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Optimized ready mixed concrete truck scheduling for uncertain factors using bee algorithm

Nuntana Mayteekrieangkrai and Wuthichai Wongthatsanekorn*

Department of Industrial Engineering, Faculty of Engineering, Thammasat University, Khlong Luang, Pathum Thani, 12120 Thailand.

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Abstract

This research proposes a systematic model by using bee algorithm to optimize ready mixed concrete truck scheduling problem from a single plant to multiple sized receivers in a large search space using uncertain factors of bee algorithm compared to genetic algorithm. The objective is to minimize the total waiting durations of RMC trucks. Four benchmark problems with 3, 5, 9 and 12 construction sites are evaluated. Furthermore, eight additional problems are created from the previous four problems by varying demands and traveling durations, in order to prove the algorithm accuracy and efficiency. Hence, a total of 12 problems would be solved using both BA and GA. The simulation results show that the BA approach can get lower total waiting durations and faster than GA for all problems. This research offers a more efficient alternative for solving RMC truck scheduling.

Keywords: bee algorithm, genetic algorithm, ready mixed concrete truck scheduling, a large search space, an uncertain factors

1. Introduction

In this study, the focus is on how to deliver Ready Mixed Concrete (RMC) to the customers' construction sites from the suppliers or the batch plants effectively. RMC is mixed according to customer's mixture recipe and it is ready to use once it is delivered at the construction site. Its usage has been expanding over the past several years because it is fast to solidify and its quality is better than manually mixed concrete. There are many RMC manufacturers in the market and the material cost is not much different. Therefore, each manufacturer competes with each other on the customer service satisfaction. Customers are looking for the vendor that can deliver RMC according to their requirements such as on-time delivery. One major constraint of RMC delivery problem is that RMC must be delivered to the construction site within certain time window after production. This is because RMC cannot be pre-manufactured and stored as an inventory at the plant due to its quick solidifying nature; RMC delivery problem is quite complex. Usually, the planner solves RMC delivery problem based on experience and this can cause dissatisfaction from the customer if the delivery is late. Since RMC delivery problem is quite complex, it draws interests from many researchers. For example, Feng *et al.* (2000) generated problems and built a systematic model to solve RMC scheduling problems using genetic algorithms (GA) to minimize the total wait duration of RMC trucks. They then developed the 'RMC Dispatching Schedule Optimizer' program (2004). Lu and Lam (2005) also proposed optimized concrete delivery scheduling using GA. Graham *et al.* (2006) presented a neural network to solve RMC problems. Naso *et al.* (2007) used a hybrid GA to optimize schedules for just-in-time production and delivery problem. Yan *et al.* (2008) presented a network flow model for an RMC carrier and employed a time-space network technique. They then developed a 'solution algorithm' to improve RMC system operating (Yan *et al.,* 2011; 2012). Srichandum and Rujira-yanyong (2010) developed Feng's research using bee colony

* Corresponding author.
Email address: wwuthich@engr.tu.ac.th

optimization compared to GA and tabu search focusing on single plant delivery to 3, 5 and 9 sites for three concrete types. Schmid *et al.* (2010) used a hybrid solution by integrating an integer multi-commodity flow optimization and a variable neighborhood search. Shi and Wang (2012) proposed a scheduling model for RMC dispatching using GA. Zhang and Zeng (2013) presented a formulation for RMC scheduling problems with dependent travel times using the local search algorithm. Su (2013) presented the fuzzy multi-objective linear program to analyze the cost-effectiveness of vehicles. Hanif and Holvoet (2014) solved dynamic scheduling of RMC delivery problems using delegate MAS that is a bio-inspired coordination machanism for optimization. Kinable *et al.* (2014) proposed a mixed integer programming and a constraint programming model to find efficient routes concerning concrete delivery problems.

Recently, modern heuristic optimization has been paid much attention by many researchers. Bee Algorithm (BA) is a typical meta-heuristic optimization which provides a search process based upon intelligent behaviors of honey bees (Pham *et al.*, 2005; 2006). It performs a type of neighborhood search combined with random searches which can efficiently explore and exploit information from the mechanism itself. This research proposes an effective optimization for solving RMC scheduling problems from a single plant to multiple sized receivers in a large search space with uncertain factors using BA compared to GA (Feng *et al.*, 2004). Matheekriang-krai and Wongthatsanekorn (2014) only attempted to solve the same problem for 3 and 5 construction sites by BA. The objective is to minimize the total waiting durations of RMC trucks. Four benchmark problems with 3, 5, 9 and 12 construction sites are evaluated. Furthermore, eight additional problems are created from the previous four problems by varying demands and traveling durations, in order to prove the algorithm accuracy and efficiency. Hence, a total of 12 problems have solved by BA and by GA and the results are compared in terms of quality solutions, algorithm efficiencies and accuracy.

2. RMC Truck Scheduling Problem Formulation

2.1 Systematic model

There are five sub-processes for RMC supply process which are material praparation, RMC mixing, quality inspection, delivery RMC and return to the batch plant. The same sub processes are iterated again for each RMC delivery to fulfill a customer's order.

There are four parts to the systematic model, which are input parameters, decision variables, constraints and system output.

Input parameters: These parameters are traveling time, casting time, mixing time, and allowable buffer time and required number of RMC deliveries.

Decision variables: These decisions are dispatching sequences of each RMC truck to different construction sites.

Constraints: The waiting time for the arrivals of the RMC truck at the construction sites must be less than the allowable buffer time. In addition, the RMC truck capacity and number of trucks are limited.

System output: The solutions are total waiting times of RMC trucks at construction sites and RMC trucks dispatching sequence.

2.2 Solution structure

The solution structure 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. 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 twelve. Second, an array of random numbers is used to avoid infeasible solutions generated within the evolution process. Figure 1 shows the process of decoding a solution with random array. This solution represents the dispatching sequence involved with construction site numbers 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.

The total solution space of the dispatching schedules can be determined by Eq. (1). For example, if there are five construction sites and each site requires four deliveries, the total solution space is 3.15×10^{11} or $(4+4+4+4+4)!/(4!4!4!4!4!)$.

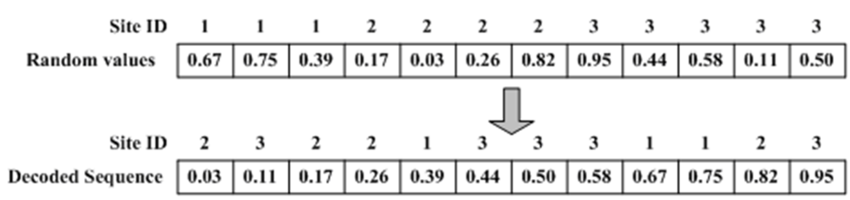


Figure 1. Example of the solution structure

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

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

2.3 Input information

RMC truck scheduling is evaluated for 3, 5, 9 and 12 sites in problem 1–4. In additional, we generate eight more problems by varying demand and travelling time of the original four problems in Table 1. In case A, we increase delivery round and in case B we adjust the travelling time between the plant and the construction site. Number of RMC truck and allowable buffer duration are also modified properly.

2.4 Fitness function

The fitness value of a dispatch schedule is determined by summing the total waiting times (TWC) that each truck must wait to place concrete at a construction site. In addition, the process of casting concrete at a construction site could be interrupted if an RMC truck is delayed longer than the allowable buffer time. A penalty function 'P' is used to aviod the interupted schedule by calculating one interruption as time in minutes of one day, as defined in Eq. (2). The fitness value 'F' is the total waiting time at a construction site (min) including a penalty for the interruption number, as defined in Eq. (3)

$$P = (\textit{the number of interruptions}) \times 60 \times 24 \tag{2}$$

The fitness value 'F' of a dispatched schedule is defined as Eq. (3):

$$F = P + TWC \tag{3}$$

Table 1. Information of 12 problems.

Problem	Site	SCT_j	CD_j	TDG_j	TDB_j	ABD_j	k_j	Trucks	Problem A		Problem B		Problem A & B		
									TDG_j	TDB_j	TDG_j	TDB_j	ABD_j	k_j	*Trucks*
	1	8:00	20	30	25	30	3		30	25	40	30	45	6	
1	2	8:00	30	25	20	20	4	5	25	20	50	40	45	6	7
	3	8:30	25	40	30	15	5		40	30	50	40	45	7	
	1	8:00	20	30	25	5	2		30	25	40	35	45	3	
	2	8:00	30	25	20	15	4		25	20	40	30	45	3	
2	3	8:30	25	40	30	15	4	5	40	30	35	25	45	4	7
	4	8:00	10	15	15	5	4		15	15	25	15	45	5	
	5	8:00	35	35	30	5	2		35	30	45	30	45	4	
	1	8:00	20	30	25	5	3		30	25	45	35	45	5	
	2	8:00	30	25	20	5	4		25	20	40	30	45	4	
	3	8:30	25	40	30	15	4		40	30	40	30	45	4	
	4	8:00	10	15	15	5	5		15	15	40	30	45	3	
3	5	8:00	35	35	30	5	2	20	35	30	45	35	45	4	20
	6	8:30	15	45	35	10	2		45	35	45	35	45	5	
	7	8:00	20	20	20	10	5		20	20	35	25	45	4	
	8	8:00	15	20	15	5	5		20	15	40	30	45	4	
	9	8:00	10	20	15	5	3		20	15	35	25	45	5	
	1	8:00	20	30	25	45	3		30	25	40	30	45	5	
	2	8:00	30	25	20	45	4		25	20	35	25	45	4	
	3	8:30	25	40	30	45	4		40	30	45	35	45	6	
	4	8:00	10	15	15	45	3		15	15	35	25	45	5	
	5	8:00	35	35	30	45	2		35	30	45	40	45	4	
4	6	8:30	15	45	35	45	2	20	45	35	39	35	45	5	20&25
	7	8:00	20	20	20	45	3		20	20	40	25	45	4	
	8	8:00	15	20	15	45	4		20	15	45	30	45	5	
	9	8:00	10	20	15	45	3		20	15	35	35	45	6	
	10	8:30	20	25	20	45	2		25	20	30	30	45	4	
	11	8:00	25	15	15	45	3		15	15	25	25	45	3	
	12	8:00	15	35	30	45	4		35	30	30	30	45	3	

where, *TWC* is the total time that RMC trucks wait to cast RMC at the construction site. A simple example to determine the fitness value of a dispatch schedule is described in problem 1, as follows;

Description of problem 1

It is assumed that the plant owns five RMC trucks, the concrete mixing time (*MD*) is 3 min per cubic meter, and the maximum load a RMC truck can bear is 6 m^3. Information concerning dispatch operations is listed in Table 1. The RMC truck should arrive at construction site '*j*' within an allowable buffer duration (ABD_j), and the next truck must arrive at the construction site on time. At the plant, RMC needs some additional time for mixing and loading the RMC. Then, there is travelling time to the construction site and a RMC truck may incur waiting or interruption times. Finally, there is travelling time back to the batch plant, and so RMC truck scheduling is associated with the departure time from the plant(*IDT*), the arrival time at the construction site (*TAC*), the leaving time from the construction site (*LT*), and finally the arrival time of the RMC truck upon its return (*TBB*), which are later described in Eqs. (8) - (15).

In practice, the distance (*km*) from the plant to the construction site can be found by using a Global Positioning System (GPS). In this study, the average speeds of RMC trucks traveling to the construction site and returning to the plant are assumed to be 20 $km\ hr^{-1}$ and 30 $km\ hr^{-1}$, respectively. Therefore, the traveling time from the plant to the construction site *j* (TDG_j) can be calculated using Eq. (4), and the return time from the construction site *j* to the plant (TDB_j) can be calculated using Eqs. (5):

$$TDG_j = D_j \times 3 \tag{4}$$

$$TDB_j = D_j \times 2 \tag{5}$$

where, D_j = The distance from the plant to the construction site (*km*).

Step 1: Determine the best departure time of each truck from the batch plant. This should occur when the RMC truck leaves the plant as soon as the concrete is loaded. Therefore, the departure time of each truck is determined by Eq. (6), and this involves the departure time of the first dispatched RMC truck from the plant to each construction site by selecting the truck with the minimum leaving time from the plant. For the first delivery, each truck is needed to arrive at the construction site at start casting time of the construction site j (SCT_j). Eq. (7) identifies the ideal departure time of i^{th} dispatched RMC truck. The plant in problem 1 is assumed to have five RMC trucks, so IDT_i for earliest delivery are determined only for i = 1 to 5 and the rest will be based upon the departure times of returned trucks in step 2:

$$FDT = \min_{j=1}^{m}\left[SCT_j - TDG_j\right] \tag{6}$$

$$IDT_i = \begin{cases} FDT + MD_i, & i = 1 \\ IDT_{i-1} + MD_i, & i = 2 \sim N \end{cases} \tag{7}$$

Where,

i	=	Dispatched order of an RMC truck.
m	=	Number of construction sites that request RMC deliveries.
k_j	=	Required RMC deliveries to construction site j
i^{th}	=	Dispatch sequence of RMC trucks to each construction site.
$N = \sum_{j=1}^{m} k_j$	=	The total number of RMC deliveries to all construction sites.
FDT	=	Departure time of the first dispatched RMC truck.
SCT_j	=	The start casting time of the construction site j
IDT_i	=	Ideal departure time of i^{th} dispatched RMC truck.
MD_i	=	Concrete mixing time for the i^{th} dispatched RMC truck.

Step 2: Calculate the departure times for the remainder of deliveries for the returned RMC trucks. This is computed based upon departure times from the batch plant, arrival times at the construction site, leaving times from the construction site, waiting times for each delivery and the returning times to the batch plant, according to Eqs. (8)-(15).

The first departure time of each RMC truck can be determined using step 1. However, the number of trucks is limited. It is possible that the delivery schedule is unfeasible. Therefore, only the departure time of the first five dispatched RMC trucks can be determined by Eqs. (6) and (7). The rest of the delivery times can be computed when all trucks have returned from the construction site by Eqs. (8)-(15). Samples of RMC dispatch sequences are generated randomly as explained in a solution structure which is illustrated as: [2, 3, 2, 1, 3, 1, 3, 3, 1, 2, 3, 2]. This represents a feasible solution to a dispatch sequence of RMC trucks for 12 delivery times to construction sites, as displayed in the simulated results of dispatch sequencing based upon the results in Table 2:

$$SDT_i = IDT_i,\ if\ i \le c \tag{8}$$

$$SDT_i = \min_l [\,TBB_l + MD\,],\ if\ c < i \le N \tag{9}$$

$$TAC_{ji} = SDT_i + TDG_j \tag{10}$$

$$PTF_{ji} = SCT_j\ \ or\ \ LT_{j(k-1)} \tag{11}$$

$$WC_{ji} = PTF_{ji} - TAC_{ji} \tag{12}$$

$$LT_{ji} = TAC_{ji} + WC_{ji} + CD_j,\quad if\ \ WC_{ji} \ge 0 \tag{13}$$

$$LT_{ji} = TAC_{ji} + CD_j,\ \ if\ \ WC_{ji} < 0 \tag{14}$$

$$TBB_i = LT_{ji} + TDB_j \tag{15}$$

Where,

SDT_i = Simulated departure time of the i^{th} dispatched truck.
TAC_{ji} = Arrival time of the i^{th} dispatched truck at construction site *j*.
j = Index of the designated construction site, where $j = 1 - m$.
k = Order of the RMC trucks that arrive at the respective construction site, wherein $k = 1 - k_j$ for each construction site *j*.
l = The order of the trucks returning to the batch plant.
c = The number of RMC trucks still at the batch plant.
PTF_{ji} = The starting time of casting at construction site *j*.
$WC_{ji} > 0$ = Waiting time of the i^{th} dispatched truck at construction site *j*.
$WC_{ji} < 0$ = Waiting time for arrival of the i^{th} dispatched truck at construction site *j*.
LT_{ji} = Leaving time of i^{th} RMC truck at construction site *j*.
TBB_i = Returning time of i^{th} dispatched RMC truck back to the batch plant.

Step 3: Determine the fitness value *TWC* from WC_{ji} in Table 2, wherein the total waiting times of RMC trucks wait for casting at construction site, summing the positive integers of WC_{ji}, is 84 min and the total waiting time of the construction site wait for truck arrivals, summing the negative integers of WC_{ji}, is 209 min. The interruption of casting concrete is 4 times (marked as *), which occurs when the waiting time for the arrival of a RMC truck is longer than the allowable buffer time. Since the interruption of casting concrete should be avoided, a penalty function is applied according to Eq. (2). The interim fitness value '*F*' of a dispatched schedule as defined in Eq. (3) is equal to $(= 4 \times 60 \times 24 + 84)$ min. As a result, the algorithm re-generates a new feasible solution and repeats the above steps until it arrives at the optimal solution. The trucks in problem 1 can be scheduled as shown in Figure 2.

In the mean time, other problems are approached by using the same process. The simulation results will be described in the next section.

3. BA for RMC Truck Scheduling

Pham *et al.* (2005; 2006) first introduced BA to solve optimization problem. BA is one of the optimization algorithms based on the behavior of honey bees. They use waggle dance to best locate food sources and locate new ones. In a colony of artificial bees, bees are dividing into two groups. They are scout bees and employed bees. Scout bees are responsible for finding new food sources and they move randomly around the hive. Once they return, those bees that found good food source go to the dance floor and perform the waggle dance. During the dance, they share the information and communicate with the employed bees which join in the exploitation of the food source.

The algorithm for BA can be described as follows:
NC = Number of iterations.
n_s = Number of scout bees which could be defined as initial feasible solutions.
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 to find best '*e*' sites.
nsp = Number of bees recruited for the other (m_B-e) selected sites.
ngh = Neighborhood search ratios, which is the swap time of solutions, it is required to be an integer. The 'rounded' function in Eq. (16) thus converts into a real number to the nearest integer:

$$ngh = round(ngh_{max} - \frac{ngh_{max} - ngh_{min}}{NC_{max}} \times NC) \quad (16)$$

This solution represents RMC truck scheduling from a single plant to different construction sites. The fitness function is obtained by interruption times and total waiting times. The procedure of BA, as shown in Figure 3, can be summarized as follows:

Table 2. Results of RMC parameter in problem 1.

FDT = Min [08:00-00:30, 08:00-00:25, 08:30-00:40] = 07:30												
i	1	2	3	4	5	6	7	8	9	10	11	12
IDT	7:30	07:33	07:36	7:39	7:42	7:45	07:48	7:51	7:54	7:57	8:00	8:03
j	2	3	2	1	3	1	3	3	1	2	3	2
k	1	1	2	1	2	2	3	4	3	3	5	4
SDT_i	7:30	7:33	7:36	7:39	7:42	8:53	8:57	9:23	9:28	9:53	10:11	10:35
TAC_{ji}	7:55	8:13	8:01	8:09	8:22	9:23	9:37	10:03	9:58	10:18	10:51	11:00
PTF_{ji}	8:00	8:30	8:30	8:00	8:55	8:20	9:20	10:02	9:43	9:00	10:28	10:48
WC_{ji}	5	17	29	-9	-33	-54*	-17*	-1	-15	-78*	-23*	-12
LT_{ji}	8:30	8:55	9:00	8:29	9:20	9:43	10:02	10:28	10:18	10:48	11:16	11:30
TBB_i	8:50	9:25	9:20	8:54	9:50	10:08	10:32	10:58	10:43	11:08	11:46	11:50

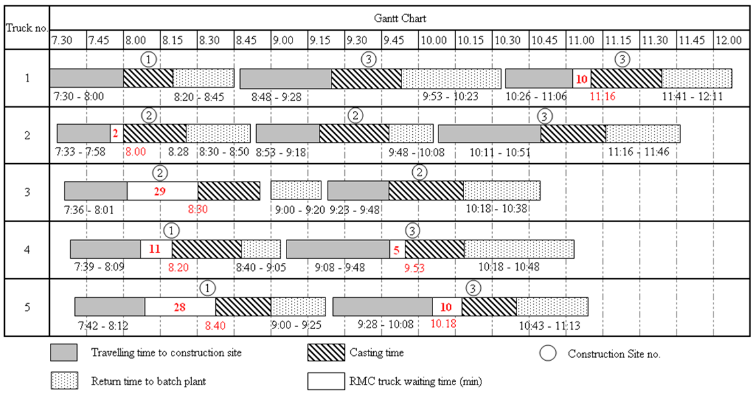


Figure 2. The Gantt chart of RMC truck schedules concerning problem 1.

Step 1: Randomly generate initial populations of n scout bees. Then, set $NC = 0$

Step 2: Evaluate the fitness value of the initial populations, which is defined by the number of interruptions and total waiting times based upon Eqs. (2) and (3). RMC truck schedule could be calculated as per Eqs. (4) - (15).

Step 3: Select m_B best solutions from step 2 for neighborhood searches in the next step based upon visiting sites.

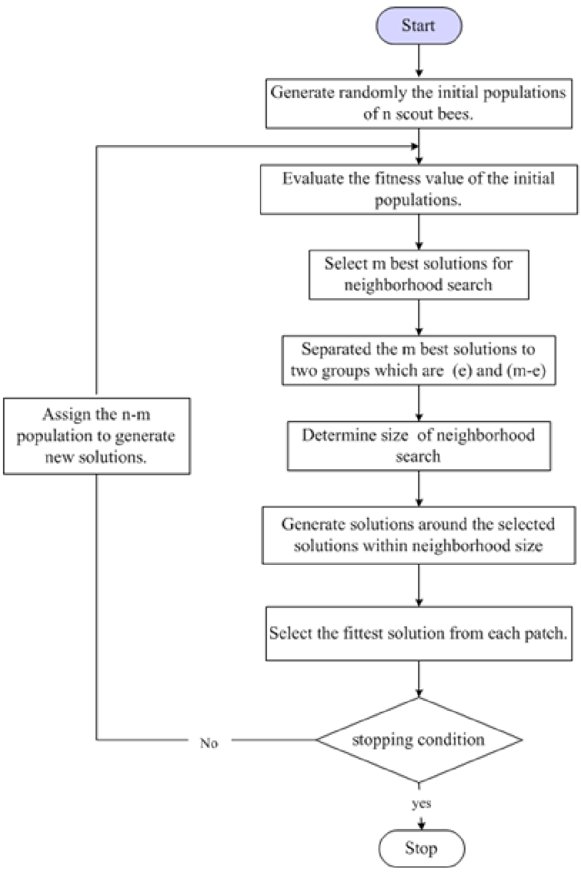


Figure 3. BA process flow (Matheekriangkrai and Wongthatsanekorn, 2014)

Step 4: Separate the m_B best solutions into two groups, whereby: Group 1 has e best solutions, and group 2 has m_B-e best solutions.

Step 5: Determine the scope of neighborhood searches for each best solution (ngh) as shown in Eq.2 for both groups 1 and 2 best solutions.

Step 6: Generate new solutions randomly around m_B (group 1) and m_B-e best solution (group 2) within the scope of the neighborhood searches, as per step 5.

Step 7: Evaluate the fitness value of new solutions and thus select the most appropriate solution for each patch.

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

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

4. Simulation Results

The BA method has been applied to solve RMC truck scheduling having twelve problems. The results were compared against GA, and all methods were performed with 30 trials for each problem. The feasible solution to each problem could be calculated as per Eq. (1), and the total solutions spaces in problems 1, 2, 3 and 4 are 27720, 18,918,900, 2.09×10^{16} and 6.6688×10^{32}, respectively. The software was implemented using MatLab® languages on an Intel® Core2 Duo 1.66 GHz Laptop with 2 GB RAM under Windows XP. The BA parameter setting using trial and error methods was performed for each problem as shown in Table 3. The GA method was implemented using the same selection, crossover and mutation methods as Feng *et al.* (2004). The selection is based on Roulette wheel selection methods, the crossover is two points crossover, and the mutation uses the self-mutation technique. The best solutions to the 12 problems after 30 trials are shown in Table 4.

Further analyse of an effectiveness of BA is all shown in Table 5. Obviously, both methods can find optimum solutions with high probabilities, however the percentage of achieving the optimum for BA is higher than for GA. Hence, the standard deviation of the solution for GA is higher than for BA. In terms of average CPU time, BA runs faster in all problem sizes except for the largest problems. BA could also take more time to exploit some problems, such as 4, 4A and 4B. Hence, it can be concluded that the BA approach outperforms GA in terms of efficiency and accuracy, in this research.

In Figure 4, GA and BA converge to optimal solutions in approximately 7 and 30 iterations of problem 1; 5 and 987 iterations of problem 2; 100 and 1400 iterations of problem 3, and 12 and 213 of problem 4, respectively. The results indicate that BA can converge to optimum solutions faster than GA can in all 4 problems. Surprisingly, problem 3 requires a higer number of iterations than problem 4 to reach the optimal solutions for both GA and BA even though problem 4 has more sites to deliver. According to Karaboga and Akay (2009), BA produces new solutions by taking the difference of randomly determined parts of the parent and choosing a solution randomly from the population while GA produces new solutions based on the current population using crossover and mutation operators. Another aspect is about keeping the best solution in every iteration. For BA, the best solution could be replaced with new random solution found by a scout bee while the best solution is always retained in the population. These differences explain why BA could speed up the convergence search for local optimum faster than GA.

Next, the best solution of each trial were considered and plotted, as shown in Figure 5. Each dot represents the best solution of each trial run for problems 1, 2, 3 and 4, respectively. All fitness values could be obtained using BA with different optimal percentages dependent upon problem constraints, such as: available RMC trucks, allowable buffer time, travelling distance and RMC orders from the customer:

Table 3. BA and GA parameter setting.

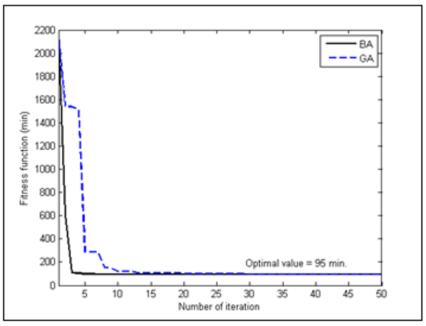
Problem	BA					GA			
	n_s	m_B	e	*nep*	*nsp*	*Popolation size*	*Generation*	*Crossover*	*Mutation*
$1, 1A, 1B$	20	5	3	10	5	200	100	0.3	0.1
$2, 2A, 2B$	250	120	20	50	20	200	100	0.3	0.1
$3, 3A, 3B$	20	10	1	5	2	300	100	0.3	0.1
$4, 4A, 4B$	40	18	1	20	2	300	100	0.3	0.1

Table 4. Optimal solutions of 12 problems.

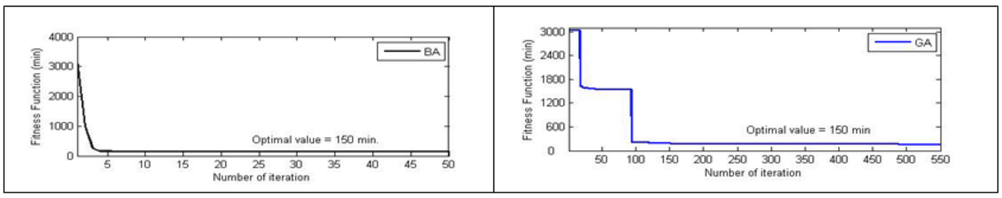
Problem	Site ID (Dispatching Sequence)	Total waiting time (min)	Interuption time (min)
1	[1, 2, 2, 1, 1, 3, 2, 3, 2, 3, 3, 3]	95	0
1A	[2, 2, 1, 1, 3, 3, 2, 3, 1, 2, 1, 3, 2, 3, 1, 2, 3, 1, 3]	99	0
1B	[2, 1, 1, 1, 1, 2, 3, 1, 3, 2, 2, 3, 1, 3, 3, 2, 3, 2, 3]	93	0
2	[4, 3, 4, 4, 4, 3, 2, 3, 2, 3, 5, 1, 1, 5]	150	0
2A	[5, 1, 5, 2, 1, 4, 4, 2, 1, 4, 3, 2, 5, 3, 4, 5, 3, 4, 3]	62	0
2B	[5, 1, 2, 4, 2, 4, 1, 1, 4, 5, 2, 3, 5, 4, 3, 3, 4, 5, 3]	59	0
3	[7, 1, 5, 2, 8, 9, 6, 3, 9, 1, 8, 9, 6, 7, 2, 5, 8, 1, 3, 7, 8, 4, 2, 4, 8, 3, 7, 4, 4, 2, 7, 3, 4]	36	0
3A	[5, 1, 9, 2, 7, 8, 4, 6, 3, 9, 1, 8, 5, 7, 2, 6, 9, 3, 1, 8, 6, 4, 7, 1, 6, 3, 9, 2, 5, 8, 7, 3, 1, 4, 9, 2, 6, 5]	18	0
3B	[5, 1, 4, 8, 2, 9, 7, 4, 1,9, 6, 4, 5, 3, 2, 1,6, 8, 9, 7, 6, 3, 5, 9, 8, 6, 1, 2, 3, 7, 9, 1, 6, 5, 8, 3, 7, 2]	0	0
4	[5, 12, 1, 2, 7, 8, 9, 4, 6, 12, 11, 3, 4, 5, 2, 7, 1, 4, 8, 6, 3, 9, 12, 10, 8, 2, 11, 1, 3, 7, 12, 8, 9, 10, 11, 2, 3].	4	0
4A	[5, 12, 1, 2, 8, 7, 9, 4, 11, 3, 9, 4, 12, 7, 8, 10, 1, 9, 3, 4, 7, 5, 4, 11, 12, 8, 1, 9, 10, 6, 2, 3, 4, 7, 9, 5, 2, 3, 6, 8, 11, 10, 1, 6, 8, 3, 5, 6, 1, 8, 10, 2, 3, 6]	4	0
4B	[9, 5, 12, 1, 11, 4, 7, 12, 9, 8, 3, 2, 9, 6, 7, 10, 12, 9, 1, 4, 5, 11, 8, 3, 6, 10, 7, 3, 9, 4, 2, 6, 1, 8, 3, 11, 5, 10, 2, 7, 4, 9, 3, 6, 1, 10, 8, 2, 4, 1, 8, 6, 5, 3]	0	0

Table 5. Summary results of 12 problems.

Problem	Algorithm	Max (min)	Avg (min)	Min (min)	S.D.	Avg CPU time	%Optimum
1	*BA*	95.00	95.00	95.00	0.00	1.41	100.00
	GA	95.00	95.00	95.00	0.00	6.68	100.00
1A	*BA*	104.00	99.17	99.00	0.91	19.68	96.67
	GA	107.00	100.43	99.00	2.87	214.50	76.67
1B	*BA*	99.00	93.27	93.00	1.14	26.20	93.33
	GA	117.00	95.47	93.00	5.44	226.85	70.00
2	*BA*	150.00	150.00	150.00	0.00	134.24	100.00
	GA	182.00	160.70	150.00	9.20	264.64	26.67
2A	*BA*	67.00	62.33	62.00	1.27	242.07	93.33
	GA	97.00	78.40	62.00	12.63	410.68	23.33
2B	*BA*	95.00	63.10	59.00	10.09	242.69	83.33
	GA	102.00	83.17	59.00	15.99	412.38	26.67
3	*BA*	59.00	37.90	36.00	15.40	148.12	86.67
	GA	156.00	73.97	36.00	35.69	245.03	30.00
3A	*BA*	18.00	18.00	18.00	0.00	73.57	100.00
	GA	170.00	105.07	18.00	47.64	433.58	16.67
3B	*BA*	2.00	0.27	0.00	0.58	413.82	80.00
	GA	4.00	1.23	0.00	1.25	417.68	26.67
4	*BA*	4.00	4.00	4.00	0.00	113.81	100.00
	GA	4.00	4.00	4.00	0.00	96.61	100.00
4A	*BA*	6.00	4.17	4.00	0.46	247.49	86.67
	GA	6.00	4.27	4.00	0.58	230.09	80.00
4B	*BA*	3.00	0.30	0.00	0.75	253.15	83.33
	GA	3.00	0.30	0.00	0.75	303.25	83.33

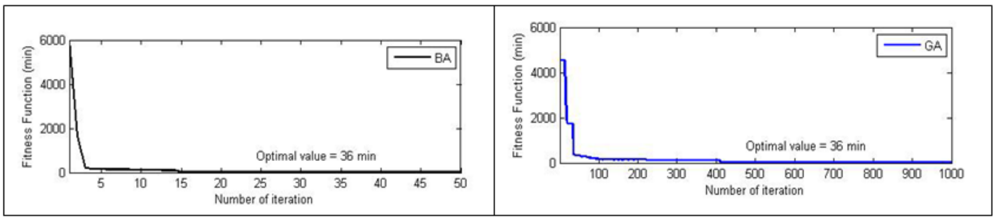


a. Problem 1

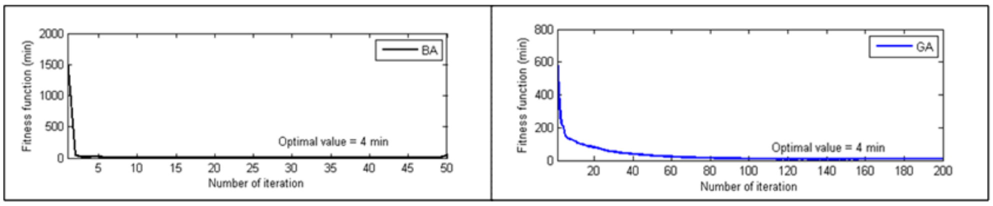


b. Problem 2

Figure 4. A comparison of BA and GA convergence curves (Matheekriangkrai and Wongthatsanekorn, 2014 for a. and b.)

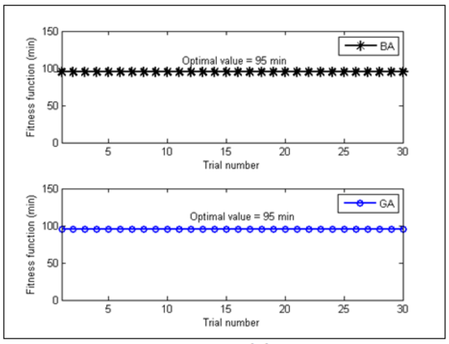


c. Problem 3

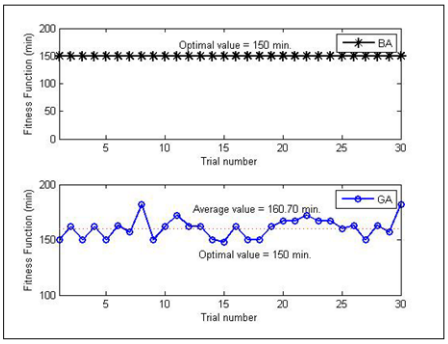


d. Problem 4

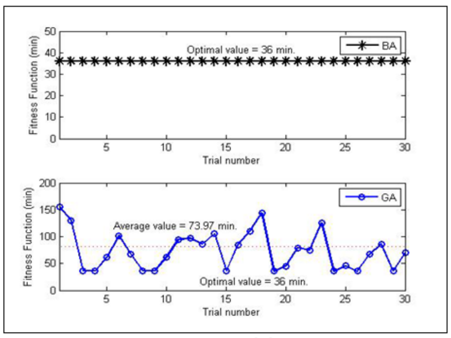
Figure 4. Continued



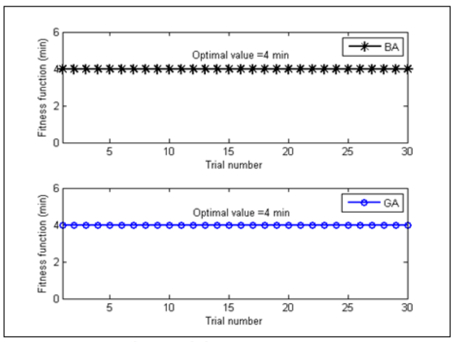
a. Problem 1



b. Problem 2



c. Problem 3



d. Problem 4

Figure 5. Best Solution of each trial by GA and BA (Matheekriangkrai and Wongthatsanekorn, 2014 for a. and b.)

5. Conclusions and Future Works

This research proposes BA for solving RMC truck scheduling problems for a large search space and uncertain factors which are an NP-hard problem. The BA concept is to perform a neighborhood search combined with random searches. This technique helps to explore and exploit search spaces and achieves optimal efficiency. In addition, GA is a search approach based upon natural selection and genetic recombination. The algorithm works by choosing solutions from the current population and then applying genetic operators such as mutations and crossovers to improve random solutions that can be changed to the worst solutions or trapped in local loops. The performance of BA was evaluated using four benchmark and eight additional problems. The results show that the BA approach can find the optimal solution better than GA in terms of efficiency and accuracy for all 12 problems. Hence, this research offers a more efficient alternative for solving RMC truck schedule.

For future research, some companies have more than one plant located in different areas in order to meet increasing customer demand, and there are many factors to consider such as fuel costs and types of concrete. Therefore, the next step is to construct a RMC scheduling problem framework from multiple plants to multiple sites in order to minimize fuel costs and total waiting times of RMC trucks by using heuristics. In addition, RMC strength types, such as RMC for beams, columns and floors, could be varied to make the problem more realistic.

Acknowledgements

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