MULTI-OBJECTIVE EVALUATION OF DYNAMIC FACILITY LAYOUT USING ANT COLONY OPTIMIZATION

by

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ABSTRACT

MULTI-OBJECTIVE EVALUATION OF

DYNAMIC FACILITY LAYOUT

USING ANT COLONY

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The Dynamic Facility Layout Problem (DFLP) deals with changes of facility layout throughout time. As an extension to Static Facility Layout Problem (SFLP), it has gathered increasing interests lately. Facility layouts are constantly modified over time either to meet customers' changing demands in product designs and functionalities or to keep pace with technological innovations. Manufacturers must stay flexible and agile and frequent facility layout changes are needed. Since there is often insufficient time and insufficient funding to build a new manufacturing plant, it is often necessary to rearrange the current plant layout. Even though the rearrangement of the plant layout

can be costly, it is far more cost effective when compared to the possibility of failure to meet customers' demands.

Although there is a great volume of research work done in the dynamic facility layout problem (DFLP), often the research in this area is typically focused on few objectives/criteria, i.e. minimizing the product of distance and flow cost, known as the distance-based objective. Focusing only on the distance based Objective Function Value or OFV is not adequate to reflect situations in the real world— little consideration is given to the "quality" aspect of facility layout such as the adjacency of facilities (e.g., noise, RF signal, dusts or safety reasons) that require placing them as far apart as possible. The adjacency-based objective should also be considered in facility planning.

The purpose of this research is to develop a technique to solve the dynamic facility layout problem with multiple objectives approach, both qualitative and quantitative, using one of the popular meta-heuristics— the Ant Colony Optimization (ACO). The results indicate this heuristic technique provides a practical decision support tool to solve the issues in the dynamic facility layout problem.

TABLE OF CONTENTS

LIST OF ILLUSTRATIONS

LIST OF TABLES

CHAPTER 1

INTRODUCTION

1.1 Overview

Facility layout planning plays an important role in the manufacturing process and seriously impacts a company's profitability. The selected layout establishes the physical relationship between activities including material handling. (Tompkins, 2003) Since material handling activities account for 20-50 percent of a manufacturing company's total operating budget (Tompkins and White, 1984), manufacturers can reduce product costs and improve their competitiveness if the departments are arranged optimally. "Facilities alone can make or lose millions of dollars per year for an organization. They can give corporate decision makers cost effective flexibility, or they can leave them without any realistic options for change". (Filley 1985, 27-39) Furthermore, a company's indirect costs are tied to the effectiveness of layouts. (Lacksonen and Enscore, 1992)

As implied earlier, facility layout design and material handling activities are much related and inseparable. An effective layout may minimize the material flows and distance between the department locations which leads to the reduction of material handling costs and often improvement in cycle time as well. In order to optimally design a new facility, both functions must be considered together.

1.2 Background

Today's dynamic manufacturing environments are going through the periods of expansion and decline due to rapidly changing business environments. To keep up with the pace, the facility layout needs to be adaptable to changes. The layout has to be "flexible enough to accommodate changes in product design, process design, and schedule design." (Tompkins, 2003) Heragu predicted that redesigning existing facilities will become more common than generating new facility layouts in future facility planning. (1997, 197)

The following sections will discuss the background of facility layout including the topics of static and dynamic layout, models used in facility layout problems, and different objectives for measuring the efficiency of facility layouts.

1.2.1 Static vs. Dynamic Layout

The traditional, or static, layout problem assumes that all the data—the departments, areas and flow—are constant. However, business conditions are constantly changing, so most layout projects are redesigns of existing facilities rather than having a new "greenfield" facility development.

Currently product manufacturing is subject to a short product life cycles, especially in the high-tech industries, where switching from manufacturing one product line to another and discontinuing production lines are often the norm. The decision makers, especially managers or facility planners, are dealing with imperfect and soon-to-be-obsolete information; they are often forced to contend with one facility configuration at the current time but worry about other facility configurations in the nearby future. Due to constantly changing environments, the enterprises are forced to be flexible, adaptable and innovative.

To keep up with fast-paced changes, the factory layout has to be re-designed to meet the demands of ever-changing product manufacturing. Therefore, the dynamic facility layout planning (DFLP) comes into the picture. Unlike the traditional static facility layout where the layout is relatively constant throughout time, the concept of dynamic facility layout introduces the time dimension into the facility layout planning. To construct a dynamic facility layout, the facility planners or managers must take the time periods into account. At each time period, the material flow costs and rearrangement cost needs to be considered and evaluated to deem if the facility rearrangement is necessary. Therefore, the pre-determination of material flows costs and department adjacency are required in dynamic facility layout.

There are several factors that a facility planner needs to consider with the "dynamic" facility layout: (1) the cost incurred due to loss in production time; (2) the cost of physically moving equipment from their existing location to the new location. (This includes planning, dismantling, construction, movement and installation costs.) (Kochhar and Heragu, 1999)

1.2.2 Models for Facility Layout Problem

The facility layout problems can be modeled in several ways, notably the quadratic assignment problem (QAP), the linear mixed-integer programming model, the quadratic set covering model, and the nonlinear model with absolute terms in the objective function and constraints. (Heragu 1997, 123). Since the quadratic assignment problem is most relevant to this research, this model is discussed as below.

1.2.2.1 Quadratic Assignment Problem (QAP)

The facility layout problem of locating departments with material flow between them is often modeled as Quadratic Assignment Problem (QAP). Introduced by Koopman and Beckman (1957), The QAP is a problem of finding the best assignment of *n* department to *n* locations. The term "quadratic" comes from the fact that it involves the product of pairs of location decision variables. The quadratic assignment problem is widely encountered not only in factory layout planning but also in campus and hospital layout, keyboard layout and construction site planning. Despite its popularity, QAP is a difficult problem to solve using the traditional optimal algorithms. According to Francis, the QAP is "computationally intractable for problems with more than 15 to 20 facilities, and this situation has changed very little since the mid-1970s." (1992, 555)

To examine it closely, suppose there are a set of n facilities and a set of n locations. For each pair of locations, a distance is specified and for each pair of facilities a weight or flow is specified. (e.g., the amount of supplies transported between the two facilities). The problem is to assign all facilities to different locations with the goal of minimizing the sum of the distance multiplied by the corresponding flows. The mathematical expression for the quadratic assignment problem is shown below (Tompkins et. al, 2003):

$$\text{Minimize } z = \sum_{j=1}^{n}\sum_{k=1}^{n}\sum_{h=1}^{n}\sum_{l=1}^{n} c_{jkhl}\, x_{jk}\, x_{hl}$$

subject to

$$\sum_{j=1}^{n} x_{jk} = 1 \qquad k = 1,...,n$$

$$\sum_{k=1}^{n} x_{jk} = 1 \qquad j = 1,...,n$$

$x_{jk} = (0,1)$ for all j and k

The drawback to the QAP formulation is that it requires an equal number of departments and locations. If there are fewer locations than departments, the problem cannot be modeled as a QAP. (Heragu, 1997, 123)

A diagram is drawn as below to represent a facility layout in QAP formulation. ABCD refer to the departments while [1][2][3][4] refer to the locations.

dept A [1]	**dept B** [2]
dept C [3]	**dept D** [4]

Figure 1.1: Facility layout in QAP formulation

1.2.3 Objectives in Facility Layout Problems

There are two approaches in facility layout algorithms surveyed to generate desired facility layouts:

1. Minimize the distance-based objective function value— quantitative approach
2. Maximize the adjacency-based objective function— qualitative approach

1.2.3.1 Distance-based (Quantitative) Objective

The aim of distance-based objective is to minimize the sum of flows multiplying distances. The material flow is expressed as the from-to chart. The from-to chart is shown as below:

		To Department			
		A	B	C	D
From Department	A	—	10	15	20
	B	10	—	10	5
	C	15	10	—	5
	D	20	5	5	—

Figure 1.2: From-to Chart used in distance-based objective

To interpret the from-to chart, observe the intersection between Department A (first row) and Department B (second column) contains the value 10. This value represents the material handling cost from Department A to Department B which can encompass the flow of material, equipment, personnel, and information between the two facilities. Notice that since the from-to chart (or matrix) is symmetric, i.e. A to B is the same as B to A, the from-to matrix can be re-written to be the following where only the bottom half of the matrix needs to be considered:

		To Department			
		A	B	C	D
From Department	A	—			
	B	10	—		
	C	15	10	—	
	D	20	5	5	—

Figure 1.3: Symmetric from-to chart

1.2.3.2 Rectilinear vs. Euclidean Distance

There are two popular ways to measure the distances between departments. First, a rectilinear metric is defined as distances measured along paths that are orthogonal (or perpendicular) to each other. An example will be a material transporter that moves along rectilinear aisles in a facility setting. The rectilinear distance between two points is calculated:

$$A_1 = (x_i, y_i) \text{ and } A_2 = (x_j, y_j);\ \text{Distance} = (x_j - x_i) + (y_j - y_j).$$

Next, the Euclidean (or straight line) metric is defined as distances measured along the straight line path between two points. One application of the Euclidean metric is to calculate the distance of a straight conveyor segment linking two workstations. The Euclidean distance between the same two points A_1 and A_2 is calculated as:

$$\text{Distance} = \sqrt{(x_j - x_i) + (y_j - y_i)}$$

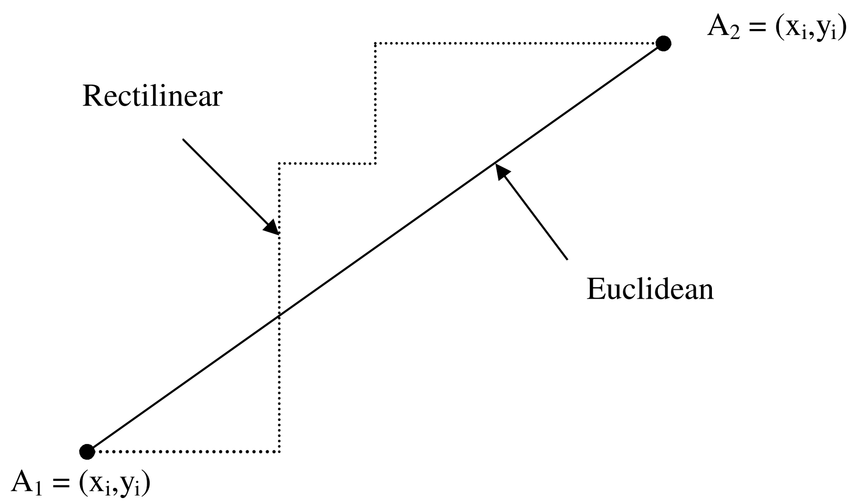

Figure 1.4: Rectilinear vs. Euclidean Distance (Rogers 1985, 8)

To measure the distance between two departments, one can measure the distance between the pick-up and drop-off points of the department pair. However, for simplicity reason or pick-up and drop-off points not known, Centroid-to-centroid (CTC) measurement is typically used. In this case, the distance is measured from the center of one department to another. The CTC is used by most of the layout algorithms even though “the CTC measure captures the essential travel pattern of materials in a facility, it does not capture other details of a facility’s internal configuration.” (Wang 1999, 4)

1.2.3.3 Adjacency-based Objective

Evaluating facility layouts based on the distance-based objective is often not enough. The qualitative aspects of facility layouts may also need to be considered. There are factors in determining the “closeness” between two facilities: (1) the level of work flow, (2) safety/technological reasons and (3) the user’s preference. The work flow between two facilities cover the total flow of material, equipment, personnel and information transferred between two facilities. Potential safety and environmental hazards between two facilities should also not be ignored if they can increase the likelihood of accidents, noise, uncomfortable temperature, pollutions, and so on. For example, the forging and heating-treatment stations must be next to each other even if there are not much work flows between them. The welding station, on the other hand, cannot be close to the painting station since the sparks generated by the welding station could possibly ignite flammable solvents in the painting stations. Therefore, in spite of the close interaction between the two departments, they must be placed as far from each other as possible. (Heragu, 2006) The third factor, the user's preference, is hard to determine but is very likely to occur. The facility manager, for any, some or no reasons, decides to have two facilities to be close together or far away from each other as possible regardless the work flows or material flows between them (Elbeltagi & Hegazy, 2001).

To determine the adjacency score among facilities, the Activity Relationship Chart can be used. The Activity Relationship Chart is part of the Systematic Layout Planning as a process to systematically evaluate the qualitative aspect of facility layout. (Muther, 1973) To determine the adjacency relationships between each pair of departments, a set of letter codes are used:

RELATIONSHIP CODE	CLOSENESS RATING
A	ABSOLUTELY NECESSARY
E	ESPECIALLY IMPORTANT
I	IMPORTANT
O	ORDINARY CLOSE
U	UNIMPORTANT
X	UNDESIRABLE

Figure 1.5: Closeness rating chart

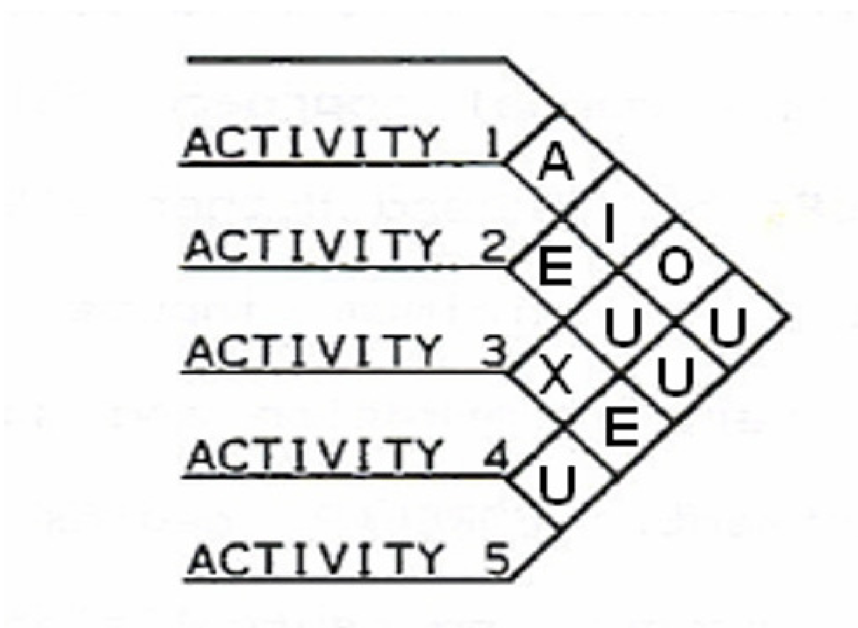

Figure 1.6: Activity relationship chart (Rogers 1985, 21)

The closeness ratings indicate the desired relative "closeness" requirement for two departments to be next to each other. For a department pair with **A** rating must be placed next to each other under any circumstance. For example, the incoming inspection department should to be placed next to the receiving docks for checking incoming materials. Also, having a shower next to the department involving acid-handling is necessary for safety reason. For a department pair with **E** rating, it is essential to place them next to each other as long as the result would not affect the departments with **A** rating to be nonadjacent. A good example is to have the receiving area next to the material storage area. With a closeness rating **I**, it is important to have the departments next to each other, but not as necessary as with closeness rating **A** and **E**. Phillips (1997, 141) suggests to place the high-tech installation close to the visitor's entrance for image purposes. With an **O** closeness rating, departments are placed together perhaps because they are traditionally placed next to each other. Having the cafeteria next to the employee's fitness center may fit this category. Department pairs with **U** rating do not have to be placed next to each other. The departments are not related for any reason. For example, the receiving area and a company president's office are usually not place next to each other unless the facility area is very small. For a department pair with **X** rating, they must **NOT** be placed next to each other under any circumstance. The example illustrates this type of relationship is the welding station and painting area. With a tiny spark from the welding station could lead to a disastrous explosion at the painting area.

The Relationship code can be converted into numerical values. For example, one can assign numerical values to the closeness ratings in such ways: 6 to A, 5 to E, 4 to I, 3 to O, 2 to U and -1 to X. Many times people use a negative value for "X" so that it is very unlikely for a pair of departments with that value to be adjacent to each other. Based on the ratings, an algorithm can be developed to place a pair of departments adjacent to each other in order to yield the highest adjacency scores. The adjacency score is computed as the sum of all the closeness ratings between those departments that are adjacent in the layout:

$$\max z = \sum_{i=1}^{m}\sum_{j=1}^{m} f_{ij}x_{ij} ,$$

where x_{ij} = 1 if departments i and j are adjacent and 0 otherwise; f_{ij} denote the flow from department i to department j.

Tompkins et. al (2003) takes one step further and develops the efficiency rating by dividing the adjacency score by the total flow in the facility. The equation for efficiency rating is shown as:

$$Z = \frac{\sum_{i=1}^{m}\sum_{j=1}^{m} f_{ij}x_{ij}}{\sum_{i=1}^{m}\sum_{j=1}^{m} f_{ij}}$$

1.2.4 Optimal vs. Heuristic Algorithm

Layout algorithms can be divided into two categories: optimal and heuristic algorithms. Optimal algorithms are defined to be those that are always guaranteed to produce the best solutions for a given problem. Heuristic algorithms (or simply heuristics) provide a solution but do not guarantee it to be the best. Both types of algorithms have their strengths and weaknesses and areas of applications.

1.2.4.1 Optimal Algorithm

Optimal algorithms produce the best solution; however, for NP-complete problems such as QAP and other layout problems, the computation time of optimal algorithms can be high—some may take years! (Heragu, 2006) If a problem is known as NP-complete, it means the problem cannot be solved in polynomial time. For small-sized problems, the optimal algorithms can be used to find the best solution; for large-sized problems, this type of algorithm is not practical to use. Some optimal algorithms include dynamic programming, Branch and Bound problems, Decomposition algorithms, and Cutting Plane Algorithms.

1.2.4.2 Heuristic Algorithm

The goal of heuristic algorithms, on the other hand, is to find a "good" solution within a reasonable computing time, but there is no guarantee the solutions could not get arbitrarily bad. Based on probabilities and randomness, heuristic algorithms (also known as heuristics) are used to solve large-sized problems. The examples of heuristic algorithms include Genetic Algorithms (GA), Tabu Search(TS), Simulated Annealing(SA) and Ant Colony Optimization (ACO).

There are three different categories of heuristic algorithms for developing a facility layout: construction algorithms, improvement algorithms, and hybrid algorithms. The following categorical definitions are taken from Heragu's *Facilities Design* (2006).

Construction algorithms, as the name implies, generate a facility layout from scratch. This type of algorithm starts with an empty layout and adds one facility (or a set of facilities) after another until all the facilities are included in the layout. The differences among various construction algorithms have something to do with the criteria used to decide:

- The first facility to enter the layout
- Subsequent facility or facilities added to the layout
- Location of the first (and subsequent) facilities in the layout.

The representation of this type of algorithm includes the Traveling Salesman Problem (TSP), where a solution is found by adding city after city in an incremental way. The Traveling Salesman Problem, a well-known problem in the heuristics field, asks the question: "Given a number of cities and the costs of traveling from any city to any other city, what is the cheapest round-trip route that visits each city exactly once and then returns to the starting city?"

Improvement algorithms are based on the notion that better layout alternatives can be found through subsequent improvements to the existing layout. The algorithms take the initial layout from the users, modify the layout and evaluate the resulting modified solution. If the result satisfies the desired criteria—better Objective Function Value (OFV), for example—the modification is made; otherwise, the modification is rejected. The improvement is continued until there is no better layout or some exiting criteria are reached.

The pair-wise exchange algorithm is a well-known improvement algorithm. Also, known as 2-opt algorithm, the pair-wise exchange algorithm modify the existing layout by systematically exchanging two departments, evaluating the OFV, and deciding whether to accept or reject the modified layout. The procedure is carried out until all possible pair-wise exchanges are considered.

Hybrid algorithms combine two or more types of solution techniques in solving the facility layout problem. For instance, algorithms employing a combination of improvement and construction techniques mentioned above fit this category. Additionally, this category also refers to techniques that employ both characteristics of optimal and heuristic algorithms.

1.3 Popular Facility Layout Software

This section provides a brief review of popular layout algorithms and software package on the market today to give readers some sense of efforts poured into the facility layout design and analysis.

BLOCPLAN is a program developed by Donaghey and Pire (Heragu 2006, 208) that can be used to create a single-story or multistory layout. Additionally, it can be used as a random construction or improvement algorithm. Based on heuristic algorithms, it allows the user three ways to enter data:

1. Entering the information in an Activity Relationship Chart to consider adjacency-based objective.
2. Entering the information in a flow matrix to consider distance-based objective.
3. Entering the type and number of parts to be manufactured as well as the routing information for each part.

For options 2 and 3, the software converts the flow matrix into an equivalent relationship chart by dividing the maximum flow value by 5 (the relationship code under consideration are A, E, I, O and U; X is not considered). It assigns an ‘A’ relationship code for any element whose flow value comes between the maximum flow value and 4/5 of the maximum flow value. It assigns an ‘E’ relationship code to flow matrix value that comes between the 3/5 and 4/5 of the maximum flow value. The same pattern applies to other relationship code I, O, and U; that is, I is assigned for flow value comes between 2/5 and 3/5, O for flow value between 1/5 and 2/5, and U for 0 and 1/5.

VisFactory is a CAD layout planning tool which contains multiple modules: FactoryFLOW, FactoryPLAN, and FactoryOPT. FactoryFLOW is used to improve existing layout generated by other software package, e.g. AutoCAD. It is applicable to the quantitative aspect of the facility design by analyzing, comparing and improving facility layouts based on material flows. FactoryPLAN is a planning tool for qualitative analysis of layout. Based on the data from the equivalent of the activity relationship chart, it analyzes and designs layouts to ensure department pairs with desirable activities, i.e. those with ‘A’ relationship are grouped closely together. FactoryOPT applies 2-opt or 3-opt algorithms to create a near-optimal layout with the generated data from FactoryPLAN and/or FactoryFLOW to further improve the facility layout (Ertay, Ruan, and Tuzkaya 2006, 245).

LayOPT is a PC-based program which automatically generates alternative facility layouts and allows the facility planners to select a good, sub-optimal layout out of all the selections. It uses an improvement algorithm that starts with an existing facility layout provided by the user as well as the flow and cost data, generates and evaluates the alternative layouts by exchanging the locations of defined departments. The algorithm that LayOPT uses is the steep-descent, pair-wise exchange optimization, which selects the department pair whose exchange leads to the smallest objective function values at each iteration. The objective function value minimized by the above algorithm is the sum of the flow costs multiplied by distances between all department pairs with non-zero parts flow between them. (Narayanaswamy n.d.) It also allows the user to solve single or multi-floor facility layout problems. (Vij n.d.).

VIP-PLANOPT is a general purpose floor-PLAN layout OPTimization computer program. It has been developed to produce high-quality optimal layouts on a PC for small, medium and large-sized problems involving unequal-area "building blocks" or "modules" with fixed or variable aspect ratios. However, Heragu (2006, 225) argued against this point that an 'optimal' solution ever exists for medium and large-sized problems because the facility layout problem is NP-hard. Moreover, "VIP-PLANOPT is a construction-type layout algorithm that works with rectangular department shapes" (Tompkins et al. 2003, 361). It has the additional capability of optimizing the layouts considering the user-specified pick-up and drop-off points. On the VIP-PLANOPT official web site, the following describes the underlying mechanism:

> The optimization algorithm of VIP-PLANOPT 2006 program is now improved and advanced. It is based on a hybrid smart growth technique. It generates high quality solutions for large scale problems with minimal computational cost. This is due to the algorithm's embedded optimization philosophy of natural constructive growth while identifying, for each module, the feasible design space with the **highest probability of local optima**. The design space is then mapped onto a straight line. A pseudo-exhaustive search is then carried out for the optimum solution at each stage of a multi-stage optimization process. (VIP-PLANOPT Web Site, 2007)

CRAFT, or Computerized Relative Allocation of Facilities Technique, is probably one of the most popular software packages on the market. Utilizing the pair-wise solution strategy, CRAFT is an improvement algorithm which takes flow cost values in a from-to chart as input data and improve on the facility layouts with the objective of minimizing the distance-based objective function values. Additionally, CRAFT does not have the constraints that departments have to be regular shape or equal in size. An extension of CRAFT is called CRAFT-M which deals with the re-layout problem by considering the fixed and variable costs of facility rearrangement. (Heragu 1997, 195). The re-layout problem is the same as the dynamic layout problem, in which the rearrangement cost of the layout is considered. To come up with the rearrangement cost is rather difficult since the estimation is not only based on the actual relocation cost of labor and equipment rental but also the cost of downtime. More than often, the rearrangement cost is guessed. (Heragu 1997, 195).

COFAD, a modified version of CRAFT, considers both facility layout and flow costs jointly. (Rogers 1985, 30) Additionally, the application considers rectilinear or Euclidean distance metrics because use of Euclidean distance metrics is more realistic than rectilinear distance in measuring some material-handling system, e.g. material flows on a conveyor or wire-guided AGVs.

CORELAP is yet another widely used software package in facility planning. Being one of the first construction algorithms, "it converts qualitative input data into quantitative data and uses this information to determine the first facility to enter the layout. Subsequent facilities are then added to the layout, one at a time, based on their level of interaction with facilities already in the layout." (Heragu 1997, 168) The inputs for CORELAP application are the closeness rating scores in the activity relationship chart and space requirements for each department (Rogers 1985, 23). CORELAP calculates the total closeness rating (TCR), the sum of closeness rating values between a particular department and others— the one with the highest TCR is centralized in the layout. Next, the application places the department with the highest closeness rating to the centralized department in the layout. The same process continues for the remaining departments not already in the layout. Unlike other popular software packages like CRAFT and COFAD, CORELAP uses the shortest path between departments rather than the centroid criteria.

ALDEP, Automated Layout Design Program, is similar to CORELAP in terms of basic data input requirements and objectives. (Tompkins et. al 2003, 380). What set them apart, though, is that CORELAP uses TCR values to place the departments in the layout as opposed to ALDEP placing the departments in the layout randomly. (Rogers 1985, 23) This difference is philosophical: "CORELAP attempts to generate the best layout, while ALDEP produces many layouts, rates each layout and leaves the evaluation of the layouts to the facilities planner" (Tompkins et. al. 2003, 381).

Table 1.1 Summary of Facility Layout Software

Name of Algorithm	**Exact/Heuristic**	**Type**	**Distance /Adjacency Based Objective**
BLOCPLAN	Heuristic	Construction/Improvement	Both
Vis-Factory	Heuristic	Improvement	Both
VIP-PLANOPT	Heuristic	Hybrid	Distance
CRAFT	Heuristic	Improvement	Distance
COFAD	Heuristic	Improvement	Distance
CORELAP	Heuristic	Construction	Adjacency-based
ALDEP	Heuristic	Construction	Adjacency-based
LayOPT	Heuristic	Improvement	Distance

CHAPTER 2

LITERATURE REVIEW

2.1 Overview

The dynamic and multi-objective facility layout problems have been emerging topics in the recent years. They have garnered interests of researchers across a wide spectrum of academic areas such as industrial engineering, operations management, computer science, and civil engineering.

"The dynamic facility layout problem (DFLP) is the problem of assigning departments to locations during multi-period planning horizon such that the sum of material handling and rearrangement cost is minimized." (Liu 2005, 6) As an extension to the Static Facility Layout Problem (SFLP), the DFLP borrows ideas extensively from SFLP.

Multi-objective facility layout problem, on the other hand, concerns with assigning facilities to locations to satisfy the multi-objectives of minimizing the distance-based objective on one hand and maximizing the adjacency-based objective on the other.

The literary review covers several areas relevant to both topics of dynamic facility layout planning (DFLP) and multi-objective evaluation of facility layouts. Those areas include static facility layout planning (SFLP), dynamic facility layout planning, closeness rating for adjacency-based objective, existing algorithms in solving DFLP, and approaches to multi-objective evaluation of facility layout problems.

The literature for solving static facility layout problems can be categorized into two groups: optimal and heuristic approaches.

2.1.1 Optimal (Exact) Algorithm

Without getting too deeply into details, there are three types of optimal algorithms applied to solve static facility layout problems formulated as quadratic assignment problem:

- Branch and bound algorithms (Gilmore 1962, 305-313) and (Lawler 1963, 568-599)
- Cutting plane algorithms (Bazaraa and Sherali 1982, 991-1003)
- Benders' decomposition algorithm (Heragu 2006, 240)

In general, optimal algorithms can be used solved small size problems optimally; however, they require high computational efforts and memory requirements. With the insights from the optimal algorithms, new and improved heuristics can be developed as the results.

2.1.2 Heuristic (Sub-optimal) Algorithms

The heuristic algorithms for SFLP can be further classified into construction, improvement, and hybrid algorithms. The description of each type is listed in the introduction.

2.1.2.1 Construction Algorithms

The algorithms in this category include Modified Spanning Tree (MST) algorithm by Heragu and Kusiak (1988, 258-268), aforementioned CRAFT, CORELAP and ALDEP as well as PLANET.

2.1.2.2 Improvement Algorithms

2-opt or pair-wise algorithm is one of the most widely used heuristic improvement algorithms. They are often combined into other algorithms as the local search. Since the proposed research incorporates the 2-opt algorithm, detail description of the algorithm is provided (Heragu 1997, 173).

The 2-opt algorithm consists of 3 steps:

1. Let S be the initial solution provided by the user and z its Objective Function Value. Assume the flow (material handling) matrix is symmetric; set S*=s, z*=z, $i = 1$; $j = i+1 = 2$. If the flow matrix is not symmetric, then set $i= 1$ and $j=1$.
2. Exchange the positions of departments i and j in the solution S. If the exchange results in a solution S' having an OFV z' < z, set z=z' and S=S'. If j < (the maximum row (m)* maximum column(n)), set j= j+ 1; otherwise, set i= i+ 1 and j=i+1. If i < (m*n), repeat step 2; otherwise go to step 3.
3. If S≠S*, set S=S*, z=z*, i=1, j=i+1=2 and go to step 2. Otherwise, return S* as the best solution to the user. Stop.

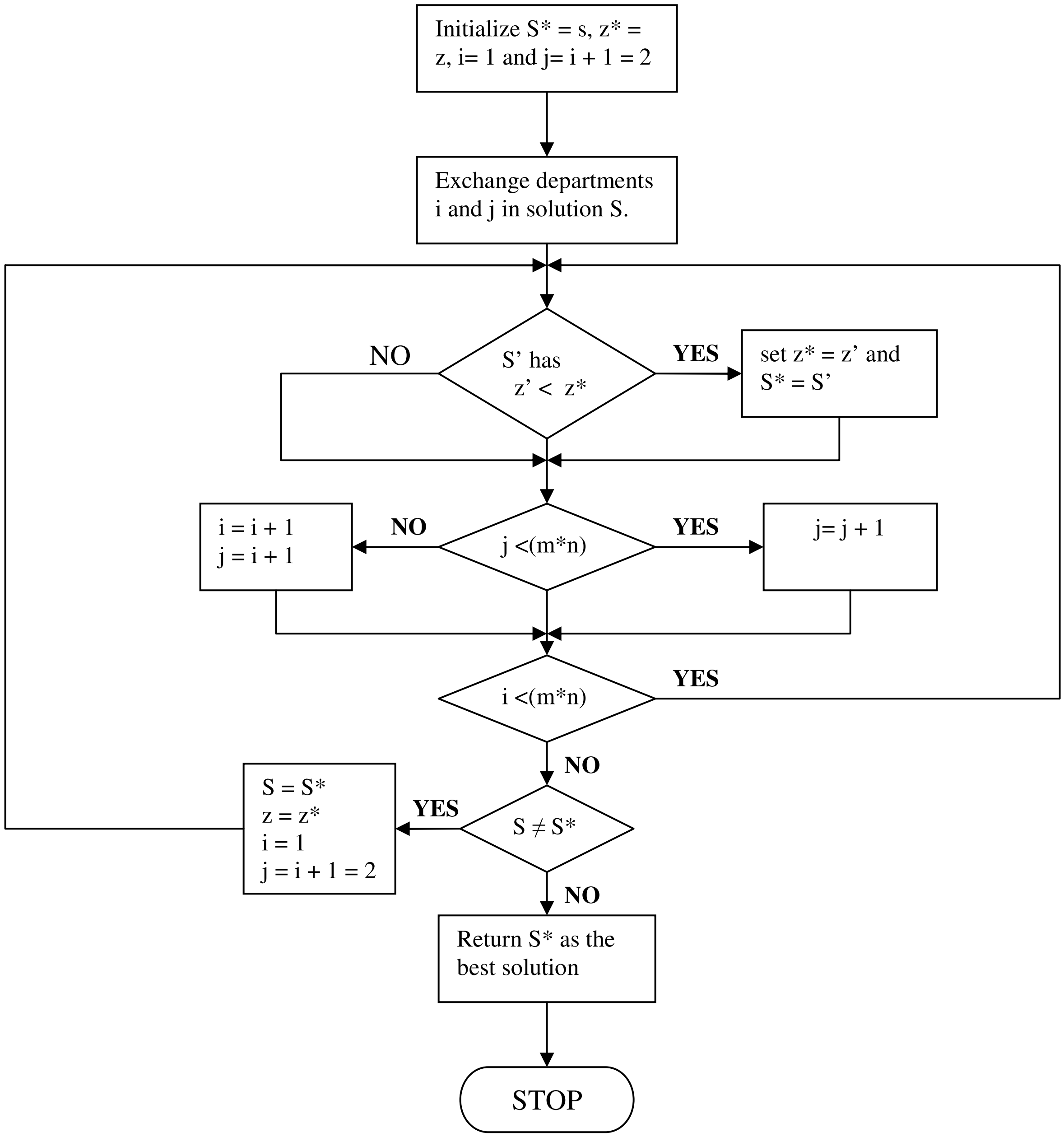

Figure 2.1: Flow chart for 2-opt algorithm

	M		
N	DEPT 1 [1]	DEPT 7 [2]	DEPT 4 [3]
	DEPT 3 [4]	DEPT 9 [5]	DEPT 2 [6]
	DEPT 5 [7]	DEPT 8 [8]	DEPT 6 [9]

Figure 2.2: M x N facility layout

Additionally, various other so-called meta-heuristic improvement algorithms have been applied to solve SFLP, with various degrees of success. “A meta-heuristic is a set of algorithmic concepts that can be used to define heuristic methods applicable to a wide set of different problems” (Dorigo and Stützle 2004, 33). To state it plainly, a meta-heuristic provides the general framework from which sub-set or problem-specific heuristic algorithms can be derived. The main objective of meta-heuristics is to avoid getting “stuck” in local optima by introducing general mechanism to extend upon the local search algorithms. The notable meta-heuristic algorithms are:

- Simulated Annealing (SA)
- Tabu Search (TS)
- Genetic Algorithm (GA)
- Ant Colony Optimization (ACO)

Simulated Annealing, inspired by a metallurgic process of heating and controlled cooling of a material to increase the size of its crystals and thus reduce their defects, has been applied to solve combinatorial optimization problems. One main feature of simulated annealing is that it accepts inferior solutions but improves on them gradually. Burkard and Rendl (1984), Wilhelm and Ward (1987) applied the SA meta-heuristic to solve the static facility layout problem. (Kuppusamy 2001, 26)

The tabu search, introduced by Glover (1989 and 1990) is a meta-heuristic with "memories". It relies on the use of memories or 'tabu lists'. The memories could be long-term or short-term. The short-term memory contains the recently explored sub-optimal solutions which are 'taboo' and forbidden to be considered. They could be considered, however, when they satisfy certain 'aspiration criteria'. The long-term memory is used for intensification and diversification purposes. The intensification process is to explore solutions in the neighborhood of a good solution while the diversification process is to 'diversify' the solutions into the uncharted territories in order to explore solutions not yet discovered. The tabu search is often combined with other heuristic (2-opt algorithm) or meta-heuristics (simulated annealing) to produce more efficient algorithms since it makes up for other algorithms' lack of memories. Skorin-Kapov (1990) applied the tabu search to QAP by creating Tabu Navigation Algorithm.

Genetic algorithm is yet another meta-heuristic that has been applied to QAP with degrees of success. Known as a population-based algorithm, it uses genetic operators (reproduction, mutation, and recombination) inspired by population genetics to explore the solution space. Works by Fleurent and Ferland (1994), Tate and Smith (1995), and Suresh et al. (1995) are related to applying genetic algorithms to facility layouts (Kuppusamy 2001, 23).

2.1.2.3 Hybrid Algorithms

As mentioned earlier, meta-heuristics provide the general framework for the heuristic algorithm; they do not dictate the specific details in the algorithms. Therefore, there are several heuristics which are hybrids of meta-heuristics.

Heragu has proposed the Hybrid Simulated Annealing (HSA) Algorithm to solve the static facility layout problem. Based on existing heuristics, initial facility layouts are generated through the modified penalty and 2-opt heuristics and then improved through the simulated annealing algorithm. (2006, 257) According to the performance comparison by Heragu and Alfa, the proposed algorithm produces better quality solutions than Skorin-Kapov's tabu search, 2-opt and 3-opt algorithms. (1992, 190-202)

Maniezzo proposed ANTS (Approximate Nondeterministic Tree-Search System), a combination of approximate branch-and-bound and Ant Colony Optimization, to solve combinatorial optimization problems (1999, 358-369). Ant Colony Optimization (ACO) will be discussed immediately later since this proposed research is based largely on the ACO concept and therefore deserves its own section.

2.1.2.4 Ant Colony Heuristics (Background)

With the introduction of real ant behavior in the paragraph above, the following section will discuss the Ant Colony Optimization Meta-heuristic. Even though there are a variety of ACO in use, Ant Colony Optimization has the following basic characteristics (Jian Shang 2002, 24):

- Using ants as computational agents to generate solutions

- Using pheromone deposition/evaporation for communication
- Using stochastic policies to decide which path to take
- Using local moves to find the shortest paths from source to destination or optimal solutions

ACO has several advantages over other heuristic methods:

- scalability
- robustness
- suitability for dynamic environment

It is scalable since the ants (computational agents) are working in a decentralized environment, each responsible for its own solution computation. It is robust since if one or few ants fail, it will not affect the overall performance of the heuristic. The ACO can be run continuously and adaptive to changes in real time— a necessity in a dynamic environment. (Lerman and Galstyan 2001)

However, there are also weaknesses associated with ACO. For one thing, the coding of ACO is not straightforward, with several types of strategies—diversification and intensification—involved. Furthermore, several parameters are used in the ACO algorithms; those parameters are determined usually arbitrarily or through trial-and-errors.

Gambardella, Taillard, and Dorigo presents the Hybrid Ant System (HAS-QAP) to solve the QAP facility layout problem. See the flow chart in Figure 2.3 for the HAS-QAP algorithm structure. Since HAS-QAP is an improvement heuristic algorithm, it would need to have set of initial solutions first. Therefore, the first step in the algorithm is to generate a set of initial solutions, each solution (facility layout) associated with one ant. The solution is then improved with the local search/optimization procedure. After the initial solutions are generated, the pheromone trails are initialized by setting all pheromone entries to the same initial value. Afterwards, the ‘pheromone trail swap’ is performed to modify each ant’s solution. The swap is performed based on a set of policies: a department *r* is randomly selected between 1 and *n*. Then a second department is selected where $s \neq r$ and based on one of two probabilistic policies. The local optimization algorithm is performed again to improve on the modified solution. If the best solution is found by one of the ants is better than that at the start of the local optimization procedure, the intensification is activated. The newly found best solution is used to start the next iteration. The intensification process is to explore the neighborhood of the best solution found so far. The pheromone matrix is next updated after all the ants have gone through the local search process. The pheromone update is carried out by first decreasing the pheromone trails to simulate the evaporation of pheromone, and then reinforcing the pheromone trails based on the solution quality. The pheromone trails are maintained in the pheromone trail matrix P, where entries P_{ij} measures the desirability of assigning department *i* to location *j*. After a certain number of iterations and the solution associated with each ant has not improved, a diversification strategy is used to ‘diversify’ the solution into unexplored solution space. Once the diversification is activated, the information in the pheromone trails would be erased and re-initialized. The entire HAS-QAP process is repeated until the maximum number of iterations is reached (1999, 167-176).

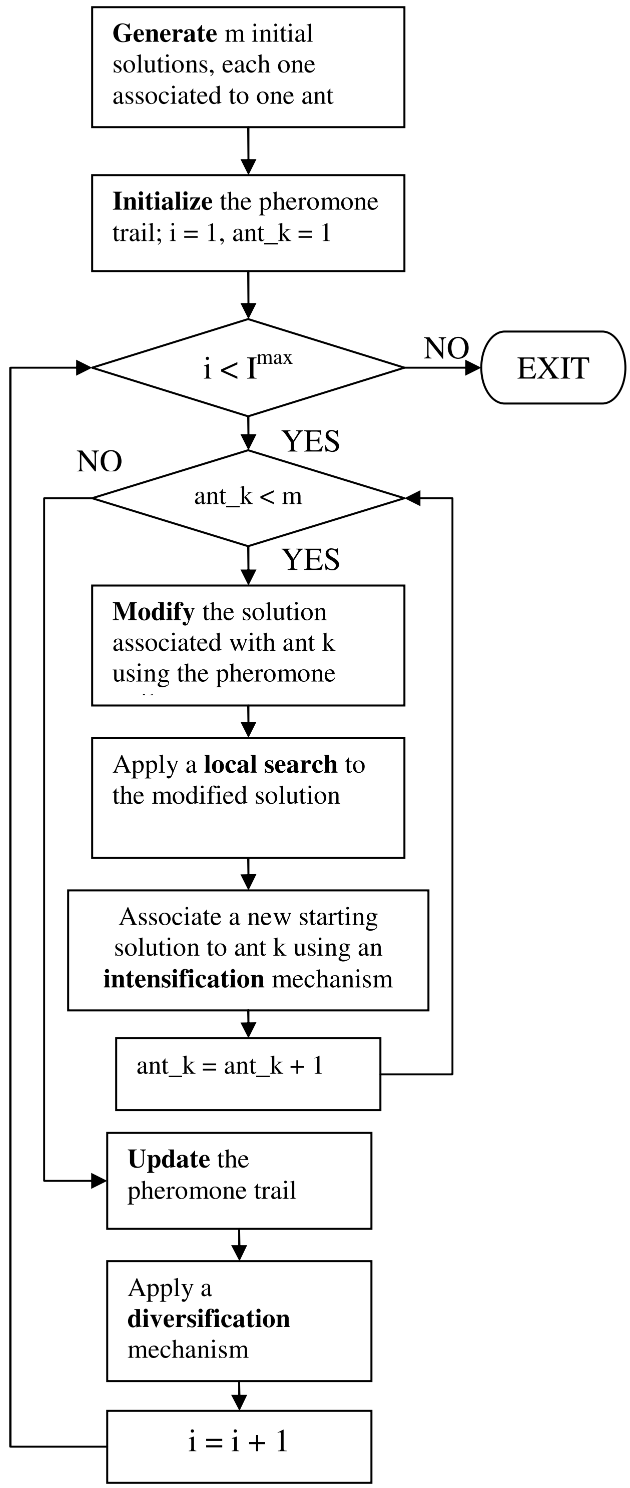

Figure 2.3: Flow chart for HAS-QAP algorithm

2.2.1 Dynamic Layout Algorithms

The dynamic layout models again can be categorized into optimal/exact and heuristics/sub-optimal.

2.2.1.1 Optimal (Exact) Models

Rosenblatt in 1986 proposed a model of dynamic layout. (Rosenblatt 1986, 76-86) This is the first paper on the dynamic facility layout problem (DFLP). To solve the problem, Rosenblatt proposed a dynamic programming model.

Lacksonen and Enscore (1993, 503-517) used five modified optimal/heuristic algorithms to solve the dynamic layout problems:

- a model based on the dynamic programming algorithm
- a model based on the branch and bound algorithm
- a model based on a modification of the cutting plane algorithm
- a model based on cut trees
- a model based on CRAFT

2.2.1.2 Heuristic (Sub-optimal) Models

Urban proposed a steep-descent pair-wise interchange procedure combined with the concept of forecast windows (1993, 57-63). Balakrishnan, Cheng and Conway proposed an improvement to Urban's (1993) forecast windows procedure for solving the dynamic layout problem by complementing it with the backward method. They also applied Urban's heuristic to dynamic programming (2000, 3067-3077).

In the genetic and evolutionary heuristics areas, there are papers by Conway and Venkataraman (1994), Balakrishnan and Cheng (2000), and Dunker, Radons and

WestKämper (2005) for solving unequal size facility layouts as well as Kochhar and Heragu's DHOPE for solving dynamic multi-floor DFLP. (1999).

The assumption that material flows (in from-to chart) can be determined in advance "may not be *realistic* in uncertain and volatile environments where changes in mix and volume may be known only just prior to the revised production run." (Heragu 1997, 195) Krishnan, Cheraghi, and Nayak proposed a new tool for the dynamic layout problem called 'Dynamic From Between Chart' (DFBC), "which can be used to capture the dynamic relationship between machines at any instant and to continuously monitor the product volume and flow between machines". (2006, 185) The from-between chart is different from the traditional from-to charts, which capture only the 'snapshot' of material flows at the beginning of a period. They validated the tool using the genetic algorithm.

Kuppusamy in his master's thesis proposed three variants based on the Simulated Annealing model. SA I is an adaptation of Simulated Annealing for dynamic layout problem. SA II is just like SA I but with reheating strategy. The third heuristic, SA COMBO, is the combination of the pair-wise exchange heuristic with time windows, SA and the backward pass pair-wise exchange heuristic. (2001)

Liu also presented three models based on the tabu search. TSbasic is the adaptation of tabu search heuristic for the dynamic layout problem. TSall incorporates frequency-based memory and diversification/intensification strategies with the tabu search. Probabilistic tabu search heuristic (PTS) discreetly selects candidates for tabu search. (2005)

Jin Shang (2002) and McKendall (2006) proposed three variants of Ant Colony Optimization models for solving the dynamic facility layout problem. The first (HAS I) is derived form Gambardella's HAS-QAP with adaptation for dynamic facility layout problem. The second heuristic (HAS II) combines the ideas of HAS I and Simulated Annealing meta-heuristics. The third heuristic (HAS III) adds the look-ahead/look-back strategy to the pair-wise exchange heuristic (local search). The author's models had performed well with the two set of input data from Lacksonen and Enscore (1993) and Balakrishnan and Cheng(2000). In summary, the main difference among the three algorithms is the local search/optimization─ HAS I uses a random descent pair-wise exchange heuristic; HAS II uses the Simulated Annealing (SA) as the local search; HAS III uses the random descent pair-wise exchange with the look-ahead/look-back strategy. (McKendall and Shang 2006, 790-803). This proposed research is based on the first model by this author.

2.3.1 Multi-objective Facility Evaluation

Rosenblatt pioneered the notion of multi-objective approach to facility layout problems (1979, 323-332). In his 1979 paper, "The facilities layout problem: a multi-goal approach", he combines both qualitative and quantitative models with conflicting objectives together to come up with a 'multi-objective formulation':

(Quantitative model)

$$\min Z_x = \sum_{i=1}^{n}\sum_{j=1}^{n}\sum_{k=1}^{n}\sum_{l=1}^{n} A_{ijkl} X_{ij} X_{kl}$$

subject to

$$\sum_{i=1}^{n} x_{ij} = 1;\ j = 1,\dots n$$

$$\sum_{j=1}^{n} x_{ij} = 1; i = 1,\dots n$$

x_{ij}= 0 or 1.

providing that

$$x_{ij} = \begin{cases} 1 \text{ if department } i \text{ is assigned to location } j \\ 0 \text{ otherwise.} \end{cases}$$

$$x_{kl} = \begin{cases} 1 \text{ if department } k \text{ is assigned to location } l \\ 0 \text{ otherwise.} \end{cases}$$

$$A_{ikjl} = \begin{cases} f_{ik} d_{jl} & \text{if } i \neq k \text{ or } j \neq l \\ f_{ii} d_{jj} + c_{ij} & \text{if } i = k \text{ and } j = l. \end{cases}$$

where:

c_{ij} = cost per unit time associated directly with assigning department i to location j;
d_{jl} = distance form location j to location l;
f_{ik} = work flow from department i to department k.
Z_x = The total cost of the generated layout

(Qualitative Model)

$$\max Z_y = \sum_{i=1}^{n}\sum_{j=1}^{n}\sum_{k=1}^{n}\sum_{l=1}^{n} W_{ijkl} X_{ij} X_{kl}$$

subject to

$$\sum_{i=1}^{n} X_{ij} = 1;\ j = 1,\dots n$$

$$\sum_{j=1}^{n} X_{ij} = 1; i = 1,\dots n$$

X_{ij}=0 or 1 $\forall$ *i*, *j*

where:

$$W_{ijkl} = \begin{cases} r_{ik} \text{ if locations } j \text{ and } l \text{ are neighbors} \\ 0 \text{ otherwise} \end{cases}$$

r_{ik} = closeness rating desirability of departments *i* and *k*

(Multi-objective Model)

$$\text{Min } Z = \alpha_2 z_x - \alpha_1 z_y = \sum_{i=1}^{n}\sum_{j=1}^{n}\sum_{k=1}^{n}\sum_{l=1}^{n}(\alpha_2 A_{ijkl} - \alpha_1 W_{ijkl})x_{ijkl}$$

subject to $\sum_{i=1}^{n} x_{ij} = 1 \quad j = 1, \ldots., n$

$\sum_{j=1}^{n} x_{ij} = 1 \quad i = 1, \ldots., n$

x_{ij} = 0 or 1

$\alpha_1 + \alpha_2 = 1$ and $\alpha_1, \alpha_2 \geq 0$

where:

α_2 and α_1 are weights assigned to the total flow cost and closeness rating, respectively. *Z* is the total rating score after weighing both quantitative and qualitative costs.

Rosenblatt also proposed a graphical method to create an ‘efficient frontier’ based on the conflicting objectives of minimizing the flow cost and maximizing the closeness rating.

Dutta and Sahu(1982,773-782) expanded on Rosenblatt’s multi-objective concepts and came up with their own mathematical model:

$$\min C' = W_2 C - W_1 R$$

where

W_1 = the weight for closeness rating score
W_2 = the weight for flow cost
C = the total flow cost
R = the closeness rating score
C' = the score for measuring the effectiveness of the generated layout based on the objectives

Based on the effective score, they applied the improvement algorithm of pair-wise exchange to come up with good solutions. Not unlike Rosenblatt's closeness rating score, their proposal is also following the same pattern:

A=6, E=5, I=4, O=3, U=2, X=1

This proposed model, however, differed from aforementioned Rosenblatt's in several ways:

- Pair-wise exchange algorithm is used to select layouts as opposed to using the graphical method.
- Only the closeness rating values for adjacent departments are added and not considering department pairs sharing a common corner.

Not long after Dutta and Sahu published their paper, Fortenberry and Cox (1985, 773-782) also proposed their mathematical model on multi-objective layout problem. Their 'multiplicity' model differed from Rosenblatt's and Dutta and Sahu in several key areas:

- The closeness rating score is assigned the following way:

  A=5, E=4, I =3, O=2, U=1, X=-1

  where the 'undesirable' X closeness rating is assigned a negative value.

- Their multiplicity model takes closeness rating values into account "regardless of whether departments have common boundaries, common corners or are separated by some distance" (775).

Urban reviewed the work done by Fortenberry and Cox, and expanded on their mathematical model. (1987, 773-782) He introduced the constant *c*, which is a positive constant (weight) to determine the importance of the closeness rating relative to the work flow. The value of the constant goes from zero to a very high number. With zero value only the quantitative aspect of the model is considered; whereas, with a high number the qualitative aspect of the model is considered. He suggested that if there is no particular reason the constant should be set to the maximum work flow between any two departments. By having the constant *c* in the model, he argued would eliminate the inherent issue of penalizing facilities with undesirable closeness ratings and high work flows more than those with undesirable closeness ratings and low work flows in Fortenberry and Cox's model. His model is shown as below:

$$a_{ijkl} = d_{jl}(a \cdot f_{ik} + c \cdot r_{jl})$$

His model provided the following benefits:

- Maintaining the negative rating for undesirable 'X' by separating the facilities as far away as possible.
- Handling facilities with no work flow between them.
- Considering closeness rating between non-adjacent facilities.

In Jen Shang's "integrated approach to the multi-objective problem" (1991, 291-304), the author approached the problem in three steps: (1) using analytical hierarchy process (AHP) to address the adjacency-based aspect of the problem, (2) considering both distance-based objective and adjacency-based objective with a modified mathematical model, (3) solving the problem through a heuristic algorithm.

Jen Shang first applied the analytic hierarchy process (AHP) to derive the closeness ratings and the objective function coefficients. AHP is a multi-objective decision tool which allows the user to evaluate the relative importance of each objective and ranking them based on the weight assigning to them.

Second, the author modified Urban's model by incorporating the sum of the qualitative weights obtained from the AHP. The modified mathematical model is presented below:

$$a_{ijkl} = d_{jl}(a \cdot f_{ik} + b \cdot c \cdot r_{jl})$$

where a is the sum of quantitative weights, b is the sum of the qualitative weights, and c is a constant. The constant c is set to the maximum work flow between any two departments divided by the average of the positive weights.

Lastly, Shang applied the simulated annealing heuristic method to come up a good facility layout solution.

In Lee's PhD dissertation, "Heuristic graph-Theoretic Approach in Facility Layout Problem", he applied the graph theory (deltahedron heuristic) to integrate the maximization of the total closeness rating problem and the minimization of the total transport cost problem. (Lee 1988, 66)

In another approach to the multi-objective layout problem, Ertay, Ruan, and Tuzkaya presented a model which utilized the commercial software package, VisFactory, to generate alternative layouts based on the distance-based objective and applied AHP analysis for adjacency-based objective and later input both scores to Data Envelopment Analysis (DEA) to "simultaneously considering both the quantitative and qualitative performance data leading to the determination of the more robust layout design alternatives" (2006, 237-262)

CHAPTER 3

RESEARCH APPROACH

The objective of this research is to solve the dynamic layout problem with multi-objective approaches. The following steps have been taken to achieve this objective.

1. Survey existing literatures on multi-objective and dynamic layout problems.
2. Develop an algorithm methodology which incorporates both a distance-based objective and an adjacency-based objective to solve dynamic layout problem. The algorithm will be developed using C++ in the Windows XP environment running on 1.82GHz Intel processor with 100 GB RAM .
3. Apply the ACO I algorithm by Jin Shang based on Gambarella's HAS-QAP to minimize the distance-based objective function value of dynamic facility layout.
4. Use Adjacency-based models by Dutta and Sahu (1982) and Urban (1987) to maximize the adjacency between departments based on closeness ratings.
5. Compare the resulting solutions with other dynamic layout algorithms and multi-objective algorithms. The objectives of the created algorithm are to minimize the overall OFV while place departments next to each other based on the activity preference chart.

6. Analyze the data from dynamic layout and multi-objective results and incorporate it into multi-objective dynamic layout problem.
7. Document a methodology for Ant Colony Optimization─ Dynamic Multi-Objective Layout (ACO-DML) potential users.

3.1 Research Methodology

The proposed model, Ant Colony Optimization Dynamic Multi-objective Layout (ACO-DML) model, takes two approaches to the dynamic layout problem─ quantitative/distance-based objective and qualitative/adjacency-based objective.

For quantitative/distance-based objective, Jin Shang's HAS I algorithm, which is the adaptation of Gambardella's Ant Colony Optimization HAS-QAP for dynamic facility layout problem, will be used. The distance-based objective is to minimize the objective function value of distance and material flow cost of a given facility layout across multiple periods. For qualitative/adjacency-based objective the two models presented by Dutta and Sahu (1982) and Urban (1987) will be used. The adjacency-based objective is to maximize the adjacency of departments based on their closeness ratings.

The proposed research incorporates those objectives and heuristics to come up with facility layouts that satisfy both objectives across multiple time periods. This capability to satisfy both distance-based and adjacency-based objectives is the contribution to knowledge. The following diagram depicts the relationship among the different models.

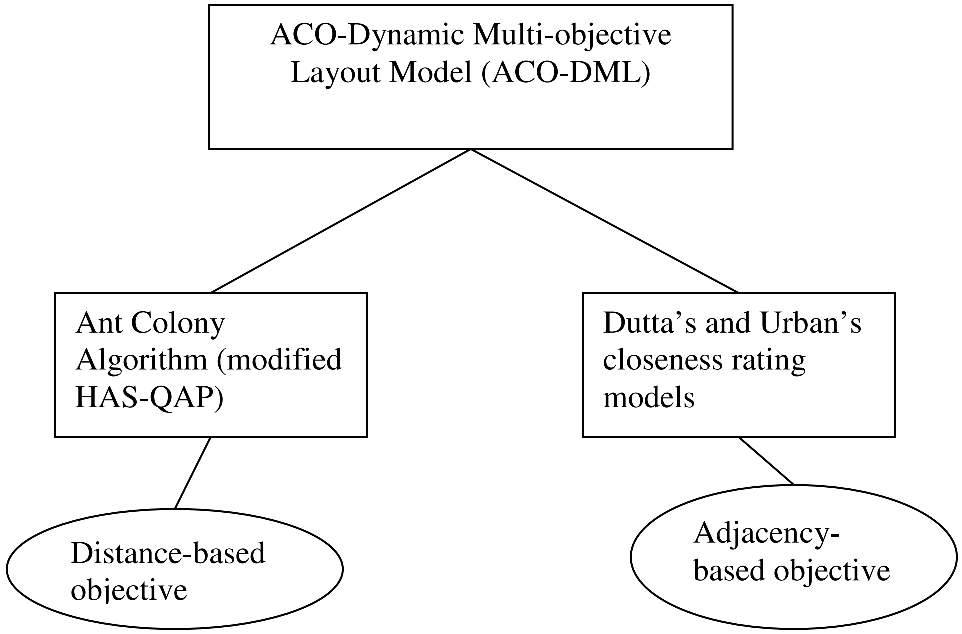

Figure 3.1: Dynamic multi-objective layout model

The users can follow the methodology described below to apply ACO-DML to optimize their facility layouts:

1. Perform data collection and material-flow analysis
2. Create From-to chart for quantitative objective
3. Interview the stakeholders on qualitative factors of facility layout
4. Create Adjacency-based chart for qualitative objective
5. Run the data through the ACO-DML heuristic algorithm.
6. Evaluate the alternative facility layouts.
7. Summarize results and make recommendation

3.1.1 Step 1: Perform Data Collection and Material-flow Analysis

The data can be collected on material flows performing the materials-flow analysis. Among the documents required in the analysis are assembly drawings, assembly charts, routing sheets, and flow-process charts. (Schroeder 2000, 112)

An assembly drawing (Figure 3.2) is a blue-print which specifies how the manufacturing parts are to be put together. An assembly chart (Figure 3.3) is prepared to show the steps of putting the manufacturing parts together. The routing sheet (Figure 3.4), or known as operations process sheet, shows the operation, departments involved as well as tools and equipments required to perform the operation. The flow-process chart (Figure 3.5) shows the material flow process based on a list of pre-defined steps represented by a set of symbols: operation (a task or work activity), inspection (an inspection of the product for quantity or quality), transportation (a movement of material from one point to another), storage (an inventory or storage of materials awaiting the next operation), and delay (a delay in the sequence of operations). For each step, the distance measuring in feet and time in minutes are recorded if they are relevant to that particular step.

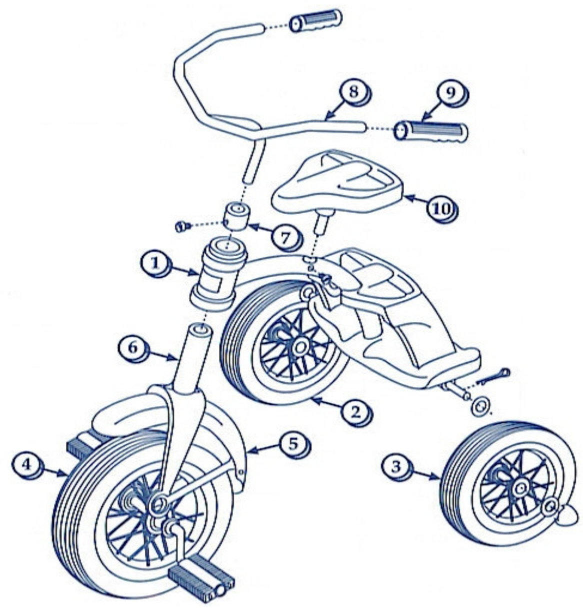

Figure 3.2: Example of Assembly Drawing (Schroeder 2000, 113)

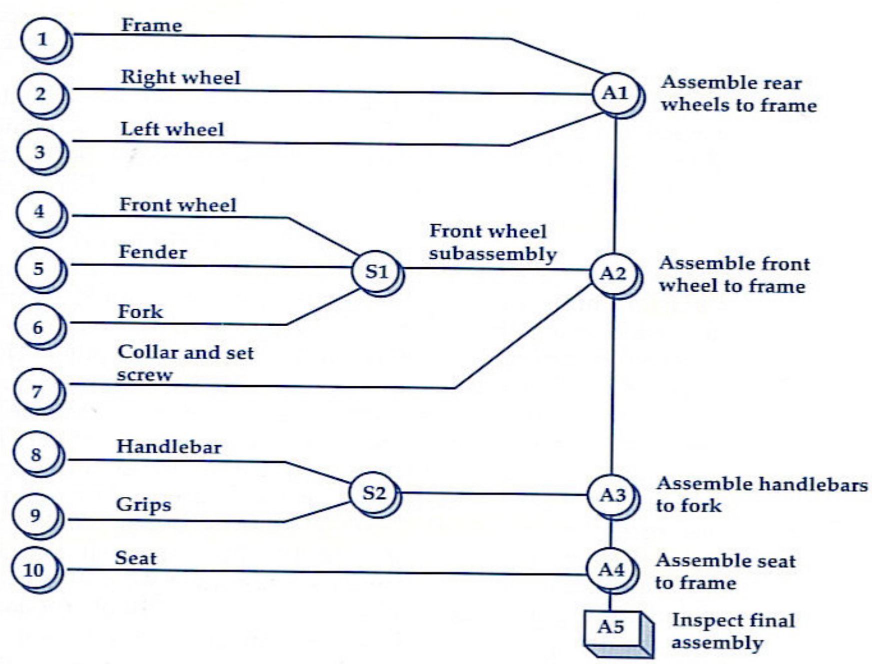

Figure 3.3: Example of Assembly Chart (Schroeder 2000, 113)

Part Name: Rear Tricycle Wheel
Date: 9/8/98
Assembly: A2936
Issued by: RGS
Part Number: 261982

Operation	Description	Dept.	Tools/Equipment
1	Cut wires for spokes	06	E10 Shear
2	Cut tubing for axle	06	F2 Hacksaw
3	Cut flat steel for rim	02	F1 Shear
4	Stamp end caps for spokes	03	A7 Press
5	Form steel for rims	03	A4 Press
6	Weld rim together	01	U9 Welder
7	Weld caps to axle tube	01	U9 Welder
8	Weld spokes to axle and rim	01	U7 Welder
9	Cut rubber tire to size	06	E7 Shear
10	Fix rubber tire on rim	09	C6 Press

Figure 3.4: Example of Routing Sheet (Schroeder 2000, 114)

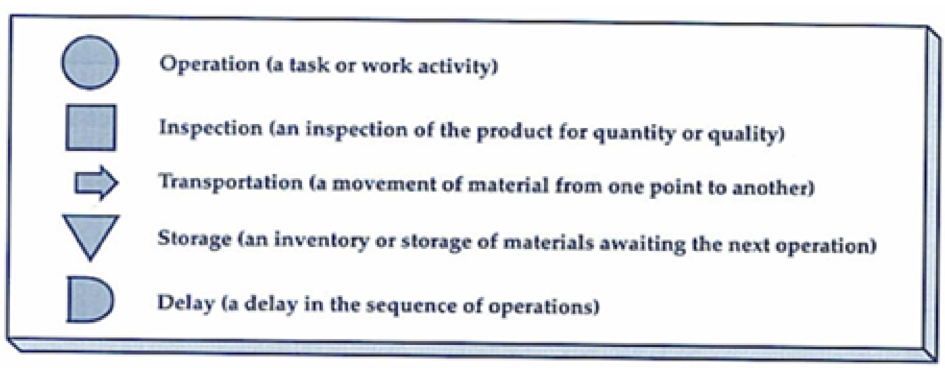

Figure 3.5: Symbols used in a flow-process chart (Schroeder 2000, 115)

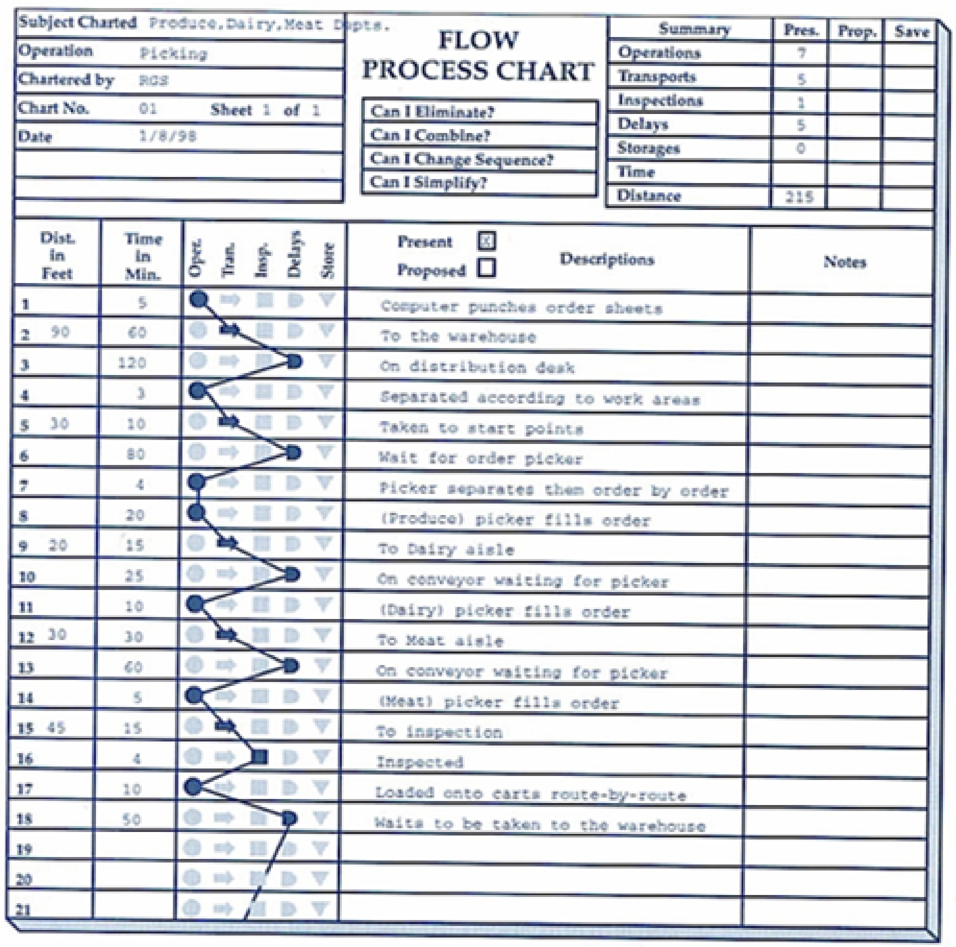

Figure 3.6: Example of a flow-process chart (Schroeder 2000, 115)

With the data from the documents described above, we can determine the material flows by performing the equivalent unit load analysis on material flows. One way to do this is to do the “mag count”. The mag count is “a system of cubic volume measure of materials adjusted for other influencing factors, such as bulkiness, risk of damage, etc.” (Phillips 1997, 85). The mag count is used for highly varied and dissimilar materials. Even though the mag count system has not won widely acceptance for quantitative measure, it was an attempt to provide a method to measure “the volume and intensity of material flow without regard to the material handling equipment used to transport the flow" (Phillips 1997, 85). To calculate the relative cost of materials flow, Phillips suggested first establishing an equivalent unit load. It is essential since materials come in different shapes, weight, size, etc. Some properties that must be considered in equivalent analysis are:

- Shape ─ Awkwardness, compactness, square, flat, round, irregular
- Weight ─ Per unit or specific weight
- Size ─ Length, width, height
- Value ─ Wood, gold
- Fragility ─ Risk of damage, hazardous
- Conditions ─ Sticky, wet, hot, frozen, etc.
- Equipment ─ Fork truck, cart, crane, etc.

Additionally, if the material flow cost is measured in terms of dollars, the time value of money needs to take into account. Because money is subject to change due to demands or economic conditions such as inflation, the value of money does not stay constant through time. The use of cost index can resolve this issue. "A cost index compares cost or price changes between periods for a fixed quantity of goods or services". (Ostwald, 1992, 170) For engineers and planners make estimation based on previous material flow costs, cost indexes convert costs applicable in the past to equivalent costs now or in the future. Ostwald (1992, 171) gives the following detailed description of cost index:

> A cost index is a dimensionless number for a given year showing the cost at that time relative to a certain base year. If a design cost at a previous period is known, then present cost is determined by multiplying the original cost by the

ratio of the present index value to the index value applicable where the original cost was obtained.

The formula for calculating the present cost in dollars is shown:

$$C_c = C_r\left(\frac{I_c}{I_r}\right) \qquad (3.1)$$

where C_c = present or future or past cost, dollars
C_r = original reference cost, dollars
I_c = index number at present or future or past time
I_r = index number at time reference cost was obtained

The general purpose indexes are usually published by the industries such as Construction Cost Index, Building Cost Index, and Materials Cost Index from ENR (Engineering News-Record), a division of McGraw-Hills construction. For specific cost indexes, there are several ways to calculate those (Ostwald, 1992, 171):

1. Adding costs and dividing by their number
2. Adding the cost reciprocals and dividing by their number
3. Multiplying the costs and extracting the root indicated by their number
4. Ranking the costs and selecting the median value
5. Selecting the mode cost
6. Adding actual cost of each year and taking the ratio of those sums.

Ostwald (1992, 172) suggests that the cost index for a particular material can be determined from the historical prices for a period of time. Since cost indexes are computed on a periodic basis, the prices collected for the material can be averaged out for the period of time such as a month, quarter of a year, a year and so on. To illustrate the concept, the cost index for a particular material may look like the following table:

Table 3.1: Cost Estimation Using Cost Index

	Period		
	1	2 (Benchmark)	3
Price	$55	$60	$68
Index	0.92	1.0	1.13

The cost index is calculated for each period by dividing the price of each period by the price of the selected (benchmark) period. In this example, period 2 is selected as the benchmark; therefore, the cost index is 1.0 ($60/$60). For period 1 the cost index is 0.92 ($55/$60). The cost index for period 3 is also calculated the same way.

The average periodic change can be determined from the calculated indexes mentioned above with the following formula adopted with a slight modification from Ostwald's *Cost Estimating* (Ostwald, 1992, 172):

$$r = \left[\left(\frac{I_e}{I_b}\right) - 1\right]^{1/n} \qquad (3.2)$$

where r = average percentage rate per period
I_e = index value at end of period
I_b = index value at beginning of period
n = number of periods

Based on the formula, the average index rate is the following value over 3 time periods:

$$r = \left[\left(\frac{1.13}{0.92}\right)^{1/3} - 1\right] = 0.07$$

The formula can be rewritten to determine the future cost index if the average index rate is assumed to be persistent (Ostwald, 1992, 173):

$$I_e = I_b(1+r)^n \qquad (3.3)$$

For example, suppose the cost index of period 5 is to be determined, it can be calculated:

$$I_5 = (0.92)(1+0.07)^5 = 1.29$$

Assume the total cost for period 2 (TC_2) is $250, using the aforementioned equation (3.1) yields the following future cost ($322.50) for period 5 (n=5):

Besides the aforementioned material flow costs, according to Kochar and Heragu (1999, 2430), alternating an existing layout incurs two types of costs:

(1) The cost of downtime in production.

(2) The cost of moving the equipment from their existing location to the new location. The rearrangement cost involves planning, dismantling, construction, movement and installation costs.

3.1.2 Step 2: Create From-to Chart for Quantitative Objective

The next step after the equivalent unit load analysis and material flow cost is to construct the from-to chart. The following procedures for constructing the from-to chart taken directly from Phillips' *Manufacturing Plant Layout* book with minor modifications (1997, 88):

1. Review the routing sheet and flow-process chart to determine those departments between which there is material flow.
2. List the departments in identical order across the top columns and down the rows on the left-hand side of the chart.

3. Establish a measure of flow that indicates equivalent unit loads or equivalent transport-related materials handling costs. When all items are equally easy to move, the projected number of trips can serve as the measure. If items vary significantly in size, shape, weight, damage potential, etc., develop transport difficulty factors to establish equivalency. If we are working on a total plant rearrangement, a sampling of moves along the paths to verify the data is recommended.
4. Using the flow paths shown on the routing sheet, record the equivalent unit load moves (combine both to and from moves in one cell) between each department pair.
5. In a multi-product manufacturing environment, construct a "sub" from-to chart for each product (or sampling of major products). When completed, combine all of these into one "total" from-to chart.

An example of the material flow matrix is shown as following

	1	**2**	**3**	**4**	**5**	**6**
1	0	6	9	5	3	8
2	6	0	2	1	1	2
3	9	2	0	6	3	3
4	5	1	6	0	7	4
5	3	1	3	7	0	2
6	8	2	3	4	2	0

Figure 3.7: Example of quantitative-based from-to chart

3.1.3 Step 3: Interview the Stakeholders on Qualitative Factors

To come up with the closeness rating scores between pairs of departments, the following steps can be performed. First, the information on the relationship between department pairs can be collected through interviews with management, line supervisors, marketing personnel, workers, receiving and shipping personnel, and others. All inputs should be considered and weighted accordingly. Phillips (1997, 140) recommends that an impartial employee or consultant with no particular self agenda should be entrusted to develop the closeness ranking. Tools such as the Relationship Diagram shown below can be used to assist with closeness rating between departments.

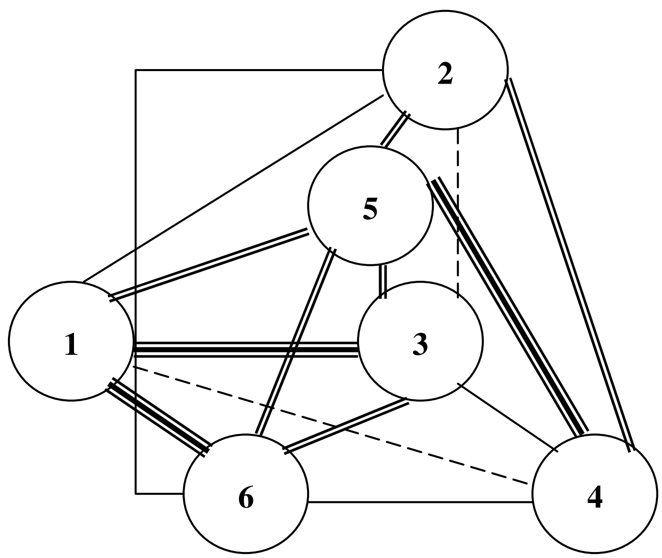

Figure 3.8: Relationship diagram

In the diagram each circle represents each department. The closeness of each department pair is represented by the thickness of the lines; thus, the thicker the line, the higher the affinity between the department pair is. For example, the closeness rating is the highest (an A rating) between department pairs of department 1 and department 6, departments 3 and 1, and departments 5 and 4. The dashed line, however, denotes the undesirable relationship (an X rating) between the department pairs. In this case, departments 2 and 3 and departments 1 and 4 represent this kind of relationship. A possible facility layout based on the relationship diagram shown could be:

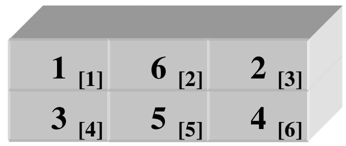

Figure 3.9: Facility layout based on relationship diagram

3.1.4 Step 4: Create Adjacency-based chart for Qualitative Objective

Afterwards, the activity relationship chart with closeness rating scores is created based on those inputs. See Figure 1.6. Later, the closeness rating scores will be converted to numerical values to be used as inputs to ACO-DML algorithm. When the weighted model of Dutta and Sahu (1982, 149) is applied to achieve adjacency-based objective, the closeness rating is converted to numerical values in the following ways:

- ***A*** is assigned a numerical value **6**
- ***E*** is assigned a numerical value **5**
- ***I*** is assigned a numerical value **4**
- ***O*** is assigned a numerical value **3**
- ***U*** is assigned a numerical value **2**
- ***X*** is assigned a numerical value **1**

Urban's model, on the other hand, assigns the closeness rating in the following ways:

- ***A*** is assigned a numerical value **4**
- ***E*** is assigned a numerical value **3**
- ***I*** is assigned a numerical value **2**
- ***O*** is assigned a numerical value **1**

- ***U*** is assigned a numerical value **0**
- ***X*** is assigned a numerical value **-1**

A sample of closeness rating matrix based on Urban's model is shown as following:

	1	**2**	**3**	**4**	**5**	**6**
1	-	O	E	I	A	X
2	O	-	I	U	E	O
3	E	I	-	E	A	X
4	I	U	E	-	O	A
5	A	E	A	O	-	I
6	X	O	X	A	I	-

Figure 3.10: Example of closeness rating matrix

	1	**2**	**3**	**4**	**5**	**6**
1	-	1	3	2	4	-1
2	1	-	2	0	3	1
3	3	2	-	3	4	-1
4	2	0	3	-	1	4
5	4	3	4	1	-	2
6	-1	1	-1	4	2	-

Figure 3.11: Closeness rating matrix with numerical values assigned.

Since the dynamic facility layout requires multiple from-to charts and activity relationship charts for every period, the procedures will be repeated several times until all the periods are covered.

3.1.5 Step 5: Run the Data through the ACO-DML Heuristic Algorithm

Next, with all the data are available, the ACO-DML algorithm can be used to generated facility layouts. Because the ACO-DML algorithm is a heuristic algorithm providing only "good" solutions, it is imperative to execute the algorithm several times to generate several alternative layouts. It is up to the user to decide how many alternative layouts will be generated depending on the factors of time constraints and quality of the solutions. After the alternative layouts are generated, the user can select the best layout out of the bunch based on the total cost.

3.1.6 Step 6: Evaluate the Alternative Facility Layouts

It seems intuitive to simply pick the best layout based on the minimal total cost computed by the ACO-DML algorithm. However, there are also economic factors to be considered. Tompkins et al (2003, 686) suggests using Systematic Economic Analysis Technique (SEAT) to justify the financial basis for layout selection:

1. Specify the feasible alternatives to be compared.
2. Define the planning horizon to be used.
3. Estimate the cash flows for each alternative.
4. Specify the discount rate to be used.
5. Compare the alternatives using a discounted cash flow (DCF) method
6. Perform supplementary analyses.

7. Select the preferred alternative.

The first step is to come up with different alternatives to be compared. The feasible alternatives may include the newly generated dynamic facility layouts and the existing facility layout. Frequently, “doing nothing” to the facility layout is chosen since it is used as the benchmark for comparing with other alternatives. (Tompkins, 2003, 686)

The second step is to define the planning horizon to evaluate the dynamic facility layout. The planning horizon is the “time period over which the economic performance of an investment will be measured and evaluated”. (Tompkins, 2003, 687) As a word of caution, the planning horizon is different from the multiple time periods in the dynamic facility layout since the planning horizon treats the evaluation of dynamic facility layout in the entire facility layout life cycle (i.e. from installation of facility layout to the retirement of the facility) while the time period deals with one particular time interval in the facility layout life cycle. The planning horizon is essential in the estimation of the cash flows, which is the next step in the analysis.

The third step is the estimation of the cash flows for each alternative. Both the tangible cash flows (such as revenues, income, or benefits) and intangible cash flows (such as increasing quality, increasing morale, etc.) must be considered. The cost estimation can be based on the past data and records.

The fourth step is to specify the discount rate to be used. The discount rate is also known as the hurdle rate or minimum attractive rate of return (MARR) in various literatures, which is used to establish the minimum acceptable rate of return that an investment must earn.

The fifth step is to compare the alternatives using a discounted cash flow (DCF) method. Because the investment must take time value of money (TVM) into account, the discounted cash flow process converts current cash flows and future cash flows to present values for comparison. The commonly used discounted cash flow methods are net present value (NPV) and internal rate of return (IRR). For detailed information on NPV and IRR, the user may consult engineering economy textbooks on those topics.

The sixth step is to perform supplementary analyses. Three types of supplementary analyses are break-even analysis, sensitivity analysis, and risk analysis.

The seventh step is to select the preferred alternative. With the financial and operational information available, the alternative can now be selected from the set of acceptable facility layouts.

3.1.7 Step 7: Summarize Results and Make Recommendation

At this step, the weighted factor analyses are performed to evaluate all the success attributes developed at the beginning of the process (Phillips 1997, 245). Those success attributes, both tangible and intangible, are evaluated accordingly. The tangible attributes are easily identified such as the rate of return or hurdle rate previously mentioned. The intangible attributes, on the other hand, are less obvious. The intangible attributes required for facility evaluation include:

- Risk of lost production (e.g. downtime)
- Security

- Alignment with operations or manufacturing goals
- Acceptance by employees
- Potential obstacles to the setup of facility layout

The success attributes or evaluation factors are then assigned with weights, preferably by the top management. To aid the evaluation process, Phillips' weight rating sheet (1997, 246), shown in Figure 3.12 and 3.13, can be used. Those ratings are typically assigned either numerical values on the scale of 1 to 5 or letters (A/B/C/D/E). The person or a group of people responsible for evaluation would assign scores to those attributes. The weight of each attribute and its score would then be multiplied. The total score is tallied for each alternative layout at the bottom of the weight rating sheet. The description of the weight rating sheet and the sample of the weight rating sheet are shown as the following:

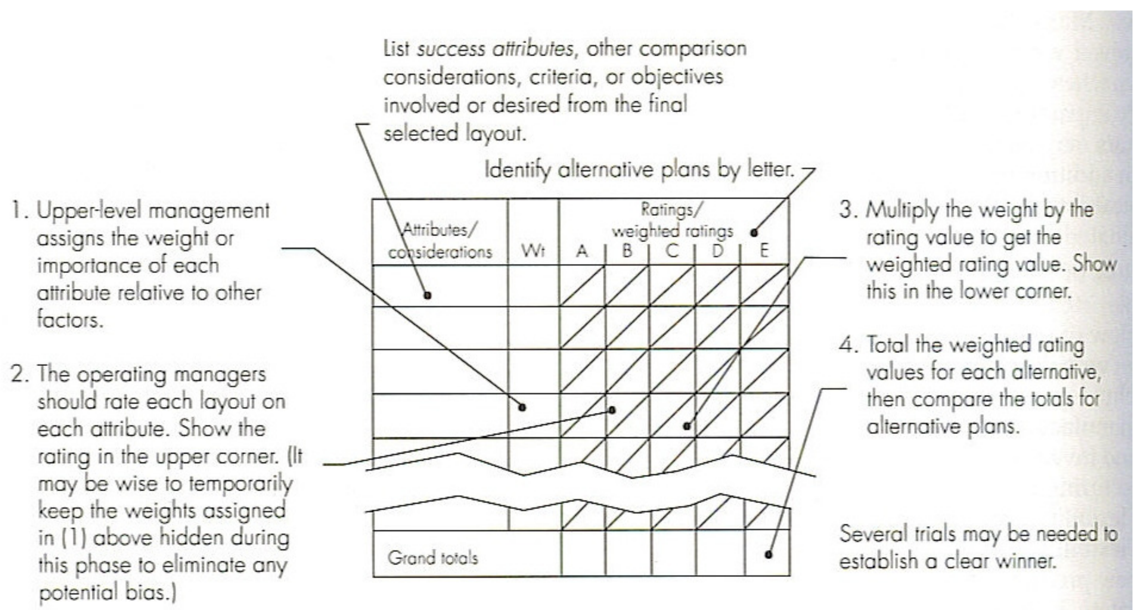

Figure 3.12: Description of weight rating sheet

Weighted Factor Analysis

Plant/area Many Foods, Ltd. Project FOODS 52101 Date 2/12

Alternatives: description or name
A. Alternative #1 East side
B.
C. Alternative #2 West side
D.
E. Alternative #3 North side
Weight set by Senior staff consensus Ratings by

Attributes/ considerations	Wt.	Ratings/weighted ratings					Comments
		A	B	C	D	E	
Initial construction costs	9*	8 / 72		9 / 81		7 / 63	
Efficiency of operations (ongoing costs)	9	9 / 81		9 / 81		8 / 72	
"Togetherness" and communications	6	8 / 48		7 / 42		7 / 42	
Flexibility	8	8 / 64		9 / 72		8 / 64	
Ease of future expansion	7	7 / 49		9 / 63		7 / 49	
Product quality and freshness	10	7 / 70		9 / 90		8 / 80	
Sharing of people and equipment resources	4	4 / 16		4 / 16		5 / 20	
Risk/production loss	10	4 / 40		8 / 80		7 / 70	
Associate convenience	6	5 / 30		5 / 30		5 / 30	
Safety of access and egress	3	9 / 27		9 / 27		8 / 24	
Corporate image/ aesthetics	7	7 / 49		7 / 49		8 / 56	
Totals		546		631		570	

*Weight for initial construction cost is shown for informational purposes only. Estimated actual costs will be used for quantitative comparisons between alternative plans.

The winner

Figure 3.13: Sample of weight rating sheet

In summary, the steps describing the methodology (adopted from Phillips (1997, 41)) are shown in the flow chart (Figure 3.10) below:

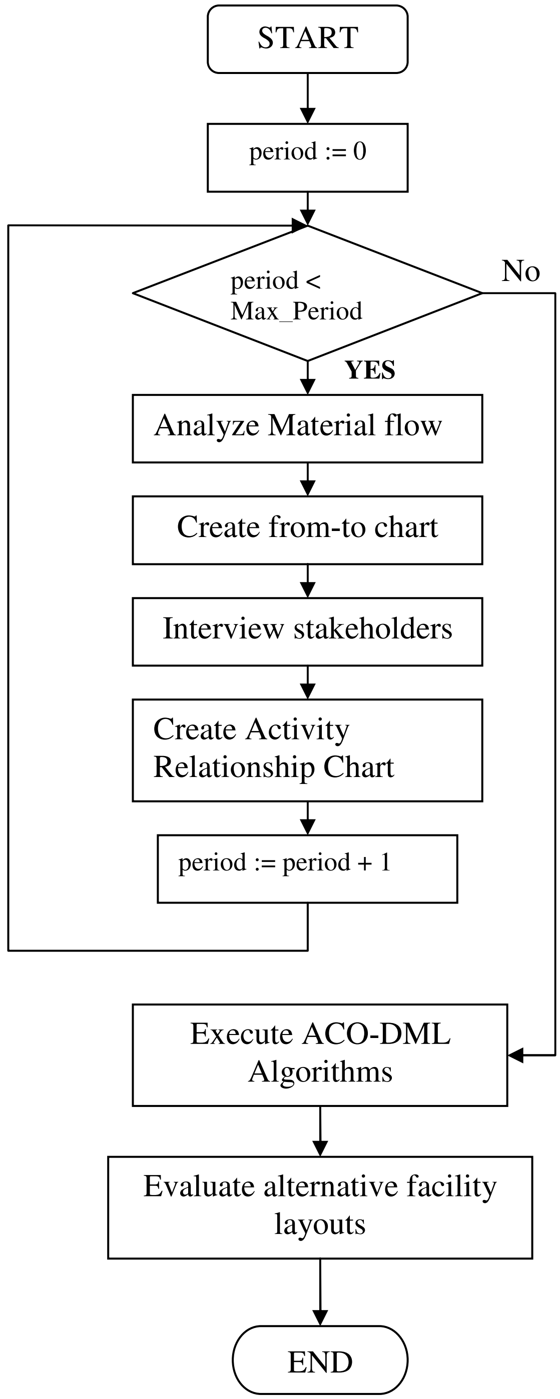

Figure 3.14: Methodology for applying ACO-DML

3.2 Assumptions/Constraints

As a model, the dynamic multi-objective facility layout model is subject to constraints. Those assumptions and constraints of dynamic multi-objective facility layout model are listed below:

- The departments are square and equal in size to be solved as a QAP problem.
- Material flows are deterministic and known ahead of time.
- Material flow occurs between the centers of facilities.
- The initial assignment cost of a department to a location is ignored.

3.3 ACO-DML Notations

Before diving into the discussion of the ACO-DML algorithm, the notations and terms used in the algorithm would first be visited:

- P: Pheromone Trail Matrix (N*N)
- $P_{\pi(i)j}$: Entries of matrix P which measures the desirability of assigning dept i to location j
- n: a specific department in the facility layout ; e.g., 1,...,n
- [n]: a specific location in the facility layout; e.g., [1],...,[n]
- I_{max}: Total number of iterations for the algorithm
- K: Number of ants
- R: Number of pheromone trail swaps
- S: Consecutive number of iterations without improvement before diversification
- q: Parameter(probability) for selecting the pheromone trail swap policies
- α_1: Parameter used to control the evaporation of the pheromone trail

- α_2: Parameter used to reinforce certain pheromone trails based on the best-found solution
- Q: Pheromone trail initialization parameter
- π^*: Best layout plan or solution
- $\pi_{(i)j}$: Department i assigned to location j
- $\pi_{(i)j}^t$: Department i assigned to location j at time period t; e.g., $\pi_{(1)3}^2$ represents department 1 assigned to location 3 at time period 2.
- $f(\pi^*)$: Current best total cost found
- $f(\pi^k)$: Total Cost of layout calculated by ant k
- N: maximum number of departments
- T: maximum time period

3.4 ACO-DML Algorithm

The ACO-DML algorithm is based on Gambardella's HAS-QAP and Jin Shang's HAS I algorithm. The algorithm allows the user to consider several cases: pure material flow model, pure close-ranking model, hybrid, and adding and removing facility layouts. Those case studies are included in the appendix sections. Overall, the algorithm can be divided into several steps. Those steps are: 1) initialization, 2) solution improvement through local search, 3) initialization of the pheromone trail, 4) R pheromone trail swaps, 5) solution improvement through local search, 6) performing intensification strategy, 7) Pheromone trail matrix update, 8) performing diversification strategy.

Step 1: Solution Initialization

At this step the solutions or layouts are initialized and associated with an ant. The example of layout combination may be like the following for each ant. The facility layout combination for each ant in this instance is generated such way:

Ant k: $\pi_{(1)1},\ldots, \pi_{(i)j}$

Ant k+1: $\pi_{(i+1)j},\ldots, \pi_{(1)j}$

Each block represents a facility in the 6-department facility layout across 3 time periods; there are two sets of dynamic layouts associated with two ants:

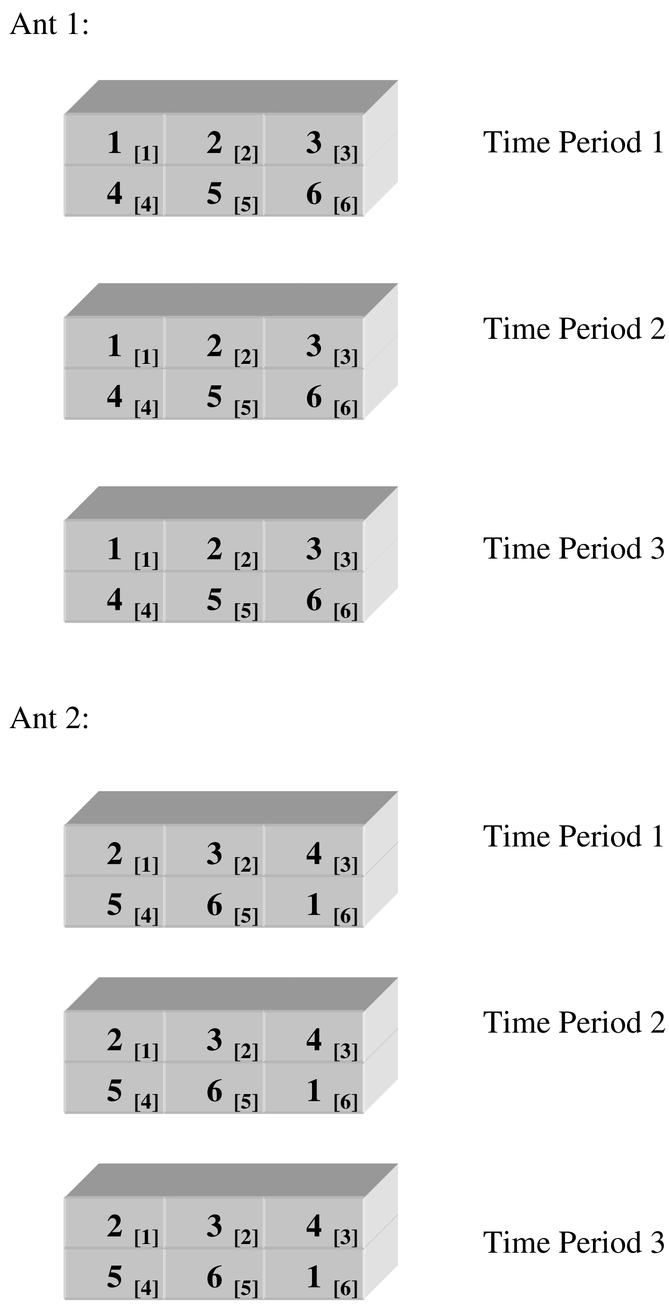

Figure 3.15: Dynamic facility layout involving two ants

The total cost of each dynamic layout is calculated based on material flow and distance from-to charts created from the material flow analysis. For example, from-to charts for ant 1 and ant 2 may look like the following. Notice that layouts are assumed to be two-row layouts and locations are static:

(Material Flow Matrix)Time Period 1						
From/To	**Dept 1**	**Dept 2**	**Dept 3**	**Dept 4**	**Dept 5**	**Dept 6**
Dept 1	0	8	4	8	6	7
Dept 2	8	0	2	1	0	3
Dept 3	4	2	0	4	8	4
Dept 4	8	1	4	0	1	7
Dept 5	6	0	8	1	0	5
Dept 6	7	3	4	7	5	0

Figure 3:16: Material flow matrix of time period 1

(Material Flow Matrix)Time Period 2						
From/To	**Dept 1**	**Dept 2**	**Dept 3**	**Dept 4**	**Dept 5**	**Dept 6**
Dept 1	0	7	8	7	6	7
Dept 2	7	0	1	1	0	5
Dept 3	8	1	0	1	7	1
Dept 4	7	1	1	0	1	3
Dept 5	6	0	7	1	0	6
Dept 6	7	5	1	3	6	0

Figure 3:17: Material flow matrix of time period 2

(Material Flow Matrix)Time Period 3						
From/To	**Dept 1**	**Dept 2**	**Dept 3**	**Dept 4**	**Dept 5**	**Dept 6**
Dept 1	0	10	10	8	5	10
Dept 2	10	0	1	1	0	1
Dept 3	10	1	0	1	4	1
Dept 4	8	1	1	0	1	6
Dept 5	5	0	4	1	0	5
Dept 6	10	1	1	6	5	0

Figure 3:18: Material flow matrix of time period 3

Distance From-to Chart						
From/To	**Loc 1**	**Loc 2**	**Loc 3**	**Loc 4**	**Loc 5**	**Loc 6**
Loc 1	0	1	2	1	2	3
Loc 2	1	0	1	2	1	2
Loc 3	2	1	0	3	2	1
Loc 4	1	2	3	0	1	2
Loc 5	2	1	2	1	0	1
Loc 6	3	2	1	2	1	0

Figure 3.19: From-to chart of distance

The total cost (distance-based) for each ant is calculated through the following formula:

$$DC = \sum_{i=1}^{N}\sum_{j=1}^{N}\sum_{t=1}^{T} d_{ij} m_{\pi_{(i)}{}^{t}\pi_{(j)}{}^{t}} + RC$$

where DC is the distance-based total cost; d_{ij} is the distance between location i and j; $m_{\pi(i)^t \pi(j)^t}$ are the material flows between department i and j at time period t. The total costs for facility layouts of ant 1 and ant 2 are 339 and 335, respectively. RC is the rearrangement cost which is incurred if there are layout differences across time periods. The particular formula considers the material flow matrix to be asymmetric—material flow cost from department A to department B is not the same as that from department B to department A. For a symmetric material flow matrix, the formula is revised as below:

$$DC = \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} \sum_{t=1}^{T} d_{ij} m_{\pi_{(i)}{}^t \pi_{(j)}{}^t} + RC$$

The adjacency-based objective according to Dutta and Sahu(1982, 148) is depicted:

$$AC = \sum_{i=1}^{n} \sum_{j=1}^{n} \sum_{p=1}^{n} \sum_{q=1}^{n} r_{ijpq} x_{ij} x_{pq}$$

subject to

$$\sum_{i=1}^{n} x_{ij} = 1, \qquad j = 1,2,\ldots,n$$

$$\sum_{j=1}^{n} x_{ij} = 1, \quad i = 1,2,\ldots,n$$

$$x_{ij} = 0 \, or \, 1$$

$$r_{ijpq} = \begin{cases} c_{pq}, \; if \; locations \; p \, and \, q \, are \, neighbors \\ 0, otherwise \end{cases}$$

where

c_{ip}: closeness ranking value between departments i and j when they are adjacent to each other with shared boundary

To consider the combination of distance-based and adjacency-based objectives together, the following formula based on Dutta's is shown:

$$TC = W_2 DC - W_1 AC$$

If Urban's additive model is used, the adjacency-based objective model is the same as that proposed by Dutta and Sahu but without the constraint that departments i and j have to share common boundaries.

Based on Urban's model, the following multi-objective formula is depicted:

$$TC = DC + c \cdot AC$$

where c is a constant (weight) to determine the weight of adjacency-based objective in respect to the distance-based objective.

Step 2: Improve the layouts through local search

After the initial layouts are obtained for each ant, the next step is to improve on the layouts through 2-opt or also known as the pair-wise exchange algorithm. As seen below in the diagram, the pair-wise exchange occurs between departments 1 and 2 at locations 1 and 2, which are randomly selected, at randomly selected time period (in this case time period 1 for ant 1); for ant 2 the local exchange occurs between departments 4 and 1 at randomly selected locations 3 and 6 at time period 2. After the exchanges, the total cost of each dynamic layout is calculated. If the total cost is less than the best total cost, then the dynamic layout is accepted; otherwise, the dynamic layout is rejected. This step is repeated for N*N*T iterations, where N corresponds to the number of departments and T the number of time periods. The best dynamic layout coming out of the step 2 is referred as **π***.

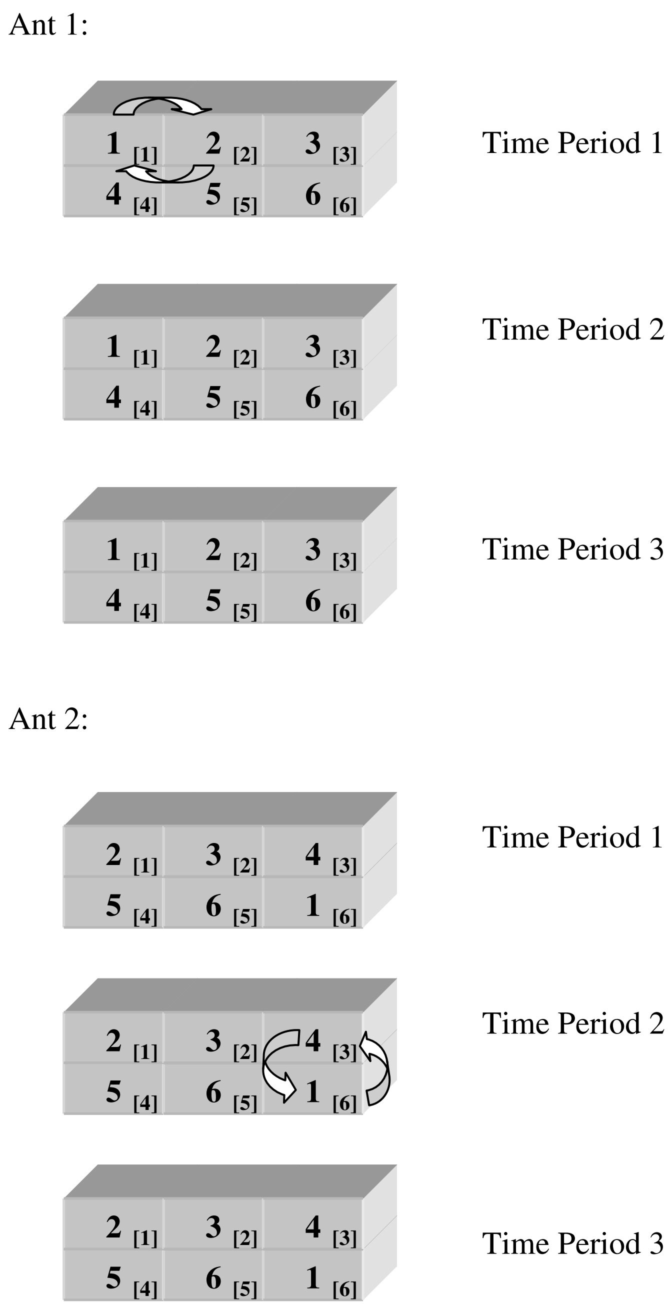

Figure 3.20: Local search in dynamic facility layout

Step 3: Initialize Pheromone Trail

The pheromone trail matrix is initialized with the formula:

$$\frac{1}{Qf(\pi^*)}$$

where Q is the pheromone initialization parameter, and f(π*) is the current best total cost found. In this instance, Q is set to 10^{-8} and f(π*) is 335. Thus, the pheromone trail initialization value is 298508.

	j (Location)					
π(i) Dept	298508	298508	298508	298508	298508	298508
	298508	298508	298508	298508	298508	298508
	298508	298508	298508	298508	298508	298508
	298508	298508	298508	298508	298508	298508
	298508	298508	298508	298508	298508	298508
	298508	298508	298508	298508	298508	298508

Figure 3.21: Initialization of pheromone trail matrix

Step 4: Perform pheromone trail swaps

The step selects two locations in the facility layouts for swapping through trail swap policies. The first location is randomly selected. The second location, however, is selected based on one of the two trail swap policies:

Policy 1: maximize $P^{k}_{u\pi(v)} + P^{k}_{v\pi(u)}$

Policy 2: $\dfrac{P^{k}{}_{u\pi(v)} + P^{k}{}_{v\pi(u)}}{\sum_{j \neq u} (P^{k}{}_{u\pi(j)} + P^{k}{}_{j\pi(u)})}$

Step 5: Improve facility layouts using local search

After the department swapping through one of the trail swap policies, the layouts are again improved through the local search (pair-wise exchange) algorithm. The pair-wise exchange routine will be executed N*N*T times. The best dynamic layout is referred as **π',** and the best dynamic layout cost is f*(π'). Later during intensification process the dynamic layout would be compared with the layout from **step 2**.

Step 6: Perform Intensification Strategy

This step is performed if the intensification process is activated when at least one ant improves its current best dynamic layout during iteration. The total costs of best dynamic layouts from step 2 and step 5 are then compared. The better dynamic layout is used as the starting dynamic layout for the next iteration for each ant.

If the intensification process is not activated, the best dynamic layout from step 5 is used as the starting dynamic layout for the next iteration for each ant.

Step 7: Update the pheromone trail matrix

According to Gambardella (1999, 170), in order to speed up the convergence of the algorithm, the current best layout cost is used to update the pheromone trail matrix. The pheromone trail matrix is first "weakened" by the following calculation:

$$P_{\pi(i)j} = (1-\alpha_1)^* \, P_{\pi(i)j}$$

where $P_{\pi(i)j}$ are the entries in the pheromone trail matrix and α_1 is the pheromone evaporation rate. A α_1 value close to 0 implies that the pheromone on the trails takes longer to evaporate, while it is close to 1 implies that the pheromone evaporates quickly and thus shorter memory of the system. Afterwards, the pheromone trail matrix is updated again with the current best layout cost:

$$P_{\pi^*(i)i} = P_{\pi^*(i)i} + \alpha_2/f(\pi^*)$$

where $P_{\pi^*(i)i}$ refers to the pheromone trail matrix entries correspond to the current best layout. α_2 is the pheromone trail reinforcement parameter which "reinforces" the current best layout/trail. $f(\pi^*)$ is the cost of best current dynamic layout (1-5-3-4-6-2).

	j (Location)					
π(i) Dept	311111	200000	200000	200000	200000	200000
	200000	200000	200000	200000	200000	311111
	200000	200000	311111	200000	200000	200000
	200000	200000	200000	311111	200000	200000
	200000	311111	200000	200000	200000	200000
	200000	200000	200000	200000	311111	200000

Figure 3.22: Updated pheromone trail matrix

Step 8: Perform Diversification Strategy

After a number of iterations (depending on *S* parameter) if the best current dynamic layout has not improved, the diversification strategy would kick in to explore unexplored solution space. Diversification process wipes all the information in the pheromone trails through pheromone trail matrix re-initialization and randomly generates current dynamic layout for all but the particular ant, which generates the current best dynamic layout.

3.5 ACO-DML Parameter Settings

One challenge of using Ant Colony Optimization (ACO) is number of parameter settings that one needs to set. The set of values in parameter settings would affect the speed of convergence of the solutions. There are currently studies under way to determine those parameters heuristically. Hao, Cai and Huang (2006) has used the Particle Swarm Optimization (PSO) to heuristically set parameters including β, ρ, q_0 and m in ACO for solving Traveling Salesman Problem (TSP). One of highlights of their research is set the ranges for those aforementioned parameters; for example, β is set with the range between 0 and 8 while ρ value falls between 0.5 and 1. Gaertner and Clark (2005) also attempted to address this issue by "conducting an exhaustive, empirical analysis of the sensitivity of the ACO algorithm to variations of parameters for different instances of the TSP". The paper by Gambardella et al. (1999) on which this dissertation is based set parameters as the following: R = n/3, $\alpha_1 = \alpha_2 = 0.1$, Q= 100, S= n/2, $q = 0.9$ and $m = 10$. Because of the scope of determining optimal parameter settings, the author of this dissertation has decided to currently rely on the empirical analysis to find the optimal parameter settings for the ACO-DML algorithm and conduct research in this area in the future work.

CHAPTER 4

DATA ANALYSIS AND RESULTS

The data sets for this proposed research are taken from Lacksonen and Enscore (1993) and Dutta and Sahu (1982).The former data set tests for the dynamic layout problems, while Dutta and Sahu deal with multi-objective problems in facility layout. The objective of using the existing data sets to test the ACO-DML is to validate the algorithm for handling dynamic facility layout as well as multi-objective facility layout problems because of the data unavailability for multi-objective dynamic facility layout problems as of now.

The Lacksonen's data set consists of sets of six departments with three and five time periods and twelve departments with three and five time periods. There are a few assumptions needed to be made with Lacksonen' data:

- Rearrangement cost is the same across multiple time periods.
- Symmetric – The material flows occurring between department A to department B is the same as that between department B to department A.

Realistically, rearrangement costs would not be the same across multiple time horizons because of facility depreciation, downtime, and so on. On the same note, the material flow costs from department A to department B may be different from that from department B to department A; it could be the case where large volume of products from department A to department B for shipping to customers as opposed to the few returned defective products received by department B are sent to department A for rework.

The multi-objective data set from Dutta and Sahu consists of seven problems with six departments and eight departments. For each problem the weights on the importance of both quantitative and qualitative objectives are considered. The multi-objective data set deals with one time period only.

The results of ACO-DML with data sets as aforementioned are presented in the following tables, Table 4.1 and 4.2.

Table 4.1: Solution Results for Dynamic Layout (Lacksonen and Enscore)

problem Size (Data Set 1)		Problem No.	Best Found Solution	ACO-DML	ACO-DML % deviation
No of Depts	No. of time period				
6	3	PL01	267	267	0%
		PL02	260	260	0%
		PL03	363	363	0%
		PL04	299	299	0%
	5	PL05	442	442	0%
		PL06	586	589	-0.51%
		PL07	424	424	0%
		PL08	428	429	-0.23%
12	3	PL09	1624	1678	-3.33%
		PL10	1973	2023	-2.53%
		PL11	1661	1747	-5.18%
		PL12	2097	2113	-0.76%
	5	PL13	2930	3065	-4.6%
		PL14	3701	3803	-2.76%
		PL15	2756	2961	-7.44%
		PL16	3364	3740	-11.18%

Table 4.2: Solution Results for Multi-objective Problem (Dutta and Sahu)

Problem Size	Problem No.	Weight1	Weight2	MUGHAL	ACO-DML	ACO-DML % Improvement
6 x 6	PD01	0.5	0.5	**35.5**	**34.0**	**4.23%**
		0.6	0.4	**23.0**	**22.4**	**2.61%**
		0.7	0.3	**10.5**	**10.5**	**0.00%**
		0.8	0.2	**-2.0**	**-2.8**	**40.00%**
		0.9	0.1	**-14.9**	**-16.4**	**10.07%**
	PD02	0.5	0.5	**35.5**	**34.0**	**4.23%**
		0.6	0.4	**23.0**	**22.4**	**2.61%**
		0.7	0.3	**10.5**	**10.5**	**0.00%**
		0.8	0.2	**-2.0**	**-2.8**	**40.00%**
		0.9	0.1	**-14.9**	**-16.4**	**10.07%**
	PD03	0.5	0.5	**36.5**	**34.0**	**6.85%**
		0.6	0.4	**23.8**	**22.4**	**5.88%**
		0.7	0.3	**10.8**	**10.5**	**2.78%**
		0.8	0.2	**-2.8**	**-2.8**	**0.00%**
		0.9	0.1	**-2.8**	**-16.4**	**485.00%**
	PD04	0.5	0.5	**34.0**	**34.0**	**0.00%**
		0.6	0.4	**23.8**	**22.4**	**5.88%**
		0.7	0.3	**10.8**	**10.5**	**2.78%**
		0.8	0.2	**-2.8**	**-2.8**	**0.00%**
		0.9	0.1	**-16.4**	**-16.4**	**0.00%**
8 x 8	PD05	0.5	0.5	**80.5**	**63.5**	**21.10%**
		0.6	0.4	**54.4**	**40.4**	**25.74%**
		0.7	0.3	**28.3**	**17.3**	**38.87%**
		0.8	0.2	**2.2**	**-5.8**	**163.60%**
		0.9	0.1	**-24.8**	**-30.5**	**22.98%**
	PD06	0.5	0.5	**73.5**	**63.5**	**13.61%**
		0.6	0.4	**49.2**	**40.4**	**17.89%**
		0.7	0.3	**23.4**	**17.3**	**26.07%**
		0.8	0.2	**-0.4**	**-5.8**	**1350.00%**
		0.9	0.1	**-25.6**	**-30.5**	**19.14%**
	PD07	0.5	0.5	**73.5**	**63.5**	**13.61%**
		0.6	0.4	**49.2**	**40.4**	**17.89%**
		0.7	0.3	**23.4**	**17.3**	**26.07%**
		0.8	0.2	**-0.4**	**-5.8**	**1350.00%**
		0.9	0.1	**-25.1**	**-30.5**	**19.14%**

4.1 Interpretation of the Results

As indicated by Table 4.1, the results of proposed dynamic multi-objective layout model (ACO-DML) match up with some of best found solutions, especially for problems consisting of six departments, three and five time periods (PL01 through PL08). For twelve-department problems, the results vary ranging from -0.76% to -11.18%. The deviation from the best found solutions may have something to do with the parameter settings, which would be investigated as the future work. While running the dynamic facility layout data sets from Lacksonen and Krishnan against the ACO-DML, the "Do-Nothing Effect" is observed. The detailed description of this effect is presented in section 4.1.1.

Table 4.2 contains the results by ACO-DML performed on the dataset from Dutta and Sahu (1982). Against Dutta and Sahu's data set, the ACO-DML is on par or even outperforms Dutta's MUGHAL algorithm, indicated by the positive deviation.. For some problem sets, the percentage deviations reach as high as 485% and 1350%! It could have something to do with the small values of those solutions that a slight improvement could magnify the percent deviation. Just as a reminder, weight 1 indicates the percentage of weight placed on closeness rating score, while weight 2 is the percentage of weight placed on material flow cost. Both weights should be added up to be 1.0.

4.1.1 Do-Nothing Effect

After interpreting the results associated with the dynamic facility layout problem, an observation is made that the best dynamic facility layout is the one with all layouts converged to a particular layout permutation across multiple time periods. See the example below:

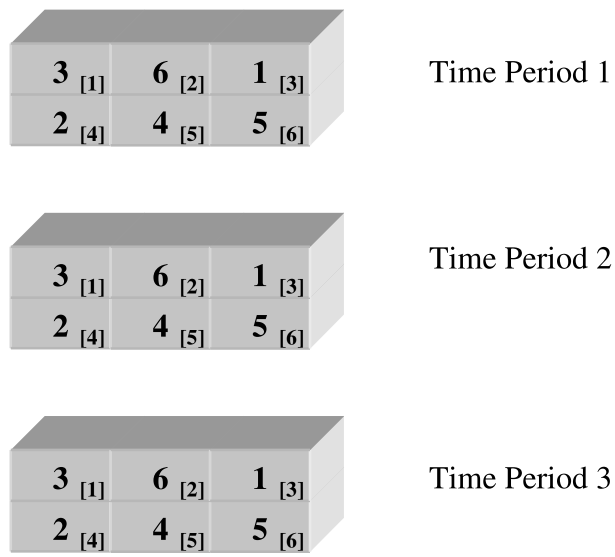

Figure 4.1: Dynamic facility layout with "Do-Nothing Effect"

Even though it is true that the optimal dynamic facility layout is the one with minimal total cost, by having one particular layout permutation across multiple time periods, the rearrangement costs are essentially eliminated. Thus, the author questions the validity of the current dynamic facility layout model by only considering the quantitative aspect of the facility layout alone.

4.2 ACO-DML Testing

Because there are no known papers published for the combined areas of dynamic multi-objective facility layout problem as of now, the author decides to create the test data sets based on Pearson's correlation coefficient or ρ between material flow and closeness rating matrices. The main reason for determining the Pearson's correlation coefficient among material flow and closeness rating matrices has to do with the possibility of correlation between quantitative and qualitative objectives affecting the outcome of the testing. (Lee 1989, 67) The correlation coefficient analysis table is included for each case study in the appendices section. There are three case studies in the appendices section different from each other by the correlation values associated with material flow and closeness rating matrices. For the first case study, the correlation between the material flow matrices and closeness rating matrices is set to be highly positive. For the second case study, the correlation between the material flow matrices and closeness rating matrices is set to be negative. For the third case study, the Pearson's correlation coefficient between the material flow matrices and closeness rating matrices is set to close to zero or no correlation.

4.2.1 Result Interpretation of Case Study #1

The data analyses are done on both ACO-DML I (Dutta's weight model) and ACO-DML II (Urban's additive model). The results interpretations are discussed in the next couple of sections. The material flow matrices and closeness rating matrices are positively correlated for case study #1.

4.2.1.1 Result Interpretation of ACO-DML (1) for Case Study #1

The ACO-DML (1) generates the dynamic multi-objective facility layout as shown in Figure 4.2.

At time period 1, departments 2 and 4 with **X** rating are separated by 2 distance units. The department pairs 1-2 and 1-4 with **A** ratings have adjacent departments. The department pair 1-5 with **E** rating also has adjacent departments.

At time period 2, departments 2 and 4 with **X** rating are separated by 2 distance units. The departments 1 and 2 with **A** rating are placed next to each other. The department pairs, 1-4, 4-6 and 5-6, with **E** ratings have adjacent departments.

At time period 3, departments 2 and 3 with high undesirability, **X** rating, are placed next to each other. The department pair 1-2 with **A** rating has adjacent departments. The department pairs 1-4, 6-4 and 6-5 with **E** rating have adjacent departments. The department pair 2-5, however, is separated by 2 distance units.

Notice that the dynamic facility layout has the same facility layout (6-4-3-5-1-2) permutation across multiple time periods. The total cost is 87.50.

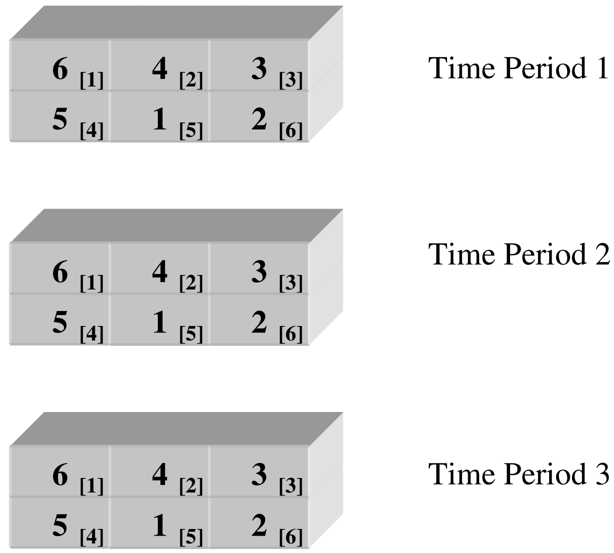

Figure 4.2: Dynamic facility layout generated by ACO-DML (1) for case study #1

4.2.1.2 Result Interpretation of ACO-DML (2) for Case Study #1

The multi-objective dynamic facility layouts generated by ACO-DML for case study #1 is shown in Figure 4.3. As one may expect, at time period 1 departments 2 and 4, which have the closeness rating of **X**, are separated apart with 3 distance units. On the other hand, the departments 1 and 4 with **A** closeness rating are placed next to each other. Departments 1 and 5 with closeness rating of E are also placed next to each other. Even though departments 1 and 2 have highest closeness rating of **A**, they are not placed next to each other. Departments 3 and 6 with **U** rating are separated by three distance units.

At time period 2, departments 2 and 4 with **X** closeness rating are separated apart at three distance units. Departments 1 and 2 with **A** rating are placed next to each other. Department pairs of 4-6 and 5-6 with **E** rating are also placed next to each other. However, for departments 1 and 4, also with **E** rating, are separated in two distance units.

At time period 3, departments 3 and 2 with **X** closeness rating are separated by 2 distance units; even though they are not separated by 3 distance units (maximum), they are still separated with department 5 in-between. Departments 1 and 2 with **A** rating are place adjacently to each other. Department pairs 2-5, 5-6 and 6-4 with **E** ratings are placed next to each other. The only exception is department pair 1-4, also with **E** rating, separated by 2 distance units.

The total cost calculated for this particular dynamic facility layout is 1220.

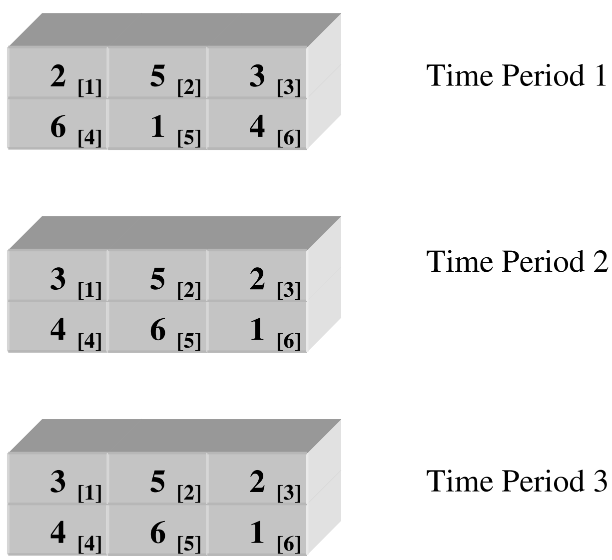

Figure 4.3: Dynamic facility layout generated by ACO-DML (2) for case study #1

As a comparison, the dynamic facility layout with quantitative-based objective only is displayed below. The total cost is 260, which matches the best found solution. Notice that the dynamic facility layout has the same facility layout (4-1-2-6-5-3) permutation across multiple time periods.

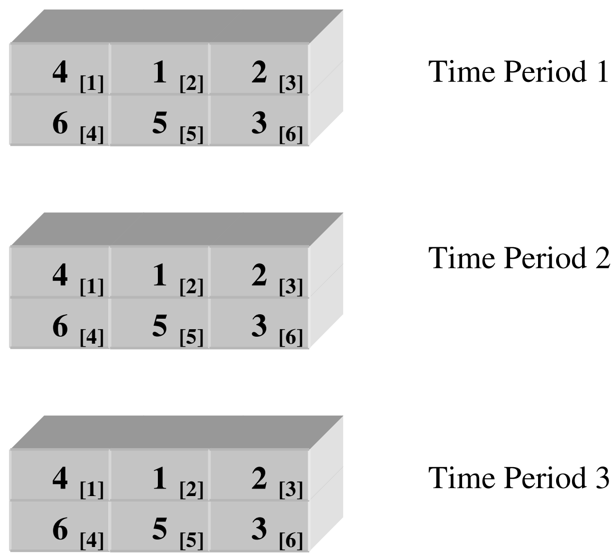

Figure 4.4: Dynamic facility layout with quantitative objective only for case study #1

4.2.2 Result Interpretation of Case Study#2

The data analyses are done on both ACO-DML I (Dutta's weight model) and ACO-DML II (Urban's additive model). The results interpretations are discussed in the next couple of sections. The material flow matrices and closeness rating matrices are negatively correlated for case study #2.

4.2.2.1 Result Interpretation of ACO-DML (1) for Case Study #2

The ACO-DML (1) generates the dynamic facility layout for case study #2 as shown in Figure 4.5.

At time period 1, department pairs 2-3 and 5-6 with **X** rating have adjacent departments. The department pairs 1-5 with **A** rating unexpectedly have departments separated by 3 distance units. The other department pair 1-4, however, has departments adjacent to each other. The department pair 1-3 with **E** rating also has adjacent departments.

At time period 2, departments 4 and 5 with **X** rating are separated by 2 distance units. The other **X** rating department pair 5-6 has departments adjacent to each other. The departments 1 and 5 with **A** rating are separated from each other by 3 distance units while the other department pair 3-5 with **A** rating is separated by 2 distance units. The department pairs, 1-3, 1-4 and 5-7, with **E** ratings all have adjacent departments.

At time period 3, departments 7 and 8 with high undesirability, **X** rating, are placed next to each other. The other X rating department pair, 3-4, has departments separated by 2 distance units. The department pairs, 1-3 and 1-4, with **A** rating have adjacent departments. The department pairs 4-8 with **E** rating has departments separated by 2 distance units while the other **E** rating department pair 4-6 is separated by 3 distance units.

Notice that the dynamic facility layout has the same facility layout (4-2-5-1-3-6; 4-7-5-1-3-6; 4-7-8-1-3-6) permutation across multiple time periods. The department 7 replaces department 2 at the time period 2 and 3while the department 8 replaces the department 5 at the time period 3. The total cost is 154.

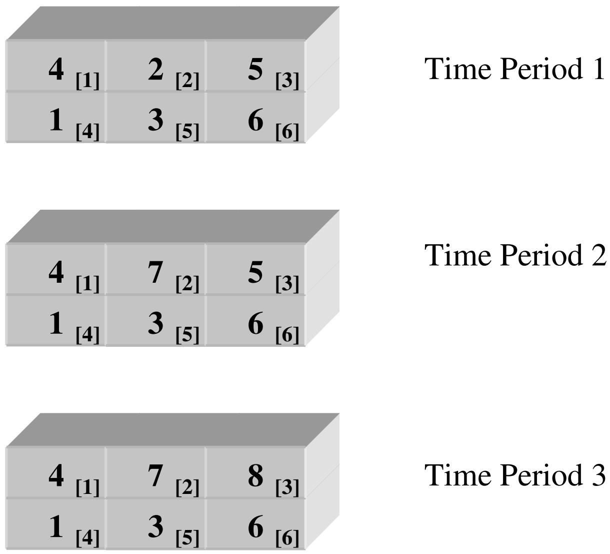

Figure 4.5: Dynamic facility layout generated by ACO-DML (1) for case study #2

4.2.2.2 Result Interpretation of ACO-DML (2) for Case Study #2

At time period 1, department pairs 2-3 and 5-6 with **X** ratings have departments separated as far apart as possible. Department pairs 1-4 and 1-5 with **A** ratings are expectedly having adjacent departments. Departments 1 and 3 with **E** rating are also adjacent to each other.

At time period 2, department 5 and 6 with **X** rating are separated by maximum distance at 3 distance units. The other department pair 4-5 with **X** rating, however, is separated only by 2 distance units. Department pairs 1-5, 1-4 and 1-3 with closeness ratings of **A**, **E** and **E**, respectively, have adjacent departments. Also note that department 7 has replaced department 2 to simulate adding and removing departments from the layout.

As for adjacencies are concerned at the time period 3, department pairs 1-3 and 1-4 (with **A** rating) and department pairs 4-6 (with **E** rating) all have adjacent departments. Also, at the time period 3 departments 7 (replacing department 2) and 8 (replacing department 5) with **X** rating are unexpectedly placed next to each other. Currently the **X** rating is assigned a numerical value of -1; In order to emphasize the 'undesirability', the author experiments with assigning **X** rating to -5, the result shows the department pairs (3-4 and 7-8) with **X** ratings at time period 3 are separated apart by at least 2 distance units. The generated dynamic facility layout is shown in Figure 4.7.

The total cost of the particular multi-objective dynamic facility layout is 1253.

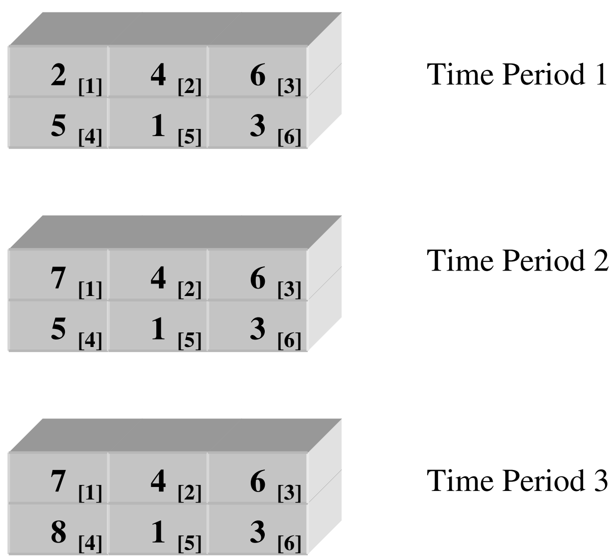

Figure 4.6: Dynamic facility layout generated by ACO-DML (2) with X rating set to -1 for case study #2

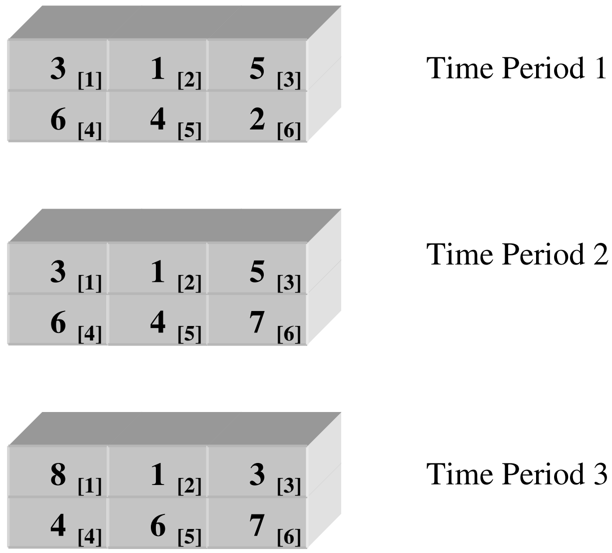

Figure 4.7: Dynamic facility layout generated by ACO-DML (2) with X rating set to -5 for case study #2

For the benchmarking purpose, the dynamic facility layout with only quantitative-based objective is displayed in Figure 4.8. The total cost of the layout is 363.

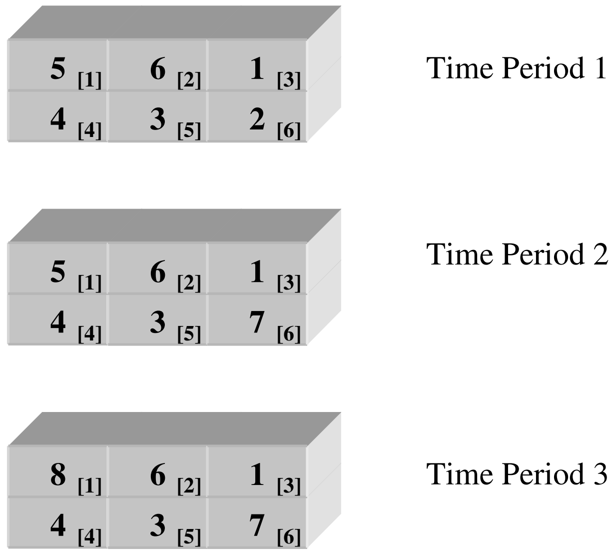

Figure 4.8: Dynamic facility layout with quantitative objective only for case study #2

4.2.3 Result Interpretation of Case Study#3

Again the data analyses are done on both ACO-DML (1) (Dutta's weight model) and ACO-DML (2) (Urban's additive model). The results interpretations are discussed in the next couple of sections. The material flow matrices and closeness rating matrices are not correlated for this particular case study.

4.2.3.1 Result Interpretation of ACO-DML (1) for Case Study #3

At time period 1, departments 2 and 5 with the undesirable rating of **X** are unexpectedly placed next to each other while departments 5 and 6 (also with **X** rating) are separated by 2 distance units. Department pairs 1-4 and 1-5 with **A** ratings have adjacent departments while the other **A** rating pair department 1 and 2 is separated by 2 distance units.

At time period 2, the department pairs, 4-5 and 5-6, with the **X** ratings have 2 distance units of separation between departments. On the other hand, department pairs of 1-4 and 1-5 with **A** ratings have departments adjacent to each other. The other **A** rating department pair 1-3, however, is separated by 2 distance units.

At time period 3, departments 7 and 8 with the **X** rating are placed next to each other while departments 6 and 8 are separated by 2 distance units. Departments 1 and 4 with **A** rating are placed next to each other while the other A rating department pair 1-3 has departments separated by 2 distance units. As for **E** rating, only the department pair 4-7 has departments next to each other; the other **E** rating department pair 4-6, however, has departments separated by 2 distance units.

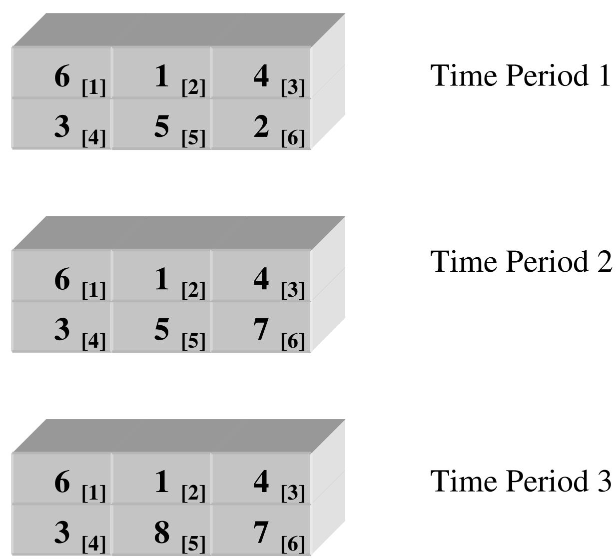

Figure 4.9: Dynamic facility layout generated by ACO-DML (1) for case study #3

4.2.3.2 Result Interpretation of ACO-DML (2) for Case Study #3

At time period 1, the department pair 5-6 with the **X** rating has departments separated as far apart as possible at 3 distance units. Departments 2 and 5 with the **X** rating, however, are separated by 2 distance units. Department pairs 1-2, 1-4 and 1-5 with the **A** ratings are expectedly having adjacent departments.

At time period 2, department 4 and 5 with **X** ratings are separated by 2 distance units as opposed to the department pair 5-6 with also **X** rating which is separated by 3 distance units. As for **A** ratings, department pairs 1-3, 1-4 and 1-5 all have adjacent departments.

At time period 3, the department pairs 1-3 and 1-4 with **A** ratings have adjacent departments. Departments 7 and 8 with **X** rating set at -1 are unexpectedly placed adjacently to each other; the other department pair 6-8 with X rating has departments separated by 3 distance units. Later, after adjusting X rating to -5, the department pair 7-8 has departments separated by the maximum distance unit at 3 while the department pair 6-8 has those separated by 2 distance units. See Figure 4.11.

Figure 4.12 shows the quantitative objective only dynamic facility layout. Note again that the same layout permutation is selected across multiple time periods (permutation: 4-2-3-1-5-6 with department 7 replacing department 2 and 8 replacing 5).

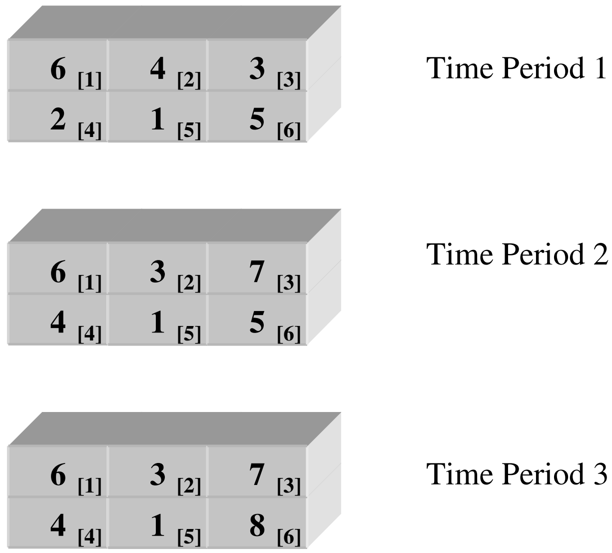

Figure 4.10: Dynamic facility layout generated by ACO-DML (2) with X rating set to -1 for case study #3

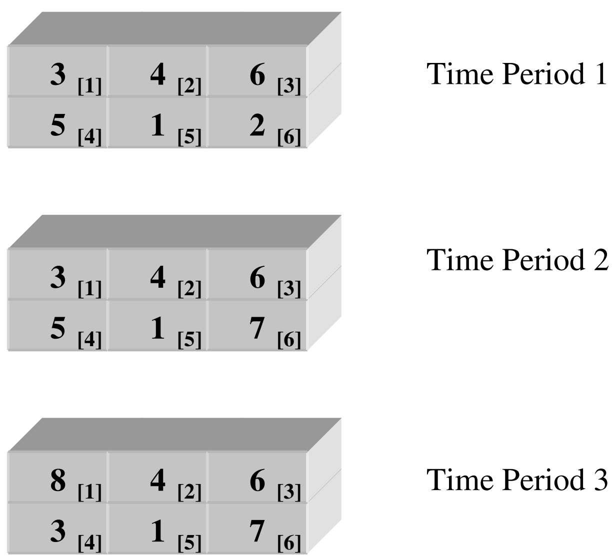

Figure 4.11: Dynamic facility layout generated by ACO-DML (2) with X rating set to -5 for case study #3

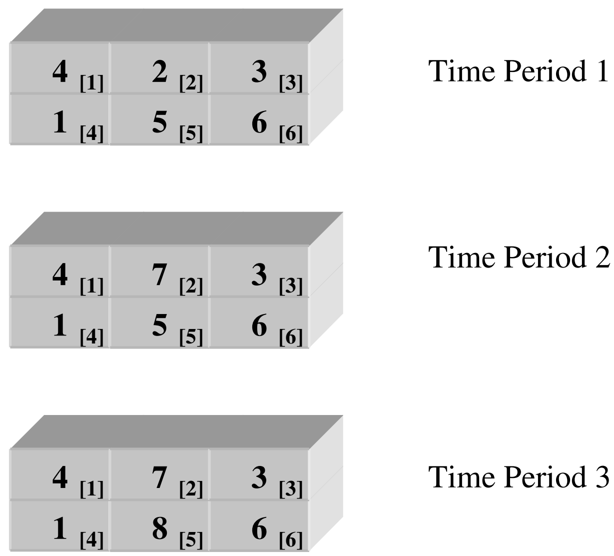

Figure 4.12: Dynamic facility layout with quantitative objective only for case study #3

4.2 Discussion of ACO-DML Results

After the results interpretation of case studies, it clearly shows that the integration of ACO with Urban's additive model performs better than that of ACO with Dutta's weight model. Among the criteria of evaluating the effectiveness of the proposed ACO-DML are the separation of undesirable department pairs and the adjacencies of departments with high desirability. Dynamic facility layouts generated by ACO-DML (2) consistently have departments with undesirability (**X** closeness rating) separated while departments with **A** and **E** ratings placed next to each other. On the other hand, the dynamic facility layout generated by ACO-DML (1) does not have such consistency. On several occasions, the departments with **X** ratings are placed adjacent to each other. Furthermore, ACO-DML (2) provides better scalability and flexibility. For example, suppose a dynamic multi-objective facility layout with the material flow costs much higher than the closeness rating. With the additive model, the disparity can be adjusted by updating the constant factor *C* to match the maximum value of material flow costs. Also, if the undesirability of departments is emphasized, the numerical value of **X** rating can easily be adjusted (for example, from -1 to -5) to reflect the emphasis. On the contrary, the layouts created from the weight model may suffer the "eclipse" effect—the quantitative objective outweighs the qualitative objective. Moreover, the "do-nothing" effect is also observed with facility layouts generated from ACO-DML (1) but not with ACO-DML (2).

CHAPTER 5

CONCLUSIONS AND FUTURE WORKS

5.1 Conclusions

In the current published literature about dynamic facility layout problems, the attention is given mainly to the quantitative or distance-based objective to find the minimum total cost among various alternative facility layouts. In the real world scenarios, the quantitative aspect of the facility layout may not be sufficient; the qualitative factors are also something to be considered. This research takes the body of knowledge one step further by combining the quantitative based objective of dynamic facility layout with the qualitative or adjacency based objective to make a "dynamic multi-objective facility layout" to set further constraints on dynamic facility layout which better reflects real-world scenarios.

Throughout this dissertation both theoretical as well as practical aspects of the dynamic multi-objective facility layout are discussed. On the theoretical side, QAP model, static and dynamic facility layout problems, multi-objective problem as well as the algorithm for solving the problem—Ant Colony Optimization (ACO) are described in detail. On the practical side, the 7-step methodology of facility layout optimization is presented based on guidelines of Phillips (1997) and Tompkins et al. (2002).

In order to test the validity of the newly proposed algorithm—Ant Colony Optimization- Dynamic Multi-objective Layout (ACO-DML)— data sets are taken from existing published papers on individual components of dynamic facility layout and multi-objective problems. The results validate the algorithm, especially for small-sized facility layout problems. During results interpretation of dynamic facility layout problems, the “do-nothing” effect is observed. The dynamic facility layout with minimal total cost turns out to be the one with the same facility layout permutation across multiple time periods.

To test the newly proposed dynamic multi-objective facility layout problem, a set of data are generated based on the positive correlation, negative correlation and non-correlation between material flow and closeness rating matrices in the absence of related work on this new topic.

After interpretation of the results, the integration of ACO with multi-objective models proves to be feasible, especially with Urban’s additive model. Urban’s additive model performs better than Dutta’s weight model in terms of integration with ACO based on several factors:

- Scalability: the weight of qualitative objective can easily be updated by adjusting the constant factor ‘C’ to match the maximum value of material flow matrix. Dutta’s weight model does not provide this flexibility. Additionally, experiments show that if ‘undesirability’ is emphasized, the **X** rating can be assigned to different numerical value and the generated dynamic facility layout reflects the change accordingly.

- Performance: The arrangement of dynamic facility layouts generated based Urban's model consistently reflect the qualitative criteria set in the closeness rating matrix; on the other hand, Dutta's weight model does not provide such consistency.
- Unexpected Effect: The "do-nothing" effect is observed with dynamic facility layout generated from Dutta's weight model but not with dynamic facility layout from Urban's weight model.

Based on the data and results collected and analyzed, the proposed algorithm, ACO-DML, shows some promises as a useful tool in solving the dynamic multi-objective facility layout problem. However, like doing anything else, the users should practice due diligence and evaluate the alternative facility layouts based on their experience and objectivity.

5.2 Future Works

There are several items that are recommended as future research to further improve or utilize on the newly proposed problem and algorithm:

- Investigate algorithms for solving the dynamic facility layout problem with unequal department size or irregular shape.
- Combine constructive algorithms (such as Modified Spanning Tree (MST) or graph theory) and improvement algorithms (such as ACO or simulated annealing) to improve and speed up convergence of better solutions for the dynamic facility layout problem.

- Investigate other factors beside incentive factor that may impact the rearrangement of facility layouts.
- Investigate the possibilities of combining the novel method of Dynamic Flow-Between Chart (DFBC) with ACO to solve dynamic multi-objective facility layout problem with stochastic flows.
- Create a user-friendly Graphical User Interface for ACO-DML algorithm.
- Investigate using heuristic algorithms to optimize parameters used in ACO-DML instead of empirically determining values through experimentation.
- Test ACO-DML on larger department sizes and more time horizons.

APPENDIX A

CASE STUDY #1

A dynamic facility layout consists of six departments and three time periods. The same departments are to be arranged or rearranged across three time periods. The rearrangement cost is 10. The material flow cost matrices (from-to charts), distance matrix, and closeness ranking matrices are listed as below:

Time Period 1						
	1	**2**	**3**	**4**	**5**	**6**
1	0	8	4	8	6	4
2	8	0	2	1	5	2
3	4	2	0	4	5	2
4	8	1	4	0	2	4
5	6	5	5	2	0	4
6	4	2	2	4	4	0

Figure A.1: Material flow matrix of time period 1 for case study#1

Time Period 2						
	1	**2**	**3**	**4**	**5**	**6**
1	0	10	2	7	5	2
2	10	0	2	1	5	1
3	2	2	0	4	5	2
4	7	1	4	0	3	6
5	5	5	5	3	0	6
6	2	1	2	6	6	0

Figure A.2: Material flow matrix of time period 2 for case study#1

Time Period 3						
	1	**2**	**3**	**4**	**5**	**6**
1	0	10	3	6	4	4
2	10	0	1	1	7	1
3	3	1	0	2	3	1
4	6	1	2	0	2	6
5	4	7	3	2	0	8
6	4	1	1	6	8	0

Figure A.3: Material flow matrix of time period 3 for case study#1

Locations						
	1	**2**	**3**	**4**	**5**	**6**
1	0	1	2	1	2	3
2	1	0	1	2	1	2
3	2	1	0	3	2	1
4	1	2	3	0	1	2
5	2	1	2	1	0	1
6	3	2	1	2	1	0

Figure A.4: Distance matrix for case study#1

Time Period 1						
	1	**2**	**3**	**4**	**5**	**6**
1	-	A	I	A	E	I
2	A	-	U	X	I	O
3	I	U	-	I	I	U
4	A	X	I	-	O	I
5	E	I	I	O	-	I
6	I	O	U	I	I	-

Figure A.5: Closeness rating matrix of time period 1 for case study#1

Time Period 2						
	1	**2**	**3**	**4**	**5**	**6**
1	-	A	U	E	I	U
2	A	-	U	X	I	U
3	U	U	-	I	I	U
4	E	X	I	-	O	E
5	I	I	I	O	-	E
6	U	U	U	E	E	-

Figure A.6: Closeness rating matrix of time period 2 for case study#1

Time Period 3						
	1	**2**	**3**	**4**	**5**	**6**
1	-	A	O	E	I	I
2	A	-	X	U	E	U
3	O	X	-	O	I	U
4	E	U	O	-	O	E
5	I	E	I	O	-	E
6	I	U	U	E	E	-

Figure A.7: Closeness rating matrix of time period 3 for case study#1

Pearson's Correlation Coefficient between Material Flow Matrices and Closeness Rating Matrices	
Time Period #1	0.949231137
Time Period #2	0.947449275
Time Period #3	0.945798531

Figure A.8: Pearson's correlation coefficients between material flow matrices and closeness rating matrices for case study #1

Table A.1: Parameter Settings Selected for Case Study #1

M	Q	q	α_1	α_2	I_{max}	S	R	W_1	W_2
3	10^{-8}	0.90	0.1	10^{7}	30	3	20	0.5	0.5

Parameter settings selected for the ACO-DML algorithm:

M: Number of ants

Q: Pheromone trail initialization parameter

q: Probability for selecting the pheromone trail swap policies

α_1: Parameter used to control the evaporation of the pheromone trail

α_2: Parameter used to reinforce certain pheromone trails

S: Consecutive number of iterations without improvement before diversification

R: Number of pheromone trail swaps

W_1: Weight for closeness rating score

W_2: Weight for material flow cost

APPENDIX B

CASE STUDY #2

A dynamic facility layout consists of six departments and three time periods. The same departments are to be arranged or rearranged across three time periods. The rearrangement cost is 25. Note that the department 7 replaces the department 2 in the time period 2, and departments 7 and 8 replace departments 2 and 5 in the time period 3, respectively. The replacement is done to simulate add and remove departments from the layouts. The material flow cost matrices (from-to charts), distance matrix, and closeness ranking matrices are listed as below:

Time Period 1						
	1	**2**	**3**	**4**	**5**	**6**
1	0	4	2	1	0	3
2	4	0	8	4	8	4
3	2	8	0	6	1	7
4	1	4	6	0	7	5
5	0	8	1	7	0	10
6	3	4	7	5	10	0

Figure B.1: Material flow matrix of time period 1 for case study#2

Time Period 2						
	1	**7**	**3**	**4**	**5**	**6**
1	0	5	1	1	0	5
7	5	0	5	6	2	7
3	1	5	0	7	1	6
4	1	6	7	0	9	4
5	0	2	1	9	0	9
6	5	7	6	4	9	0

Figure B.2: Material flow matrix of time period 2 for case study#2

Time Period 3						
	1	**7**	**3**	**4**	**8**	**6**
1	0	3	1	1	3	3
7	3	0	7	5	9	7
3	1	7	0	9	6	6
4	1	5	9	0	2	2
8	3	9	6	2	0	8
6	3	7	6	2	8	0

Figure B.3: Material flow matrix of time period 3 for case study#2

Locations						
	1	**2**	**3**	**4**	**5**	**6**
1	0	1	2	1	2	3
2	1	0	1	2	1	2
3	2	1	0	3	2	1
4	1	2	3	0	1	2
5	2	1	2	1	0	1
6	3	2	1	2	1	0

Figure B.4: Distance matrix for case study#2

Time Period 1						
	1	**2**	**3**	**4**	**5**	**6**
1	-	O	E	A	A	I
2	O	-	X	I	U	O
3	E	X	-	O	A	U
4	A	I	O	-	U	O
5	A	U	A	U	-	X
6	I	O	U	O	X	-

Figure B.5: Closeness rating matrix of time period 1 for case study#2

Time Period 2						
	1	**7**	**3**	**4**	**5**	**6**
1	-	O	E	E	A	O
7	O	-	O	O	E	U
3	E	O	-	U	A	O
4	E	O	U	-	X	I
5	A	E	A	X	-	X
6	O	U	O	I	X	-

Figure B.6: Closeness rating matrix of time period 2 for case study#2

Time Period 3						
	1	**7**	**3**	**4**	**8**	**6**
1	-	I	A	A	I	I
7	I	-	U	O	X	U
3	A	U	-	X	O	O
4	A	O	X	-	E	E
8	I	X	O	E	-	U
6	I	U	O	E	U	-

Figure B.7: Closeness rating matrix of time period 3 for case study#2

Pearson's Correlation Coefficient between Material Flow Matrices and Closeness Rating Matrices	
Time Period #1	-0.579256104
Time Period #2	-0.580065388
Time Period #3	-0.552941176

Figure B.8: Pearson's correlation coefficients between material flow matrices and closeness rating matrices for case study#2

Table B.1: Parameter Settings Selected for Case Study #2

M	Q	q	α_1	α_2	I_{max}	S	R	W_1	W_2
3	10^{-8}	0.9	0.1	10^{7}	30	3	20	0.5	0.5

Parameter settings selected for the ACO-DML algorithm:

M: Number of ants

Q: Pheromone trail initialization parameter

q: Probability for selecting the pheromone trail swap policies

α_1: Parameter used to control the evaporation of the pheromone trail

α_2: Parameter used to reinforce certain pheromone trails

S: Consecutive number of iterations without improvement before diversification

R: Number of pheromone trail swaps

W_1: Weight for closeness rating score

W_2: Weight for material flow cost

APPENDIX C

CASE STUDY #3

A dynamic facility layout consists of six departments and three time periods. The same departments are to be arranged or rearranged across three time periods. The rearrangement cost is 25. Note that the department 7 replaces the department 2 in the time period 2, and departments 7 and 8 replace departments 2 and 5 in the time period 3, respectively. The replacement is done to simulate add and remove departments from the layouts. The material flow cost matrices (from-to charts), distance matrix, and closeness ranking matrices are listed as below:

Time Period 1						
	1	**2**	**3**	**4**	**5**	**6**
1	0	4	2	1	5	2
2	4	0	8	4	5	2
3	2	8	0	6	2	4
4	1	4	6	0	4	4
5	5	5	2	4	0	2
6	2	2	4	4	2	0

Figure C.1: Material flow matrix of time period 1 for case study#3

Time Period 2						
	1	**7**	**3**	**4**	**5**	**6**
1	0	3	1	1	1	3
7	3	0	4	8	9	3
3	1	4	0	2	5	3
4	1	8	2	0	3	1
5	1	9	5	3	0	1
6	3	3	3	1	1	0

Figure C.2: Material flow matrix of time period 2 for case study#3

Time Period 3						
	1	**7**	**3**	**4**	**8**	**6**
1	0	7	1	4	9	4
7	7	0	3	7	6	1
3	1	3	0	1	2	1
4	4	7	1	0	6	3
8	9	6	2	6	0	7
6	4	1	1	3	7	0

Figure C.3: Material flow matrix of time period 3 for case study#3

Locations						
	1	**2**	**3**	**4**	**5**	**6**
1	0	1	2	1	2	3
2	1	0	1	2	1	2
3	2	1	0	3	2	1
4	1	2	3	0	1	2
5	2	1	2	1	0	1
6	3	2	1	2	1	0

Figure C.4: Distance matrix for case study#3

Time Period 1						
	1	**2**	**3**	**4**	**5**	**6**
1	-	A	I	A	A	I
2	A	-	U	I	X	O
3	I	U	-	I	A	U
4	A	I	I	-	U	O
5	A	X	A	U	-	X
6	I	O	U	O	X	-

Figure C.5: Closeness rating matrix of time period 1 for case study#3

Time Period 2						
	1	**7**	**3**	**4**	**5**	**6**
1	-	O	A	A	A	O
7	O	-	O	O	U	U
3	A	O	-	U	A	O
4	A	O	U	-	X	O
5	A	U	A	X	-	X
6	O	U	O	O	X	-

Figure C.6: Closeness rating matrix of time period 2 for case study#3

Time Period 3						
	1	**7**	**3**	**4**	**8**	**6**
1	-	U	A	A	I	I
7	U	-	U	U	X	U
3	A	U	-	U	O	O
4	A	U	U	-	E	E
8	I	X	O	E	-	X
6	I	U	O	E	X	-

Figure C.7: Closeness rating matrix of time period 3 for case study#3

Pearson's Correlation Coefficient between Material Flow Matrices and Closeness Rating Matrices	
Time Period #1	0.025377768
Time Period #2	-0.044642857
Time Period #3	0.01254363

Figure C.8: Pearson's correlation coefficients between material flow matrices and closeness rating matrices for case study#3

Table C.1: Parameter Settings Selected for Case Study #3

M	Q	q	α_1	α_2	I_{max}	S	R	W_1	W_2
3	10^{-8}	0.9	0.1	10^{7}	30	3	20	0.5	0.5

Parameter settings selected for the ACO-DML algorithm:

M: Number of ants

Q: Pheromone trail initialization parameter

q: Probability for selecting the pheromone trail swap policies

α_1: Parameter used to control the evaporation of the pheromone trail

α_2: Parameter used to reinforce certain pheromone trails

S: Consecutive number of iterations without improvement before diversification

R: Number of pheromone trail swaps

W_1: Weight for closeness rating score

W_2: Weight for material flow cost

REFERENCES

Ant Colony Optimization. http://en.wikipedia.org/wiki/Ant_colony_optimization. (accessed May 19, 2007).

Balakrishnan, Jaydeep and Chun Hung Cheng. 2000. Genetic search and the dynamic layout problem. *Computers and Operations Research* 27: 587-593.

Balakrishnan, Jaydeep, Chun Hung Cheng, and Daniel G. Conway. 2000. An improved pair-wise exchange heuristic for the dynamic plant layout problem. *International Journal of Production Research* 38, no. 13: 3067-3077.

Bazaraa, Mokhtar S. and Hanif D. Sherali. 1982. On the use of and heuristic cutting plane methods for the quadratic assignment problem. *Journal of Operational Research Society* 33, no. 11(November): 991-1003.

Bingual, Zafer. 2007. Adaptive genetic algorithms applied to dynamic multiobjective problems. *Applied Soft Computing* 7, no. 3(June): 791-799.

Burkard, Rainer E. and Franz Rendel. 1984. A thermodynamically motivated simulated procedure for combinatorial optimization problems, *European Journal of Operational Research* 17: 169-174.

Conway, Daniel G. and M.A. Venkataramanan. 1994. Genetic search and the dynamic facility layout problem, *Computers in Operations Research* 21: 955-960.

De Castro, L. N. and Von Zuben, F.J. (2005). Recent Developments in Biologically Inspired Computing. Idea Group Publishing. Hershey, PA. P.183.

Dorigo, Marco and Thomas Stützle. 2004. *Ant Colony Optimization*. Cambridge, Massachusettes: The MIT Press.

Dunker, Thomas, Günter Radons, and Engelbert Westkämper. 2005. Combining evolutionary computation and dynamic programming for solving a dynamic facility layout problem. *European Journal of Operational Research* 165: 55-69.

Dutta, Kedar N. and Sadananda Sahu. 1982. A Multigoal Heuristic for Facilities Design Problems: MUGHAL. *International Journal of Production Research* 20, no. 2 (1982): 147-154.

Elbeltagi, Emad and Tarek Hegazy. 2001. A Hybrid AI-Based System for Site Layout Planning in Construction. *Computer-Aided Civil and Infrastructure Engineering* 16: 79-93.

Ertay, Tijen, Da Ruan, and Umut Rifat Tuzkaya. 2006. Integrating data envelopment analysis and analytic hierarchy for the facility layout design in manufacturing systems. *Information Sciences* 176:237-262.

Filley, Richard. 1985. Three Emerging Computer Technologies Boost Value of, Respect for Facilities Function. *Industrial Engineering* 17 (May): 27-29.

Francis, Richard L., Leon F. McGinnis, Jr, and John A. White. 1992. *Facility Layout and Location: An Analytical Approach* 2nd edition. Englewood Cliffs, New Jersey: Prentice-Hall, Inc.

Fleurent, C. and J.A. Ferland. 1994. Genetic hybrids for the quadratic assignment problem. *DIMACS Series in Discrete Mathematics and Theoretical Computer Science* 16: 173-188.

Gaertner, Dorian and Keith Clark. On optimal parameters for ant colony optimization algorithms. *Proceedings of International Conference on Artificial Intelligence 2005*: 83-89.

Gambardella, L.M., E.D. Taillard, and M. Dorigo. 1999. Ant colonies for the quadratic assignment problem. *Journal of the Operational Research Society* 50: 167-176.

Gilmore, P.C. 1962. Optimal and suboptimal algorithms for the quadratic assignment problem. *Journal of the Society for Industrial and Applied Mathematics* 10, no. 2(June):305-313.

Glover, Fred. Tabu Search─Part I. *ORSA Journal on Computing* 1, no. 3: 190-206.

Glover, Fred. Tabu Search─Part II. *ORSA Journal on Computing* 2, no.1: 4-32.

Hao, Zhi-Feng, Rui-Chu Cai, and Han Huang. 2006. An adaptive parameter control strategy for ACO. *Proceedings of the Fifth International Conference on Machine Learning and Cybernetics*. Dalian, 13-16 August 2006.

Heragu, Sunderesh S. 1997. *Facilities Design* 1st Edition. Boston: PWS Publishing Company.

Heragu, Sunderesh S. 2006. *Facilities Design* 2nd Edition. Boston: PWS Publishing Company.

Heragu, Sunderesh S. and A.S. Alfa. 1992. Experimental analysis of simulated annealing based algorithms for the layout problem. *European Journal of Operational Research* 57, no.2: 190-202.

Heragu, Sunderesh and J.S. Kochhar. 1994. Material handling issues in adaptive manufacturing systems. *The Materials Handling Engineering Division 75th anniversary commerorative volume*: 9-13.

Heragu, Sunderesh and A. Kusiak. 1998. Machine layout problem in flexible manufacturing systems. *Operations Research* 36, no. 2: 258-268.

Kochhar, J.S. and S. S. Heragu. 1999. Facility layout design in a changing environment. *International Journal of Production Research* 37, no. 11: 2429-2446.

Koopmans, T.C. and Beckman, M. 1957. Assignment problems and the location of economic activities, *Econometrica* 25:53-76.

Krishnan, Krishna K., S. Hossein Cheraghi and Chandan N. Nayak. 2006. Dynamic from-between chart: a new tool for solving dynamic facility layout problems, *International Journal of Industrial and Systems Engineering* 1, no. 1/2:182–200.

Kuppusamy, Saravanan. 2001. Simulated annealing heuristics for the dynamic facility layout problem. Master's thesis, West Virginia University.

Lacksonen, T. A. and Enscore, E.E (1993), Quadratic Assignment Algorithms for the Dynamic Layout Problem. *International Journal of Production Research.* Vol.31, No. 3, 503-517.

Lawler, Eugene L. 1963. Quadratic assignment problem. *Management Science* 9, no.4(July):568-599.

Lee, Hoo Joon. 1988. Heuristic graph-theoretic approach in facility layout problem: the development of a decision support system. PhD diss, the University of Texas at Arlington.

Lerman, Kristina and Aram Galstyan. 2001. A general methodology for mathematical analysis of multiagent systems. *Technical Report ISI-TR-529*. University of California, Information Sciences Institute.

Liu, Wen-Hsing. 2005. Tabu search for the dynamic facility layout problem. Master's thesis, West Virginia University.

Maniezzo, Vittorio. 1999. Exact and approximate nondeterministic tree-search procedures for the quadratic assignment problem. *INFORMS Journal on Computing* 11, no. 4: 358-369.

Narayahnaswamy, Ramu. n.d. *Strategic layout planning and simulation for lean manufacturing a LayOPT Tutorial*.

Nicols, L.M. and R.H. Hollier. 1983. Plant layout in practice. *Material Flow* 1: 177-188.

Ostwald, Phillip F. 1992. Engineering Cost Estimating 3rd Edition. Englewood Cliffs, New Jersey: Prentice Hall.

Phillips, Edward J. 1997. *Manufacturing Plant Layout*. Dearborn, Michigan: Society of Manufacturing Engineers.

Rogers, K.J. 1985. The Development of a Multiobjective Knowledge-based Systematic Methodology for Medium Range Space and Facilities Planning in a Dynamic Environment. PhD diss, the University of Texas at Arlington.

Rosenblatt, Meir J. 1979. The facilities layout problem: A multi-goal approach. *International Journal of Production Research* 17, no. 4:323-332.

Rosenblatt, Meir J. 1986. The dynamics of plant layout. Management Science 32, no. 1 (Jan.): 76-86.

Shang, Jen S. 1993. Multicriteria facility layout problem: An integrated approach. *European Journal of Operational Research* 66: 291-304.
Shang, Jin. 2002. Ant colony heuristics for the dynamic facility layout problem. Master's thesis, West Virginia University.

McKendall, Alan R and J. Shang. 2006. Hybrid ant systems for the dynamic facility layout problem. *Computers and Operations Research* 33: 790-803.

Schroeder, Roger G. 2000. *Operations Management: Contemporary Concepts and Cases*. Boston: McGraw-Hill Higher Education.

Tompkins, James A. et al. 2003. *Facilities Planning* 3rd edition. New York: John Wiley & Sons, Inc.

Urban, Timothy L. 1987. A Multiple criteria model for the facilities layout problem. *International Journal of Production Research* 25, no.12:1805-1812.

Urban, Timothy L. 1993. A heuristic for the dynamic facility layout problem. *IIE Transactions* 25, no. 4: 57-63.

VIP-PLANOPT. http://www.planopt.com/VIP-PLANOPT/algorithm.htm (accessed May 19, 2007).

Vij, Paul et. al. n.d. *Strategic Layout Planning and Design for Lean Manufacturing: A LAYOPT Case Study*.

Wang, Chi-Tai. 1999. Static and Dynamic Facility Layout Problems. PhD diss. the University of Michigan.

Wilhem, M.R. and T.L. Ward. 1987. Solving the quadratic assignment problems by simulated annealing. *IIE Transactions* 19: 107-119.

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