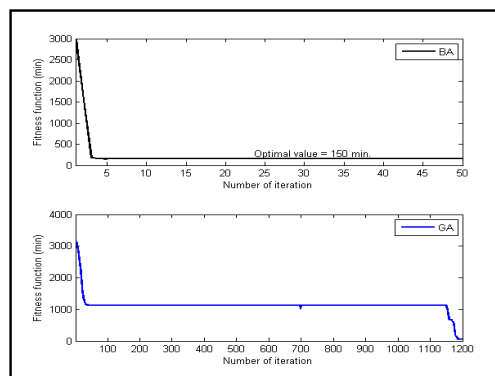
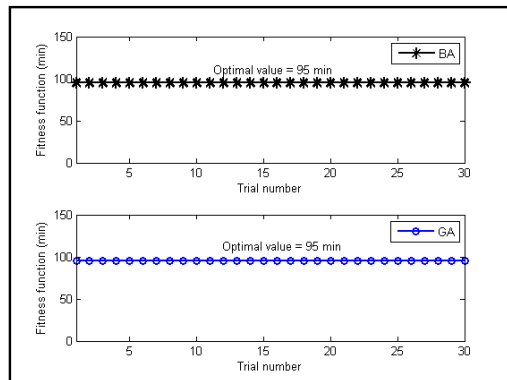


Fig. 8 Convergence of BA and GA for 5-site problem

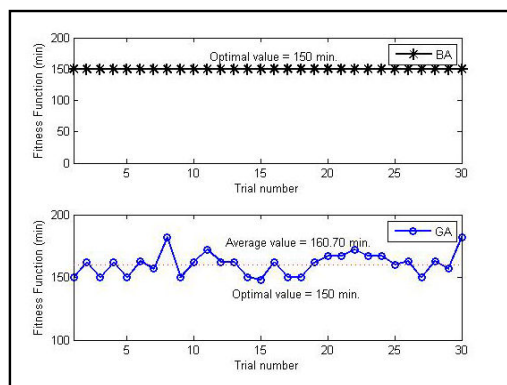
From Figs. 6 and 8, the results show the comparison of



convergence curve between BA and GA in 3-site and 5-site problems. BA converges to optimal solution quicker than GA. Next, the best solution of each trial are considered and plotted as shown in Fig. 9 in order to see the details of each run. Each dot represents the best solution of each trial run (1-30). For 3-site problem, both BA and GA can obtain the optimal solution in every trial run. However, for 5-site problem, only BA can find the best schedule in every trial run while GA can only obtain the best solution 8 out of 30 trial runs or 26.67%.



(a) 3-site problem



(b) 5-site problem

Fig. 9 Best Solution of each trial by GA and BA

## VI. CONCLUSION

This research develops BA for solving RMC truck dispatching problem which is an NP-hard problem. BA concept is to perform a neighborhood search combined with random search. This technique helps explore and exploit search space efficiently. The performance of BA is evaluated on two benchmark problems (3 and 5 construction sites). The simulation results show that BA approach can find the same optimal solution as GA with better efficiency. Hence, this research offers more efficient alternative to solve RMC scheduling problem for single batch plant to multiple construction sites.

For future research, some companies have more than one batch plant located in different areas to meet increasing customer demand and there are many factors to consider such

as fuel cost, type of concrete. Therefore, the next step is to construct RMC scheduling problem framework from multiple batch plants to multiple sites to minimize fuel cost and total waiting time of RMC truck by using heuristic. In addition, RMC strength type such as RMC for beam, column and floor could be varied to make the problem more realistic.

## ACKNOWLEDGMENT

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## REFERENCES

- [1] M. Lu, and H.C. Lam. 2005. "Optimized concrete delivery scheduling using combined simulation and genetic algorithms." Winter Simulation Conference: 2572-2580.
- [2] D. Naso, M. Surico, B. Turchiano, and U. Kaymak. 2007. "Genetic Algorithms for supply-chain scheduling, A case study in the distribution of ready-mixed concrete." European Journal of Operational Research, vol.177, no.3: 2069-2099.
- [3] M. Surico, U. Kaymak, D. Naso and R. Dekker. 2007. "A Bi-Objective Evolutionary Approach to Robust Scheduling." IEEE: 1-6.
- [4] D. L. Graham, D.R. Forbes and S.D. Smith. 2006. "Modeling the ready mixed concrete delivery system with neural networks." Automation in Construction 15: 656-663.
- [5] S. Yan, and W. Lai. 2006. "An optimal scheduling model for ready mixed concrete supply with overtime considerations." Automation in Construction 16: 734-744.
- [6] S. Yan, W. Lai, and M. Chen. 2008. "Production scheduling and truck dispatching of ready mixed concrete." Transportation Research Part E 44: 164-179.
- [7] V. Schmid, K.F. Doerner, R.F. Hartl, M.W.P. Savelsbergh, and W. Stoecher. 2009. "A hybrid solution approach for ready-mixed concrete delivery." Transportation Science 43 (1): 70-85.
- [8] V. Schmid, K.F. Doerner, R.F. Hartl, and J.J. Salazar-González. 2010. "Hybridization of very large neighborhood search for ready-mixed concrete delivery problems." Computers and Operations Research 37 (3): 559-574.
- [9] C.W. Feng, and H.T. Wu. 2000. "Using Genetic Algorithms to Optimize the dispatching Schedule of RMC Cars." Proceedings of the 17<sup>th</sup> International Symposium on Automation and Robotics in Construction, Taipei, Taiwan: 927-932.
- [10] C.W. Feng, T.M. Cheng, and H.T. Wu. 2004. "Optimizing the schedule of dispatching RMC trucks through Genetic Algorithms." Automation in Construction 13: 327-340.
- [11] C.W. Feng, and H.T. Wu. 2006. "Integrating fmGA and CYCLONE to optimize the schedule of dispatching RMC trucks." Automation in Construction 15: 186-199.
- [12] D.T. Pham, A. Ghanbarzadeh, E. Koç, S. Otri, S. Rahim S, and M. Zaidi. 2005. "The Bees Algorithm." Technical Note, Manufacturing Engineering Centre, Cardiff University, UK.
- [13] D.T. Pham, A. Ghanbarzadeh, E. Koç, S. Otri, S. Rahim S, and M. Zaidi. 2006. "The Bees Algorithm - A Novel Tool for Complex Optimisation Problems, Proceedings of IPROMSConference: 454-461.
- [14] Holland, John. 1975. "Adaptation in Natural and Artificial System." University of Michigan Press, Ann Arbor, Michigan.