行政院國家科學委員會專題研究計畫 成果報告

以演化式計算多目標最佳化可重組製造系統之研究
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行政院國家科學委員會補助專題研究計畫 ■成果報告
□期中進度報告

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I、報告

在過去這幾年來, 可重組製造的概念已經漸漸開始浮現在製造系統的研究當中。跟彈性製造系統相比較，可重組製造系統(RMS)是一種全新的製造系統概念。可重組製造系統(RMS)的創新概念在於它的模組性、可結合性、彈性、可擴展性、可轉換性和可診斷性。當環境或是組織決定要進行系統改變的時候，可重組製造系統能夠簡單快速且節省成本的達成系統規劃的變更。可重組製造系統企圖在製造系統的設計當中達到功能的可更換性和容量的可擴展性，也就是說機器元件、機器、單元、或是材料運輸系統在需要進行系統改變重組的時候都可以被重新增加、移除、修改甚至是進行交換。可重組製造系統的設計可以分為硬體設計和邏輯設計兩大領域。這兩大領域內包含了所有有關機器、操作、製程、產品結構、物料運送、生產控制、繞線、生產規劃，以及產量、容量和其擴增減少等等之彈性設計。

由於可重組製造系統的特性需求，因此可重組製造系統便需要一些有效的設計方法來達成它系統所需之種種目標並且規劃可重組製造系統的用途以便滿足它的各項目標需求。要研發與可重組製造系統有關的設計方法便需要對製造系統有深入的背景知識且對於智慧型最佳化演算法有扎實的理論與實際應用基礎。

由於自動搬運系統性能之好壞將嚴重影響整個工廠之效能，本計畫提出了一個以多目標基因演算法為基礎之最佳化路徑規劃方法，期能同時考量最短距離、路線平滑性、路線平緩性和安全距離等四個目標，規劃出適合可重組式製造工廠自動搬運系統機器人之路徑。本研究中，如何在可重組式製造工廠的整體產能評估，自動搬運系統中搬運機器人的路徑規劃是一項非常重要的研究主題。因為工件在搬運系統內所需的運輸時間可能會高於製造系統的產品生產時間。因此如何在佈滿重要設施的工廠環境之中，事先規劃出合理的路徑給搬運機器人從起點行進到終點是一件重要的生產準備工作。

在實際的情況下，根據不同工廠的性質，機器人運輸路徑的最佳化通常會考量一些特定的成本目標函數，例如最短路徑、路徑平滑平緩度、路徑與設備之路徑搜尋花費的最短時間、環境的設計…等等。本計畫考量在新一代的可重組式製造工廠中，因為製造設施具有高度的可重組性和可擴充性，所以自動搬運系統之路徑規劃必須具有一定的彈性以容忍設施之變動，並且其路徑必須足夠平滑平緩且與設施保持一定的安全距離。因此，本論文將這些系統考量設計成四種不同的目標函式:最短距離、路線平滑性、路線平緩性和安全距

離，以匹配可重組式製造工廠內自動搬運系統路徑規劃之需求。

此一方法首先先針對廠房設施佈置自動建立一個避障路徑知識庫，然後在基因演算法中使用了特別的基因運算子去取代傳統運算子，並結合了避障路徑知識庫來快速修正路徑，以期達到快速避障和快速收斂的效果。由數項實驗結果顯示，本計畫所提出之方法可以同時考量四項目標函數搜尋出多種路徑規劃方案以提供給決策者和系統使用，而且其結果並不遜色於傳統只考量最短距離規劃之方法。本計畫研究成果發表於[1].

[1]盧金榮, 陳建宏*, 以多目標基因演算法最佳化規劃可重組式製造工廠搬運機器人之路徑, 2010 年科技創新與智慧生活國際研討會, 亞東技術學院, 台灣, 2010 年 6 月 4-5 日

以多目標基因演算法最佳化規劃可重組式製造工廠搬運機器人之路徑

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摘　　要

在新一代的可重組式製造工廠中，由於製造設施具有高度的可重組性和可擴充性，也因此造成廠房設施和自動搬運系統再規劃的必要性。由於自動搬運系統性能之好壞將嚴重影響整個工廠之效能，本篇論文提出了一個以多目標基因演算法為基礎之最佳化路徑規劃方法，期能同時考量最短距離、路線平滑性、路線平緩性和安全距離等四個目標，規劃出適合可重組式製造工廠自動搬運系統機器人之路徑。此一方法首先先針對廠房設施佈置自動建立一個避障路徑知識庫，然後在基因演算法中使用了特別的基因運算子去取代傳統運算子，並結合了避障路徑知識庫來快速修正路徑，以期達到快速避障和快速收斂的效果。由數項實驗結果顯示，本論文所提出之方法可以同時考量四項目標函數搜尋出多種路徑規劃方案以提供給決策者和系統使用，而且其結果並不遜色於傳統只考量最短距離規劃之方法。

1. 簡介

在可重組式製造工廠的整體產能評估中，自動搬運系統中搬運機器人的路徑規劃是一項非常重要的研究主題。因為工件在搬運系統內所需的運輸時間可能會高於製造系統的產品生產時間。因此如何在佈滿重要設施的工廠環境之中，事先規劃出合理的路徑給搬運機器人從起點行進到終點是一件重要的生產準備工作。在實際的情況下，根據不同工廠的性質，機器人運輸路徑的最佳化通常會考量一些特定的成本目標函數，例如最短路徑、路徑平滑平緩度、路徑與設備之路徑搜尋花費的最短時間、環境的設計…等等。近年來，針對行動機器人的路徑規劃問題，基因演算法[2][8][11]已經被成功運用於解決此類型之相關最佳化問題。本論文考量在新一代的可重組式製造工廠中，因為製造設施具有高度的可重組性和可擴充性，所以自動搬運系統之路徑規劃必須具有一定的彈性以容忍設施之變動，並且其路徑必須足夠平滑平緩且與設施保持一定的安全距離。因此，本論文將這些系統考量設計成四種不同的目標函式:最短距離、路線平滑性、路線平緩性和安全距離，以匹配可重組式製造工廠內自動搬運系統路徑規劃之需求。

在本論文中，我們應用多目標基因演算法來求解路徑規劃最佳化問題。針對可重組式製造工廠設施之高變動性，我們假設可以推估其大致的設施變動範圍，然後考量現有設施變動範圍自動建立一個避障路徑知識庫。除此之外，在基因演算法中，我們採用了特別的基因運算子: 突變(mutation operation)、修補(refine operation)、刪除(deletion operation)的幾個運算來取代傳統基因演算法運算子，並結合了避障路徑知識庫來快速修正路徑，以達到快速避障和快速收斂的效果。本論文將所設計之方法與數篇文獻中之實驗與方法進行比較，其結果顯示本論文所提出之方法可以同時考量四項目標函數搜尋出多種路徑規劃方案以提供給決策者和系統使用。而且其數項實驗之結果比較分析後，證

明本論文之方法並不遜色於傳統只考量最短距離規劃之方法。

2. 相關研究與探討

近年來，陸續有相當多學者專家對於行動機器人路徑規劃的研究做過不同的探討，例如旅行家問題即為最著名之路徑最佳化問題。但是如果將旅行家問題延伸應用在機器人路徑規劃問題上，只尋求最短合理路徑的解答對於可重組式製造工廠路徑規劃的要求來說卻是不足的。因此，Sugihara 以及 Smith 提出在以格點表示的行動機器人環境下，使用固定長度(fix-length)二元字串的染色體為編碼方式的基因演算法來進行路徑規劃[10]。但是這種二元字串表示法，對路徑規劃卻是一種較簡單且效果較差的表示法。Tu 以及 Yang [12]於 2003 年提出使用可變長度(variable-length)的染色體取代傳統固定長度的染色體為編碼方式的基因演算法來進行路徑規劃，而此種方法的效果比固定長度的表示法來的好。

在行動機器人路徑規劃的問題之中，如何表示路徑是件重要的議題。Hu 以及 Yang [5]提出一個簡單又有效率的方式，使用格點結合座標的圖形表示方法。他們提出以整數基因的表示法，去取代以座標為主的浮點數的表示法，以代表機器人行進的路徑。在這種設計之下，機器人的移動並不受到改變和限制，但是卻能以較簡單的方式來表示染色體的結構以及進行基因演算法的運算過程。而在規劃路徑遇到障礙物的情況之下，傳統上的解決方法是計算路徑與障礙物是否有交點。然而在基因演算法的相關研究之中，針對路徑規劃的問題，有些研究發現如果結合一些啟發式規則(heuristic rules)可以有效的改善其路徑規劃之結果。Li, Zhang, Yin, 以及 Wang [6]則提出三個建立於單點交配(one-point crossover)運算的啟發式規則交配(heuristic crossover)。它比起傳統的單點交配來得更加有效，因為這些交配方式可以快速處理規劃路徑遇到障礙的情況，並且產生一段合理的有效路徑來避開障礙物。Guo 以及 Yang [4] 提出一個避障礙物的策略，他們是以計算障礙物與路徑的角度來產生一段合理的有效路徑避開障礙物。

3. 可重組式製造工廠搬運機器人之路徑規劃問題

3.1. 多目標最佳化問題

一個多目標最佳化的問題，顧名思義就是包含了不只一個的目標函式。而其所求出之解集合，通常不保證能使每一個目標函式，都達到最佳的解答。因為有些目標函式，它們之間有可能是互相牽制或是有所衝突的。舉一個日常生活中，簡單的例子來說好了，假設我們要組一台電腦，就站在我們消費者的立場而言，當然是功能越強大、價格越便宜的，能夠吸引我們的目光。但是，往往功能強大的，其價格往往比較昂貴，而價格便宜的，其功能性往往就比價格貴的來的差一些。這個就是所謂的牽制及衝突了。所以，不可能每一個目標，都能達到最佳化的解果，所以必定會存在二組或是多組的最佳解。這幾組解答，通常會有一個目標值勝過對方，但或許再另一個目標值就輸給對方，所以每一個解答都擁有著不輸給其他解答的特性，這一組的解答，我們稱之為 Pareto 最佳解集合(Set of Pareto-optimal Solutions)。

一般而言，多目標最佳化的問題，通常是將多個目標最大化或最小化的過程，可能問題希望第一個目標達到最大化的動作，而第二個目標也許就是希望達到最小化的動

作。然而，對於每一個目標而言，都可以用一個目標函式來表示，並且每個目標函式，可能會擁有許多的目標參數，其定義如(1)式所示：

$$Maximize/Minimize \quad F(X)=\{f_1(X), f_2(X), f_3(X),..., f_n(X)\}. \\ S.T.(x_1, x_2, x_3,...x_m)\in X \tag{1}$$

其中 X 稱之為決策向量 $F(X)$ 目標向量。

由上面的內容中提到，在多目標最佳化的問題中，不會只存在單一的解答，而會是一組解集合，而那組解集合中，每一個解答都會是一樣的好，就是我們上述內容中的 Pareto 最佳解集合，從 Pareto 的理論中，我們假設有 n 個望大(Maximization)的目標，而其中 X_1 及 X_2 扮演兩個決策的向量，其表示式如下：

$$\forall_i : f_i(X_1)\geq f_i(X_2)\wedge \exists_j : f_j(X_1)\geq f_j(X_2) \tag{2}$$

稱之 X_1 支配(Dominate) X_2 ($X_1 \succ X_2$)。另一種情況為：

$$\forall_i : f_i(X_1)\geq f_i(X_2) \tag{3}$$

則稱之為 X_1 弱支配(Weakly dominate) X_2 ($X_1 \succeq X_2$)。

3.2 路徑規劃問題的四個目標函式

本篇論文中所探討的問題是機器人搬運工件的路徑規劃。自動搬運系統之路徑規劃必須具有一定的彈性以容忍設施之變動，並且其路徑必須足夠平滑平緩且與設施保持一定的安全距離。因此，本論文將這些系統考量設計成四種不同的目標函式:最短距離、路線平滑性、路線平緩性和安全距離，以匹配可重組式製造工廠內自動搬運系統路徑規劃之需求。

在本篇論文的問題中，我們假設路徑 P 中存在 N 個節點(m_1,…,m_N)。四種不同的目標函式分別可以用下列的數學方程式定義:

(1) 最短距離：

Dist(*p*)所代表的是機器人行進路徑的總長，使其最小化，其數學方程式如下[5][3][7][13]：

$$Minimize \qquad dist(p)=\sum_{i=1}^{n-1} d(m_i, m_{i+1}) \tag{4}$$

在此處，$d(m_i, m_{i+1})$是代表相鄰的 m_i 點與 m_{i+1} 點的距離。

(2) 路線平滑性：

Smooth(*p*) 所代表的是機器人行進路徑的平滑性，使其最大化，其數學方程式如下[8][13]：

$$s(m_i)=\frac{\theta_i}{\min\{d(m_{i-1}, m_i), d(m_i, m_{i+1})\}} \tag{5}$$

$$Maximize \quad smooth(p)=\max_{i=2}^{n-1} s(m_i) \tag{6}$$

在此處，$\theta_i \in [0,\pi]$是代表 m_i 點與 m_{i+1} 點所形成線段與 m_{i+1} 點與 m_{i+2} 點所形成線段，所形成的夾角。

(3) 路線平緩性：

Smooth2(*p*) 所代表的是機器人行進路徑的平緩性，使其最小化，其數學方程式如下：

$$s(m_i) = \frac{\theta_i}{\min\{d(m_{i-1}, m_i), d(m_i, m_{i+1})\}} \tag{7}$$

$$Minimize \quad smooth2(p) = \min(\mathrm{var}_{i=2}^{n-1} s(m_i)) \tag{8}$$

在此處，$\theta_i \in [0,\pi]$是代表 m_i 點與 m_{i+1} 點所形成線段與 m_{i+1} 點與 m_{i+2} 點所形成線段，所形成的夾角。

(4) 安全距離

Clear(*p*) 所代表的是機器人行進中，與所有障礙物所保持的距離，使其最大化，其數學方程式如下：

$$c_i = d(ob, m_i) \tag{9}$$

$$Maximize \quad clear(p) = \max\left(\min_{i=2}^{n-1} c_i\right) \tag{10}$$

在此處，c_i 是代表障礙物到所有偵測目標點的距離。

4. 路徑避障知識庫

在行動機器人路徑規劃的過程中，如何避開障礙是一件非常重要的議題。因為如何快速且有效的避開障礙會影響演算法的收斂速度與路徑規劃的結果良劣與否。所以我們必須設計有效率的方法來快速且有效的避開障礙。在下面的內容中，我們將逐一介紹如何計算障礙物是否存在，然後根據運算結果建立路徑的避障知識庫以供多目標基因演算法使用。

4.1. 工廠環境與規劃路徑的表示法

行動機器人的路徑規劃問題，其目的是在有設施障礙的環境之下，去找到一條從起點到終點的合理路徑。因此本論文中假設工廠環境為格點環境。舉例來說，圖 1 展示了一個 10 x 10 的格點環境。點與點所形成的線段，就形成一條路徑。所以，從起點到終點，這些路徑的點，便可編譯成一串格點的整數。以圖 1 的例子來說，路徑的字串可以編譯為(0,36,66,74,84,99)。

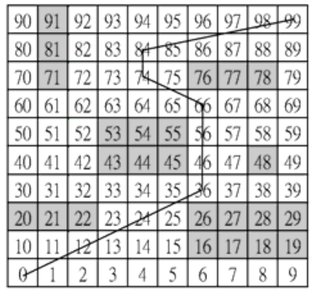


圖 1 行動機器人路徑規劃圖

4.2. 障礙物計算

這個方法是根據數學方法最小外接矩形法(Minimum Enclosing Rectangular)[1]來判斷線段之間是存在交點。它是運用包含矩形的方法(包含多邊形(polygon)或弧形(Arc)之最小矩形，不則規矩形)是否相交來判斷線段與矩形相不相交與否。以下是其方法說明:

設任意四點 A,B,C,D，其座標值分別為(a_1, a_2), (b_1, b_2), (c_1, c_2), 及(d_1, d_2)。若座標值符合方程式(11)(12)(13)(14)式下列情形之一時，則 AB 與 CD 兩條線段必定不相交。如圖 2 所示。否則會相交，如圖 3 所示。

$$(1)\ \mathrm{MIN}\ (c_1,d_1) > \mathrm{MAX}\ (a_1,b_1) \tag{11}$$

$$(2)\ \mathrm{MIN}\ (a_1,b_1) > \mathrm{MAX}\ (c_1,d_1) \tag{12}$$

$$(3)\ \mathrm{MIN}\ (c_2,d_2) > \mathrm{MAX}\ (a_2,b_2) \tag{13}$$

$$(4)\ \mathrm{MIN}\ (a_2,b_2) > \mathrm{MAX}\ (c_2,d_2) \tag{14}$$

其中 MIN 與 MAX 分別表示取最小值和最大值。

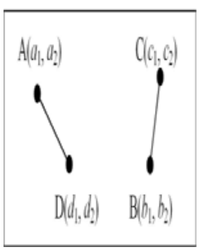


圖 2 兩線段不相交

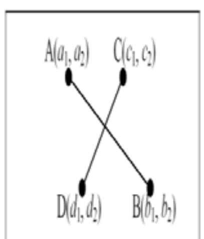


圖 3 兩線段相交

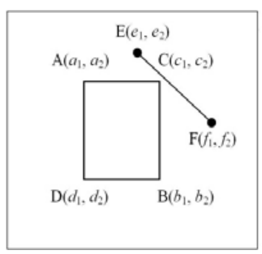


圖 4 線段與面不相交

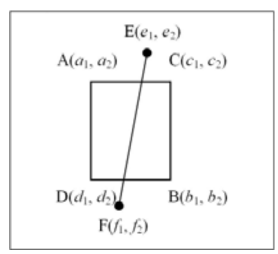


圖 5 線段與面相交

將最小外接矩形法(Minimum Enclosing Rectangular)由線與線延伸至線與面的作法，假設一個面 ABCD，其座標值分別為(a_1, a_2), (b_1, b_2), (c_1, c_2), 及(d_1, d_2)，而平面上一線段為 E,F，其座標值分別為(e_1, e_2), (f_1, f_2)。若座標值符合方程式(15)(16)(17)(18)式下列情形之一時，則面 ABCD 與線段 EF 必定不相交，代表可以避過障礙物，如圖 4 所示。否則會相交，代表不可以避過障礙物，如圖 5 所示。

$$(1)\ \mathrm{MIN}\ (a_1,b_1, c_1,d_1) > \mathrm{MAX}\ (e_1, f_1) \tag{15}$$

$$(2)\ \mathrm{MIN}\ (e_1, f_1) > \mathrm{MAX}\ (a_1,b_1, c_1,d_1) \tag{16}$$

$$(3)\ \mathrm{MIN}\ (a_2,b_2, c_2,d_2) > \mathrm{MAX}\ (e_2, f_2) \tag{17}$$

$$(4)\ \mathrm{MIN}\ (e_2, f_2) > \mathrm{MAX}\ (a_2,b_2, c_2,d_2) \tag{18}$$

其中 MIN 與 MAX 分別表示取最小值和最大值。

4.3. 避障路徑知識庫的產生

在上述的內容中，我們介紹障礙物的判定方法。接下來我們將建立一個避障路徑知識庫，將避障路徑事先儲存在資料庫中，使得多目標基因演算法在規劃路徑遇到障礙物的情況之下，可以利用避障路徑知識庫的內容來修正其所規劃的路徑，以達到快速有效的路徑建構。

避障路徑知識庫的主要的七個步驟如下：

步驟一：膨脹障礙物的安全距離，如圖 6 所示。

步驟二：儲存安全距離的邊 $L_1(P_1, P_2)$，$L_2(P_2, P_3)$，…，$L_n(P_n, P_1)$，如圖 7 所示。

步驟三：檢查 L_1， L_2，…，L_n，是否有被機器人通過，是否有在 t_1,t_2 形成之正方形內。如果有在 t_1,t_2 形成之正方形內，則代表有經過障礙物。如圖 8。反之，則沒有經過障礙物，如圖 9。

步驟四：計算線 $T_1(t_1,t_2)$與 L_1， L_2，…，L_n，之所有交點 ($C_1, C_2,\ldots, C_k$) ，如圖 10。

步驟五：可建出兩條路徑。$t_1 \rightarrow C_1 \rightarrow P_1 \rightarrow P_2 \rightarrow P_3 \rightarrow C_2 \rightarrow t_2$ 以及 $t_1 \rightarrow C_1 \rightarrow P_4 \rightarrow C_2 \rightarrow t_2$。

步驟六：遞回刪除優化。$t_1 \rightarrow P_2 \rightarrow P_3 \rightarrow t_2$ 以及 $t_1 \rightarrow P_4 \rightarrow t_2$。

步驟七：比較選擇，以距離最短優先當其選擇，所以選擇的是 $t_1 \rightarrow P_4 \rightarrow t_2$。

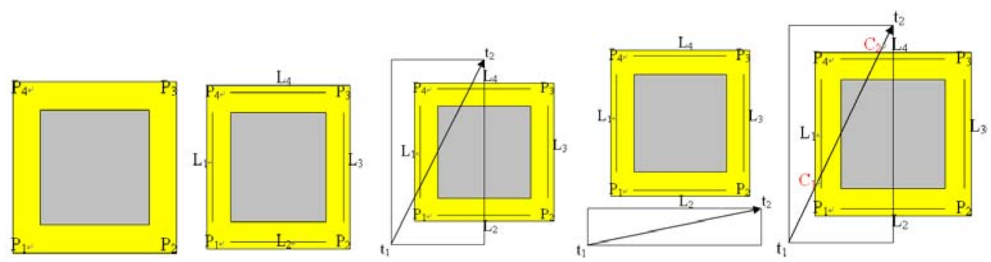


圖 6　圖 7　圖 8　圖 9　圖 10

圖 6-10

圖 6 膨脹障礙物的安全距離，圖 7 儲存安全距離的邊，圖 8 有障礙物出現的情況，圖 9 沒有障礙物出現的情況，圖 10 T_1 與 L_1，L_2，…，L_n 之所有交點，C_1 以及 C_2

5. 多目標基因演算法

5.1. 染色體表示法

在多目標基因演算法中，去解行動機器人最佳路徑的規劃過程，染色體的資訊是一件非常重要的事情。在本論文中所探討的機器人路徑規劃問題，我們採用不固定長度的染色體，其中每一個基因代表一個格點的位置，每一個格點分別可代表一組整數 x ,y 座標。而其初始的染色體是隨機產生的。

5.2. 多目標適應函數

在多目標基因演算法中，由於必須同時滿足多個目標函式的最佳化，所以利用適應函數來表示，我們採用一個基於 Pareto 理論基礎，所設計出的評估函數 GPSIFF(Generalized Pareto-base Scale-Independent Fitness Function)於本文的演算法中，其 GPSIFF 的數學方程式如下：

$$F(Y) = p - q + c \tag{19}$$

5.3. 基因演算法的運算子

本篇文章中使用了以下的一些基因運算，包含選擇(selection)，三種特殊的交配法，突變，修補，以及刪除的運算。

5.3.1. 選擇

本文所採用的是二元競爭式選擇法(binary tournament selection)。

5.3.2. 交配

隨機一點交配的交配法(one-point random crossover)[10]有可能會使結果產生迴路或是不合理的路徑。為了去避免這種情況，Li, Zhang, Yin, 以及 Wang 提出及使用三種 knowledge-based 單點交配法[6][9]，我們在本文中亦使用這三種交配法。

5.3.2.1. 相同點單點交配法(crossover at the location of the common node)

以下我們舉一個特別的例子，可以簡單且清楚地說明這個交配的方法。假設，母代的兩條染色體分別是 V1(0,30,33,47,98,99)以及 V2(0,5,35,33,83,99)。我們可以很明顯的看出兩條染色體有相同的點為 33。所以，我們選擇 33 當作其交配的點，其產生的子代就為 V1(0,30,33,83,99)以及 V2(0,5,35,33,47,98,99)。如圖 11 所示。

5.3.2.2. 相同邊單點交配法(crossover at the location of the interconnected)

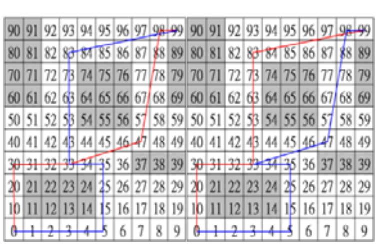
接下來，另外一種特殊的交配法，不同於上面的相同點單點交配法，其交配的方法如下。假設，母代的兩條染色體分別是 V1(0,7,15,46,47,97,99)以及 V2(0,5,35,33,83,99)。我們可以很明顯的看出 V1 有潛在的點 15 與 V2 點 5 與點 35 所形成的邊，可構成一直線。所以，我們在 V2 插入點 15，而 V2 就變成(0,5,15,35,33,83,99)，在將其作相同點的單點交配，其產生的子代就為 V1(0,7,15,35,33,83,99)以及 V2(0,5,15,46,47,97,99)。如圖 12 所示。

5.3.2.3. 相近點單點交配法(crossover at the location of the potential node)

接下來，另外一種特殊的交配法，不同於上面的兩種交配法，其交配的方法如下。假設，母代的兩條染色體分別是 V1(0,7,26,46,47,98,99)以及 V2(0,5,35,33,83,99)。我們可以很明顯的看出兩條染色體有相近的點為 46 以及 35。所以，我們在點 46 插入點 35 及點 35 後面插入點 46，而形成新的兩條染色體(0,7,26,46,35,47,98,99)及(0,5,35,46,33,83,99)，在依其作相近點的交配其產生的子代就為 V1(0,7,26,46,35,33,83,99) 以及 V2(0,5,35,46,47,98,99)。如圖 13 所示。

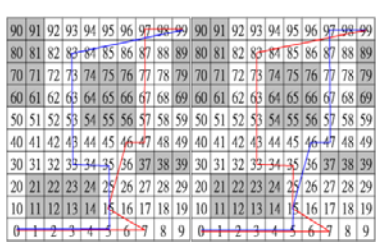
5.3.3. 突變

突變是隨機選擇一個點並且以不相同的點加以取代。突變的主要工作是造成族群解的差異性。所以，突變完後，其結果並不一定要比突變前來的好。



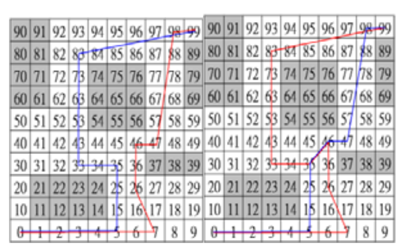
(a)母代染色體圖形 (b)子代染色體圖形

圖 11 相同點單點交配法



(a)母代染色體圖形 (b)子代染色體圖形

圖 12 相同邊單點交配法



(a)母代染色體圖形 (b)子代染色體圖形

圖 13 相同邊單點交配法

5.3.4. 修補

修補的目的是在將一條不合理的路徑修正為合理的路徑。修補通常可以分為點的修補(node_repair)以及線的修補(line_repair)。線的修補是配合前述的避障知識庫所完成，如果發現所規劃的路徑有經過障礙物，則會自動擷取避障知識庫的避障路徑來替代該段經過障礙的路徑。而點的修補主要的作用，就是如果機器人的行經路徑座標落在障礙物內，則試著隨機產生一個新的座標點來替代此座標，以期能夠使行經路徑座標落在障礙物之外。

5.3.5. 刪除

刪除可以應用在合理以及不合理的點上。針對合理的路徑，會有一定的機率會進行刪除以使路徑平滑平緩。對於不合理的點如果刪除點，對於整個染色體是有益的就將點刪除。

6. 實驗與討論

根據參考文獻，我們將本論文所提出的多目標基因演算法應用四種不同的工廠環境進行實驗。以參考文獻[5]為例，我們將使用 16×16 的格點當作我們的實驗環境，並與文獻[5]的結果做一些比較。

本論文所提出的多目標基因演算法的參數設定如下：染色體最大長度 50，交配機率 0.5，突變機率 0.01，刪除參數則設為 0.2。在這邊我們將比較四個不同的格點環境的結果。

6.1. 環境 HY1 的路徑規劃

我們所提出的多目標基因演算法，可以簡單的處理這種類型的障礙。在這邊，一開始的路徑是亂數產生，而且不一定是合理的路徑。參考文獻[5]在基因演算過程可以在第 30 代，找到最短路徑的解。而我們所提出的多目標基因演算法，可以在第 10 代就找到相同的路徑。表 1 展示了參考文獻[5]最短路徑四個目標的值，以及我們所找到四個目標的最佳值。圖 14-1 展示了四個目標最佳的路徑，以及參考文獻[5]最短路徑的解。

6.2. 環境 HY2 的路徑規劃

在這個部份，我們將討論另外一種的障礙環境。參考文獻[5]在基因演算過程可以找到最短路徑的解為 29.83，我們實驗的則最短路徑的解為 30.86，因為實驗架構的有所不同，我們的實驗有考慮安全距離的設定，機器人不會碰觸到障礙物，所以距離有所差別。參考文獻[5]在第 346 代才找到其最短路徑，我們在第 20 代就找到了。表 2 展示了參考文獻[5]最短路徑四個目標的值，以及我們所找到四個目標的最佳值。圖 14-2 展示了四個目標最佳的路徑，以及參考文獻[5]最短路徑的解。

6.3. 環境 HY3 的路徑規劃

參考文獻[5]在基因演算過程可以找到最短路徑的解為 23.0643，我們實驗的則最短路徑的解為 23.5747，因為實驗架構的有所不同，我們的實驗有考慮安全距離的設定，機器人不會碰觸到障礙物，所以距離有所差別。我們在第 25 代就找到了距離的最佳解。表 3 展示了參考文獻[5]最短路徑四個目標的值，以及我們所找到四個目標的最佳值。圖 14-3 展示了四個目標最佳的路徑，以及參考文獻[5]最短路徑的解。

表 1　環境 HY1 的路徑規劃比較

四個目標值 目標最佳值	dist(p)	smooth(p)	Smooth2(p)	clear(p)
參考文獻〔5〕	29.099	90	29.6836	0.707
最短路徑	29.099	90	29.6836	0.707
最大 smooth(p)	30.1451	315	3.79256	1.5
最小 smooth2(p)	29.9563	90	3.12266	2.5
最大 clear(p)	35.0623	45	9.26662	4.57

表 2　環境 HY2 的路徑規劃比較

四個目標值 目標最佳值	dist(p)	smooth(p)	Smooth2(p)	clear(p)
參考文獻〔5〕	29.8312	37.9819	42.5867	0.707
最短路徑	30.8559	25.3213	14.9853	0.707
最大 smooth(p)	33.8581	90	3.75817	1.5811
最小 smooth2(p)	33.6936	27.625	1.09828	1.5811
最大 clear(p)	36.8072	26.23	2.35759	2.54951

表 3　環境 HY3 的路徑規劃比較

四個目標值 目標最佳值	dist(p)	smooth(p)	Smooth2(p)	clear(p)
參考文獻〔5〕	23.0643	17.0496	2.35074	0.707
最短路徑	23.5747	22.0918	5.12961	0.707
最大 smooth(p)	48.6526	270	15.2401	1.5811
最小 smooth2(p)	23.7222	31.7275	2.89092	0.707
最大 clear(p)	38.368	90	11.4408	3.5355

表 4　環境 HY4 的路徑規劃比較

四個目標值 目標最佳值	dist(p)	smooth(p)	Smooth2(p)	clear(p)
參考文獻〔5〕	27.8019	35.4928	27.1522	0.707
最短路徑	28.3501	10.8702	7.83609	0.707
最大 smooth(p)	29.1878	90	16.975	1.5811
最小 smooth2(p)	32.2175	90	1.70534	1.5811
最大 clear(p)	31.3355	13.6818	7.7937	3.5

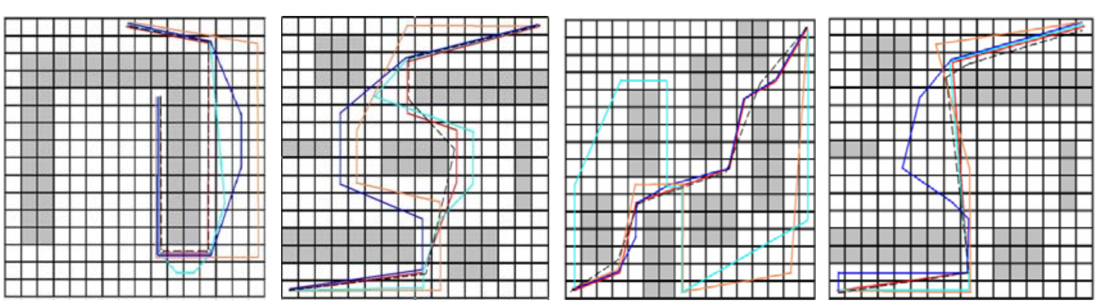


圖 14-1　HY1 多目標最佳路徑　圖 14-2　HY2 多目標最佳路徑　圖 14-3　HY3 多目標最佳路徑　圖 14-4　HY4 多目標最佳路徑

圖 14 多目標最佳路徑圖

(a)黑色虛線所代表的是參考文獻[5]的最點路徑，(b)紅色實線所代表的是最短路徑，(c)綠色實線所代表的是最大smooth值，(d)藍色實線所代表的是最小smooth2值，(e)橘色實線所代表的是最大clear值。

6.4. 環境 HY4 的路徑規劃

參考文獻[5]在基因演算過程可以找到最短路徑的解為 27.8019，我們實驗的則最短路徑的解為 28.3501，因為實驗架構的有所不同，我們的實驗有考慮安全距離的設定，機器人不會碰觸到障礙物，所以距離有所差別。我們在第 8 代就找到了距離的最佳解。表 4 展示了參考文獻[5]最短路徑四個目標的值，以及我們所找到四個目標的最佳值。圖 14-4 展示了四個目標最佳的路徑，以及參考文獻[5]最短路徑的解。

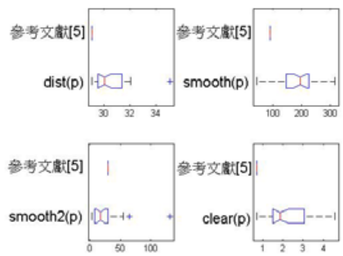


圖 15 HY1 四個目標值的盒鬚圖

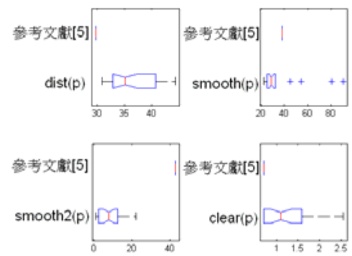


圖 16 HY2 四個目標值的盒鬚圖

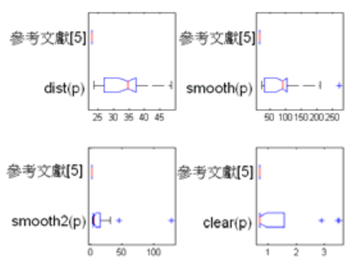


圖 17 HY3 四個目標值的盒鬚圖

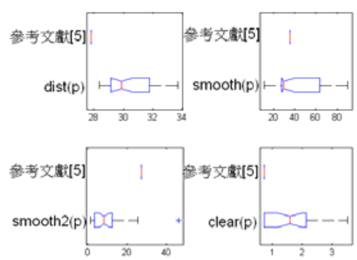


圖 18 HY4 四個目標值的盒鬚圖

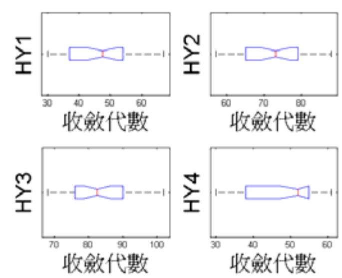


圖 19 四種地圖收斂情形的盒鬚圖

6.5. 討論

圖 15、圖 16、圖 17、圖 18 展示了 HY1，HY2 已及另外兩種的 HY3，HY4 環境的盒鬚圖(boxplot)，由盒鬚圖我們可以看出實驗 30 次的數據分佈，本篇文章所提出的四個目標值的情形。而在圖 19 中，則展現了四個環境 30 次實驗收斂代數的情形，其收斂條件為連續 5 代四個目標的差距均在 1%以內。

7. 結論

路徑規劃對於行動機器人是一件非常重要的事情。主要的目的是在具有設施障礙環境中找到最佳的路徑規劃。本篇論文提出一個結合避障知識庫的多目標基因演算法來解決機器人在路徑規劃的問題。本篇論文所提出的方法結合了三種特殊的交配機制，以及一些特殊的運算，去改善傳統的路徑規劃問題。本論文將所設計之方法與數篇文獻中之實驗與方法進行比較，其結果顯示本論文所提出之方法可以同時考量四項目標函數搜尋出多種路徑規劃方案以提供給決策者和系統使用。而且其數項實驗之結果比較分析後，證明本論文之方法並不遜色於傳統只考量最短距離規劃之方法。

在本論文未來研究方向上，有幾個方向可以去加以延伸其研究。例如，一個工廠可能不只一台搬貨的機器人，所以就可以考慮多台機器人同時出發的路徑規劃的情況，並同時避開工廠內的設施或是堆放的貨物，且使得多台機器人不會互相碰撞。

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行政院國家科學委員會補助國內專家學者出席國際學術會議報告

98 年 9 月 5 日

附件三

報告人姓名	陳建宏	服務機構及職稱	中華大學 資訊工程系 助理教授
會議 時間 地點	98 年 8 月 29 日至 98 年 8 月 31 日 加拿大溫哥華	本會核定補助文號	
會議名稱	（中文）IEEE 12th 計算科學與工程國際會議 (CSE-09) （英文）IEEE 12th Inernational Conference on Computational Science and Engineering		
發表論文題目	（中文）以演化式計算方法解決多目標 3D 感測網路佈建 （英文）An Evolutionary Approach for Multi-objective 3D Differentiated Sensor Network Deployment		

一、參加會議經過

本人於8月26日搭機前往西雅圖，然後開車前往溫哥華。8月29日註冊報到，與會人士共計約600名來自學術界和工商業界之專業人士與學生。同一時段並有SocialCom等國際會議共同舉辦。29-31日分別依不同的主題舉辦專題演講，並分別依不同的主題在不同的會議室舉行口頭報告。29日晚間舉辦歡迎會。會議中邀請到8位知名專家前來給予專題演講。本人於30日早上擔任第一場論文議場主持人，隨即第二場發表本次論文，會中各國學者也給與寶貴意見分享。在30日晚間所有專家學者被邀請主會場進行聚餐會並舉辦頒獎儀式。31日結束本次會議議程。

二、與會心得

透過參加此次國際會議與來自各國的學者交流研究心得並且同時建立溝通管道。與本次會議中，與會的各國學者就其研究領域充份探討及意見交流，本人更於會後與美國和加拿大等各國學者共同討論研究方向。會議所見所得對於未來個人學術研究開拓更寬廣的視野。個人能參與該會議備感榮幸

三、建議

由此次的經驗，個人認為補助參與國際會議的政策對提昇本校研究能量和知名度有非常正面的助益，個人認為此一政策應持續推行，並且應鼓勵本校教授和博士生於寒暑期參訪各國學者且積極參與國際會議，不僅可增加本校學者與碩博士研究生的國際觀和研究能力，更有助於促進本校學術研究和學術交流。

四、攜回資料名稱及內容

1. 會議論文集光碟片 一片。

行政院國家科學委員會補助國內專家學者出席國際學術會議報告

99 年 5 月 2 日

附件三

報告人姓名	陳建宏	服務機構及職稱	中華大學 資訊工程系 助理教授
會議 時間 地點	99 年 4 月 6 日至 99 年 4 月 9 日 Orlando, Florida USA	本會核定 補助文號	
會議 名稱	（中文）國際複雜度、資訊與控制會議 （英文）The International Multi-Conference on Complexity, Informatics and Cybernetics		
發表 論文 題目	（中文）以多目標演化式演算法解決汽電共生系統之環境經濟調度問題 （英文）Combined Heat and Power Environmental/Economic Power Dispatch Using Multi-Objective Evolutionary Algorithms		

一、參加會議經過

4月6日註冊報到，與會人士共計約千名來自學術界和工商業界之專業人士與學生。6日起分別依不同的主題舉辦專題討論和tutorial，並同時在不同的會議室舉行口頭報告。會議中邀請到多位知名專家前來給予專題演講，包含Dr. Donald Poochigian與Prof. DI Harald Wahl探討科技教育研究和Dr. Dmitry Zinoview之Facebook社群研究。本人於7日下午發表論文7日晚上舉辦歡迎晚會，9日晚間舉辦頒獎典禮晚會。

二、與會心得

透過參加此次國際會議與來自各國的學者交流研究心得並且同時建立溝通管道。與本次會議中，與會的各國學者就其研究領域充份探討及意見交流，本人更於會後與美國、挪威、日本學、香港、中國等各國學者共同討論研究方向，並獲邀請前往參訪其所屬大學。會議所見所得對於未來個人學術研究開拓更寬廣的視野。個人能參與該會議備感榮幸。

三、建議

由此次的經驗，個人認為補助參與國際會議的政策對提昇台灣學者之研究能量和知名度有非常正面的助益，個人認為此一政策應持續推行，並且應鼓勵台灣學者教授積極攜帶博士生於寒暑期參訪各國學者且積極參與國際會議，不僅可增加台灣學者與碩博士研究生的國際觀和研究能力，更有助於促進台灣學術研究和學術交流之風氣。

四、攜回資料名稱及內容

1. 會議論文集光碟片 一片。

2009 International Conference on Computational Science and Engineering

An Evolutionary Approach for Multi-objective 3D Differentiated Sensor Network Deployment

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***Abstract*—This paper describes a multi-objective evolutionary approach for solving multi-objective 3D deployment problems in differentiated wireless sensor networks (WSNs). WSN is a wireless network consisting of spatially distributed autonomous sensors to monitor physical or environmental conditions. Deciding the location of sensor to be deployed on a terrain with the consideration of different criteria is an important issue for the design of wireless sensor network. A multi-objective genetic algorithm is proposed to solve 3D differentiated WSN deployment problems with the objectives of the coverage of sensors, satisfaction of detection levels, and energy conservation. The preliminary experimental results demonstrated that the proposed approach is suitable for solving 3D deployment problems of WSNs with different requirements.**

Keywords- Wireless sensor network, multi-objective optimization, genetic algorithms

I. INTRODUCTION

A wireless sensor network (WSN) is a wireless network consisting of spatially distributed autonomous sensors to monitor physical or environmental conditions. WSN constitute a large number of applications related to national security, surveillance, military, health care, and home automation. Sensor nodes of a WSN are deployed over a region to sense events on geographical areas and transmit collected data to a sink node for further operations. Depending on the requirements, sensors could be deployed in diverse scenarios [4,9]. Therefore, deciding the location of sensor to be deployed on a terrain is an important issue. Several different objectives should be considered and fulfilled in the design phase of WSNs, such as the coverage and accuracy, reaction time and survivability of the sensor network. However, these objectives may be in conflict with one another and of different importance to mission planners [10].

Coverage is one of the fundamental issue in the deployment of WSNs. WSNs need to maintain sufficient coverage quality to capture the timely changing targets [13]. For enhanced coverage, a large number of sensors are typically deployed in the sensor field and, if the coverage areas of multiple sensors overlap, they may all report a target in their respective zones [3].

Differentiated sensor network deployment, which considers the satisfaction of detection levels in different geographical characteristics, is also an important issue [1]. In many real-world WSN applications, such as underwater sensor deployment, the supervised area may require different detection levels, depending on the event's location. Therefore, the sensing requirements are not uniformly distributed within the area. In other words, all the points of the area under monitoring are considered with the different importance. As a result, the deployment strategy of WSN should take into consideration the geographical characteristics of the monitored events.

Energy conservation for the lifetime of sensors is another rising issue [5]. Due to the limited energy resource in each sensor node, we need to utilize the sensors in an efficient manner so as to increase the lifetime of the network. There are two different approaches to the problem of conserving energy in sensor networks. The first approach is to plan a schedule of active sensors that enables other sensors to go into a sleep mode. The second approach is adjusting the sensing range of sensors for energy conservation. In this paper, we focus on adjusting the sensing range of each sensor in order to reduce the overlaps among sensing ranges while keep the detection ability above a predefined detection level.

In this paper, a 3D differentiated WSN deployment considering coverage, satisfaction of detection levels, and energy conservation is formulated into a multi-objective optimization problem. We represent the sensor field as a three-dimensional grid of points. Three objectives are to be optimized: maximizing coverage of sensors, satisfying the required probability of detection level, and minimizing the detection power by adjustable sensing range. To solve the aforementioned multi-objective optimization problem, we developed a multi-objective genetic algorithm (MOGA) framework. The proposed approach can obtain a set of non-dominated solutions for mission planner to deploy sensor nodes considering different requirements of applications.

II. RELATED WORK

A. *WSN Deployment Problem*

Coverage issue is one of the most important tasks in WSN. The ultimate goal is to have each location in the physical space of interest within the sensing range of at least one sensor. However, due to the number of sensors is limited, complete coverage cannot be guaranteed. Therefore, many approaches are proposed to deal with the 2D coverage problem. Oh et al.

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[10] proposed a genetic algorithm for the optimal selection of the number and type of sensors available from a suite of sensors. Dhawan et al. [7] proposed a novel searching algorithm based on improved NSGA-II to select an optimal cover set. It maintains the full coverage in large sensor networks by a small number of sensor nodes. For a practical approach, a probabilistic sensor detection model is adopted in combination with the detection error range and coverage threshold. Recently, Oktug et al. [9] proposed an approach to solve coverage problem by simulating sensor deployment strategies on a 3D terrain model and to find answers to questions that how many sensors are needed to cover a specified 3D terrain at a specified coverage percentage.

Different applications require different degrees of sensing coverage. While some applications may require a complete coverage in a region, others may only need a high percentage of coverage. Such WSN is called differentiated WSN [1]. Take underwater sensor deployment [2] as an example, sensor field of underwater is characterized by the geographical irregularity of the sensed events because some area may be inaccessible or the event area may not be uniformly distributed. To efficiently monitor such area with differentiated detection levels, fulfillment of detection levels in different area is the major concerns instead of maximizing the coverage of sensors. In [11], three density control protocols by considering the tradeoff between energy usage and coverage was developed to select sensors. Few studies have considered the case of geographical irregularity of the sensed event. Aitsaadi et al. [1] proposed a probabilistic event detection model. In this model, each grid point has a required minimum probability detection threshold. A tabu Search method is proposed to solve this differentiated WSN deployment problem.

In recent years, utilizing limited energy efficiently in a wireless sensor network has become an important issue. In [8], the problem is to prolong maximum network lifetime when all grid points are covered and sensor energy resources are constrained. In [4], they proposed a method to extend the network lifetime is to divide the sensors into a number of sets, such that only one set is responsible for monitoring the targets, and all other sensors are in sleep mode. In the sleep mode, it consumes the least energy. If all the sensor nodes operate in the active mode simultaneously, an excessive amount of energy will be wasted and the data collected will be redundant. In [12], two new energy-efficient models of different sensing ranges are proposed. They used scheduling models with adjustable sensing ranges of each sensor in order to reduce the overlaps among detection ranges.

B. Multi-objective Evolutionary Optimization

Assume the multi-objective functions are to be minimized. Mathematically, MOOPs can be represented as the following vector mathematical programming problems

$$\textit{Minimize} \quad F(Y) = \{F_1(Y), F_2(Y), ..., F_i(Y)\}. \qquad (1)$$

where Y denotes a solution and $f_i(Y)$ is generally a nonlinear objective function. Pareto dominance relationship and some related terminologies are introduced below. When the following inequalities hold between two solutions Y_1 and Y_2, Y_2 is a non-dominated solution and is said to dominate Y_1 ($Y_2 \succ Y_1$):

$$\forall i : F_i(Y_1) > F_i(Y_2) \wedge \exists j : F_j(Y_1) > F_j(Y_2). \qquad (2)$$

When the following inequality hold between two solutions Y_1 and Y_2, Y_2 is said to weakly dominate Y_1 ($Y_2 \succeq Y_1$):

$$\forall i : F_i(Y_1) \geq F_i(Y_2). \qquad (3)$$

A feasible solution Y^* is said to be a Pareto-optimal solution if and only if there does not exist a feasible solution Y where Y dominates Y^*, and the corresponding vector of Pareto-optimal solutions is called Pareto-optimal front.

By making use of Pareto dominance relationship, multi-objective evolutionary algorithms (MOEAs) are capable of performing the fitness assignment of multiple objectives without using relative preferences of multiple objectives. Thus, all the objective functions can be optimized simultaneously. As a result, MOEA seems to be an alternative approach to solving production planning and inspection planning problems on the assumption that no prior domain knowledge is available [6].

III. PROBLEM STATEMENT

A. Notations

In order to formulate problems, the following notations are introduced:

- i : sensor index, $i = 1,2,3,...,N$.
- j : grid point index, $j = 1,2,3,...,M$.
- k : sensing range index, $k = 1,2,3,...,K$.

B. Environment

We assume that N sensors $s_1,s_2,..., s_N$ are deployed to cover the sensor field. Let the sensor field T consist of n_x, n_y, and n_z grid points $p_1,p_2,..., p_M$ in the x, y, and z dimensions, respectively [3]. Each sensor has an initial sensor energy E and has the capability to adjust its sensor range. Sensing range options are $r_1,r_2,..., r_K$, corresponding to energy consumptions of $e_1,e_2,..., e_K$ and detection error ranges $f_1,f_2,..., f_K$ ($f_k < r_k$) [4]. We assume that each grid point p_j in sensor field is associated a required minimum probability detection level, denoted $t(p_j)$.

C. Mathematical Formation of 3D Deployment Problem

1) Maximization of Coverage

In many WSN applications, the main task is the surveillance of certain geographical areas [9]. Target location can be simplified considerably if the sensors are placed in such a way that every grid point in the sensor field is covered by sensors. In this way, the sensors reporting a target at time t uniquely identifies the grid location for the target at time t. The trajectory of a moving target can also be easily determined in this fashion from time series data [3].

Assume that sensor s_i is deployed at grid point. For any grid point p_j, the Euclidean distance between sensor s_i and grid point p_j is denoted as

$$d(s_i, p_j) = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2 + (z_i - z_j)^2} \quad (4)$$

where x_i, x_j, y_i, y_j, z_i and z_j are coordinate location values. The way to compute the sensor and target coverage relationship is to consider that a sensor covers a target if the Euclidean distance between the sensor and target is no greater than a predefined sensing range. The following equation shows a binary coverage model expressing the coverage $c_b(s_i, p_j)$ of a grid point p_j by sensor s_i.

$$c_b(s_i,p_j) = \begin{cases} 1, & if\ d(s_i,p_j) < r_k(s_i) \\ 0, & otherwise \end{cases} \quad (5)$$

, where $r_k(s_i)$ is the sensing range of the sensor s_i.

The coverage rate optimization problem F_1 can be defined by

$$Max. \quad F_1 = \frac{\sum_{j=1}^{M} c_b(p_j)}{M} \quad (6)$$

, where $c_b(p_j)$ is the coverage of all sensors at grid point p_j by the Equation (5). This objective is to be maximized.

2) Maximization of Differentiated Detection Levels

Considering differentiated detection levels, assumed that each grid point p_j in sensor field T is associated a required minimum detection level, denoted $t(p_j)$. A terrain may have different required detection levels, as illustrated in Figure 1. Ideally, a good deployment for differentiated WSN should satisfy the following condition: for each p_j in T, the measured detection probability of p_j should be greater than or equal to $t(p_j)$ [1].

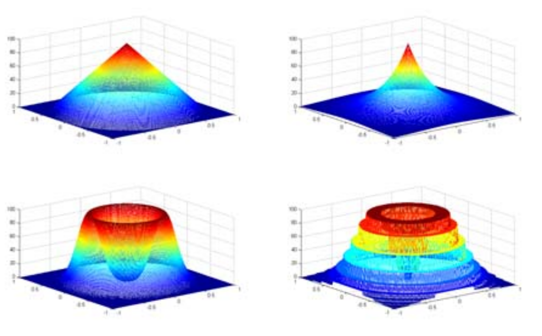

Figure 1. Terrain with different required detection levels: decreasing linear, normal, Poisson, and exponential distributions.

In literature, a 0/1 binary detection model for grid points is often used if a grid is covered by a sensor. However, in reality, the detection of events may be influence by weather or obstacles. In such cases, the 0/1 binary detection model has limitations due to the imprecise detection probability, which plays a significant role in sensor detection [7]. Hence, a detection error range is introduced to measure the uncertainty of sensor detection [7]. Each grid point covered by sensors has different detection probabilities according to their realistic conditions, such as distance to sensors or weather conditions. If a gird point in sensor field T is covered only by one sensor and far from other sensors, it may have a low detection probability. In this case, it is necessary to reallocate sensors, so that the detection area of sensors can be overlapped to compensate for the low detection probability of those grid points that are far from any sensor.

In this paper, we adopted a probabilistic detection model for sensor deployment [1]. Assume that event detection probability of a sensor diminishes as its distance to the sensed point increases. A probabilistic detection model of sensors is expressed as

$$c_p(s_i,p_j) = \begin{cases} 0, & if\ r_k(s_i) + f_k(s_i) \le d(s_i,p_j) \\ e^{-\lambda\alpha^\beta}, & if\ r_k(s_i) - f_k(s_i) < d(s_i,p_j) < r_k(s_i) + f_k(s_i) \\ 1, & if\ r_k(s_i) - f_k(s_i) \ge d(s_i,p_j) \end{cases} \quad (7)$$

, where $\alpha = d(s_i, p_j) - (r_k(s_i) - f_k(s_i))$, λ and β are parameters that measure the detection probabilities when an object is within a certain distance from the sensor, and $f_k(s_i)$ is the error ranges of the sensor s_i. Each sensor s_i has a detection probability $c_p(s_i, p_j)$ at grid point p_j. A grid point p_j might be covered by more than one detection range of different sensors [8]. When a detection area is overlapped by multiple sensors, the closer are the sensors to each other, the higher is the detection probability of the grid points [7]. The conjunctive detection probability of all sensors at grid point p_j is given by

$$c_p(p_j) = 1 - \prod_{i=1}^{N}(1 - c_p(s_i, p_j)). \quad (8)$$

The optimization of the satisfaction required probability of detection level F_2 is expressed by:

$$Max. \quad F_2 = \frac{\sum_{j=1}^{M} DP(p_j)}{\sum_{j=1}^{M} t(p_j)} \quad (9)$$

,where $DP(p_j) = \begin{cases} t(p_j) & if\ c_p(p_j) - t(p_j) \ge 0 \\ 0 & otherwise \end{cases}$.

This objective is to be maximized.

3) Minimization of Energy Consumption

In terms of energy consumption, we only consider the energy used in sensing, but not including the power consumed by radio communication and computation. The sensing ranges of a sensor determine the energy consumed by the sensor [4]. We attempt to make the detection regions of sensors not overlapped, thereby minimizing the wasted overlap area and covering more grid points with a small number of sensors. We apply an energy model in our evaluation, in which the power consumption is proportional to the square of the sensing range r_k [11]. The energy consumption model is expressed as follows:

$$e_k(s_i) = \mu \times r_k(s_i)^2, \quad (10)$$

where μ is an energy consumption parameter. The optimization of the detection power minimization with adjustable sensing range F_3 can be formulated as

$$Min. \quad F_3 = \frac{\sum_{i=1}^{N} e_k(s_i)}{\sum_{i=1}^{N} e_{\max}(s_i)} \tag{11}$$

, where $e_{max}(s_i)$ is the maximum detection range of each sensor. This objective is to be minimized.

IV. MULTI-OBJECTIVE GENETIC ALGORITHM

A. Chromosome Representation

A chromosome has gene information for solving the problem in MOGA. Each chromosome has fixed gene size, which is determined by the number of sensors in the WSN. Each gene has a *x, y,* and *z* coordinate location and a sensing range. The ranges of each gene of coordinate location are [0, n_x], [0, n_y], and [0, n_z] in the *x, y,* and *z* dimensions. Hence these sensors will have coordinate values to denote their location. Each gene of sensing range is one of $r_1, r_2, \ldots, r_K$, which represent the detection ability of the sensor.

B. Fitness Assignment

We use a generalized Pareto-based scale-independent fitness function (GPSIFF) considering the quantitative fitness values in Pareto space for both dominated and non-dominated individuals. GPSIFF makes the best use of Pareto dominance relationship to evaluate individuals using a single measure of performance. The used GPSIFF is briefly described below. Let the fitness value of an individual *Y* be a tournament-like score obtained from all participant individuals by the following function:

$$F(Y) = p - q + c \tag{12}$$

, where *p* is the number of individuals which can be dominated by the individual *Y*, and *q* is the number of individuals which can dominate the individual *Y* in the objective space. Generally, a constant *c* can be optionally added in the fitness function to make fitness values positive. *c* is usually set to the number of all participant individuals.

C. Genetic Operators

The genetic operators used in the proposed approach are widely used in literature. The selection operator uses a binary tournament selection without replacement, which works as follows. Choose two individuals randomly from the population and copy the better individual into the intermediate population.

Crossover is a recombination process in which genes from two selected parents are recombined to generate offspring chromosomes. The uniform crossover is used in MOGA. In a uniform crossover operation, first requires a randomly created binary string, called crossover mask. The genes of offspring chromosomes are swapped from the parents according to this mask. If the crossover mask bit is 0, then the characters in the corresponding string position are not swapped and if the crossover mask bit is 1, than the mating string characters at that position are swapped.

A simple mutation operator is used to alter genes. For each gene, randomly generate a real value from the range [0, 1]. If the value is smaller than the mutation probability pm, replace its index with a randomly generated integer among its possible values.

D. Procedure of MOGA

The procedure of MOGA is written as follows:

Input: population size N_{pop}, recombination probability p_c, mutation probability p_m, the number of maximum generations G_{max}.

Output: The optimum solutions ever found in *P*.

Step 1: Initialization Randomly generate an initial population *P* of N_{pop} individual*s*.

Step 2: Evaluation For each individual in the population, compute all objective function values F_1, F_2, and F_3.

Step 3: Fitness assignment Assign each individual a fitness value by using GPSIFF.

Step 4: Selection Select N_{pop} individuals from the population to form a new population using the binary tournament selection.

Step 5: Recombination Perform the uniform crossover operation with a recombination probability p_c.

Step 6: Mutation Apply the mutation operator to each gene in the individuals with a mutation probability p_m.

Step 7: Termination test If a stopping condition is satisfied, stop the algorithm. Otherwise, go to Step 2.

V. RESULT AND DISCUSSION

In this section, we present some results of simulation experiments as the performance evaluation of our proposed algorithm.

A. Simulation Environment and Parameters

A 3D WSN deployment benchmark generator for WSN environment is designed to generate different scale of sensor fields with different models of detection probability levels.

In this paper, a sensor field with 50×50×50 grid points is used. The same terrain with four different required minimum detection probability levels are illustrated as four different benchmarks. The detection probability levels considered in this paper are decreasing linear, normal, Poisson, and exponential distributions, respectively. Figure 2 illustrates a terrain with linear decreasing levels. For the sensors of WSN, we assume each sensor has five adjustable sensing ranges 6, 8, 10, 12, 14, and the detection error ranges are half of the sensing range of each sensor. The power consumption parameter μ is 1. The probabilistic detection model parameter β is 0.5 and the detection radio wave parameter λ is 0.5.

The parameter settings of MOGA are listed as follows: population size N_{pop}=200, recombination probability p_c=0.9, mutation probability p_m=0.01, the number of maximum generations G_{max}=500 and 1000. Thirty independent runs are conducted for each problem.

To identify the difficulties of problems and evaluate the performance of our algorithm, the number of sensor nodes to be deployed is limited to 20 and 50, respectively. Figures 3-7 show the results of deployment using 20 sensors. Figures 8-12 show the results of deployment using 50 sensors.

Figures 3,4,8,9 depict the box plots of obtained non-dominated solutions and the maximum and minimum objective values obtained in different objective functions, using 20 and 50 sensors. Figures 5-7 and 10-12 depict the convergence speed of a typical run in solving the 3D WSN deployment problem with four different required minimum detection probability levels, using 20 and 50 sensor nodes. The results indicate that different detection levels pose different difficulties for MOGA. The problems with normal and Poisson detection levels are more difficult to find a good deployment plan than problems with decreasing linear and exponential detection levels using the same number of sensors. The number of sensors required for a terrain with normal and Poisson detection levels should be bigger than the same terrain with decreasing linear and exponential detection levels.

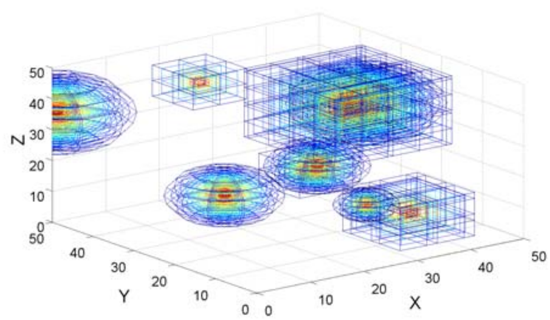

Figure 2. A terrain with decreasing linear detection levels.

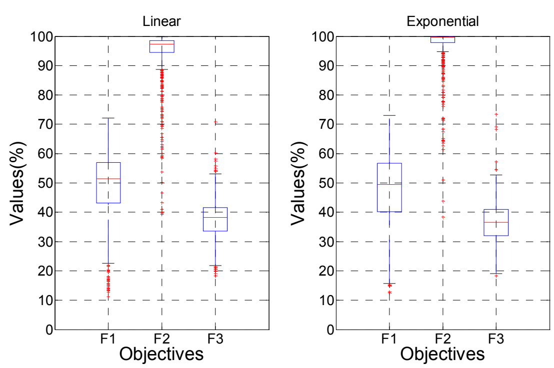

Figure 3. Box plots of non-dominated solutions for solving the 3D deployment problem with linear and exponential detection levels, using 20 sensors.

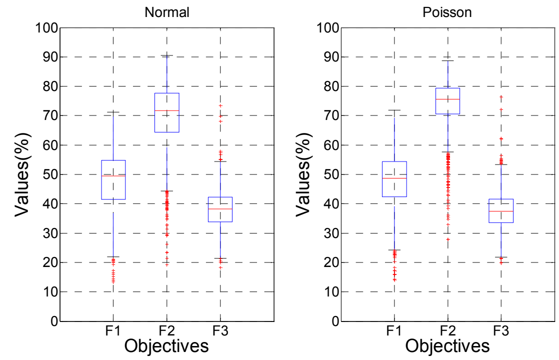

Figure 4. Box plots of non-dominated solutions for solving the 3D deployment problem with normal and Poisson detection levels, using 20 sensors.

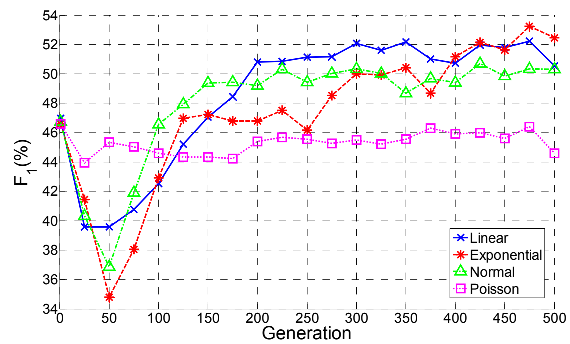

Figure 5. The mean objective value F_1 of non-dominated solutions in each generation, for four problems with different detection levels, using 20 sensors.

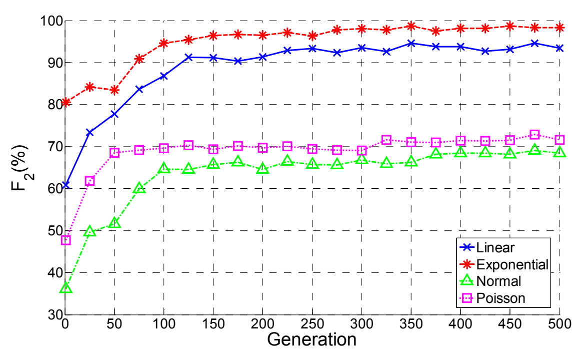

Figure 6. The mean objective value F_2 of non-dominated solutions in each generation, for four problems with different detection levels, using 20 sensors.

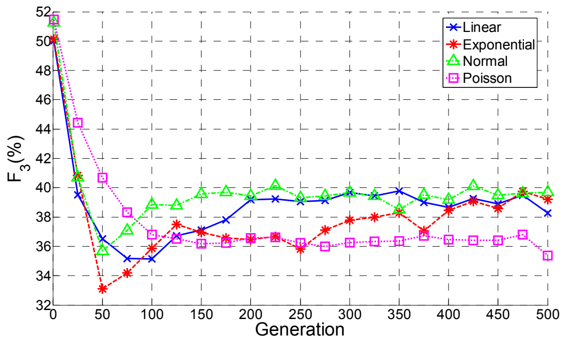

Figure 7. The mean objective value F_3 of non-dominated solutions in each generation, for four problems with different required detection levels, using 20 sensors.

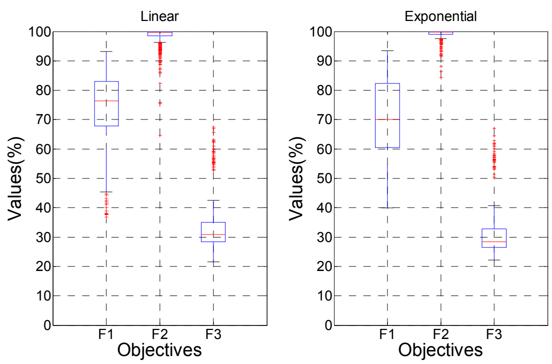

Figure 8. Box plots of non-dominated solutions for solving the 3D deployment problem with linear and exponential detection levels, using 50 sensors.

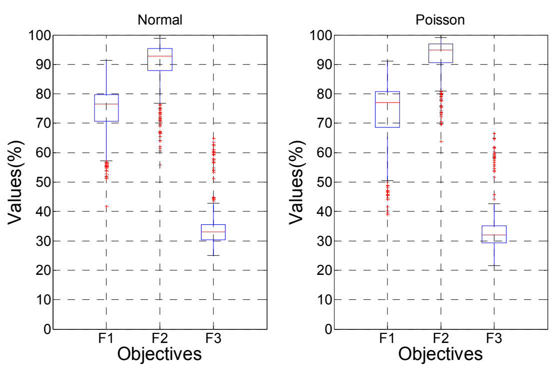

Figure 9. Box plots of non-dominated solutions for solving the 3D deployment problem with normal and Poisson detection levels, using 50 sensors.

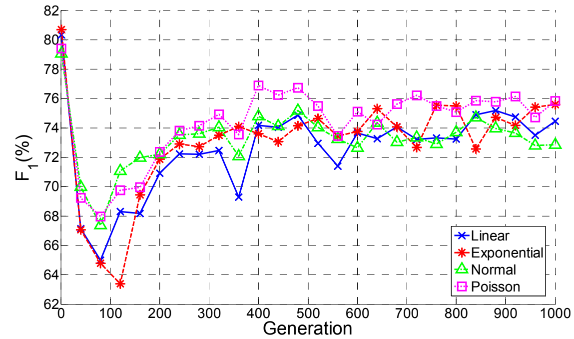

Figure 10. The mean objective value F_1 of non-dominated solutions in each generation, for four problems with different detection levels, using 50 sensors.

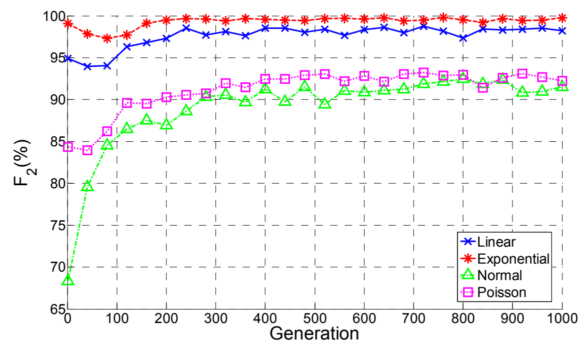

Figure 11. The mean objective value F_2 of non-dominated solutions in each generation, for four problems with different detection levels, using 50 sensors.

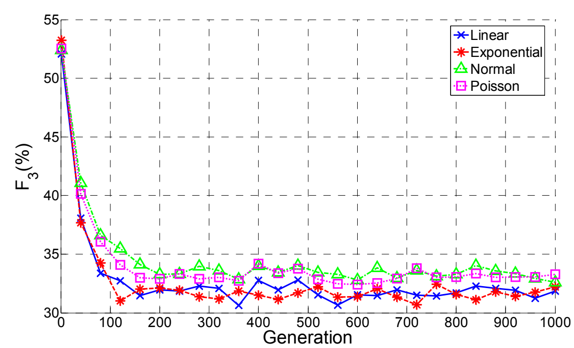

Figure 12. The mean objective value F_2 of non-dominated solutions in each generation, for four problems with different detection levels, using 20 sensors.

VI. CONCLUSION

In this paper, a multi-objective evolutionary approach is proposed to solve 3D differentiated WSN deployment problems. Experimental results demonstrated MOGA is capable of optimizing coverage, satisfaction of detection levels, and energy conservation. Moreover, MOGA can provide mission planers a set of non-dominated solutions for deployment of sensor nodes. The results also indicate that some problems with unusual detection levels requirements may require more sensor nodes for MOGA than those of problems with usual detection levels requirements. Our future work will develop specialized techniques for 3D WSN deployment problems with unusual detection levels.

ACKNOWLEDGMENT

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Combined Heat and Power Environmental/Economic Power Dispatch Using Multi-Objective Evolutionary Algorithms

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Abstract— **Economic dispatch is to determine an efficient, low-cost and reliable operation of a power system by dispatching the available electricity generation resources to supply the demands. Basically, the primary objective of economic dispatch is to minimize the total cost of generation while satisfying the operational constraints of the available generation resources. Recently, due to environmental awareness and environmental policies, the design and operation of electric utilities are forced to restructure their power system systems to account for their emission impacts. In this paper, a combined heat and power environmental/economic dispatch (CHPEED) problem in a combined heat and power systems is formulated. Three objectives: fuel cost, emission, power overhead and heat overhead are considered in CHPEED problems. A multi-objective evolutionary algorithm with a modified schemata-based local search operator is proposed to solve the CHPEED problems.**

Keywords-Cogeneration, Heat and power dispatch, Economic/environmental dispatch, multi-objective optimization, genetic algorithms

I. INTRODUCTION

Economic dispatch (ED) is to determine an efficient, low-cost and reliable operation of a power system by dispatching the available electricity generation resources to supply the demands in such a manner that the cost of operation is minimized while all operational constraints are satisfied. However, due to increasing concerns on environmental issues and the implementation of the Clean Air Act Amendments, environmental constraints have topped the list of utility management concerns. This issue that has attracted much attention is pollution minimization due to the pressing public demand for clean air. Therefore, operating power systems at absolute minimum fuel cost can no longer be the only criterion for dispatching electric power nowadays [1].

In the past decades, increasing demand for power and heat resulted in the existence of cogeneration units [2]. Cogeneration is also referred to as a combined heat and power (CHP) system. It produces electricity and useful heat simultaneously. Some industrial processes have large heat requirements, either as process steam or piped hot fluid, as well as large power demands [3]. Traditional, the primary objective of combined heat and power economic dispatch (CHPED) is similar to economic dispatch problems. The objective of CHPED is to find the optimal point of power and heat generation with minimum fuel cost such that both heat and power demands are met while the combined heat and power units are operated in a bounded heat versus power plane. The mutual dependencies of heat and power generation introduce a complication in the integration of cogeneration units into the power system economic dispatch [2].

The generation of power and heat from fossil fuel releases several contaminants, such as Sulfur Oxides, Nitrogen Oxides and Carbon Dioxide, into the atmosphere [4]. However, the increasing public awareness of the environmental protection has forced the utilities to modify their design or operational strategies to reduce pollution and environmental emissions of the thermal power plants [5]. Therefore, it becomes very complicated when dealing with increasingly complex dispatch problems for conventional techniques.

As a result, economic/environmental dispatch is a multi-objective problem with conflicting objectives because pollution minimization is conflicting with minimum cost of generation [1]. In this paper, a combined heat and power environmental/economic dispatch (CHPEED) problem, considering the fuel cost, emission, power overhead and heat overhead, is formulated. A multi-objective evolutionary approach is proposed in this paper to optimize these four objectives simultaneously.

II. RELATED WORK

A. Environmental/Economic Dispatch Problem

Environmental issue has become one of the most important factors in environmental/economic dispatch (EED) problem. Emissions are taken into consideration except fuel cost for it is more and more important to save environment from the pollutants caused by power plants. In [6], it treats the emission as a constraint with a permissible limit. This formulation, however, has a severe difficulty in getting the trade-off relations between cost and emission [5]. In [7-10], the emission is treated as another objective in addition to usual cost objective. However, the EED problem was converted to a single objective problem either by linear combination of both objectives or by considering one objective at a time for optimization. Unfortunately, this approach requires multiple runs as many times as the number of desired Pareto-optimal solutions and tends to find weakly non-dominated solutions [5]. In [11-13], both fuel cost and emission are taken into consideration simultaneously. The approach proposed in [11-13] handles both fuel cost and emission simultaneously as competing objectives. Stochastic search and fuzzy-based multi-objective optimization techniques have been proposed for the EED problem. However, the algorithms do not provide a systematic framework for directing the search towards Pareto-optimal front and the extension of these techniques to include more objectives is a very involved question. In addition, these techniques are computationally involved and time-consuming [5]. Genetic algorithm based multi-objective optimization techniques have been adopted in [14, 15] where a set of good non-dominated solutions can be obtained from each evolution generation. However, GA-based techniques suffer from premature convergence and the technique presented in [14] is computationally involved due to ranking process during the fitness assignment procedure. In [5], a new multi-objective particle swarm optimization (MOPSO) technique for environmental/economic dispatch (EED) problem is proposed. The proposed MOPSO technique evolves a multi-objective version of PSO by proposing redefinition of global best and local best individuals in multi-objective optimization domain.

When some industrial processes have large heat requirements, the heat load becomes as important as power load. As a result, the combined heat and power economic dispatch (CHPED) problem of a system has been raised to determine the unit heat and power production, so that the system production cost is minimized while the heat and power demands and other constraints are met. In [2], a self adaptive real-coded genetic algorithm (SARGA) is implemented to solve the problem. However, environmental emission is not considered in this paper.

Nevertheless, these EED and CHPED problems only considered a fixed number of power/cogeneration units or heat-alone units while optimizing fuel costs and emissions. None of them consider environmental/economic dispatch with a variable number of units.

B. Multi-objective Evolutionary Optimization

Assume the multi-objective functions are to be minimized. Mathematically, MOOPs can be represented as the following vector mathematical programming problems

$$\textit{Minimize} \quad F(Y) = \{F_1(Y), F_2(Y), ..., F_i(Y)\}. \tag{1}$$

where Y denotes a solution and $f_i(Y)$ is generally a nonlinear objective function. Pareto dominance relationship and some related terminologies are introduced below. When the following inequalities hold between two solutions Y_1 and Y_2, Y_2 is a non-dominated solution and is said to dominate Y_1 ($Y_2 \succ Y_1$):

$$\forall i : F_i(Y_1) > F_i(Y_2) \wedge \exists j : F_j(Y_1) > F_j(Y_2). \tag{2}$$

When the following inequality hold between two solutions Y_1 and Y_2, Y_2 is said to weakly dominate Y_1 ($Y_2 \succeq Y_1$):

$$\forall i : F_i(Y_1) \geq F_i(Y_2). \tag{3}$$

A feasible solution Y^* is said to be a Pareto-optimal solution if and only if there does not exist a feasible solution Y where Y dominates Y^*, and the corresponding vector of Pareto-optimal solutions is called Pareto-optimal front.

By making use of Pareto dominance relationship, multi-objective evolutionary algorithms (MOEAs) are capable of performing the fitness assignment of multiple objectives without using relative preferences of multiple objectives. Thus, all the objective functions can be optimized simultaneously. As a result, MOEA seems to be an alternative approach to solving production planning and inspection planning problems on the assumption that no prior domain knowledge is available [13].

III. PROBLEM STATEMENT

The CHPEED problem is to minimize four competing objective functions, fuel cost, emission, power overhead and heat overhead, while satisfying several equality and inequality constraints. The CHPEED problem is formulated as follows.

A. Problem objectives

1) Minimization of fuel cost

The total US$/h fuel cost F_{cost} can be expressed as

$$F_{\cos t} = \sum_{i=1}^{N_p} C_i(P_i) + \sum_{j=1}^{N_c} C_j(O_j, H_j) + \sum_{k=1}^{N_h} C_k(T_k) \tag{4}$$

, where C_i, C_j and C_k are the unit production costs of the conventional power, cogeneration and heat-alone units, respectively; P_i and O_j are power generations of conventional power and cogeneration units; H_j and T_k are heat generation of cogeneration and heat-alone units.

2) Minimization of emission

$$E = \sum_{i=1}^{N_p} E_i(P_i) + \sum_{j=1}^{N_c} E_j(O_j, H_j) + \sum_{k=1}^{N_h} E_k(T_k) \tag{5}$$

, where E_i, E_j *and* E_k are the emission (kg/h) caused by the conventional power, cogeneration and heat-alone units, respectively.

$$E_i(P_i) = \alpha + \beta P_i + \gamma P_i^2 \tag{6}$$

$$E_j(O_j) = \mu O_j \tag{7}$$

$$E_k(T_k) = T_k(\mu_{NO_x} + \mu_{CO_2} + \mu_{CO}) \tag{8}$$

, where α, β *and* γ represent to the emission function coefficients of the conventional power unit.

3) Minimization of power overhead and heat overhead

$$O_p = \sum_{i=1}^{N_p} P_i + \sum_{j=1}^{N_c} O_j - P_d \tag{9}$$

$$O_h = \sum_{j=1}^{N_c} H_j + \sum_{k=1}^{N_h} T_k - H_d \tag{10}$$

, where H_d and P_d are heat and power demands; N_p, N_c and N_h denote the number of conventional power, cogeneration and heat-alone units, respectively.

B. Problem constraints

$$\sum_{i=1}^{N_p} P_i + \sum_{j=1}^{N_c} O_j \geq P_d \tag{11}$$

$$\sum_{j=1}^{N_c} H_j + \sum_{k=1}^{N_h} T_k \geq H_d \tag{12}$$

$$P_i^{\min} \leq P_i \leq P_i^{\min}, \quad i = 1, \ldots, N_p \tag{13}$$

$$O_j^{\min}(H_j) \leq O_j \leq O_j^{\max}(H_j), \quad j = 1, \ldots, N_c \tag{14}$$

$$H_j^{\min}(O_j) \leq H_j \leq H_j^{\max}(O_j), \quad j = 1, \ldots, N_c \tag{15}$$

$$T_k^{\min} \leq T_k \leq T_k^{\max}, \quad k = 1, \ldots, N_h \tag{16}$$

with

$$C_i(P_i) = a_p + b_p P_i + c_p P_i^2 \tag{17}$$

$$C_j(O_j, H_j) = a_c + b_c O_j + c_c O_j^2 + d_c H_j + e_c H_j^2 + f_c O_j H_j \tag{18}$$

$$C_k(T_k) = a_h + b_h T_k + c_h T_k^2 \tag{19}$$

, where P_i^{min} and P_i^{max} are the minimum and maximum power generation limits of the conventional units; O_j^{min} and O_j^{max} are the minimum and maximum power generation limits of the cogeneration units; H_j^{min} and H_j^{max} are the minimum and maximum heat generation limits of the cogeneration units; T_k^{min} and T_k^{max} are the minimum and maximum heat generation limits of the heat-alone units; a_p, b_p and c_p are fuel cost coefficients of the conventional power unit ; a_c , b_c , c_c , d_c , e_c and f_c are fuel cost coefficients of the cogeneration unit; a_h, b_h and c_h are fuel cost coefficients of the heat-alone unit. The value of fuel cost coefficients are given in Table I.

TABLE I. GENERATOR FUEL COST COEFFICIENTS.

coefficients	**unit**		
	Conventional power	***Cogeneration***	***Heat-alone***
a	451.32513	2650	0
b	46.15916	14.5	23.4T_1
c	0.10587	0.0345	0
d		4.2	
e		0.03	
f		0.031	

IV. MULTI-OBJECTIVE GENETIC ALGORITHM

A. Chromosome Representation

A chromosome has gene information for solving the problem in MOGA. Each chromosome has dynamic gene size, which is determined by the max number of all units in combined heat and power (CHP) systems. The first gene is numbers of conventional power unit and the second one stands for numbers of cogeneration, and the third one represents numbers of heat-alone unit. The remains of the genes are the dispatch value of all units.

B. Fitness Assignment

We use a generalized Pareto-based scale-independent fitness function (GPSIFF) considering the quantitative fitness values in Pareto space for both dominated and non-dominated individuals. GPSIFF makes the best use of Pareto dominance relationship to evaluate individuals using a single measure of performance. The used GPSIFF is briefly described below. Let the fitness value of an individual Y be a tournament-like score obtained from all participant individuals by the following function:

$$F(Y) = p - q + c \tag{20}$$

, where p is the number of individuals which can be dominated by the individual Y, and q is the number of individuals which can dominate the individual Y in the objective space. Generally, a constant c can be optionally added in the fitness function to make fitness values positive. c is usually set to the number of all participant individuals.

C. Genetic Operators

The genetic operators used in the proposed approach are widely used in literature. The selection operator uses a binary tournament selection without replacement, which works as follows. Choose two individuals randomly from the population and copy the better individual into the intermediate population.

Crossover is a recombination process in which genes from two selected parents are recombined to generate offspring chromosomes. The order crossover (OX) in GA literature is used in our approach.

A simple mutation operator is used to alter genes. For each gene, randomly generate a real value from their given range. If the value is smaller than the mutation probability p_m, replace its index with a randomly generated integer among its possible values. A modified schemata-guided local search strategy based on our previous work [17] is applied in our algorithm.

D. Procedure of MOGA

The procedure of MOGA is written as follows:

Input: population size N_{pop}, recombination probability p_c, mutation probability p_m, the number of maximum generations G_{max}.

Output: The optimum solutions ever found in *P*.

Step 1: Initialization Randomly generate an initial population *P* of N_{pop} individuals.

Step 2: Evaluation For each individual in the population, compute all objective function values F_1, F_2, and F_3.

Step 3: Fitness assignment Assign each individual a fitness value by using GPSIFF.

Step 4: Selection Select N_{pop} individuals from the population to form a new population using the binary tournament selection.

Step 5: Recombination Perform the order crossover operation with a recombination probability p_c.

Step 6: Mutation Apply the mutation operator to each gene in the individuals with a mutation probability p_m.

Step 7: Local Search The current population is classified into *Q* species by the best solutions in each objective. For each species, compute the locations of its similarity and dissimilarity genes. Hereafter, the locations of its dissimilarity genes in the selected solutions are perturbed to new solutions. If the new solutions are non-dominated solutions, the selected solutions are replaced.

Step 7: Termination test If a stopping condition is satisfied, stop the algorithm. Otherwise, go to Step 2.

V. RESULTS AND DISCUSSIONS

A. Simulation Environment and Parameter Settings

This power system considers a type of conventional power unit, cogeneration unit and heat-alone unit, respectively. The power generation limits of the conventional power unit are 0 and 150 MW and heat generation limits of heat-alone units are 0 and 2695.2 MW_{th}. The feasible operating regions of the cogeneration unit are given in figure 1. The value of emission coefficients α, β *and* γ are given as 13.85932, 0.32767 and 0.00419, respectively. The emission factors of heat-alone units are obtained from the average heat generation from residential boilers in urban areas, with an equivalent fuel mix as input [16]. The emission factors μ_{NOx}, μ_{CO2} *and* μ_{CO} are given as 0.2 kg/MW, 0.27 kg/MW and 0.04 kg/MW, respectively.

The feasible operating regions of the cogeneration unit from Figure 1 can be expressed as inequality constraints as follows:

$$1.781914894H - O - 105.74468090 \leq 0 \tag{21}$$

$$0.177777778H + O - 247.0 \leq 0 \tag{22}$$

$$-0.169847328H - O + 98.8 \leq 0 \tag{23}$$

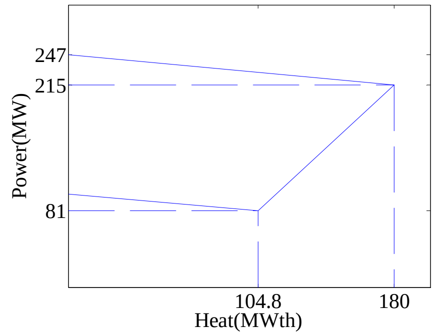

Figure 1. Feasible operating regions of cogeneration unit.

Based on the given environment and constraints, three benchmark problems "demand (200, 115)", "demand (700, 615)" and "demand (2000, 1115)" are designed to validate our approach. The notation "demand (P, H)" represents that the power demand is P and the heat demand is H.

The parameter settings of our MOGA are listed as follows: population size N_{pop}=50, recombination probability p_c=0.9, mutation probability p_m=0.01, the number of maximum generations G_{max}=100. *Q*=3 and quarter population are selected for our local search operator. Thirty independent runs are conducted for each problem.

Figures 2-4 shows the distributions of non-dominated solutions in four objectives by means of boxplot. The results indicate that the proposed approach is capable of obtaining a set of wide-spread and non-dominated solutions.

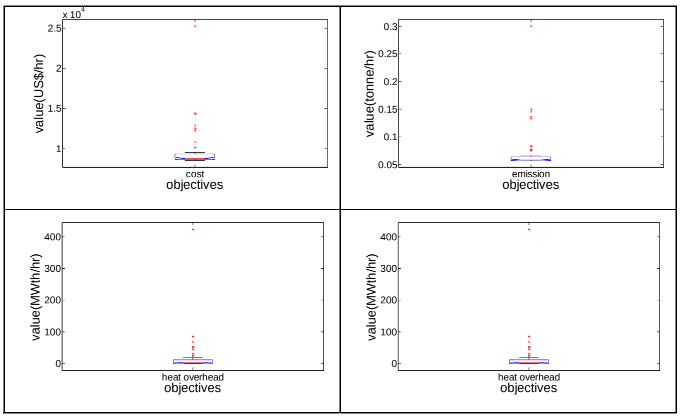

Figure 2. Boxplot of non-dominated solutions in solving "demand (200,115)" problem.

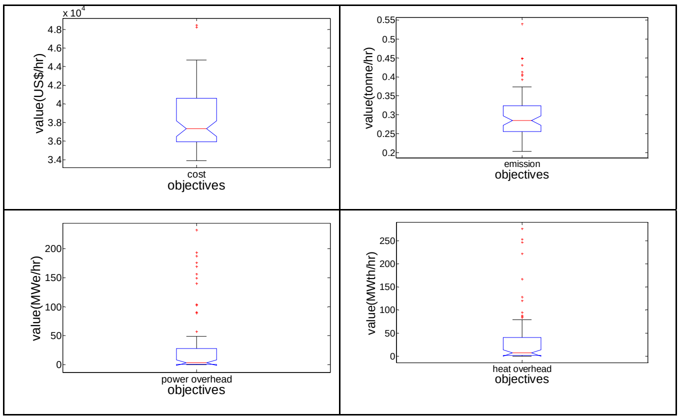

Figure 3. Boxplot of non-dominated solutions in solving "demand (700,615)" problem.

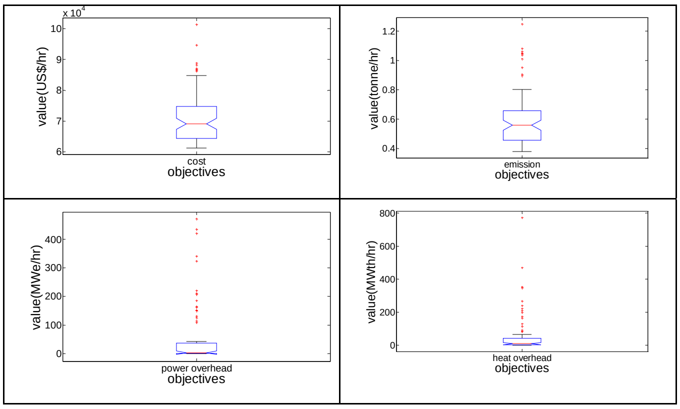

Figure 4. Boxplot of non-dominated solutions in solving "demand (2000,1115)" problem.

VI. CONCLUSION

In this paper, a multi-objective evolutionary approach is proposed to solve the combined heat and power environmental/economic dispatch problem. The problem is formulated as multi-objective optimization problem with competing economic and environmental objectives. Experimental results demonstrated the proposed method is capable of optimizing fuel cost, emission, power overhead and heat overhead simultaneously. Moreover, the proposed approach can provide decision makers a set of non-dominated solutions to choose a suitable dispatch plan.

ACKNOWLEDGMENT

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國科會補助計畫衍生研發成果推廣資料表

日期:2010/12/31

國科會補助計畫	計畫名稱: 以演化式計算多目標最佳化可重組製造系統之研究
	計畫主持人: 陳建宏
	計畫編號: 98-2221-E-216-027- 學門領域: 人工智慧

無研發成果推廣資料

98 年度專題研究計畫研究成果彙整表

計畫主持人：陳建宏	計畫編號：98-2221-E-216-027-
計畫名稱：以演化式計算多目標最佳化可重組製造系統之研究	

成果項目			量化			單位	備註（質化說明：如數個計畫共同成果、成果列為該期刊之封面故事...等）
			實際已達成數（被接受或已發表）	預期總達成數(含實際已達成數)	本計畫實際貢獻百分比		
國內	論文著作	期刊論文	0	0	100%	篇	
		研究報告/技術報告	0	0	100%		
		研討會論文	1	1	100%		
		專書	0	0	100%		
	專利	申請中件數	0	0	100%	件	
		已獲得件數	0	0	100%		
	技術移轉	件數	0	0	100%	件	
		權利金	0	0	100%	千元	
	參與計畫人力（本國籍）	碩士生	3	3	100%	人次	
		博士生	0	0	100%		
		博士後研究員	0	0	100%		
		專任助理	0	0	100%		
國外	論文著作	期刊論文	0	0	100%	篇	
		研究報告/技術報告	0	0	100%		
		研討會論文	0	0	100%		
		專書	0	0	100%	章/本	
	專利	申請中件數	0	0	100%	件	
		已獲得件數	0	0	100%		
	技術移轉	件數	0	0	100%	件	
		權利金	0	0	100%	千元	
	參與計畫人力（外國籍）	碩士生	0	0	100%	人次	
		博士生	0	0	100%		
		博士後研究員	0	0	100%		
		專任助理	0	0	100%		

其他成果 (無法以量化表達之成果如辦理學術活動、獲得獎項、重要國際合作、研究成果國際影響力及其他協助產業技術發展之具體效益事項等，請以文字敘述填列。)	無

	成果項目	量化	名稱或內容性質簡述
科教處計畫加填項目	測驗工具(含質性與量性)	0	
	課程/模組	0	
	電腦及網路系統或工具	0	
	教材	0	
	舉辦之活動/競賽	0	
	研討會/工作坊	0	
	電子報、網站	0	
	計畫成果推廣之參與（閱聽）人數	0	

國科會補助專題研究計畫成果報告自評表

請就研究內容與原計畫相符程度、達成預期目標情況、研究成果之學術或應用價值（簡要敘述成果所代表之意義、價值、影響或進一步發展之可能性）、是否適合在學術期刊發表或申請專利、主要發現或其他有關價值等，作一綜合評估。

1. 請就研究內容與原計畫相符程度、達成預期目標情況作一綜合評估

■達成目標

□未達成目標（請說明，以 100 字為限）

□實驗失敗

□因故實驗中斷

□其他原因

說明：

2. 研究成果在學術期刊發表或申請專利等情形：

論文：■已發表 □未發表之文稿 □撰寫中 □無

專利：□已獲得 □申請中 ■無

技轉：□已技轉 □洽談中 ■無

其他：（以 100 字為限）

3. 請依學術成就、技術創新、社會影響等方面，評估研究成果之學術或應用價值（簡要敘述成果所代表之意義、價值、影響或進一步發展之可能性）（以 500 字為限）

由於可重組製造系統的特性需求，因此可重組製造系統便需要一些有效的設計方法來達成它系統所需之種種目標並且規劃可重組製造系統的用途以便滿足它的各項目標需求。要研發與可重組製造系統有關的設計方法便需要對製造系統有深入的背景知識且對於智慧型最佳化演算法有扎實的理論與實際應用基礎。

由於自動搬運系統性能之好壞將嚴重影響整個工廠之效能，本計畫提出了一個以多目標基因演算法為基礎之最佳化路徑規劃方法，期能同時考量最短距離、路線平滑性、路線平緩性和安全距離等四個目標，規劃出適合可重組式製造工廠自動搬運系統機器人之路徑。