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Hybrid ant systems for the dynamic facility layout problem

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Abstract

Today's consumer market demands that manufacturers must be competitive. This requires the efficient operation of manufacturing plants and their ability to quickly respond to changes in product mix and demand. In addition, studies show that material-handling cost make up between 20 and 50 percent of the total operating cost. Therefore, this paper considers the problem of arranging and rearranging, when there are changes in product mix and demand, manufacturing facilities such that the sum of material handling and rearrangement costs is minimized. This problem is called the dynamic facility layout problem (DFLP). In this paper, hybrid ant systems (HASs) are developed to solve the DFLP. To test the performance of the meta-heuristics, two data sets taken from the literature are used in the analysis. The results show that the HASs are efficient techniques for solving the DFLP. More importantly, HASs found new best solutions for more than one-half of all the test problems.

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1. Introduction

The facility layout problem is the arrangement of departments within a facility with respect to some objective. Since studies show that material-handling cost makes up between 20 and 50 percent of the total operating cost and between 15 and 70 percent of the total cost of manufacturing a product (Tompkins et al. [1, p. 138]), the most common objective considered is the minimization of material-handling cost. Material-handling costs are determined based on the amounts of materials that flow between the departments and the distances between the locations of the departments. When the flow of materials

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between the departments is fixed during the planning horizon, this problem is known as the static (single period) facility layout problem (SFLP), which can be formulated as a quadratic assignment problem (QAP). For a review of the SFLP literature, see Meller and Gau [2]. When the flow of materials between departments changes during the planning horizon, this problem is known as the dynamic (multiple-period) facility layout problem (DFLP). Some of the factors associated with changes in the flow between departments are as follows and were taken from Shore and Tompkins [3].

- Changes in the design of an existing product;
- the addition or deletion of a product;
- replacement of existing production equipment;
- shorter product life cycles and
- changes in the production quantities and associated production schedule.

For the DFLP, it is assumed that the flow data for each period remains constant throughout the period. Therefore, the layout for each period in the planning horizon can be obtained by solving the SFLP for each period using the QAP formulation. If π_t is used to represent the layout for each time period t ($t = 1, 2, \dots, T$) with N departments, then one solution representation is $\pi_t = (\pi_{1t}, \pi_{2t}, \dots, \pi_{Nt})$, where π_{it} represents the department assigned to location i ($i = 1, 2, \dots, N$) at time period t . Hence, a solution representation for the DFLP is

$$\pi = \{\pi_1, \pi_2, \dots, \pi_T\} = \{(\pi_{11}, \pi_{21}, \dots, \pi_{N1}), (\pi_{12}, \pi_{22}, \dots, \pi_{N2}), \dots, (\pi_{1T}, \pi_{2T}, \dots, \pi_{NT})\}.$$

The material-handling cost for each layout π_t in each time period t can be obtained by calculating

$$\sum_{i=1}^N \sum_{j=1}^N f_{\pi_{it}\pi_{jt}} d_{ij} \quad \text{for } t = 1, 2, \dots, T,$$

where $f_{\pi_{it}\pi_{jt}}$ and d_{ij} represent the flow of materials between departments π_{it} and π_{jt} in time period t and the distance between locations i and j , respectively. As a result, the total material-handling cost for the layout plan, π , is

$$\sum_{i=1}^N \sum_{j=1}^N \sum_{t=1}^T f_{\pi_{it}\pi_{jt}} d_{ij}.$$

If the layout between consecutive periods changes (i.e., the locations of two or more departments change), then the cost of moving departments from one location to another needs to be considered. This cost is called rearrangement cost. The rearrangement cost is

$$\sum_{i=1}^N \sum_{t=2}^T r_{\pi_{it}} x_{it},$$

where $r_{\pi_{it}}$ is the arrangement cost for moving department π_{it} to location i in period t . The variable x_{it} ensures that if department π_{it} assigned to location i at period t is different from the department $\pi_{i(t-1)}$ assigned to location i at period $t - 1$, then rearrangement cost is incurred. This is considered by

3	5	1
2	4	6

5	3	1
2	4	6

5	3	1
2	4	6

$t = 1$
 $t = 2$
 $t = 3$

Fig. 1. A DFLP instance with 6 departments and 3 time periods.

defining

$$x_{it} = \begin{cases} 1 & \text{if } \pi_{it} \neq \pi_{i(t-1)}, \\ 0 & \text{otherwise.} \end{cases}$$

See Fig. 1 for a DFLP instance with 6 departments and 3 time periods in the planning horizon. In period 1, departments 3, 5, 1, 2, 4, and 6 are assigned to locations 1, 2, 3, 4, 5, and 6, respectively. The layout of period 1 is represented as the permutation $\pi_1 = (3, 5, 1, 2, 4, 6)$, where departments 3 and 5 are assigned to locations 1 and 2 (i.e., $\pi_{11} = 3$ and $\pi_{21} = 5$), respectively, and so on. The layout plan for the DFLP instance is

$$\pi = \{(3, 5, 1, 2, 4, 6), (5, 3, 1, 2, 4, 6), (5, 3, 1, 2, 4, 6)\}.$$

Since departments 3 and 5 are assigned to different locations (i.e., locations 2 and 1, respectively) in period 2, rearrangement costs for period 2 is the cost of moving department 3 to location 2 plus the cost of moving department 5 to location 1. Because the layout is the same in periods 2 and 3, there are no rearrangement costs in period 3. Also, the material-handling costs for each period can be determined. Therefore, the DFLP is the problem of efficiently arranging the departments within a facility during a multi-period planning horizon such that the sum of material handling and rearrangement costs is minimized.

Rosenblatt [4] presented a dynamic programming algorithm to solve the DFLP optimally. However, since the number of possible solutions or layout plans is $(N!)^T$ for DFLP instances with N departments and T time periods, only small problem instances can be solved optimally in reasonable time. Therefore, the author presented two heuristics using dynamic programming. The approach is similar to the approach presented by Ballou [5] for a dynamic warehouse location problem. Lacksonen and Ensore [6] modified five heuristics to solve the DFLP: a heuristic based on the dynamic programming algorithm presented in Rosenblatt [4]; a heuristic based on a branch and bound algorithm for the QAP presented by Pardalos and Crouse [7]; a heuristic which is a modification of the cutting plane algorithm for the QAP developed by Burkard and Bonniger [8]; a heuristic based on cut trees presented by Gomory and Hu [9]; and a heuristic similar to CRAFT (Armour and Buffa [10]) for the QAP. Urban [11] developed a steepest descent pairwise exchange technique similar to CRAFT presented by Armour and Buffa [10], which consider forecast windows. Conway and Venkataramanan [12] used a genetic algorithm to solve the DFLP, and Kaku and Mazzola [13] used a tabu search heuristic. Balakrishnan and Cheng [14] improved the genetic algorithm presented in Conway and Venkataramanan [12]. Also, Balakrishnan et al. [15] improved the pairwise exchange heuristic with time windows presented in Urban [11] by presenting a backward-pass pairwise exchange heuristic with forecast windows. The authors also presented a heuristic, which combines dynamic programming and Urban's pairwise exchange heuristic with time windows.

Baykasoglu and Gindy [16] presented a simulated annealing (SA) heuristic, and Balakrishnan et al. [17] presented a hybrid genetic algorithm for the DFLP. For a review of the problem assumptions and solution approaches for the DFLP, see Balakrishnan and Cheng [18].

More recently, new techniques, which use the idea of the way ants forage for food and find the shortest paths between a food source and the colony, have been used to solve combinatorial optimization problems such as the traveling salesperson problem (Dorigo and Gambardella [19]) and the QAP (Gambardella et al. [20]). The shortest path between a food source and the colony is determined based on the chemical trail (called the pheromone trail) an ant leaves while returning back to the colony from the food source so that other ants can find the food source. The amount of the pheromone trail left by an ant is based on the amount of food found. If the paths between the food source and the colony are far apart, fewer ants will travel these paths, and the trail will eventually evaporate. However, when the path between the food source and the colony are close, more ants will travel this path, which will be indicated by a strong pheromone trail.

In this paper, hybrid ant systems (HASs) are developed for the DFLP, which are modifications of the hybrid ant colony system applied to the QAP (HAS–QAP) presented by Gambardella et al. [20]. In Section 2, the descriptions of the HASs are presented for the DFLP. The computational results of the HASs on two sets of test problems taken from the literature are given in Section 3 followed by conclusions, in Section 4.

2. HASs for the DFLP

In this section, HASs for the DFLP are presented. Ant colonies were first proposed by Colomi et al. [21] as a solution technique for solving the traveling salesman problem. More often, these algorithms are construction algorithms used to generate solutions from scratch. However, several authors developed hybrid ant algorithms for the QAP such as Gambardella et al. [20], Maniezzo and Colomi [22], and Stutzle and Dorigo [23]. Among them, Gambardella et al. [20] proposed the so-called HAS (HAS–QAP). This technique was modified for the DFLP and is briefly summarized below. This technique is called HAS I.

The HAS I heuristic starts with an initial set of layout plans (i.e., M solutions or ants). The initial set of M solutions is improved using a pairwise exchange heuristic, and the cost of each layout plan is obtained. The minimum cost is used to initialize the pheromone trail matrix P . The entries of matrix P , $p_{\pi_{it}jt}$, measures the desirability of assigning department π_{it} in location i to location j at time period t . At the initial or current iteration, each layout plan is modified using the pheromone trail matrix. More specifically, a layout plan is modified by performing department location exchanges using the pheromone trail matrix and one of two probabilistic policies, which will be explained later. The modified solutions are improved using a random descent pairwise exchange heuristic. If necessary, the best solution is updated. Next, an intensification strategy is used to determine the set of starting solutions for the next iteration (i.e., a solution for each ant), and the pheromone trails (entries in matrix P) are updated such that all the trails are first weakened and then, the pheromone trails corresponding to the best solution are strengthened. Also, a diversification strategy is implemented. In other words, after S iterations without improving the best solution, the solutions (all except the best solution) and the pheromone trail matrix are erased, and the heuristic is started from the beginning where only the best solution (or ant) and the current iteration number are used. As a result, the other $M - 1$ initial solutions are randomly generated.

A pairwise exchange technique is used in the HAS I heuristic to improve the initial set of solutions and the set of modified solutions, obtained using the pheromone trail matrix. Hence, the pairwise exchange heuristic is an important component of the HAS I heuristic. The steps for the pairwise exchange heuristic for the HAS I heuristic are as follows.

Step 1: Given a layout plan (or solution) $\pi = \{\pi_1, \pi_2, \dots, \pi_T\}$ and its cost $f(\pi)$. Randomly select a time period t ($t = 1, 2, \dots, T$).

Step 2: Randomly select two departments, π_{it} and π_{jt} , for exchange in period t , resulting in a new layout plan π' .

Step 3: Calculate the change in total cost, $\Delta f = f(\pi) - f(\pi')$. If $\Delta f > 0$, accept the exchange, and set $\pi = \pi'$. Otherwise, reject the exchange.

This pairwise exchange technique is a random descent heuristic, which is repeated $N * N * T$ times for each ant. The change in total cost (Δf) is the sum of the change in material-handling cost and in rearrangement cost, as a result of exchanging the locations of departments π_{it} and π_{jt} in period t .

The following is the HAS I heuristic developed for the DFLP, which is a modification of the HAS–QAP heuristic presented by Gambardella et al. [20].

Step 1: Randomly generate a set of initial solutions or layout plans $\pi^1, \pi^2, \dots, \pi^M$, which represents a colony of M ants, and calculate the costs of each layout plan (i.e., $f(\pi^1), f(\pi^2), \dots, f(\pi^M)$).

Step 2: Use the pairwise exchange heuristic to improve the solution or layout plan for each ant, and let π^* represent the best solution or ant such that $f(\pi^*) = \min\{f(\pi^1), f(\pi^2), \dots, f(\pi^M)\}$.

Step 3: Set the heuristic parameters:

Q = parameter used to determine the initial values of the pheromone trail matrix P .

R = number of exchanges used to modify each layout plan.

q = probability that policy 1 will be selected to modify a layout plan. As a result, policy 2 is chosen with a probability of $1 - q$.

α_1, α_2 = parameters used to weaken and enforce pheromone trails, respectively.

S = number of consecutive iterations, without improving best solution π^* , before implementing diversification strategy.

Step 4: Initialize the pheromone trail matrix P .

Step 5: Modify the solutions $\pi^1, \pi^2, \dots, \pi^M$ using the pheromone trail matrix and one of two policies, which is discussed below. The modified solutions are represented as $\tilde{\pi}^1, \tilde{\pi}^2, \dots, \tilde{\pi}^M$.

Step 6: Use the pairwise exchange heuristic to improve the solutions $\tilde{\pi}^1, \tilde{\pi}^2, \dots, \tilde{\pi}^M$ and obtain $\hat{\pi}^1, \hat{\pi}^2, \dots, \hat{\pi}^M$. Update the best solution π^* and $f(\pi^*)$.

Step 7: If the best solution π^* has not improved after S consecutive iterations, then perform the diversification strategy and go to Step 4. Otherwise, use the intensification strategy (discussed below) to determine the set of solutions $\pi^1, \pi^2, \dots, \pi^M$, which will be used to start the next iteration.

Step 8: Update the pheromone trail matrix P , and go to Step 5.

First, a permutation (or layout) for the first period is generated by assigning departments $1, 2, \dots, N$ to locations $1, 2, \dots, N$, respectively. Then this layout is used for all of the remaining periods (i.e., $t = 2, 3, \dots, T$), and all the ant are assigned this layout plan. Thus, the layout plans for all ants are the same. Therefore, the rearrangement cost is zero. Next, calculate the total material-handling cost, which gives the total cost of the layout plan. In Step 2, the pairwise exchange heuristic is used to improve the initial solution so that the best solution π^* can be used to initialize the pheromone trail matrix in Step 4. Entries of matrix P , $p_{\pi_{it}jt}$, represents the desirability of assigning department π_{it} in location i to location j at time period t . In Step 4, all the entries of P are set to $Q/f(\pi^*)$, where Q is a heuristic parameter

used to control the initial values of P . In Step 5, each of the solutions $\pi^1, \pi^2, \dots, \pi^M$ are modified by performing R department location exchanges, using the pheromone trail matrix. First, a period t and a department π_{ut} are randomly selected. Second, a location $v \neq u$ is selected using one of the following two policies:

- (1) Location v is chosen such that $p_{\pi_{ut}vt} + p_{\pi_{vt}ut}$ is maximized.
- (2) Location v is chosen with probability $\frac{p_{\pi_{ut}vt} + p_{\pi_{vt}ut}}{\sum_{j \neq u} (p_{\pi_{ut}jt} + p_{\pi_{jt}ut})}$.

The first policy is selected with a probability of q . This policy uses the pheromone trail to select a location v based on the most desirable exchange between the department assigned to location u and each department assigned to all locations except location u (ties are broken randomly). The second policy selects a location v randomly, but there is a higher probability that the v with the largest $p_{\pi_{ut}vt} + p_{\pi_{vt}ut}$ will be accepted. After selecting a location v , the departments assigned to locations u and v are exchanged. This procedure is executed R times for each ant, and the modified solutions $\tilde{\pi}^1, \tilde{\pi}^2, \dots, \tilde{\pi}^M$ are obtained. In Step 6, the solutions $\tilde{\pi}^1, \tilde{\pi}^2, \dots, \tilde{\pi}^M$ are improved by using the pairwise exchange heuristic, and the solutions $\hat{\pi}^1, \hat{\pi}^2, \dots, \hat{\pi}^M$ are obtained. Also, the best solution π^* and $f(\pi^*)$ are updated, if they have changed.

In Step 7, if the best solution π^* has not improved after S consecutive iterations, a diversification strategy is implemented. That is, the best solution π^* and a new set of $M - 1$ layout plans or solutions $\pi^1, \pi^2, \dots, \pi^{M-1}$, which are randomly generated as defined in Step 1, are used to start the next iteration. The $M - 1$ solutions are improved by using the pairwise exchange heuristic, and the best solution π^* is obtained out of the M solutions and used to re-initialize the pheromone trail matrix P , as defined in Steps 2 and 4, respectively. Then, the heuristic continues, as before at Step 5.

If the diversification strategy is not implemented, then the intensification strategy may be performed. Initially, the intensification strategy is activated, which means that the better solution between π^k and $\hat{\pi}^k$ for each ant k is used as the starting solution for the next iteration. This strategy remains active if at least one ant improves its solution during an iteration. Otherwise, the intensification strategy is inactive, and each ant k starts its next iteration with the solution $\hat{\pi}^k$. If the strategy is inactive, it becomes activated when the best solution π^* is improved.

After obtaining the starting solutions for the next iteration for each ant (i.e., $\pi^1, \pi^2, \dots, \pi^M$), update the pheromone trail matrix P , in Step 8. First, all of the trails are weakened by using the formula

$$p_{\pi_{it}jt} = (1 - \alpha_1)p_{\pi_{it}jt},$$

where $0 < \alpha_1 < 1$ is a parameter used to control the evaporation of the trails. A value close to 0 indicates that the trails will remain active for a long time, and a value close to 1 indicates a high degree of evaporation and a shorter memory of the system. Afterwards, pheromone trails corresponding to the best solution π^* are reinforced by using the formula

$$p_{\pi_{it}^*it} = p_{\pi_{it}^*it} + \alpha_2/f(\pi^*),$$

where α_2 is a parameter used to control the reinforcement of the pheromone trails corresponding to the best solution π^* . Using only the best solution π^* speeds up the convergence of the heuristic (Gambardella et al. [20]). Once the pheromone trail matrix P is updated, the next iteration continues at Step 5. The heuristic is terminated after running for a pre-defined number of minutes.

The second heuristic, called the HAS II heuristic, uses the ideas of the HAS I and SA heuristics. SA is a stochastic approach for solving combinatorial optimization problems, in which the basic idea comes from the annealing process of solids. In this process, a solid is heated until it melts, and then the temperature of the solid is slowly decreased (according to an annealing schedule) until the solid reaches the lowest energy state (or ground state). If the initial temperature is not high enough or if the temperature is decreased rapidly, the solid at the ground state will have many defects or imperfections. Kirkpatrick et al. [24] were the first to use SA to solve combinatorial optimization problems. As well as others, Wilhelm and Ward [25] and Heragu and Alfa [26] presented SA heuristics for the SFLP. As mentioned previously, Baykasoglu and Gindy [16] presented the first SA heuristic for the DFLP.

The HAS II heuristic performs Steps 1–8 of the HAS I heuristic. However, a SA heuristic is used in place of the pairwise exchange heuristic in Steps 2 and 6. The steps for the SA heuristic for the HAS II heuristic are as follows.

Step 0: Define the SA parameters: T_0 = initial temperature, α = cooling ratio, $AM = 2(N)(T^2)$ = attempted number of moves at each temperature, $T_{\min} = 0.01$ = minimum temperature.

Step 1: Initialize the temperature change counter: $r = 1$.

Step 2: Given a layout plan (or solution) $\pi = \{\pi_1, \pi_2, \dots, \pi_T\}$ and its cost $f(\pi)$. Set current solution and $Best_sol = \pi$ and $Best_cost = f(\pi)$.

Step 3: If current temperature $T \leq T_{\min}$, then stop and return $Best_sol = \pi$ and $Best_cost = f(\pi)$. Else, initialize counter for the number of attempted moves at each temperature: $a = 0$, and set the current temperature according to the annealing schedule, $T = T_0\alpha^{r-1}$.

Step 4: Randomly select a time period t ($t = 1, 2, \dots, T$), and randomly select two departments, π_{it} and π_{jt} , for exchange in period t such that $i \neq j$, resulting in a new layout plan π' .

Step 5: Update $a = a + 1$, and calculate the change in total cost, $\Delta f = f(\pi') - f(\pi)$.

If $(\Delta f < 0)$ or $(\Delta f > 0 \text{ and } x = \text{random}(0, 1) < P(\Delta f) = \exp(-\Delta f/T))$, accept the exchange, (i.e., set $\pi = \pi'$), and

if $Best_cost > f(\pi)$, then set $Best_cost = f(\pi)$, and $Best_sol = \pi$. Otherwise, reject the exchange.

Step 6: If $a \geq AM$, then update $r = r + 1$, and go to Step 3. Else, go to Step 4.

This SA technique is repeated for each ant. In order to determine the parameter settings for the SA heuristic, both theoretical and experimental techniques were used. The initial temperature T_0 was determined by using the formula $P(\Delta f) = \exp(-\Delta f/T_0)$ such that $\Delta f = 0.10f(\pi)$, $P(\Delta f) = 0.25$, where 0.10 and 0.25 were obtained experimentally. In other words, the initial temperature is obtained by the formula $T_0 = -0.10f(\pi)/\ln(0.25)$, which means that there is a 25% chance of accepting a solution 10% more than the cost of π . Furthermore, α and AM were set to 0.99 and $2(N)(T^2)$, which were obtained experimentally.

The third heuristic, called the HAS III heuristic, adds a look-ahead/look-back strategy to the pairwise exchange heuristic within the HAS I heuristic. Similarly, the pairwise exchange heuristics for HAS I and III randomly selects a period t and the locations i and j of two departments for exchange, and the change in the total cost $\Delta(f)$ is obtained. If $\Delta f > 0$, then the exchange is accepted. Otherwise, it is rejected, and the heuristic starts from the beginning. If the exchange is accepted in the simple pairwise exchange heuristic in HAS I, then the exchange is performed, and the current solution is updated. This process is repeated for $N * N * T$ iterations. However, if the exchange is accepted in the pairwise exchange heuristic in HAS III, then the exchange is performed, and the current solution is updated. In addition, the changes in the total cost of performing the exchange in the preceding $(t - 1)$ and succeeding $(t + 1)$ periods

are considered. If the exchange is accepted for both periods, update the current solution and consider the exchange in the preceding and succeeding ($t - 2$ and $t + 2$) periods. If the exchange is accepted for only one of the periods, say $t - 1$, then update the current solution, consider the exchange in the previous ($t - 2$) period, and reject the exchange in period $t + 1$. Continue considering the exchange in the preceding or succeeding periods until there are no more periods to consider or the exchange does not improve the solution (i.e., $\Delta f \leq 0$). If the exchange is rejected for both periods, then repeat the above process for $N * N * T$ iterations. The diagram of the look-ahead/look-back pairwise exchange heuristic is given in Fig. 2.

3. Computational results

In this section, the computational results of the HASs applied to 80 DFLP instances are presented. The first 32 test problems (data set 1), which were provided by Lacksonen and Ensore [6], contain problems with 6, 12, 20, and 30 departments each with 3 and 5 time periods. The remaining 48 test problems (data set 2), which were obtained from Balakrishnan and Cheng [14], contain problems with 6, 15, and 30 departments each with 5 and 10 time periods. The proposed HAS heuristics were programmed using the C++ programming language, and the two sets of test problems were solved on a Pentium IV 2.4 GHz PC. Each test problem was solved three times for each heuristic.

All the parameter settings for the proposed HAS heuristics were obtained experimentally and are given in Tables 1 and 2 for data sets 1 and 2, respectively. Each test problem was solved three times for each heuristic, and the best solution was recorded. Tables 3 and 4 summarize the results obtained for data sets 1 and 2, respectively, in the HAS I, HAS II, and HAS III columns. The bold numbers gives the best solution for each test problem. The best solution found in the literature and the best solution found by a HAS heuristic are given in columns 6 and 10, respectively. Also, the percent deviations of the best HAS solutions away from the best found solutions are given in the last column. For data set 1, the results for the HAS heuristics are compared to the results obtained by the tabu search (TS) heuristics presented by Kaku and Mazzola [13] and the cutting planes (CP) algorithm presented by Lacksonen and Ensore [6]. For data set 2, the HAS results are compared to the best results obtained by the SA heuristic presented by Baykosaglu and Gindy [16] and the hybrid genetic algorithm (GADP) presented by Balakrishnan et al. [17]. It is important to note that the correct results for the SA heuristic presented by Baykosaglu and Gindy [16] were taken from Baykosaglu and Gindy [27]. The HAS heuristics are compared to the above heuristics since these heuristics are considered to be the best heuristics in the literature for the DFLP.

In Table 3, the solutions with an asterisk are the solutions that Lacksonen and Ensore [6] verified as the optimal. Therefore, the CP, TS, HAS I, HAS II, and HAS III heuristics obtained the optimal solutions for 7 out of the 8 six-department test problems, and all except CP obtained the best solution for problem 6. For the 12-, 20- and 30-department problems, the HAS I heuristic produced the best solutions for 8, 5, and 1 of the test problems, respectively. The HAS II heuristic produced the best solution for 8, 6, and 3 of the test problems, respectively, and the HAS III heuristic produced the best solution for 8, 7, and 8 of the test problems, respectively. In other words, out of the 24 problems (i.e., the problems with 12, 20, and 30 departments), the HAS I, II, and III obtained the best solution for 14, 17, and 23 of the problems, respectively. Therefore, HAS III clearly outperformed HAS I and II, and HAS II outperformed HAS I for this data set. For the 32 test problems, the CP and TS heuristics obtained the best solution for 18 and 25 problems, respectively. However, the HAS I, II, and III obtained the best solution for 22, 25,

Fig. 2. Diagram of the look-ahead/look-back pairwise exchange procedure.

Table 1
HAS parameter settings for data set 1

No. of departments	No. of time periods	M	Q	q	α_1	α_2	S	R	Running time (min)
6	3	5	2×10^4	0.9	0.1	2×10^4	100	3	0.1
	5	5	2×10^4	0.9	0.1	2×10^4	150	3	0.5
12	3	10	5×10^4	0.9	0.1	5×10^4	200	3	1.5
	5	10	5×10^4	0.9	0.1	5×10^4	250	3	3.0
20	3	15	1×10^4	0.8	0.2	1×10^4	300	2	4.5
	5	20	1×10^4	0.8	0.2	1×10^4	350	2	8.0
30	3	25	3×10^4	0.8	0.2	3×10^4	400	2	15.0
	5	25	3×10^4	0.8	0.2	3×10^4	450	2	25.0

Table 2
HAS parameter settings for data set 2

No. of departments	No. of time periods	M	Q	q	α_1	α_2	S	R	Running time (min)
6	5	5	3×10^5	0.9	0.1	3×10^5	100	3	0.5
	10	10	3×10^5	0.9	0.1	3×10^5	150	3	2.0
15	5	15	3×10^6	0.9	0.1	3×10^6	300	3	6.0
	10	20	3×10^6	0.8	0.2	3×10^6	350	2	15.0
30	5	25	2×10^6	0.8	0.2	2×10^6	400	2	25.0
	10	30	4×10^6	0.8	0.2	4×10^6	450	2	45.0

and 31 problems, respectively. In other words, HAS III obtained the best solution for all the problems except problem 20, where it was within 0.2% above the best solution found. Therefore, HAS III clearly outperformed the other heuristics, and HAS II and TS were comparable with respect to solution quality for this data set.

Kaku and Mazzola [13] gave the average computation times for their TS heuristic. The average computation time for the TS heuristic for the larger size problems (problems 29–32) was approximately 2 h and 47 min on a Pentium 200 MHz PC. For the HAS heuristics, the average computation time was 20 min for each run (3 runs) on a Pentium IV 2.4 GHz PC.

In Table 4, out of the 48 problems the SA and GADP heuristics obtained the best solution for 2 and 13 problems, respectively. However, the HAS I, II, and III obtained the best solution for 19, 30, and 36 problems, respectively. Therefore, HAS III outperformed all of the heuristics, and HAS II and I were the second and third best heuristics with respect to solution quality for this data set. Balakrishnan et al. [17] solved the 30 department problems with 10 periods in approximately 16.7 min on DEC Alpha machines.

Table 3
Solution results for data set 1

Pb#	<i>N</i>	<i>T</i>	CP	TS	Best found	HAS I	HAS II	HAS III	Best HAS	% Deviation
P01	6	3	267*	267*	267	267	267	267	267	0
P02			260*	260*	260	260	260	260	260	0
P03			363*	363*	363	363	363	363	363	0
P04	5	5	299*	299*	299	299	299	299	299	0
P05			442*	442*	442	442	442	442	442	0
P06			589	586	586	586	586	586	586	0
P07			424*	424*	424	424	424	424	424	0
P08			428*	428*	428	428	428	428	428	0
P09	12	3	1624	1624	1624	1624	1624	1624	1624	0
P10			1973	1973	1973	1973	1973	1973	1973	0
P11			1661	1661	1661	1661	1661	1661	1661	0
P12			2097	2097	2097	2097	2097	2097	2097	0
P13			2930	2930	2930	2930	2930	2930	2930	0
P14	5	5	3726	3701	3701	3701	3701	3701	3701	0
P15			2756	2756	2756	2756	2756	2756	2756	0
P16			3364	3364	3364	3364	3364	3364	3364	0
P17			2763	2758	2758	2758	2758	2758	2758	0
P18			5318	5318	5318	5318	5318	5318	5318	0
P19	20	3	3048	3056	3048	3098	3034	3034	3034	−0.5
P20			5873	5903	5873	5897	5914	5881	5881	0.2
P21			4581	4605	4581	4575	4629	4575	4575	−0.1
P22			9825	9746	9746	9724	9724	9724	9724	−0.2
P23			4654	4654	4654	4667	4654	4654	4654	0
P24	30	3	8985	8979	8979	8979	8979	8979	8979	0
P25			7163	7130	7130	7133	7130	7130	7130	0
P26			14,583	14,478	14,478	14,478	14,524	14,478	14,478	0
P27			8066	8115	8066	8138	8128	8066	8066	0
P28			14,940	14,925	14,925	14,934	14,947	14,925	14,925	0
P29	5	5	13,719	13,606	13,606	13,908	13,606	13,374	13,374	−1.7
P30			26,027	25,583	25,583	25,640	25,747	25,521	25,521	−0.2
P31			12,351	12,163	12,163	12,193	12,163	12,163	12,163	0
P32			24,409	24,200	24,200	24,354	24,200	24,200	24,200	0

4. Conclusion

In this paper, the HAS for the QAP (HAS–QAP) was modified to solve the DFLP, since HASs were never used to solve this computationally intractable problem. The first heuristic, called HAS I, is a direct application of the HAS–QAP heuristic for the DFLP. However, this heuristic uses a random descent pairwise exchange heuristic to improve the set of layout plans after performing *R* pairwise exchanges using the pheromone trail matrix. The second heuristic, called HAS II, is exactly like HAS I, except that a SA heuristic is used as the local search heuristic, instead of the random descent pairwise exchange heuristic. The third heuristic, called HAS III, is exactly like HAS I, except that the random descent pairwise exchange heuristic has a look-ahead/look-back strategy. The proposed HAS heuristics performed well for two data sets taken from the literature.

Table 4
Solution results for data set 2

Pb#	N	T	SA	GADP	Best found	HAS I	HAS II	HAS III	Best found	% Deviation
P01	6	5	107,249	106,419	106,419	106,419	106,419	106,419	106,419	0
P02			105,710	104,834	104,834	104,834	104,834	104,834	104,834	0
P03			104,800	104,320	104,320	104,320	104,320	104,320	104,320	0
P04			106,515	106,515	106,515	106,399	106,399	106,399	106,399	−0.11
P05			106,282	105,628	105,628	105,628	105,628	105,628	105,628	0
P06			103,985	104,053	103,985	103,985	103,985	103,985	103,985	0
P07			106,447	106,439	106,439	106,439	106,439	106,439	106,439	0
P08			103,771	103,771	103,771	103,771	103,771	103,771	103,771	0
P09		10	215,200	214,313	214,313	214,313	214,313	214,313	214,313	0
P10			214,713	212,134	212,134	212,134	212,134	212,134	212,134	0
P11			208,351	207,987	207,987	207,987	207,987	207,987	207,987	0
P12			213,331	212,741	212,741	212,530	212,530	212,530	212,530	−0.10
P13			213,812	210,944	210,944	210,906	210,906	210,906	210,906	−0.02
P14			211,213	210,000	210,000	209,932	209,932	209,932	209,932	−0.03
P15			215,630	215,452	215,452	214,252	214,252	214,252	214,252	−0.56
P16			214,513	212,588	212,588	212,588	212,588	212,588	212,588	0
P17	15	5	501,447	484,090	484,090	481,511	481,395	480,453	480,453	−0.76
P18			506,236	485,352	485,352	484,761	484,761	484,879	484,761	−0.12
P19			512,886	489,898	489,898	490,899	488,748	490,398	488,748	−0.24
P20			504,956	484,625	484,625	485,561	485,658	484,446	484,446	−0.04
P21			509,636	489,885	489,885	489,012	487,722	489,206	487,722	−0.44
P22			508,215	488,640	488,640	487,417	486,685	486,965	486,685	−0.40
P23			508,848	489,378	489,378	486,853	486,853	486,853	486,853	−0.52
P24			512,320	500,779	500,779	493,963	492,074	491,016	491,016	−1.99
P25		10	1,017,741	987,887	987,887	982,208	980,351	980,351	980,351	−0.77
P26			1,016,567	980,638	980,638	981,802	978,271	980,197	978,271	−0.24
P27			1,021,075	985,886	985,886	978,027	985,056	984,065	978,027	−0.80
P28			1,007,713	976,025	976,025	978,987	974,694	975,854	974,694	−0.14
P29			1,010,822	982,778	982,778	980,611	980,548	979,196	979,196	−0.37
P30			1,007,210	973,912	973,912	973,508	971,827	971,548	971,548	−0.24
P31			1,013,315	982,872	982,872	985,659	982,951	980,752	980,752	−0.22
P32			1,019,092	987,789	987,789	987,986	986,087	985,707	985,707	−0.21
P33		30	604,408	578,689	578,689	578,854	576,886	580,240	576,886	−0.31
P34			604,370	572,232	572,232	570,349	571,528	570,349	570,349	−0.33
P35			603,867	578,527	578,527	578,152	576,053	578,176	576,053	−0.43
P36			596,901	572,057	572,057	569,694	572,005	566,777	566,777	−0.93
P37			591,988	559,777	559,777	560,433	558,353	558,353	558,353	−0.26
P38			599,862	566,792	566,792	569,725	570,567	566,792	566,792	0
P39			600,670	567,873	567,873	570,899	567,190	567,131	567,131	−0.13
P40			610,474	575,720	575,720	576,980	575,998	575,280	575,280	−0.08
P41		10	1,223,124	1,169,474	1,169,474	1,166,164	1,169,688	1,166,164	1,166,164	−0.28
P42			1,231,151	1,168,878	1,168,878	1,169,407	1,177,398	1,168,878	1,168,878	0
P43			1,230,520	1,166,366	1,166,366	1,166,916	1,166,366	1,166,720	1,166,366	0
P44			1,200,613	1,154,192	1,154,192	1,190,140	1,148,202	1,148,202	1,148,202	−0.52
P45			1,210,892	1,133,561	1,133,561	1,128,855	1,142,776	1,133,664	1,128,855	−0.42

Table 4 (continued)

Pb#	<i>N</i>	<i>T</i>	SA	GADP	Best found	HAS I	HAS II	HAS III	Best found	% Deviation
P46			1,221,356	1,145,000	1,145,000	1,153,982	1,141,344	1,149,040	1,141,344	−0.32
P47			1,212,273	1,145,927	1,145,927	1,152,805	1,151,735	1,140,773	1,140,773	−0.45
P48			1,231,408	1,168,657	1,168,657	1,172,787	1,170,349	1,166,157	1,166,157	−0.21

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