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摘　要

本文爲此次參加美國生產與作業管理學會主辦的年會暨學術研討會，其目的之一在於了解該學術組織之性質及美國的生產與作業管理學門的最新發展趨勢。目的之二在於發表學術論文兩篇，並藉此與「鄰避設施位址與車輛途程問題」之相關研究領域的專家學者，進行學術交流，藉以獲得廣泛的研究心得與經驗。整體而言研討會在理論、實務、與應用的大會主題之下，與會討論的學者及專家極爲踴躍，研究主題大致仍以學術導向及實務導向兩方向爲主。建議事項如下：(1) 國內已申請成立該學會的台灣分會，應可擴大參與層面自下屆起組團前往，以增強國際學術交流。(2) Operations Management 的研究領域除傳統的領域之外，已逐漸擴充含蓋至：Behavioral Operation Management, Healthcare Operation Management, Logistics Management & Applications 等領域，直得國內學者及專家深思。

目 次

1. 目的

此次本人參加美國生產與作業管理學會主辦的年會暨學術研討會，其目的之一在於了解該學術組織之性質及美國的生產與作業管理學門的最新發展趨勢。目的之二在於發表學術論文兩篇，並藉此與「鄰避設施位址與車輛途程問題」之相關研究領域的專家學者，進行學術交流，藉以獲得廣泛的研究心得與經驗。

2. 過程

本次 2006 POMS 國際研討會，於2008年05月09日至05月12日，在美國加州南部的La Jolla市Hyatt Regency La Jolla 會議中心舉行。本次研討會共計有800篇摘要提出，及700篇左右的學術論文提出討論，分屬23個子題(Tracks)，出席會議的各國學者及專家共計42個國家及地區代表與會。四天的研討會期間，除例行的學會的行政會議之外，論文發表部份：每天的上下午均有四個時段並行發表，每時段約有20場次同時進行學術論文發表，各場次討論熱列、交流與激盪的成果豐碩。

此次研討會本人發表的論文共兩篇：分別爲「Location Decisions for Two Obnoxious Facilities by Balancing Compensation Cost and Transportation Cost」(全文詳見附錄一)、及「A Framework for Aftermarket Condition-Based Maintenance Driven Field Service Planning and Scheduling」(全文詳見附錄二)，分屬於Supply Chain Management (Paper ID: 008-0068)及Service Operations (Paper ID: 008-0087)兩子題，大會安排於Session 31場次及Session 162場次分別發表。第一篇論文探討雙鄰避設施之位址選擇與系統的車輛途程規劃問題，該議題在環保意識抬頭及運輸能源上漲的現今環境之下更顯重要，與會學者及專家對於本研究的構想與解析均持肯定態度，並對後續的研究方向與研究方法亦提出中肯而建設性的意見；第二篇論文探討主題是對維修規劃與排程建構系統架構，該文是由Southern Illinois University的Dr. Stephen C. Shih爲主筆，由Dr. Stephen C. Shih與本人共同發表，亦均獲得許多熱烈的迴響。

3. 心得

　　整體而言：在理論、實務、與應用的大會主題之下，與會討論的學者及專家極為踴躍，研究主題大致仍以學術導向及實務導向兩方向為主。在學術導向方面，著重於問題的模型與解析的方法為主，同時探討較佳的解題方法與概念；在實務導向方面，對於產業的實際應用及實務成效，亦具有相當可貴的經驗分享。此外，本次研討會的特色之一為安排多場 Panels，由資深企業主管或資深學者主持，對理論與實務相互印證而言效果良好；本次研討會的特色之二為安排多場 Workshops 及 Tutorials，對於後續的研究觀念及生產與作業管理學門的最新發展趨勢深具啓發意義，可謂收獲豐碩。

4. 建議事項

(1) 國內已申請成立該學會的台灣分會，應可擴大參與層面自下屆起組團前往，以增強國際學術交流。

(2) Operations Management 的研究領域除傳統的領域之外，已逐漸擴充含蓋至：Behavioral Operation Management, Healthcare Operation Management, Service Operations, Logistics Management & Applications 等領域，直得國內學者及專家深思。

Abstract Number: 008-0068

Location Decisions for Two Obnoxious Facilities by Balancing Compensation Cost and Transportation Cost

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Abstract

This research considers the location and routing problem for two obnoxious facilities. One obnoxious facility is given and existing and the other obnoxious facility needs a new site to be located. Both obnoxious facilities are served as two independent depots which involve vehicle routings to be arranged. A mathematic model is developed first by considering the compensation cost and the vehicle routing cost. A heuristic algorithm is then proposed to solve the location problem and vehicle routing problem simultaneously. Three experiments focused on location are conducted for decision making: (a) the impacts of increasing compensation cost, (b) the impacts of increasing transportation cost, and (c) the suitable allocation of service capacity for both obnoxious facilities. It is believed that the experimental results are useful for management decisions and future applications.

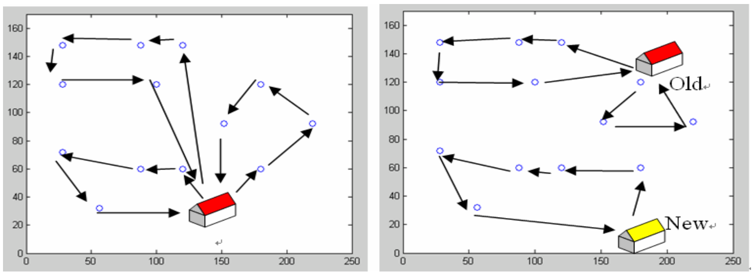
Keywords: Location Problem, Obnoxious Facility, Compensation Cost, Vehicle Routing Problem.

1. Introduction

A traditional location problem can be easily solved according to different objective functions. If a location problem and a vehicle routing problem (VRP) come together, the solution approach becomes more complicated. Most of these combined problems in the past are based on single depot to develop vehicle routings. Solution of the combined problem should include a suitable location for the depot and suitable routings regarding the depot, as indicated in Figure 1(a). In the real world situation, one depot may be extended to two depots since service requirement increases. This is an interesting topic which we will further discuss in this paper.

An obnoxious facility or undesired facility can provide service or benefit to its users, however, it will also have undesired effects on the people or environment near by. Typical obnoxious facilities include waste treatment station, chemical plant, nuclear power plant, etc. In general, obnoxious facilities produce pollutions in different types such as air, water, noise, or even radiation pollution. Location of obnoxious facility tends to near the boundary of the feasible region by considering the objective of maxi-sum or maxi-min criterion (Rodriguez *et al*. 2006). If the location problem combines a transportation problem, the obnoxious facility serves as the depot of this transportation system. The objective function should take into account environment impact and transportation cost, simultaneously. The solution of this problem tries to balance the environment impact and transportation cost.

This research investigates two obnoxious facilities and the associated vehicle routing problems. One facility is the existing facility with fixed location and service capacity. The other is a new facility to be located. Both obnoxious facilities are served as depots for the vehicle routing problem. This research focuses on (1) locating the new facility and (2) arranging vehicle routings for both, existing and new, facilities at the same time. A conceptual vehicle routing problem with two obnoxious facilities is presented in Figure 1(b). To balance the transportation cost and the bad impact on the new obnoxious facility is the major concern of this research. In addition, the bad impact will be represented by the "social cost" which should be further defined.



(a) Single obnoxious facility (b) Two obnoxious facilities

Figure 1 The location problem and vehicle routing problems

2. Literature Review

In this section, the reviewed papers focus on (1) the impacts of obnoxious facility measured by different cost items and (2) solution approach for the location routing problems.

2.1 Social Cost

Researches in Taiwan found that a obnoxious facility will devaluate the prices of building and land near this facility. In addition, pollution of obnoxious facility will cost higher medical expense which is also proportional to the distance between the facility and the residence near by. Some researchers further indicate that the compensation cost is closely related to distance and capacity (scale) of the obnoxious facility. Based on previous findings, we define a special cost item, called the social cost, to represent all costs related to the bad impacts of a obnoxious facility. The social cost is proportional to distance and population. Concepts of the social cost are based on the following two reasons: (1) Shorter distance between the obnoxious facility and residence will cost higher social cost. (2) Higher density of population will increase the social cost. The detailed definition of social cost is given in section 3.2.

2.2 Location and Vehicle Routing Problem

The genetic algorithm (GA) had been used to solve vehicle routing problems and the results show in good solution quality within short time. Yao applies the tabu search (TS) using three types of initial solution and the neighborhood approach shows the best result. In addition, the internal and external exchanges are also tested. Tuzun and Burke designed a two-phase tabu search to solve location routing problem. This approach can generate the solution better than other heuristic algorithms. Wu (2002) suggests the simulated annealing algorithm to solve the multiple depots vehicle routing problem. Solutions include the optimal number of depot, location of depot, and dispatching of vehicle routings.

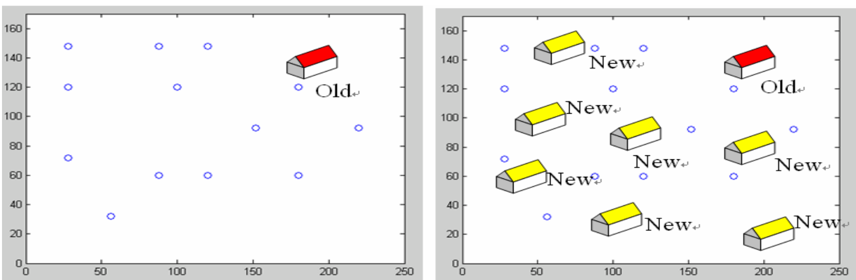
In this research, a mathematical model of location vehicle routing problem is developed based on two obnoxious facilities. Two searching heuristics, i.e. GA and SA, are combined in the solution algorithm, simultaneously. The genetic algorithm is used for solving the double-depot vehicle routing problem and the simulated annealing algorithm is applied to locating the new obnoxious facility under the situation of one existing facility. In addition, we will modify the neighborhood approach as the initial solution and use the internal and external exchanges to improve vehicle routings.

3. Model Development

The following subsections will describe the problem area and given environment, the cost items and assumptions, the variables and decision variables used, and the mathematical model.

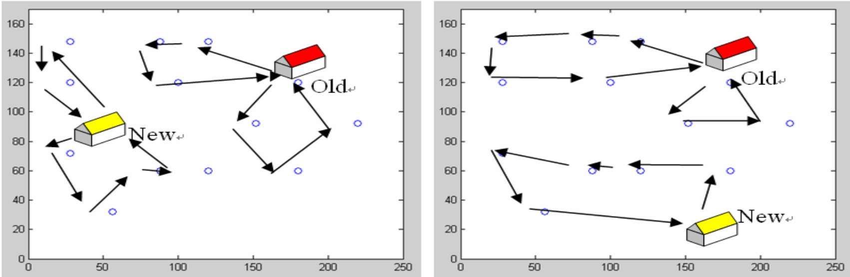
3.1 Problem Statement

This research assumes that there are *N* service points given in a limited planar area. Each service point produces fixed quantity of waste material which should be treated by the obnoxious facilities through the vehicle transportation system. One existing obnoxious facility is fixed in the current planar area and it serves as a treatment plant for waste material as well as the depot for waste material in the transportation system. This existing obnoxious facility has a fixed and given service capacity to treat the waste material for all service points, as indicated in Figure 1(a). The problem comes to this research when the existing service capacity is not enough to serve all service points. A new obnoxious facility is planning to build in this planar area, which also increases the total service capacity to meet new service requirement for all service points. In this situation, the problem of this research will focus on: (1) the location for the new obnoxious facility (as indicated in Figure 2(a) and 2(b)) and (2) the vehicle routings for the two depots, i.e. the existing and the new obnoxious facilities (as the examples indicated in Figure 3).



(a) Location of the original facility (b) Possible locations for new facility

Figure 2 Locations for existing facility and new facility



(a) Alternative A (b) Alternative B

Figure 3 Possible alternatives for two-depot vehicle routing problem

By carefully observing the situations in Figure 3, a few interesting comments can be made which should be further investigated in this paper: (1) Different locations for the new obnoxious facility will cause different degrees of impact on this limited planar area. (2) Different locations for the new obnoxious facility shall rearrange the service areas for both two depots. (3) Different locations for the new obnoxious facility shall re-dispatch vehicle routings. (4) The objective for the transportation system and the objective for the environment impacts (location issues) are conflicts in this research. A compromised solution for both objectives is necessary and unavoidable.

3.2 Cost Items and Assumptions

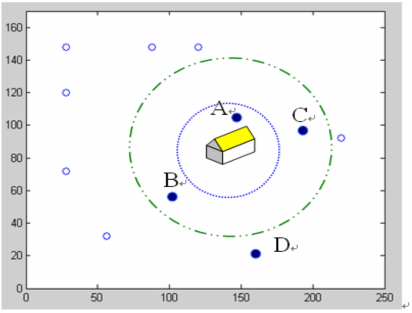
This research considers two cost items in the mathematic model, i.e. the transportation cost and the social cost. The transportation cost comes from vehicle routings of two-depot transportation system and the definition of transportation cost is same as the traditional vehicle routing problems. The social cost defined in this research includes all extra costs caused by the bad impacts of the new obnoxious facility. The typical social cost covers the following costs or expenses: the medical expenses, the devaluated prices for building and lands, the preventive costs for pollutions, and the compensation costs for the residence within the impacted area. Measurement of the social cost includes: (1) impact range represented by distance and (2) population within the impacted area. In general, the quantified social cost should be proportional to the distance and the population, simultaneously.

Figure 4 illustrates the calculation of social cost. Service point A in Figure 4 is one of the service points within the highest impact range (i.e. the blue circle), therefore, the highest social cost will apply. In addition, both the service point B and the service point C are impacted within the same impact range. In this case, if service point B has higher population than point C, then the service point B causes a higher social cost than the service point C. The service point D is out of the minimal impact range (i.e. the green circle), therefore, no social cost will be considered.

The transportation cost and the social cost are closely related to the distance between population (the service point) and the location of an obnoxious facility. In general concept, a longer distance do reduce the social cost, however, a longer distance will also increase the transportation cost, simultaneously. Figure 5 shows this concept by drawing cost curves for the social cost and the transportation cost.

Assumptions of this location and vehicle routing problem are summarized as follows:

1. Service capacities of the existing (original) and the new obnoxious facility are given and known. The total service capacity is equal to the total service requirement.



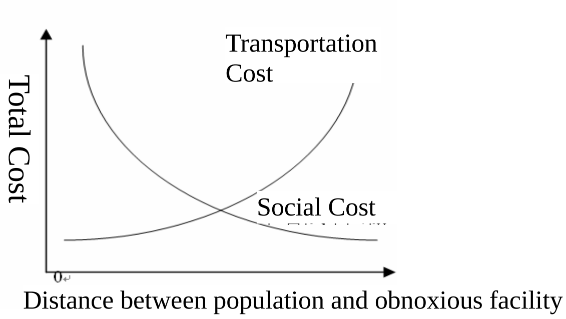


Figure 4 Illustration of social costs   Figure 5 Relationship of cost and distance

2. Location of the existing obnoxious facility is given, fixed, and known.
3. The social cost caused by the existing obnoxious facility is fixed and known, therefore, this cost will not be considered in the mathematical model of this research.
4. Location of each service point, population of each service point, and the quantity of waste material produced by each service point are given, fixed, and known.
5. Each service point can be served by one vehicle once in one route only.
6. Loading capacity of each vehicle is all the same. The loading capacity is fixed, given, and known. Over loading is not acceptable for each vehicle.
7. One vehicle serves one route and one route is served by one vehicle only. In each route, a vehicle should start from an obnoxious facility (depot) and it will come back to the same depot at the end of this route. Overlapped-zone transportation is avoided.
8. Euclidean distance is used in all distance calculations.
9. Basic unit of the social cost, transportation cost per unit distance, fixed cost of vehicle are fixed, given, and known.
10. All service points and all obnoxious facilities are located within a limited planar area.
11. The social cost is defined and calculated by considering the population of service point and the distance from the service point to the new obnoxious facility.

3.3 Mathematical Model

This subsection proposes a mathematic model for the single location and double depots vehicle routing problem. The basic idea of this model comes from the model developed by Wu (2002) and the model has been modified to fit the two-depot environment in our study. The objective function of this model is to minimize both the social cost and the transportation cost. The variables and decision variables are defined as follows:

I : A set of all possible locations for the new obnoxious facility in the feasible planar area
J : A set of all service points
V : A set of all activated vehicles
k : Index of obnoxious facility. k=1 represents the existing obnoxious facility. k=2 represents the new obnoxious facility.
v : Index of vehicle or index of route
n : Service point ID
d_{ij} : Distance from service point i to service point j. i =0 or j =0 represent the point of obnoxious facility and the depot for waste material transportation system

D_C : Transportation cost per unit distance, a constant

P_C : Social cost per person, a constant

V_C : Foxed cost of one vehicle, a constant

Q_j : Quantity of waste material produced by service point j , $j \in J$ 。

P_j : Population of service point j , $j \in J$ 。

V_L : Maximal loading capacity of a vehicle, a constant

F_L^k : Maximal capacity of obnoxious facility k , k =1, 2 。

$\mu(j)$: Weighting factor of social cost for service point j , $j \in J$ 。

$$\mu(j) = \begin{cases} W_1, & R_j \le r_1 \\ W_2, & r_1 < R_j \le r_2 \end{cases}$$

For the cases of $R_j > r_2$, then $\mu(j) = 0$

R_j : Euclidean distance from service point j to the new obnoxious facility,

$$R_j = \left[\left(x_j - F_{X2} \right)^2 + \left(y_j - F_{Y2} \right)^2 \right]^{1/2}$$

where: (F_{X2}, F_{Y2}) is the coordinates of the new obnoxious facility. (x_j, y_j) is the coordinates of the service point j , $j \in J$

r_1 : Maximal impact range represented by the minimal radius r_1. The highest weighting factor W_1 applies when the range is shorter or equal to the distance r_1 .

r_2 : Minimal impact range represented by the maximal radius r_2. The lowest weighting factor W_2 applies when the range is between distance r_2 and r_1 .

Z_i : If the location i is activated as the new obnoxious facility, then Z_i =1. Otherwise, Z_i =0.

X_{jv}^k : If the service point j is serviced by vehicle v assigned to the obnoxious facility k (k =1, 2) as the depot, then X_{jv}^k =1. Otherwise, X_{jv}^k = 0.

Y_{ijv}^k : If the path segment from service point i to the service point j is serviced by the vehicle v ($\forall v \in V$) assigned to the obnoxious facility k (k =1, 2), then Y_{ijv}^k =1. Otherwise, Y_{ijv}^k =0.

V_v^k : If the vehicle v (route v) is assigned to the obnoxious facility k (k=1, 2), then V_v^k =1. Otherwise, V_v^k =0.

A minimized mathematical model and the associated constraints are developed as follows:

The objective function:

$$Minimize \left[\sum_{i \in I} \sum_{j \in J} P_C \times (P_j \times \mu(j)) \times Z_i \right] + \left[\sum_{k=1}^{2} \sum_{i=0}^{n} \sum_{j=0}^{n} \sum_{v \in V} D_C \times d_{ij} \times Y_{ijv}^k \right] + V_C \times \sum_{k=1}^{2} \sum_{v \in V} V_v^k \tag{1}$$

Subject to:

$$\sum_{j=1}^{n} X_{jv}^k \times Q_j \le V_L \quad \forall v \in V \quad k=1, 2 \tag{2}$$

$$\sum_{i=0}^{n} Y_{ijv}^{k} - \sum_{i=0}^{n} Y_{jiv}^{k} = 0 \quad j=0, 1, 2, \ldots\ldots, n \quad \forall v \in V \quad k=1, 2 \tag{3}$$

$$\sum_{k=1}^{2} \sum_{v \in V} X_{jv}^{k} = 1 \quad j \in J \tag{4}$$

$$\sum_{v \in V} \sum_{j \in J} Q_j \times X_{jv}^{k} \le F_L^{k} \quad k=1, 2 \tag{5}$$

$$\sum_{i \in I} Z_i = 1 \tag{6}$$

$$\sum_{v \in V} V_v^{k} > 0 \quad k=1, 2 \tag{7}$$

$$Z_i = 1 \text{ or } 0 \quad i \in I \tag{8}$$

$$X_{jv}^{k} = 1 \text{ or } 0 \quad j \in J \quad \forall v \in V \quad k=1, 2 \tag{9}$$

$$Y_{ijv}^{k} = 1 \text{ or } 0 \quad i=0, 1, 2, \ldots, n \quad j=0,1, 2,\ldots, n \quad \forall v \in V \quad k=1, 2 \tag{10}$$

$$V_v^{k} = 1 \text{ or } 0 \quad \forall v \in V \quad k=1, 2 \tag{11}$$

The objective function of this research is indicated in equation (1) which has three terms. The first term represents the social cost which is caused by the new obnoxious facility. The social cost is defined by the population and the distance. The second term is the cost of vehicle routing which is proportional to the distance. The third term is the fixed cost for the vehicle which is activated. Equation (2) indicates that overload is prohibited in each route. Equation (3) shows that a vehicle arrives one service point and the same vehicle should leave this service point. Equation (4) restricts each service point is served by one vehicle only. Equation (5) restricts the maximal service capacity of each obnoxious facility. Only one location can be selected for the new obnoxious facility, which is indicated in equation (6). For each obnoxious facility, at least one vehicle routing should be activated as indicated in equation (7). Equation (8), (9), (10), and (11) limit the decision variables to be 0 or 1.

4. Solution Algorithm

A heuristic algorithm is developed for solving the proposed problem. The proposed algorithm combines both the genetic algorithm and the simulated annealing algorithm simultaneously. The genetic algorithm is used to solve the vehicle routing problems for both facilities and the simulated annealing algorithm is used to solve the location problem for the new obnoxious facility. The Figure 6 presents a general logic of this proposed algorithm. The challenge of this solution algorithm is the efficiency of computation, since vehicle routings should be re-dispatched for both obnoxious facilities when a new location is found.

This algorithm consists of three major subroutines: construction of an initial vehicle routings, improvement of vehicle routing, construction of initial location, and improvement of location. The initial location is randomly generated and the initial vehicle routings are designed by using the nearest neighborhood approach. The genetic algorithm and the simulated annealing algorithm are applied in the improvement of vehicle routing and the improvement of location, respectively. The following subsection will describe each part in details.

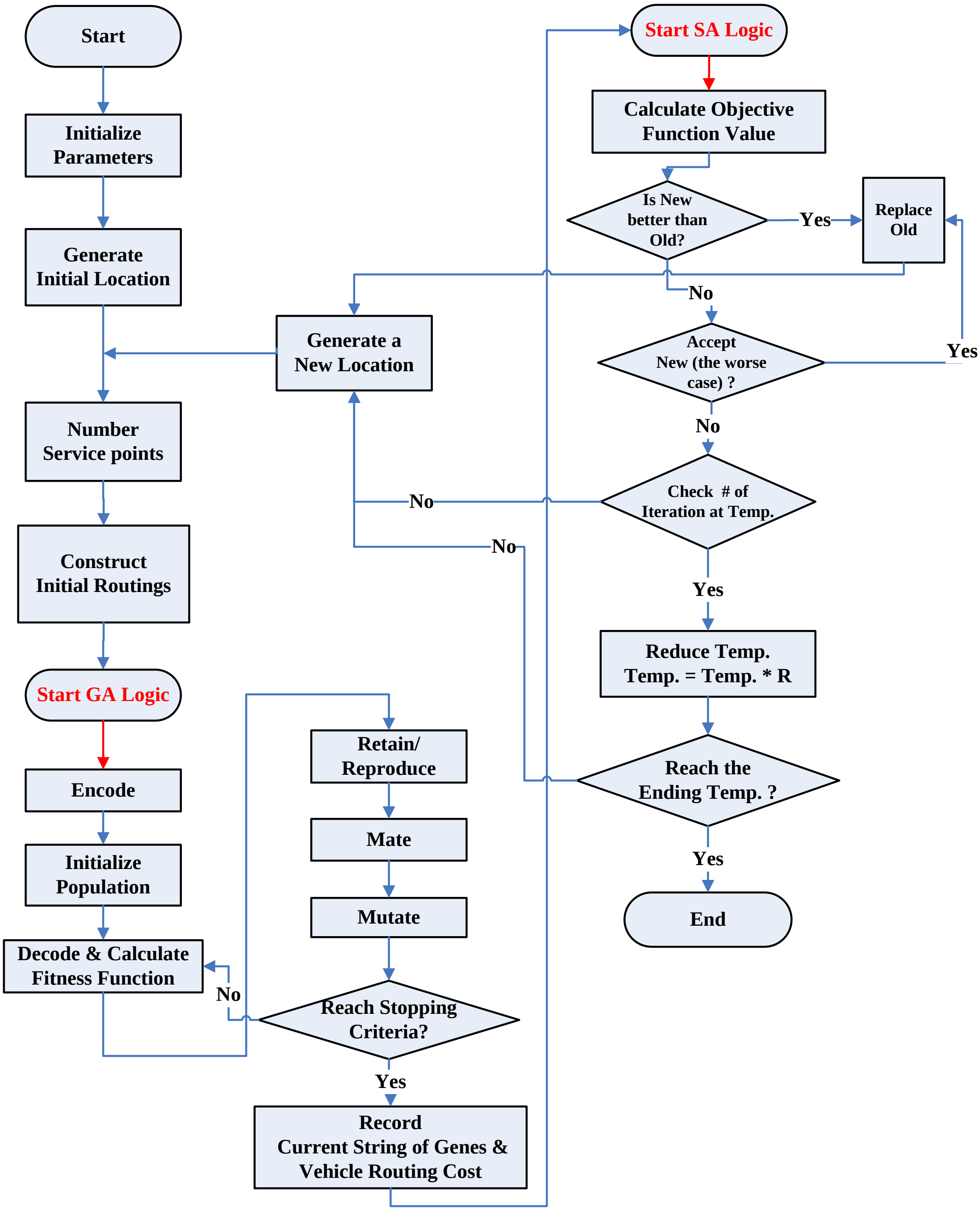


Figure 6 A general logic of the solution algorithm

4.1 Construction of an Initial Vehicle Routings

Based on the nearest neighborhood approach, the procedure of initial routings can be developed as follows:

Step 1: Number service point from 1 to *N* and from a assignment set A.

Sept 2: Select a service point i from the set A, which has the shortest distance from the obnoxious facility to the service point i. The point i will be the first point to serve in the first route. Delete the point i from the set A.

Step 3: Select a service point j from the set A, which has the shortest distance from service point i to point j. The point j is the next point to serve in the current route. Delete point j from the set A and set $i = j$.
Repeat step 3 until the loading quantity of current vehicle to the limit.

Step 4: Start the next route by selecting a service point j from the set A. The point j has the shortest distance between j and i. The point j is the first point in the current route. Delete point j from the set A and set $i = j$.

Step 5: Repeat step 3 and step 4 until all service points have been assigned to the routings.

4.2 Improvement of Vehicle Routings

This research applies the genetic algorithm to the improvement of the vehicle routings. The improvement process is described as follows:

Step 1: Setup parameters of genetic algorithm.
Step 2: Initialize population.
Step 3: Calculate the value of fitness function.
Step 4: Retain, mate, and mutate the string of genes.
Step 5: Repeat step 3 and step 4 until the stopping criteria is reached.

4.3 Improvement of Location

In this research, the location is improved by the logic of the simulated annealing algorithm. The general procedure can be described as follows:

Step 1: Check the starting condition: the current location is confirmed and the current vehicle routings for this location have been decided by the genetic algorithm.
Step 2: Generate a new feasible location and arrange vehicle routings.
Step 3: Calculate the objective function value for the new location.
Step 4: Check the acceptability for the worse location.
Step 5: Check the temperature reduction.
Step 6: Repeat step 1 to step 5 until the stopping criteria is reached.

5. Numerical Example and Analysis

In this section, a numerical example is tested and verified by using the algorithm developed in section 4. Three experiments are also conducted by considering impacts of different social costs, different transportation costs, and different allocation of service capacity. Subsection 5.1 describes the example problem and the solutions in details. The following three subsections describe three experimental results with a short discussion.

5.1 Basic Data and Solution of the Example Problem

This example problem contains 50 service points located in the predefined and limited area, as indicated in Figure 7. The coordinates of each service point, quantity of waste material generated by the service point, and the population of each service point are summarized in Table 1. The detailed description of these service points are described as follows:

1. Two obnoxious facilities and all service points are located within the square: (0, 0), (0, 100), (100, 100), and (100, 0). 5 groups of service point spread this area.
2. Quantity of waste material generated by each service point ranges from 20 to 40. The population of each service point ranges from 50 to 100.
3. The existing (old) obnoxious facility locates at (15, 20).
4. The service capacity of the new obnoxious facility is 40% of the total capacity. The service capacity of the existing obnoxious facility is 60% of the total capacity.
5. The loading capacity of a vehicle is 100. The fixed cost of a vehicle is 15 and variable cost per unit distance is 5.
6. The maximal impact distance of social cost is 30 or less and the weighting factor within this range is 2. The minimal impact distance is 50, therefore, the medium impact ranges from 30 to 50. The medium weighting factor within this range is 1. If distance is over 50, no environment impact applies. The weighting factor is 0 for this case. Figure 7 indicates this concept.

The initial location of the new obnoxious facility is located at (36, 24) which generates 3,096 as the initial social cost. The initial transportation cost for both the existing and the new facilities is 10,849. The initial total cost is 13,945 which include the social cost and the transportation cost.

After the solution process, the new obnoxious facility is relocated to (84, 65), as indicated in Figure 7 and the total cost reduces to 10,896 (i.e. 2,354 for the social cost and 8,542 for the transportation cost). The total cost reduction reaches 21.85%. At final location of the new facility, Figure 8 (a) and (b) indicate the initial vehicle routings and the final vehicle routings. In this final location, there is a 9.97% improvement from the transportation cost view point.

5.2 Impact of Different Social Costs

This subsection tests several special cases for “what happens if the social cost increases”. The analysis and discussion are focus on the impact of the location for the new obnoxious facility. Five different social costs ranging from 100% (i.e. the current cost) to 1000% (i.e. 10 times of current cost) will be tested by the solution algorithm proposed in section 4. The unit transportation cost will keep the same in all cases. Table 2 indicates the basic data of each case including the increasing percentage of the social cost, the weighting factor for the maximal impact distance, and the weighting factor for the minimal impact distance. Since each case will be independently tested 5 times, the average total cost including the social cost and the transportation cost is drawn in bar charts as indicated in Figure 9. Figure 10 plots the locations of the new obnoxious facility for each case, including 5 independent runs.

In general, cost data shown in Figure 9 indicates that the social costs are proportional to the increasing percentages. By observing the locations in Figure 10, a significant trend can be found: when the social cost increased, the locations tend to move towards the corners or edges of the feasible area. It also represents the impact of social cost is greater than the impact of transportation cost in this case.

Table 1 Basic data for 50 service points

Type \ ID	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25
X axis	36.0	49.5	39.2	5.3	84.1	96.3	87.4	86.5	37.3	80.5	88.3	81.6	81.6	74.2	90.8	32.2	91.7	51.2	58.1	6.7	81.6	36.7	17.3	49.8	54.2
Y axis	34.1	17.6	90.9	97.3	29.2	31.1	30	8.4	60.3	96.3	87.9	66.7	19.9	46.9	67.4	97.3	33.6	11.9	29	45.6	9.6	65.5	41.2	27.3	88.9
Quantity	36.0	24.0	28.0	29.0	21.0	35.0	40.0	27.0	25.0	21.0	32.0	26.0	25.0	32.0	24.0	24.0	29.0	37.0	21.0	22.0	34.0	28.0	33.0	21.0	39.0
Population	51.0	61.0	87.0	99.0	57.0	71.0	82.0	99.0	63.0	62.0	78.0	100	98.0	73.0	73.0	51.0	54.0	63.0	89.0	51.0	59.0	74.0	85.0	52.0	65.0
Type \ ID	26	27	28	29	30	31	32	33	34	35	36	37	38	39	40	41	42	43	44	45	46	47	48	49	50
X axis	57.5	9.9	32.7	51.6	91.9	41	3.5	4.8	20	30.1	36.5	84.2	73.1	60.5	82.8	48.8	84.3	29.9	20	97	38.4	99.8	2.2	16.1	21.3
Y axis	77.2	30.3	78.3	95.4	62	30.1	5	85.8	30.2	32.7	33.9	99.6	37.1	37.6	62	9.1	33.6	2.3	6.5	69.5	15.9	92.1	54.9	68.7	75.5
Quantity	34.0	25.0	39.0	38.0	25.0	37.0	37.0	22.0	31.0	34.0	36.0	27.0	22.0	26.0	34.0	32.0	27.0	38.0	32.0	31.0	38.0	30.0	25.0	36.0	24.0
Population	64.0	80.0	52.0	51.0	75.0	76.0	53.0	56.0	66.0	92.0	54.0	62.0	77.0	87.0	54.0	68.0	67.0	83.0	55.0	53.0	78.0	78.0	85.0	59.0	68.0

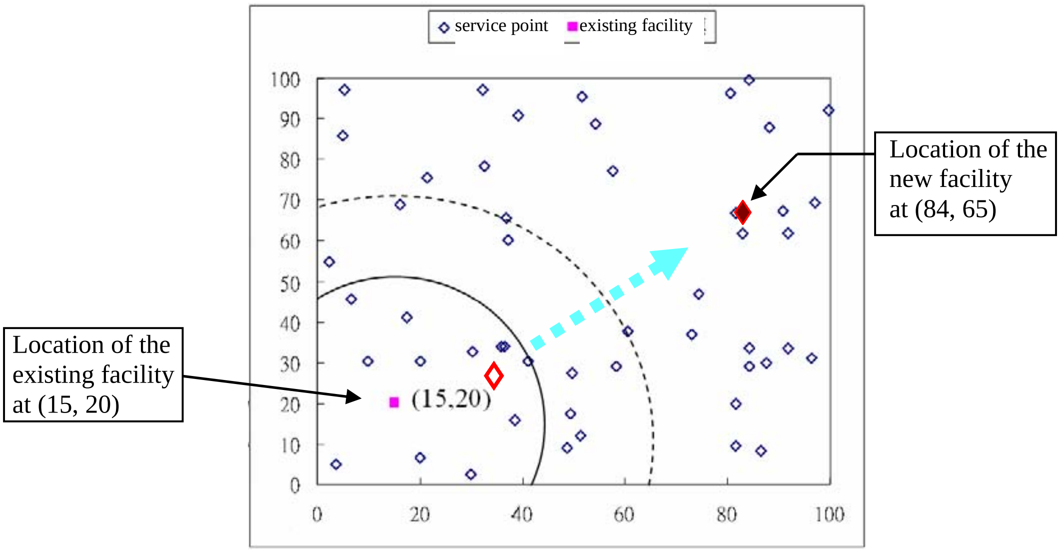
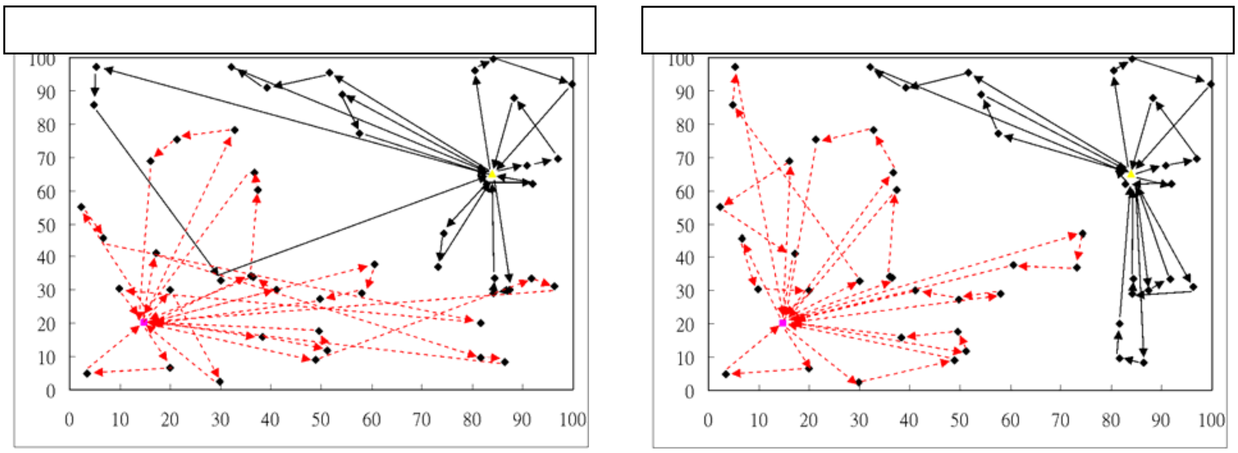


Figure 7 Locations of two facilities and example of impact ranges



(a) Initial vehicle routings (b) Final vehicle routings

Figure 8 Improvement of vehicle routings for the final location at (84, 65)

Table 2 Five cases of different social costs

Case ID	(A)*	(B)	(C)	(D)	(E)	(F)
Social Cost Increasing Percentage	100%	120%	150%	200%	500%	1000%
Weighting Factor for Maximal Impact Distance	2	2.4	3	4	10	20
Weighting Factor for Minimal Impact Distance	1	1.2	1.5	2	5	10

Remark: * represents the original case with no increasing of social cost.

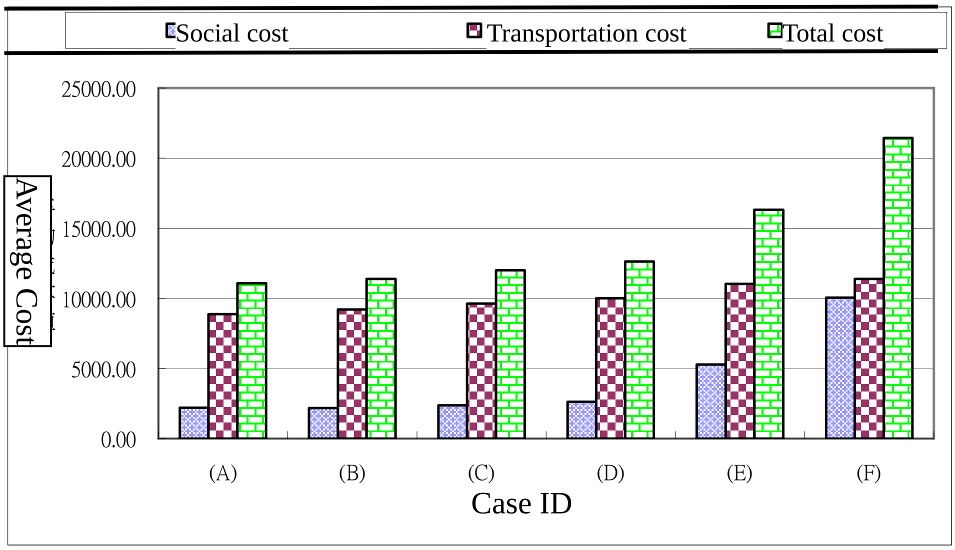


Figure 9 Total costs (social cost and transportation cost) for increasing social costs

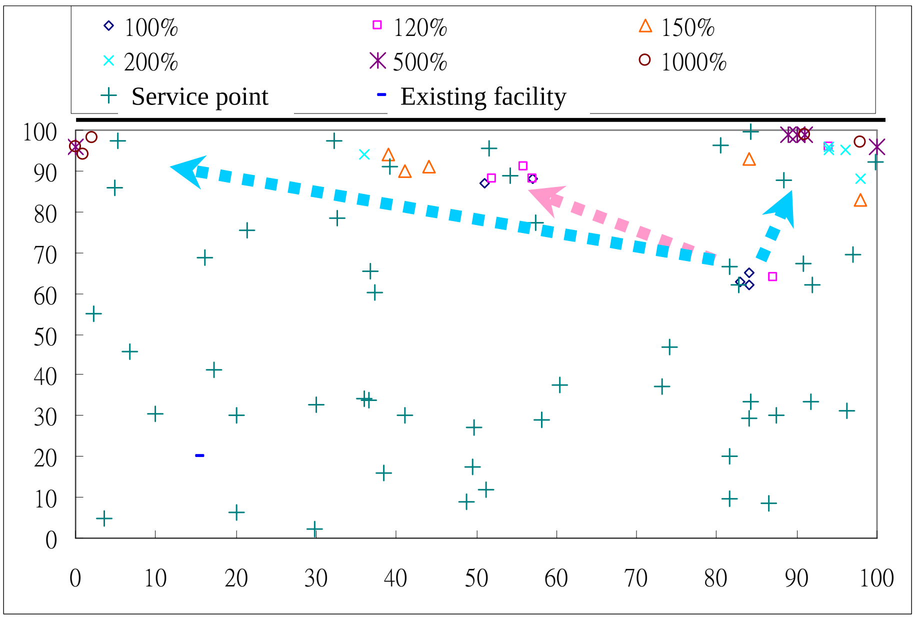


Figure 10 Locations of new obnoxious facility for different social costs

5.3 Impact of Different Transportation Costs

This subsection will focus on the impact of transportation cost when the unit distance cost increased. The increasing energy cost is the hot issue in the current global energy environment. We evaluate 5 levels of unit transportation cost from 110% to 150% as indicated in Table 3. Case (A) is the base line with no increasing of unit transportation cost. Calculation and definition of the social cost will keep the same in all cases. In each case, 5 independent runs are executed and the averaged total cost including the social cost and the transportation cost is drawn as the bar charts in Figure 11. Figure 12 plots the locations of the new obnoxious facility for each case, including 5 independent runs.

Data from Figure 11 indicates that: (1) the social cost does not change significantly when the unit transportation cost increased and (2) the transportation cost is proportional to the increased unit transportation cost. For locations of the new obnoxious facility, Figure 12 shows no significant changes. Most of the cases, the X axes of new location are ranging between 75 to 90 and the Y axes of new location are ranging from 50 to 70. In this case, the changes of unit transportation cost do not vary location of the new obnoxious facility. This observation may not be still true in other cases.

Table 3 Five cases of different unit transportation costs

Case ID	(A)*	(B)	(C)	(D)	(E)	(F)
Increasing Percentage of Unit Transportation Cost	100%	110%	120%	130%	140%	150%
Unit Transportation Cost	5.0	5.5	6.0	6.5	7.0	7.5

Remark: * represents the original case with no increasing of transportation cost.

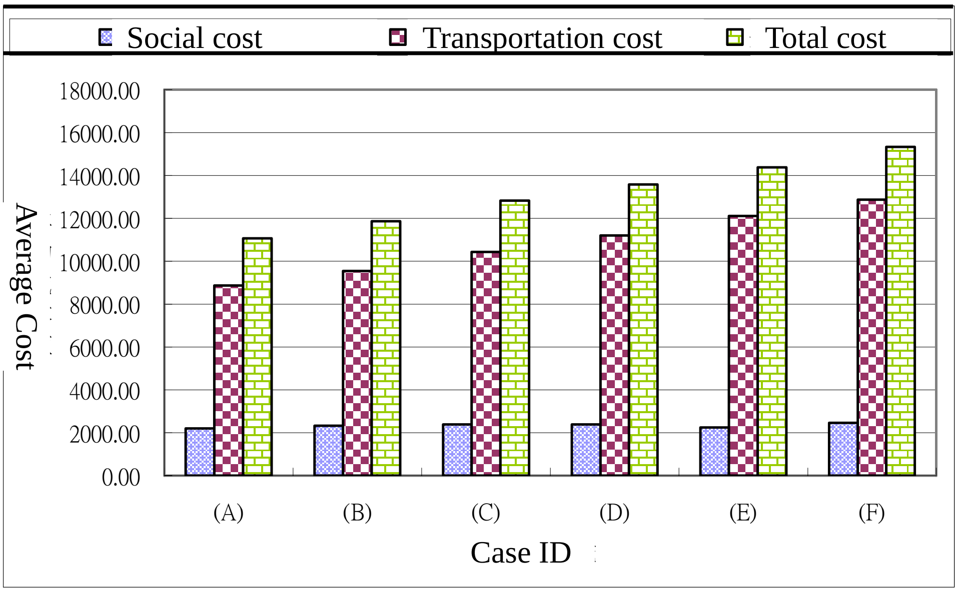


Figure 11 Total costs (social cost and transportation cost) for increasing transportation costs

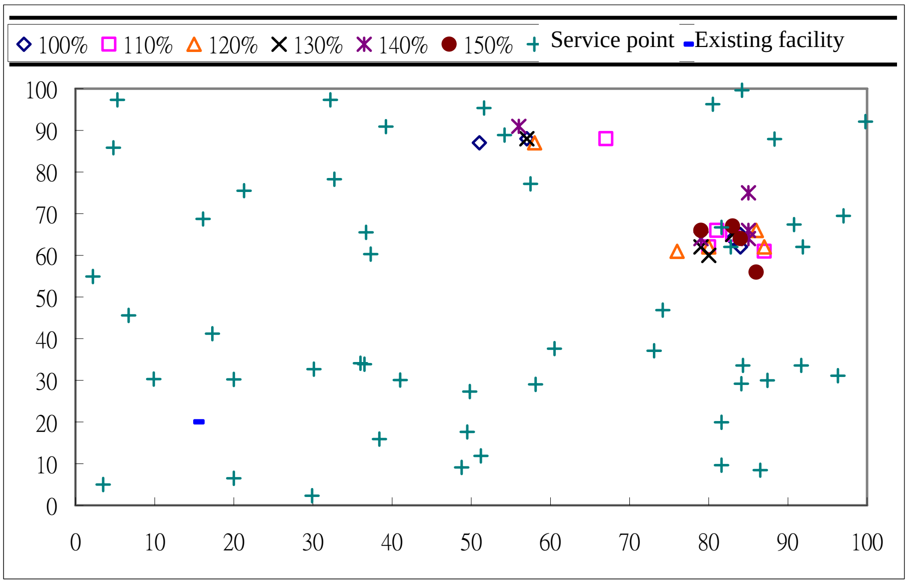


Figure 12 Locations of new obnoxious facility for different transportation costs

5.4 Impact of Allocation of Service capacity

In the original example problem, we assume that the capacity of new obnoxious facility is fixed on 40% of the total service capacity. This constraint may be relaxed in this subsection. The experiment of this subsection will further investigate different allocation of service capacity for both obnoxious facilities. The capacity of new facility is ranging from 10% to 90% with 10% increment in each case. All cases are represented by case (A) to case (I) in sequence. The total service capacity will keep the same in all cases, i.e. in 9 different cases. In each case, 5 independent runs are executed and the averaged costs are plotted as the bar charts in Figure 13. Figure 14 plots the locations of the new obnoxious facility for each case, including 5 independent runs.

By observing the variation of total cost from Figure 13, the total costs are different due to different allocation of service capacity. In this example problem, the near optimal allocation of capacity for the new facility occurs between 30% to 40% of total capacity. Figure 14 further implies a trend that when the capacity of new facility increases, the locations of the new facility tend to move from the up-right corner towards the bottom-left corner, i.e. almost the direction of the existing obnoxious facility. This phenomenon seems reasonable to explain: when the location with higher capacity, it should be as close to the center of service points as possible.

6. Conclusions

This research proposes a model based on the new single location problem and the double-depot vehicle routing problems of two obnoxious facilities. A heuristic algorithm using genetic algorithm and simulated annealing algorithm is proposed for solving this complicated problem. A numerical example is also used to demonstrate the effectiveness of this solution approach. Three experiments are conducted by considering changes of social cost, changes of unit transportation cost, and allocation of service capacity. In general, the experimental results indicate that the proposed model and solution algorithm are useful in decision making for the location and vehicle routing problem of two obnoxious facilities.

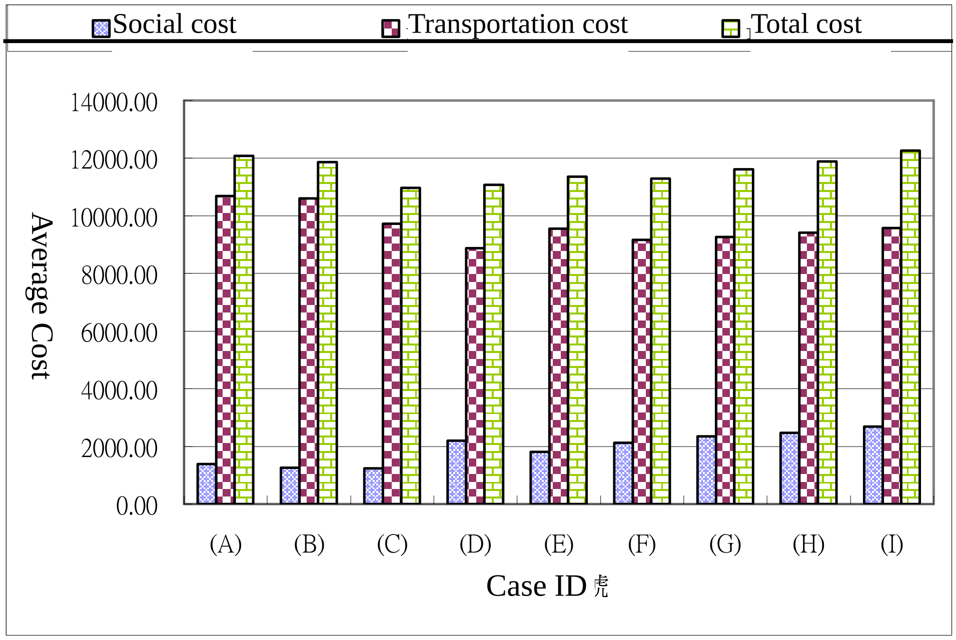


Figure 13 Total costs for different allocations of service capacity

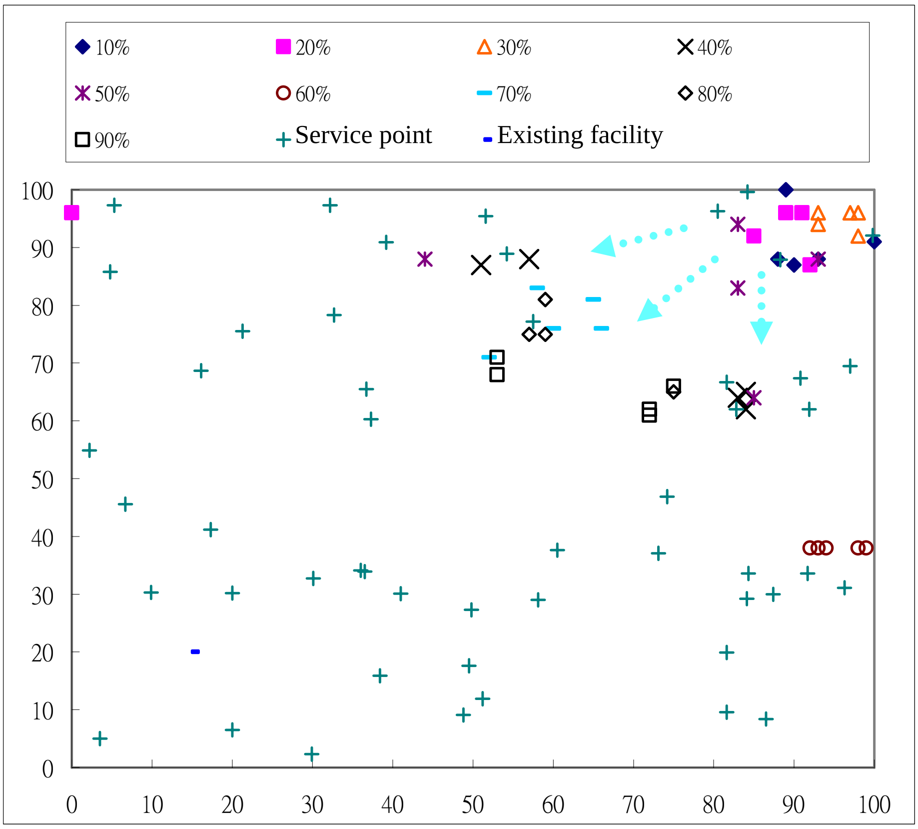


Figure 14 Locations of new obnoxious facility for different allocations of service capacity

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A Framework for Aftermarket Condition-Based Maintenance Driven Field Service Planning and Scheduling

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Abstract

The primary objective of this paper is to propose a framework for aftermarket condition-based maintenance (CBM) driven field service planning and scheduling. Aftermarket operations represent all the maintenance, repair, and overhaul (MRO) services. As part of aftermarket operations, an integrated CBM and field service management system is a vital competitive factor for providing effective MRO services. The ability to continuously monitor the equipment data on current health conditions as well as to optimize field service operations based on the equipment health data is essential. Addressing the unique characteristics presented in managing aftermarket operations, the proposed framework renders an innovative approach to intelligent field service management based on large-scale prognostic data on critical equipment health conditions. Specifically, the proposed framework focuses on an integrated field service automation solution by synergizing data-mining enabled CBM, pre-scheduling field service job planning and clustering, and multi-criteria field service scheduling.

Keywords: aftermarket condition based maintenance, field service planning, clutering, and scheduling.

1. Introduction

The primary objective of this paper is to propose a framework for aftermarket condition-based maintenance (CBM) driven field service planning and scheduling. The key areas underlined in this paper include the design and modeling of integrated structural health monitoring (SHM), condition-based maintenance (CBM), and field service automation. A Web-based *three-stage intelligent maintenance (3S-IM) model* is proposed for integrated SHM/CBM as well as aftermarket field service automation. The 3S-IM model renders an innovative approach to intelligent maintenance systems design on large-scale data acquisition, mining, and diagnosis of critical equipment health conditions for structural anomaly detection. Another thesis of the development of this model is to synergize optimization theories, mathematical modeling techniques, and advanced information technologies (e.g., fuzzy logic and knowledge management) in the area of field service management.

Historically, manufacturing enterprises have focused mostly on the supply chain management of designing and manufacturing physical products while paying little attention to the so-called "forgotten supply chain" of their aftermarket (or called post-sales) businesses. Aftermarket businesses represent all the maintenance, repair, and overhaul (MRO) services that are either not included in the original equipment sales or not delivered by the original equipment manufacturers (OEMs). For the post-sales service intensive enterprises (e.g., Boeing, Xerox, United Technologies Corporation, and Caterpillar, Inc.), the profit margin of their MRO businesses is usually much greater than that of original goods or equipment sales.

With combined higher net margins and decreased capital requirements of the post-sales service operations, greater financial value can be significantly created. As a prime example, the Otis Elevator Company of United Technologies Corporation generated about 50% of its revenue from post-sales services and repairs while creating only 35% from installation of escalators and elevators. For Otis, installing new equipment often has relatively modest impact on its market capitalization. Every equipment installation typically guarantees a steady revenue stream generated from required MRO services following the installation. In addition, sales from MRO services are generally considered less cyclical or seasonal than original equipment sales. In other words, post-sales services are usually not subject to market-specific or industry-specific seasonality, thus leading to greater financial value for the companies. As a matter of fact, Wall Street normally places higher value on the service lines of business for those world-class post-sales service intensive organizations, such as Otis. As a result, in today's complex and competitive marketplace, managing the post-sales service supply chain is no longer an option for many companies. Reliable and superior post-sales service is extremely important to establishing a long-term customer relationship and sustaining a competitive advantage. As more and more companies race to boost their field service management capabilities and performance, it is imperative to effectively manage and optimize this historically neglected area in supply chain management—the post-sales service operations.

As part of aftermarket service supply chain management, an integrated structure health monitoring and condition-based maintenance system is a vital competitive factor for those industries that provide MRO services for their equipment such as aircrafts, elevators, medical equipment, and networking equipment. The ability to continuously update the equipment data on current health conditions and monitor structure physical changes is crucial to those companies to differentiate themselves from the rest. In addition, the ability to plan and optimize field service operations based on the equipment health prognostic data is essential. Among the field service operations, service territory planning and field workforce scheduling are two of the most critical tasks for improving the quality of field service management. In reality, these tasks are often very challenging due to a number of interweaved factors and unique characteristics presented in managing field services. First, there is profound complexity caused by the dynamic, demand-responsive nature of field service operations. Often times, the magnitude of complexity can make the decision-making processes in scheduling more complex than those in manufacturing settings. Second, to achieve an optimized workforce scheduling solution, the dispatcher must incorporate different types of service work into dispatching decisions.

From a broader perspective, the primary types of field service work include planned maintenance orders and emergency service calls. Planned maintenance is typically performed at regular intervals on the serviced units through service contracts. Emergency service calls are unplanned service requests due to equipment failure that may arise randomly over time. In other words, emergency service demand, or so-called, stochastic demand, is primarily driven by unpredictable event probabilities (e.g., equipment failures). In essence, both work types have very different scheduling requirements. Combining these two work types in one optimized scheduling solution presents a highly dynamic and challenging problem. In real-life scenarios, adding to the considerations of other business rules (such as terms in the service contracts) and constraints (e.g., spatially separated service sites, travel times, expiration times, and field technician skill requirements) can make the task of field service scheduling far more complicated than that of production scheduling. Due to the effect of “unbuffered demand,” unlike production work orders, it is impossible to queue the field service orders into a master production schedule with a given frozen time fence. Furthermore, it is not feasible to store service outputs in the form of “finished goods inventory,” as those in the physical goods production environment. Finally, planning necessary service parts and handling returned items are some notoriously daunting tasks for those OEMs or aftermarket organizations to manage. Lacking a rigorous service resources planning mechanism usually leads to significant supply and demand imbalances across field service depots. Uncertainty and bias involved in service parts demand forecasting and replenishment will further plague the effectiveness of scheduling tasks.

To address the dynamic nature of the aftermarket MRO operations, this proposal presents a preliminary version of a Web-based *three-stage intelligent maintenance (3S-IM) model* for integrated SHM/CBM as well as aftermarket field service automation. The proposed 3S-IM renders an innovative approach to intelligent maintenance systems design on large-scale data acquisition, mining, and diagnosis of critical equipment health conditions for structural anomaly detection. Another thesis of the development of this model is to synergize optimization theories, mathematical modeling techniques, and advanced information technologies (e.g., fuzzy logic and knowledge management) in the area of field service management. This synergy has presented an unprecedented territory of challenge, opportunity, and innovation.

2. The 3S-IM Model

Maintenance is typically performed in two ways: preventive maintenance and corrective maintenance. With the first approach, some pre-maintenance actions are taken to prevent or minimize equipment breakdown by predicting possible faults. With corrective maintenance, maintenance is performed after a breakdown or an obvious fault has occurred. The preventive maintenance can be further divided into two categories: Condition Based Maintenance (CBM) and predetermined maintenance. The predetermined is scheduled in time, while CBM can have dynamic or on request intervals. In essence, CBM is an approach that seeks high asset availability and low maintenance costs by using equipment health conditions as a guide for taking maintenance actions (Williams and Davies, 2002). The core R&D challenges for CBM usually requires highly multi-disciplinary solutions focusing on system level issues. A potential technical sweet spot involves developing the capability to confidently recognize the onset of a failure process, and then to track and predict the evolution of that failure process to a point that economic, engineering, or other business criteria determine if it is appropriate to repair or replace the equipment or parts. To achieve this goal, improved intelligent systems capabilities, such as data mining, are indispensable.

Specifically, the 3S-IM model focuses on implementing SHM/CBM and intelligent field service solutions in four areas: (1) integrated SHM/CBM capabilities enabled by data mining, (2) pre-scheduling service territory and field service planning by mathematical programming and service job clustering techniques, (3) multi-criteria field service scheduling and post-scheduling systems learning using fuzzy logic, and (4) web-centric information sharing and knowledge management for the purpose of enhancing service supply chain performance and integrating and streamlining the entire supply chain operations.

As shown in Figure 1, the preliminary version of the proposed 3S-IM model consists of the following three interrelated stages:

- Stage I: Integrated structural health monitoring and condition-based maintenance system
- Stage II: Pre-scheduling field service territory planning and task clustering
- Stage III: Fuzzy logic based field service scheduling and post-scheduling systems learning

These three stages involve two important aspects of MRO operations: preventive maintenance and corrective maintenance. Stage I deals with "before-the-facts" preventive maintenance through prognostic SHM/CBM capability. With the notion of "prediction and prevention," the primary goal in the first stage is to sustain near-zero breakdown performance and thus maximize the degree of preventive maintenance. In other words, it strives to minimize emergent service requests and subsequent corrective maintenance efforts. Stages II and III primarily tackle the "after-the-facts" corrective maintenance tasks. In response to the alerts, maintenance plans, and work scope generated from the SHM/CBM system, the major tasks in Stage II are to plan, balance, and allocate the service resources in advance and undertake necessary pre-scheduling work, such as service territory assignment and service job clustering. Consequently, the resource utilization can be optimized. Based on the maintenance plans created from the second stage, the third stage involves fuzzy logic based field service scheduling and dispatching. Stage III also involves the system self-learning capability for deriving and incorporating more new facts and rules on preventive MRO operations.

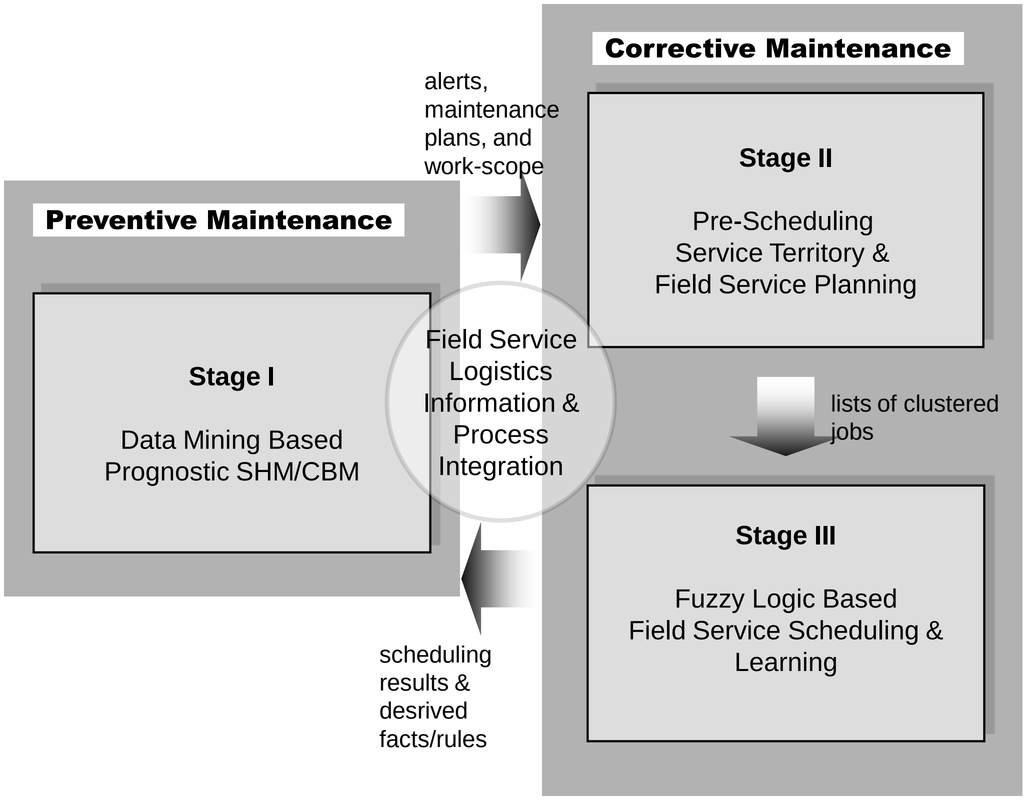

Figure 1. The 3S-IM Model

Field service organizations have been troubled by the inefficiencies engendered by loose integration and communications among different field service resources and operations. To achieve seamless and zero-latency connectivity, seamless integration of the field service processes and information in these three stages is the key tenet of the proposed model. A web-centric information sharing and knowledge management portal is developed for enhancing service supply chain performance and integrating and streamlining the entire supply chain operations. The following sections describe the three stages of the proposed 3S-IM model in detail.

2.1 Stage I: Data mining-based SHM/CBM

This stage identifies and develops the key technical capabilities for generic SHM/CBM applications, including automatic patterns extraction and maintenance schedule planning. Successful SHM/CBM implementations need the generic data mining capability for applications to a broad range of data sets and models. Data mining is an advanced data processing and analytical technique to extract implicit, previously unknown, and potentially useful information and knowledge as well as discovering hidden patterns from a large group of data by using machine learning, statistical models, mathematical algorithms, and visualization techniques (Adriaans and Zantinge, 1999; Witten and Eibe, 2005).

In addition, integrating generic knowledge discovery capabilities into SHM/CBM systems entails the establishment of specific data sets and models about the systems under maintenance. Another objective of the technology developed in this stage is to achieve optimal field service planning prior to actual occurrences of equipment fault so as to minimize overall costs (i.e. costs of maintenance and down-time). Still another technology development goal is to bootstrap maintenance actions and equipment utilization with the diagnostics algorithms developed in this stage. This enables a learning process that improves cost reduction over time, given that scheduling achieved optimality is tied to the condition forecast accuracy. Figure 2 synopsizes a conceptual diagram of the proposed data mining-based SHM/CBM system:

- **Equipment Model:** This model includes equipment wear data, diagnostics, and fault detection algorithms. The data on equipment wears show how much and the conditions in which the equipment is used. There are two contributions to wear: one is stimulated by a wear model (physics-based or black box in source) and the other by a random event generator. Both these processes, along with performed maintenance actions, are subsequently integrated into an overall condition. The wear data generated from the wear model and condition monitoring data from fault detection and prognostics algorithms are then imported into the maintenance condition database and further integrated in the maintenance condition warehouse for future uses.

- **Prognostication Model:** This model includes three prognostication components: (1) estimation of remaining useful life (or time to failure or time for degraded performance) based on the condition of the equipment; (2) development of confidence levels (uncertainty estimates); and (3) recording an audit trail of how the estimate and confidence level are obtained. In developing these three parts of prognostication models, quality diagnostics and sensor information are considered imperative. Data is thus needed not only for use by prognostication models, but also to train and validate the models.

- **Data-Mining Model:** Receiving data from the equipment and prognostication models, the data mining engine extracts an extensive set of features and patterns that describe each maintenance and equipment wear condition, and generates rules that accurately capture the behavior of maintenance activities. In other words, it can prescribe if the equipment health in the monitored component, sub-system, or system has degraded. Diagnostic records are then generated and fault possibilities are proposed. The diagnosis should be executed based upon trends in the equipment health history, operational status, and loading and maintenance history.

- **Maintenance Schedule Planning Model:** The maintenance scheduling policy utilizes current and forecasted equipment condition patterns discovered from the data mining engine, along with current and future costs of downtime, to generate an a preliminary maintenance schedule. It contains an algorithm to convert equipment conditions into work-scope. *Work-scope* is the bill of inspection, parts replacement, repair, and rebuild actions which are required to tear down, refurbish, and rebuild the equipment under maintenance to a given build standard. These models are refined using the results of the maintenance action and the equipment condition history.

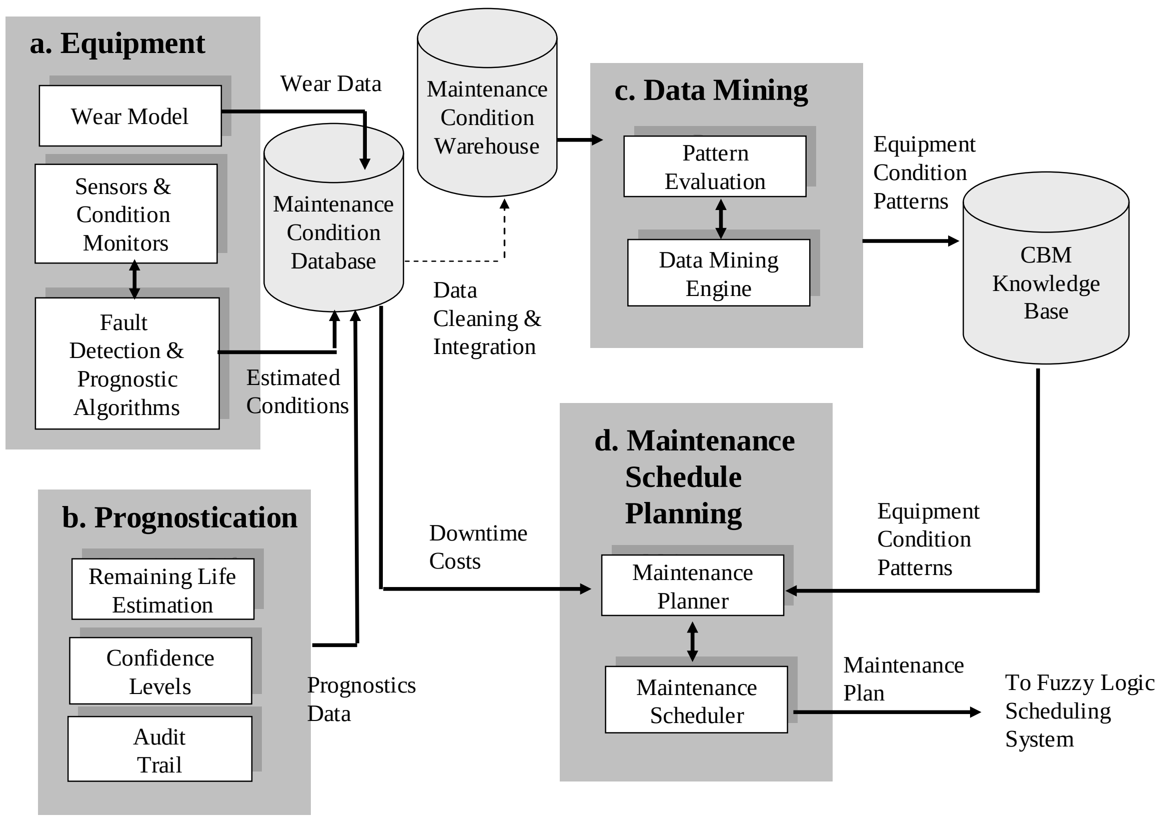

Figure 2: Data Mining Based SHM/CBM System

2.2 Stage II: Pre-scheduling field service planning and job clustering

Following the effort in Stage I, a work-scope listing all the required service jobs over a certain period of time (e.g., a day) is generated. In the 3S-IM model, a scheduling job is a 3-way assignment of "service jobs," "resources" (service technicians, parts, tools, service vehicles, etc.), and "time slots," subject to business constraints ("hard" business rules) and objectives ("soft" business rules). A service job may consist of a "cluster" of work orders, each of which may be a series of tasks or procedures, performed on an equipment unit in a single on-site visit. Relevant resources include field service engineers or technicians, transportations (e.g. vehicle), communication devices (e.g. wireless personal digital assistants), parts and materials, and tools. Service jobs are assigned a time slot to match the expected job duration, based on desired performance criteria as well as given business constrains and objectives.

"Hard" rules are those constraints that cannot be violated in any conditions. For instance, according to the agreed terms indicated in a specific service contract, no more than 3 hours of overtime is allowed per day and the schedule must include a 1-hour rest break per shift. A feasible schedule must satisfy all hard rules without any exception. On the other hand, "soft" rules indicate preferences or objectives, such as "a particular Customer X is preferably serviced by Technician Y" or "a technician should preferably not work beyond end of shift." Any soft rule can be relaxed or violated, but a "penalty" will be incurred.

Considering savings on travel time and set-up time, it may be beneficial to cluster some of the service work orders as a pre-processing step to scheduling. For maximum resource efficiency and utilization, all types of service work orders are properly grouped together by using two clustering methods: distance proximity and time proximity clustering. With distance proximity clustering, the work orders are clustered based on the geographical location of the equipment and the proximity of the resources (mainly the field service technicians). To complement the distance proximity clustering, a mathematical service territory modeling (MSTM) method is developed for computing the expected distance and variance of distance as well as to predict the mean travel time and mean response time over a specified geographical service area. Of great economic significance, travel time is a crucial aspect of service territory performance modeling since it can often save sizable direct costs by a fraction of travel time reduction. Travel time is further affected by other integral factors, such as the territory shape and size, dispatching rules, and equipment density. Response time is defined as the sum of queue time and travel time. The mathematical model is constructed on the basis of evaluation of a number of imperative factors regarding field service performance measures. The shape of a service proximity shape is defined as a fan chart, shown as in Figure 3. With mathematical distance proximity modeling, both the cases of "single-depot" and "multiple-depot" are considered. (A depot is a field service management office that handles all service requests in a specific territory.) Typically, the travels of field service can be divided into two categories: a round-trip travel from a central facility to the failure location and a sequential-trip travel from one repair location to another.

As an example, a single-depot model considering only the sequential-trip travels is used to illustrate how the service work orders are clustered, given the assumption of finite machines distributed over a given service region. It is assumed that the closest available technician is dispatched to a service request, which is at the foremost position in a queue within a certain service territory. Since the technicians make sequential trips to the calling locations that are distributed over a service region; therefore, the travel distance can be considered as between two points (x_1, y_1) and (x_2, y_2). The distance between these two points can be defined by two ways, which are L_1 metric and L_2 metric.

L_1 metric: $$D = |x_1 - x_2| + |y_1 - y_2|$$

L_2 metric: $$D = \left[(x_1 - x_2)^2 + (y_1 - y_2)^2\right]^{\frac{1}{2}}$$

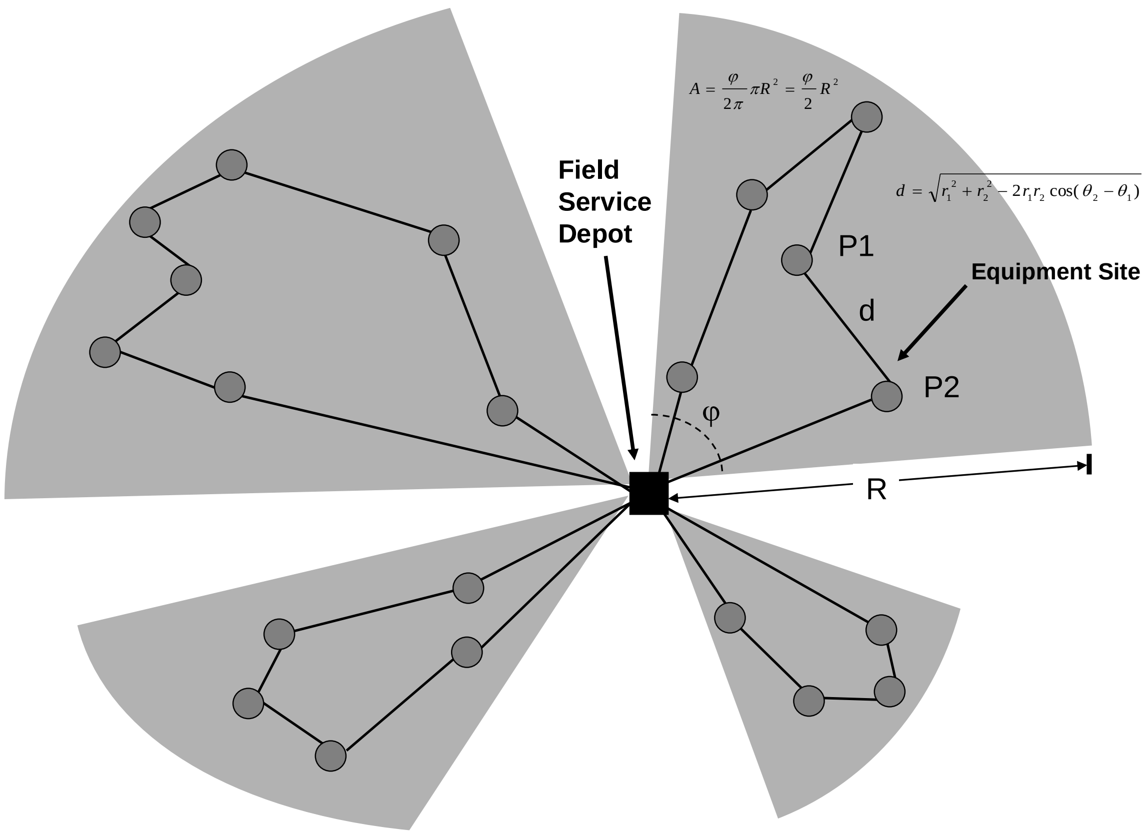

Figure 3

The expected distance and variance of distance of any two points (two equipment sites) are then modeled with L_2 and L_1 metrics. The polar co-ordinate is used to indicate these two points, P_1 (r_1, θ_1) and P_2 (r_2, θ_2). The area of the chart is $A = \frac{\varphi}{2\pi}\pi R^2 = \frac{\varphi}{2}R^2$. The expected distance, *E(d)*, and variance of distance, *V(d)*, between the two given equipment sites with L_2 metric are expressed as:

$$E(d) = \int_0^R \int_0^R \int_0^\varphi \int_0^\varphi \sqrt{r_1^2 + r_2^2 - 2r_1r_2\cos(\theta_2 - \theta_1)}\,\frac{r_1r_2\,dr_1\,dr_2\,d\theta_1\,d\theta_2}{A^2}$$

$$= \frac{1}{A^2}\int_0^R r_1\,dr_1 \int_0^R r_2\,dr_2 \int_0^\varphi \int_0^\varphi \sqrt{r_1^2 + r_2^2 - 2r_1r_2\cos(\theta_2 - \theta_1)}\,d\theta_1\,d\theta_2$$

$$V(d) = \int_0^R \int_0^R \int_0^\varphi \int_0^\varphi \left(r_1^2 + r_2^2 - 2r_1r_2\cos(\theta_2 - \theta_1)\right)\frac{r_1r_2}{A^2}\,dr_1\,dr_2\,d\theta_1\,d\theta_2 - \left(E(d)\right)^2$$

$$= \frac{1}{A^2}\int_0^R r_1\,dr_1 \int_0^R r_2\,dr_2 \int_0^\varphi \int_0^\varphi \left(r_1^2 + r_2^2 - 2r_1r_2\cos(\theta_2 - \theta_1)\right)dr_1\,dr_2\,d\theta_1\,d\theta_2$$

With the embedded distance proximity clustering algorithm, the system will then cluster and sequence the work orders into appropriate service jobs based on the calculated E(d) and V(d).

Overall travel time for completing those service jobs can then be significantly reduced thanks to work order clustering.

2.3 Stage III: Multi-criteria fuzzy logic based field service scheduling and dispatching

As a subsequent step, the third stage focuses on the tasks of scheduling service jobs with available, qualified field engineers or technicians for the objective of minimizing total weighted stress (tardiness). According to the pre-scheduling plans generated in Stage II, a multi-criteria fuzzy logic-based field service scheduling (MCFL-FSS) system is developed to adaptively guide the selection of dispatching rules or scheduling procedures for different corrective maintenance problems. By choosing an appropriate dispatching rule or scheduling procedure, near-optimal and optimal solutions can be found.

2.3.1 Basic MCFL-FSS components

The MCFL-FSS system consists of the following interconnected components:

- **Inputs to the Fuzzy Logic Engine:** (1) service call patterns and clustered jobs, (2) field service technician status on availability, proximity, skill levels, etc., (3) other service resource availability (parts, tools, vehicles, etc.) and (4) performance criteria (travel time, response time, tardiness, etc.)

- **Scheduling Procedures:** This component is a set of applicable scheduling procedures, each of which is considered to be excellent for a given set of patterns of the service call, maintenance plans, the technician status, and other set criteria. A database storing expertise and observations is used to direct the selection of the scheduling procedures. Usually the expertise and observations are represented in the form of fuzzy IF- THEN rules.

- **Fuzzy Logic System:** This is the core of the scheduling system. After training, it is used to dynamically guide the selection of scheduling procedures at different time point.

- **Scheduling Procedure Selection Algorithms:** This component is the scheduling procedure selection process that chooses one of the predetermined scheduling algorithms based on the inputs about the environment of service call and technician status.

- **Simulation Results Evaluation:** This component stores the simulation results and previously running results. All the results are used to train the fuzzy logic system.

According to Wang (1997). the main notion of fuzzy logic is that many problems in the real world are mostly imprecise and vague rather than exact. The effectiveness of the human brain is achieved not only from precise cognition, but also from the process of fuzzy judgment and reasoning. In general, fuzzy systems reason with a set of multi-valued data or so called fuzzy sets (i.e., the sets of values between 0 and 1) instead of bi-valued sets or crisp sets (i.e., the sets of value of 0 and 1). One of the advantages of fuzzy logic techniques lies in the fact that they render a “soft” decision, a value that describes the degree to which a pattern fits with a certain class, rather than just a “hard” decision which indicates a pattern matches a class or not (Yen, 1999). Recently, fuzzy logic and fuzzy systems have been successfully embraced in tackling various real world problems, such as control systems and pattern classification problems. Some well-known fuzzy systems are fuzzy-rule-base methods (Ishibuchi, 1992). fuzzy c-means (Bezdek, 1981). fuzzy k-nearest-neighbor (Bezdek, 1986; Keller, 1985). and fuzzy decision tree (Chang, 1977).

Given a fixed set of service requests, available technicians, and performance criteria (e.g., minimizing the total weighted stress), it is possible to find a schedule to optimize the performance with respect to specific criteria. Nonetheless, for a variety of reasons, including inevitable uncertainty in equipment breakdown and associated emergent service requests, it is not feasible to completely attain the optimization objective. Hence, many of the scheduling algorithms available today are mostly heuristic. In other words, these algorithms are based on some simple rules, such as FCFS (First Come First Served) or NC (Nearest Call). Each of these scheduling algorithms has distinct advantages over the others. In general, no single algorithm is the best under all situations. To cover a wide variety of service call and technician situations, the proposed scheduling system integrates a variety of scheduling algorithms, including FCFS (First Come First Served), NC (Nearest Call), EET (Earliest Expiration Time), NSNC (Negative Slack-Nearest Call), NCPS (Nearest Call with Positive Slack), and CTTET (Composite Travel Time Expiration Time).

The fuzzy logic control decision network can be constructed automatically by learning the training examples. By combining both unsupervised (self-organized) and supervised learning schemes, the learning speed converges much faster than the conventional back-propagation learning algorithm. The basic configuration of a fuzzy logic system with fuzzifier and defuzzifier is shown in Figure 4.

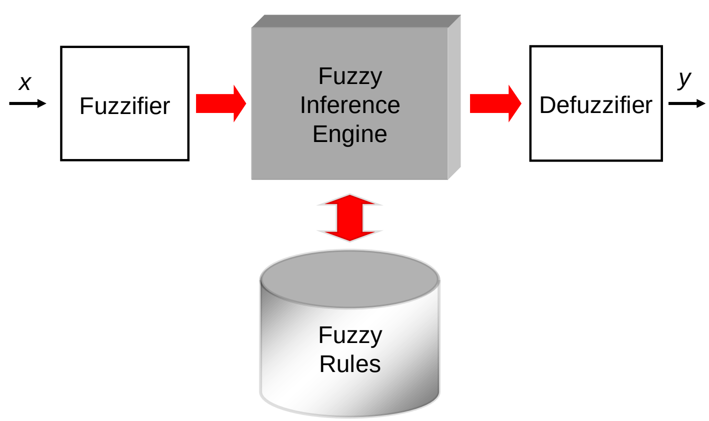

Figure 4: Fuzzy Logic System

The function of the fuzzifier is to determine the degree of membership of an incoming input on service demand in a fuzzy set. The fuzzy rule base stores a collection of rules representing the fuzzy relationships between input-output fuzzy variables. The output of the fuzzy rule base is then determined according to the degree of membership specified by the fuzzifier. The fuzzy inference engine calculates the rule's conclusion based on its membership degree. Finally, the defuzzifier is employed to convert outputs of the fuzzy rule base into crisp values.

2.3.2 Fuzzy logic reasoning and training process

This section describes the objective function of the scheduling problem, fuzzy logic reasoning procedures, and training algorithms used in the MCFL-FSS system. First, the objective of the scheduling problem is to minimize the total weighted stress, which is defined as follows:

$$S(k) = \sum_{i \in C(k)} [w_q q_i(k) + w_t t_i(k) + w_T T_i(k)]$$

where

$S(k)$ = stress for the schedule for the technician k .
$q_i(k)$ = queue time for the service call i when assigned to the technician k. (queue time is the time from the point when a service call arrives to the system until it is assigned to an available and qualified technician)
$t_i(k)$ = travel time for the service call i when assigned to the technician k.
$T_i(k)$ = tardiness for the service cal i when assigned to the technician k.
w_q = parameter associated with queue time.
w_t = parameter associated with travel time.
w_T = parameter associated with tardiness.

As far as the practical procedure is concerned, the simulation results of service call and technician features with the best scheduling procedure are evaluated. The result is represented as a vector, ((x_1, x_2, x_3), y), where (x_1, x_2, x_3) are the vector of the features, and y is the number of a scheduling procedure. The scheduling procedures are numbered to facilitate the selection process. Next, appropriate fuzzy rules are selected in terms of the field service features.

If the number of simulation results is not very large, the nearest neighborhood clustering algorithm is used to train the fuzzy logic system. A selected step-by-step training algorithm used in the 3S-IM model as follows:

Step 1: A fuzzy system with center average defuzzifier, schedule rule, singleton fuzzifier can be expressed as follows:

$$y = f(x_1, x_2, x_3) = \frac{\sum_{i=1}^{N} y^i \exp(-(x - x^i)^2 / \sigma^2)}{\sum_{i=1}^{N} \exp(-(x - x^i)^2 / \sigma^2)}$$

where

N is the number of simulation results.
$x = (x_1, x_2, x_3)$, $x^i = (x_1^i, x_2^i, x_3^i)$, and y is the number of the rule. σ is design parameter.

Step2: Starting with the first vector $((x_1^1, x_2^1, x_3^1), x^1)$, establish a cluster center (x_1^1, x_2^1, x_3^1) at (x_1^1, x_2^1, x_3^1) and set $A^1(1) = y$, $B^1(1) = 1$, select a radius r.

Step 3: Continue the procedure with k^{th} vector $((x_1^k, x_2^k, x_3^k), y^k)$, k = 2, 3, …. Suppose there are already M clusters with centers $(x_1^{k'}, x_2^{k'}, x_3^{k'})$, k' = 1, …, M. Computer the Euclidean distance of (x_1^k, x_2^k, x_3^k) to these centers and find the smallest one.

Step 4: If the distance is less than *r*, then establish (x_1^k, x_2^k, x_3^k) as a new cluster.

Step 5: The adaptive fuzzy logic system at the k^{th} step is constructed as follows:

$$f_k(x_1, x_2, x_3) = \frac{\sum_{i=1}^{M} A^i(k)\exp(-\left|x - x^i\right|^2 / \sigma^2)}{\sum_{i=1}^{M} B^i(k)\exp(-\left|x - x^i\right|^2 / \sigma^2)}$$

If $x = (x_1^k, x_2^k, x_3^k)$ does not establish a new cluster, then $A^{ik}(k) = A^{ik}(k\text{-}1) + y^k$, $B^{ik}(k) = B^{ik}(k\text{-}1) + 1$, here *ik* is the number of the nearest cluster; otherwise, increasing *M* by 1, and $A^i(k) = A^i(k\text{-}1)$, $B^i(k) = B^i(k\text{-}1)$.

Step 6: Add fuzzy rules to the above fuzzy logic system as follows:

$$f(x) = \alpha f^L(x) + (1-\alpha) f_k(x)$$

where $f^L(x)$ is a fuzzy logic system constructed from a fuzzy IF- THEN rule, and $\alpha \in [0, 1]$ is a weight for incorporate the simulation results and fuzzy rules.

Through the fuzzy logic reasoning process, the MCFL-FSS system is capable of automatically selecting the most appropriate scheduling algorithm based on the type of service call, technician conditions and other resource availability, and given set of constraints and objectives. In addition, the developed system is flexible enough to take other important factors, such as proximity or current task occupancy, into consideration when determining which technician to send. For instance, if the most qualified technician is 100 miles from the site or is occupied in an emergency callback/repair job, the system should consider alternative technicians who might be in closer proximity to the site and who could be more readily available.

3. Model Implementation and Essential Tasks

Six major tasks are identified to implement the proposed model, including (1) system requirements definition and baseline establishment, (2) development of an information system architecture, (3) evaluation of data acquisition methods/tools, (4) evelopment of structure health data models, (5) development of large-scale simulation model for data transfer, interpretation, and diagnosis as well as structural condition assessment, and (6) Demonstration and validation.

The first task emphasizes on system requirements definition to ensure that essential functionalities of the proposed system are thoroughly captured. As an indispensable prerequisite to this task, a detailed functional requirements document along with a baseline statement should be developed. This document will consist of the formulation of essential system functions, assessment of dependencies among various system components, evaluation of alternative solutions, estimation of value and risk associated with each alternative solution.

The subsequent task involves identifying information systems requirements and developing information system architecture to support maximum availability, scalability, manageability and performance of the proposed system. A holistic approach is to be adopted to balance all the high-performance system requirements and to provide an e-service solution to the rigorous requirements of the web-based service transaction and decision support systems.

To ensure a concrete understanding and proper assessment of how the system will operate, a test-bed environment will be created to drive the simulation of the SHM/CBM as well as field service planning and scheduling operations. A large-scale discrete event simulation model will be developed to reflect the generic natures of the underlying problems. A real-time monitoring will be performed to simulate a real-time rescheduling of resources as a response to unexpected interruptions due to a number of possible scenarios. The developed test-bed environment will help isolate and control for potentially confounding variables of a complex environment.

A baseline demonstration and a proof-of-concept demonstration will be made during the 12-week residency. These two demonstrations will focus on the feasibility analysis by demonstrating how implementation of the 3S-IM model. This demonstration represents a key decision point for determining whether the top line goals can be reached and an indication of how long this may take. Based on the information acquired from this demonstration, the level of risk reduction achieved at the project mid-point will be quantified under the Collaborative Innovation process, and a refined risk-reduced development plan will be formulated. The value of the innovations accessible through continuation of the project will then be assessed to provide a key decision point.

4. Expected Benefits and Intellectual Merits

This research has the potential to extend operations research, modeling and simulation techniques, and information technology to an important economic sector, the aftermarket service sector, that has been overlooked in the past. First, the research shall significantly contribute to the fundamental theory and practice of condition-based maintenance and intelligent structured health monitoring systems for improving the competitiveness and reliability of aftermarket service enterprises. Additionally, this research will open a new area in condition-based maintenance, intelligent structured health monitoring systems, and service supply chain optimization, and e-service systems design. It will provide the foundation for introducing the subject of integrated CBM/SHM in the supply chain management course, which is becoming an important course in the curricula of many disciplines, such as industrial engineering, manufacturing engineering, operations research, and information systems.

The next wave of value for many companies resides within their service supply chains. To be a successful customer-driven company, an enterprise should go beyond delivery of better-quality products to delivery of superior post-sales services. The CBM model and IM&HM system will bring forth a significant impact on the aftermarket service industry as a whole due to the expected huge improvement of intelligent equipment health monitoring, service workforce efficiency, increased overall utilization of resources, and flexibility to handle dynamic changes. The research results can be further delivered to a broad range of companies in the aftermarket service sector. The technologies and models developed in this research will enable corporations to deliver higher quality and lower cost services. It is expected that these technologies will eliminate significant inefficiency from the service and maintenance supply chain. Equipment monitoring and maintenance logistics have long been implemented as costly and time consuming point solutions, which illustrates the extensive scope of the opportunity and potential applications of this proposed research.

5. Conclusions

Effectively managing and optimizing their service supply chains, on top of managing their product supply chains, is critical for the companies to survive and success in this fiercely competitive marketplace. Companies that strive to act upon this business wisdom can benefit from the value and competitive advantage garnered by the best-in-class bellwethers in product supply chain management, such as Wal-Mart, Toyota, and Dell Computer. The proposed 3S-IM model will help a company excel from a merely equipment maintainer to a world-class service enterprise by embracing expanded and integrated solutions for effective field service management and resources planning. The proposed model will help facilitate a business paradigm shift by driving new levels of overall cost and customer service performance in lieu of selling more visits paid to maintain and/or repair the equipment.

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