行政院所屬各機關因公出國人員出國報告書
（出國類別： 實習 ）

電廠熱效率分析儀測及運轉最佳化技術

服務機關 ：台灣電力公司
出國人： 職　　稱：一般工程師
姓　　名：楊泰然
（姓名代號）： 823450

出國地區：美國 日本
出國期間：90 年 09 月 09 日 至 90 年 09 月 24 日
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行政院及所屬各機關因公出國人員出國報告書審核表

出國報告名稱：電廠熱效率分析儀測及運轉最佳化技術	
出國計畫主辦機關名稱：台灣電力公司	
出國人姓名/職稱/服務單位：楊泰然/一般工程師/台灣電力公司	
出國計畫主辦機關審核意見	☑1.依限繳交出國報告 ☑2.格式完整 ☑3.內容充實完備 ☑4.建議具參考價值 ☑5送本機關參考或研辦 ☐6送上級機關參考 ☐7退回補正，原因： ☐（1）不符原核定出國計劃 ☐（2）以外文撰寫或僅以所蒐集外交資料爲內容 ☐（3）內容空洞簡略 ☐（4）未依行政院所屬各機關出國報告規格辦理 ☐（5）未於資訊網登錄提要及傳送出國報告電子檔 ☐8其他處理意見：
層轉機關審核意見	☐同意主辦機關意見 ☐全部　☐部份 ________（填寫審核意見編號） ☐退回補正，原因：________（填寫審核意見編號） 其他處理意見：

說明：

一、出國計畫主辦機關即層轉機關時，不須填寫「層轉機關審意見」。

二、各機關可依需要自行增列審核項目內容，出國報告審核完畢本表請自行保存

三、審核作業應於出國報告提出後 二個月內完成。

總經理

副總經理

單位主管： 90.11.26 劉志放

直接主管： 90.11.21 徐真明

報告人： 90.11.19 楊泰然

行政院及所屬各機關出國報告提要

出國報告名稱：電廠熱效率分析儀測及運轉最佳化技術
頁數 24 含附件：□是 ■否
出國計畫主辦機關/聯絡人/電話: 臺電/楊泰然/02-26815424
出國類別：□ 1 考察 □ 2 進修 □ 3 研究 ■4 實習 □ 5 其他
出國期間：90.09.09.~90.09.24. 出國地區：美、日
報告日期：
分類/號目
關鍵詞：ACM, Optimization, Performance, Heat rate, NOx
內容摘要：（二百至三百字）

此次實習任務主要為學習電廠熱功性能儀器校準監測系統、瞭解鍋爐最佳化軟體相關技術。計畫緣起於公司現有火力電廠普遍缺乏對儀器狀況及鍋爐運轉效率之掌握，因此如何建置有效之熱功性能儀器校準監測系統並建立鍋爐運轉最佳化應用之相關技術，實為時勢所趨也是本公司當前各火力電廠迫切之需求。

計畫實施主要與相關廠家技術人員討論建置系統之主要程序、蒐集相關技術資料、實習應用軟體、討論如何提昇電廠儀測品質及如何規劃發電鍋爐運轉最佳化專案，最後就實習任務提出兩項主要心得報告與實際施行之建議:

(1)儀測校準監視系統 ACM

--功能及任務、運作程序、整合慣常模式、電廠之應用。

(2)鍋爐運轉最佳化技術

--最佳化之基本概念、商業化產品、鍋爐之應用實績。

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第 壹 章　行程及內容

一、出國任務

此次實習主要任務為赴美國 PCS (Performance Consu-lting Service)公司、及日本 Pavillion 公司瞭解電廠熱功性能儀器校準監測系統、學習鍋爐最佳化軟體相關技術之專案規劃與應用。

計畫緣起於公司現有火力電廠普遍缺乏對儀器狀況及鍋爐運轉效率之掌握，因此如何建置有效之熱功性能儀器校準監測系統並建立鍋爐運轉最佳化應用之相關技術，為時勢所趨也是本公司當前各火力電廠迫切之需求。

此次實習之目標主要瞭解電廠熱功性能儀器校準監測系統(ACM)建置技術與應用經驗、討論燃煤電廠熱效率分析儀測相關問題、觀摩 B&V 公司的"熱功性能連線監測系統"、研討鍋爐運轉最佳化系統特性及應用實績、學習鍋爐最佳化軟體建置過程/使用管理/維護工作應留意之相關技術。

計畫實施要領主要與相關廠家技術人員討論建置系統之主要程序、蒐集相關技術資料、實習應用軟體、討論如何提昇電廠儀測品質及如何規劃發電鍋爐運轉最佳化專案，最後就實習任務提出心得報告與建議。

二、行程及內容

本次出國期間從 90 年 09 月 09 日至 90 年 09 月 24 日，前後共計 16 天，前往美國 Kansas , Overland Park 的 PCS, Inc. 以及日本 Tokyo 的 Pavillion, Inc. ，實習 ACM 應用軟體及發電鍋爐運轉最佳化系統、討論系統建置程序、蒐集相關技術資料、討論提昇電廠儀測品質及規劃最佳化專案等相關技術。

(1) 90年09月09日~09月12日，共四天

Performance Consulting Service, Inc.

(Overland Park, Kansas, USA)

- 公司簡介 & 實習"電廠儀測校準監視系統"--ACM
- 討論 ACM(Advanced Calibration Monitor)建置技術與應用經驗
- 觀摩 B&V 公司的"熱功性能連線監測系統"
- 討論燃煤電廠熱效率分析儀測相關問題

(2) 90年09月13日~09月24日，共十二天

Pavilion, Inc. (Tokyo, Japan)

- 公司簡介、部門拜會
- Pavilion最新應用軟體介紹及實習
- 討論燃煤鍋爐熱效率分析儀測相關問題
- 研討鍋爐運轉最佳化系統、建置程序及應用實績
  - ➢ 鍋爐運轉最佳化系統之特性
  - ➢ 鍋爐最佳化系統之比較
  - ➢ 鍋爐最佳化系統之建置程序
  - ➢ 鍋爐最佳化系統之應用實績

第貳章　心得與感想

一、 電廠儀測校準監視系統--ACM

現今面對高競爭性的環境,多年以來美國許多的發電廠已朝向應用電腦系統來輔助運轉及監測,諸如:熱平衡計算程式(Heat balance program)、熱功性能連線監測系統(Performance monitoring system)、機組最佳化諮詢系統(Unit optimization advisory system)以及專家系統(Expert system)等等,這些系統皆有共通的需求:必需有特定的輸入數據,其大部份應用系統必需經由電廠儀器取得訊號進行計算而求出結果,如果對於輸入數據缺乏高度的信心,則計算求出的結果也將缺乏實質的代表性,也容易因此做出不當的運轉決策。

電廠儀測校準監視系統ACM (Advanced Calibration Monitor)為美國PCS, Inc.(Performance Consulting Service)所開發之產品,目前已普遍應用於程序控制系統(Ex:傳統火力電廠,複循環電廠,化工廠等),所運用的型態辨識技術可強化整廠儀測訊號,達成兩項主要任務:

- 為下游各類應用系統提供更可靠而準確的儀測輸入數據.［各類應用系統諸如:熱平衡程式、熱功性能連線監測系統、機組最佳化諮詢系統、專家系統、控制系統等等。］

- 可監視整廠的儀測狀態,掌握有問題之儀測,提供作為更合理及有效的儀測校準及運用。

(1) ACM的功能及任務

ACM系統在設計上具有以下各種功能:

- 儀測錯誤偵測 (Fault detection)
- 輸入數據諧調 (Data validation)
- 輸入數據過濾 (Data filtering)
- 動態警訊掌控 (Dynamic alarm handling)
- 儀測校準監視 (Instrument calibration monitoring)
- 對有問題之儀器及設備提供預警 (Provides early warning of problems with plant instruments and equipment)
- 偵測出已漂移或失靈的特定儀測 (Detects specific plant instruments that have drifted or failed)
- 能夠量化特定儀測的漂移量 (Quantifies the amount of instrument drift)
- 為已失靈的特定儀測提供準確的替代值 (Provides accurate replacement values for faulted instruments)
- 確認出大修時應留意之儀測 (Identifies instruments that require attention during outage)
- 輔助評估整廠運轉情況 (Assesses overall plant health and operating conditions.)

經由上述的功能,ACM系統可提供準確的數據達成下列各項任務而降低運轉成本:

- 提供準確且可信賴的數據協調 (Provides Accurate and Reliable Data Validation)
- 不需要使用複雜的程序模式 (Does Not Require Complex Process Models)
- 增加對程序數據的信心 (Increases Confidence in Process Data)
- 可成功地應用至:
  - » 諧調測試數據 (Validating Test Data)
  - » 診斷機組運轉偏移 (Diagnosing Shifts in Unit Operation)
  - » 提供問題儀測取代值 (Providing Replacement Values)
  - » 降低不必要之儀測校準(Decreasing Needless Calibration)
  - » 指出應進行之儀測校準(Pinpointing Needed Calibration)

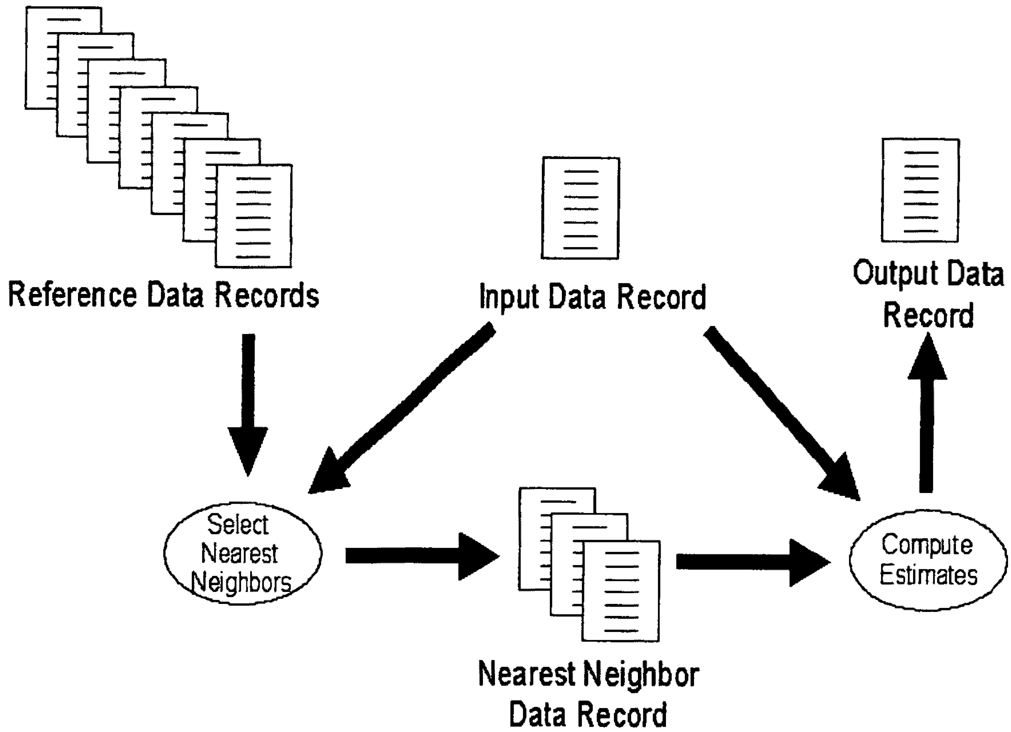
(2) ACM 的運作程序

基本而言ACM的運作程序，無論在系統內有多少變數(variables)，每一個變數於使用ACM技術進行模式化時其基本程序都是相同的，首先必需在電廠預期的各個運轉範圍內，針對所進行監視的數據或變數加以收集，然後將所收集的數據予以通則化以產生一個對應適用的效能曲線(performance curve)，最後再運用此效能曲線來進行判別，以確認系統或者系統內的個別變數目前之狀況是否與過去的系統行為相互吻合?換言之，觀念上ACM的運作程序應包括有三個進行步驟:

a. 在系統整個運轉範圍內收集數據值.

b. 經由收集的數據找出合用的效能曲線用以代表系統運轉狀態.

c. 於稍後使用效能曲線獲取系統資訊及進行研判。



圖一. ACM系統的運作程序

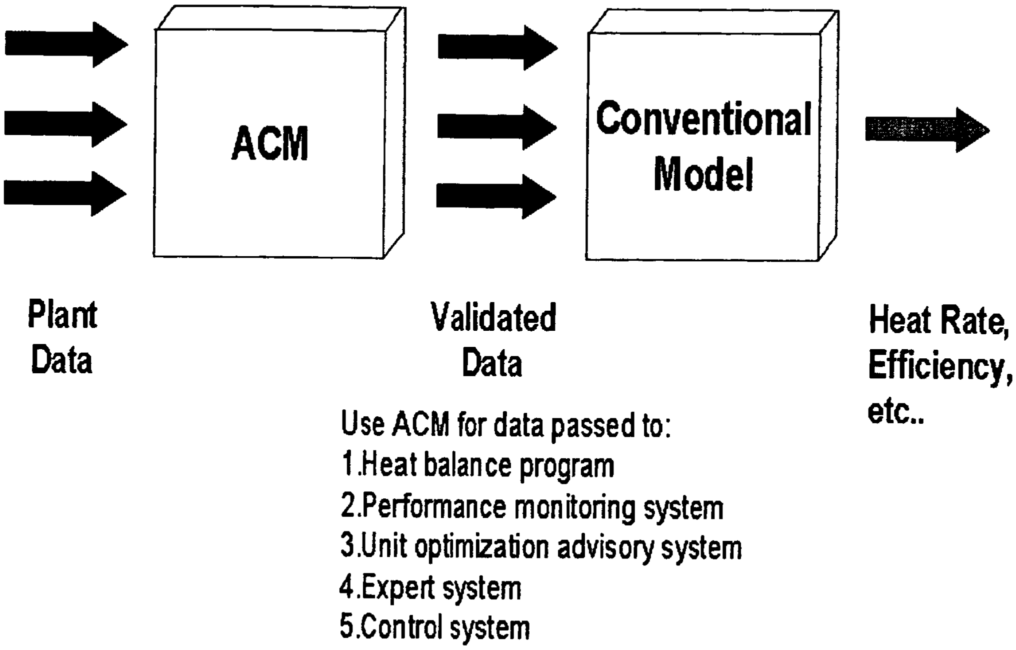
如圖一. ACM系統的運作程序示意圖, ACM分析的第一個步驟必需先行收集的數據組簡稱為參考數據紀錄(**a set of reference data records**),任一被分析當時的數據組就如同一組快照, 為包括了電廠內的溫度、壓力、流量等的數據快照, 而參考數據組則為延伸在整個電廠運轉範圍內且代表著完好的數據("good" data), 其次將輸入數據紀

錄(the Input Data Record)或想進行諧調的數據之快照和參考數據紀錄相互比較以選定一群最接近的鄰近紀錄**(Nearest Neighbor Records).** 所謂的最接近的鄰近紀錄,為參考數據紀錄當中最為計近似輸入數據紀錄者, 各個最接近的鄰近紀錄(Nearest Neighbor Records)其間的相似性形成了目前機組運轉的辨識矩陣(recognition matrix) 或效能面(the performance surface), 辨識矩陣用來計算預測值組成輸出數據(Output Data Record),即基於過去的效能和目前的操作準確地代表系統應如何運轉, 這些相似性可用以計算每一個預測值的的不確定度,對於不同數據紀錄及不同數據的單點ACM分析對此種相似性採用了量化的方式,ACM內部以一個介於0與1之間大小的數值定義所謂的相似性,"1"代表完全相同的紀錄,"0"代表完全不相同的紀錄。

(3) ACM 與慣常模式之整合

ACM系統是一項工具它提供我們依據著過去的效能找出一組高品質且協調的儀測數據供電廠運用,它和過去在電廠較常被使用的模式的關係如圖二.ACM與貫常模式(conventional models)之整合所示, ACM系統將原本直接用至貫常模式的輸入數據予以預先處理(pre-process),所有的輸入數據經過熱平衡計算程式(Heat balance program)、熱功性能連線監測系統(Performance monitoring system)、機組最佳化諮詢系統(Unit optimization advisory system)及專家系統(Expert system)等全都可予以協調。

如此對於運用來做廠內各項決策的輸入數據及計算結果都更準確與可靠,舉凡執行運轉決策、維護工作、大修排程、營運策略等將更具有信心及效率。



圖二.ACM與慣常模式(conventional models)之整合

(5) ACM在電廠之應用

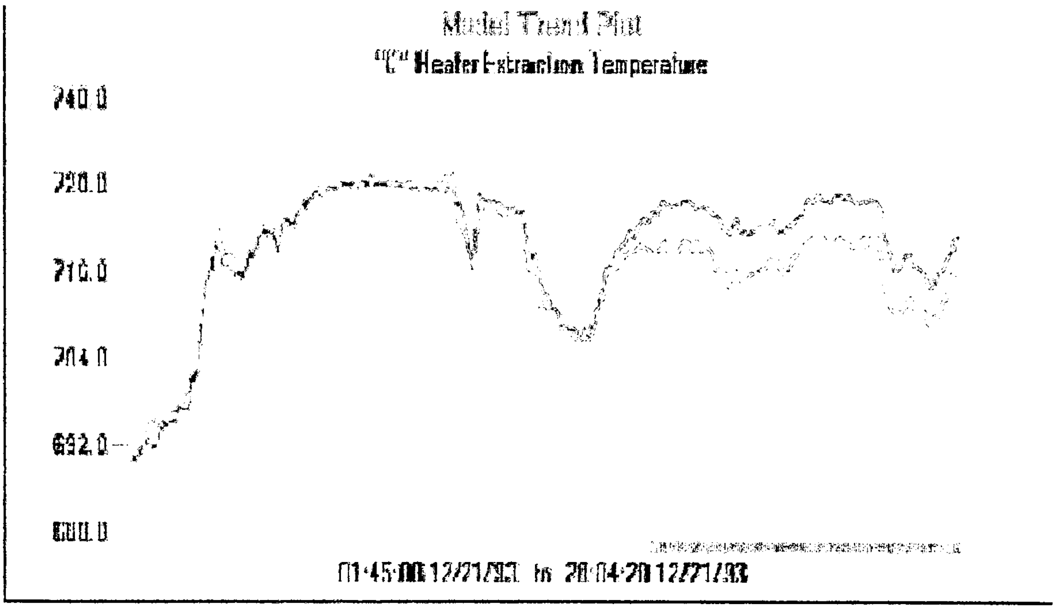
以下簡單舉例說明ACM系統在發電電廠之各項應用:

■ 測出儀器訊號漂移(Drifting siganal)

如圖三所示，電廠實際趨勢圖著代表ACM系統於安裝後所收集之數據，觀察飼水加熱器的加熱蒸氣溫度值隨著時間之變化，其中紅色曲線為實際的儀測數據，藍色曲線則代表ACM model相對的預測數據。

如果只觀察單一的實際儀測(紅色)曲線，沒有a. ACM model的預測數據(藍色曲線)作比較，b. 於右下角及早提出紅色橫線警訊，則很難察覺出(如圖三.)後半段所發生的現象--儀測數據(紅色曲線)實際上

經產生漂移(Drift)狀況;而從前半段時間中紅色曲線與藍色曲線良好的密合情況亦可看出ACM model協調數據方法具有高準確的預測能力。



圖三. ACM model 檢測出儀器訊號漂移(Drifting signal)

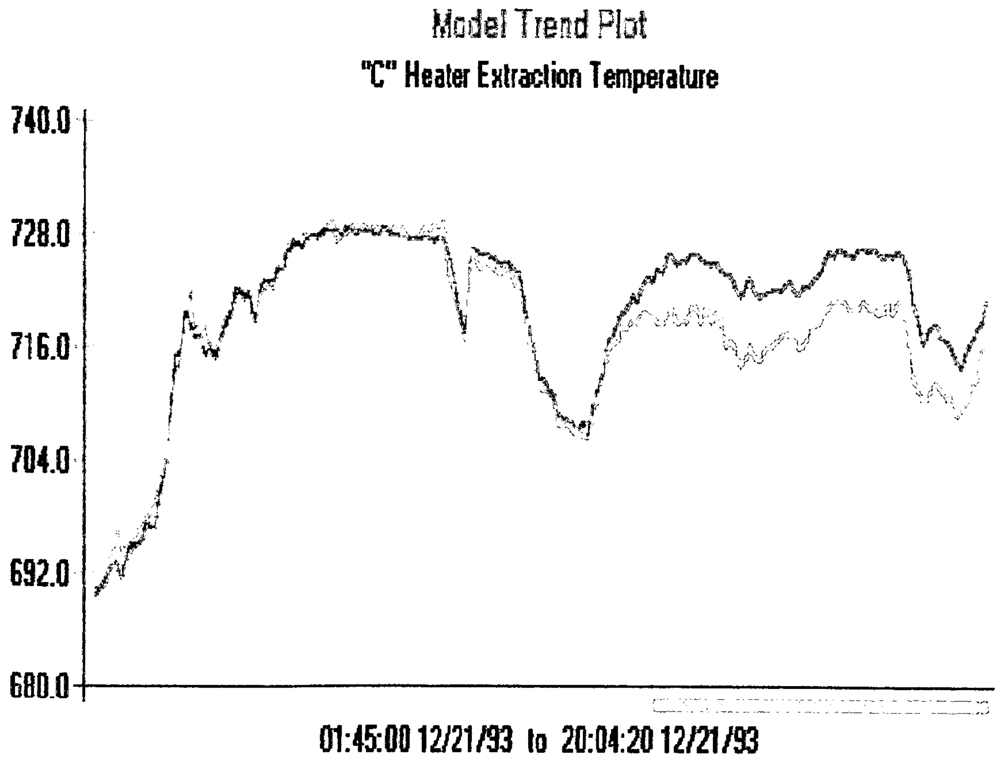
■ ACM的動態警示限值

查證量測值與ACM的預測值之間的偏差,並決定量測值是否落入使用者特定的協調準則內,在ACM內了提供三種不同的動態協調準則,分別為絕對偏差(absolute deviation),百分比偏差(percent deviation), 及標準偏差(standard difference)等。

以某溫度值ACM的動態警示為例子,選用絕對偏差可以規定量測值與ACM的預測值之間允許的偏差設定為5 度以內,選用百分比偏差時若量

測值與ACM的預測值之間的偏差超過3個百分比則產生警訊, 標準偏差類似於統計分析的標準差,如圖四. ACM的動態警示--灰色曲線為警示限值,利用此方法可以省去像絕對偏差、百分比偏差方法運用時,必需耗費繁複的工作決定可被接受的設定值。

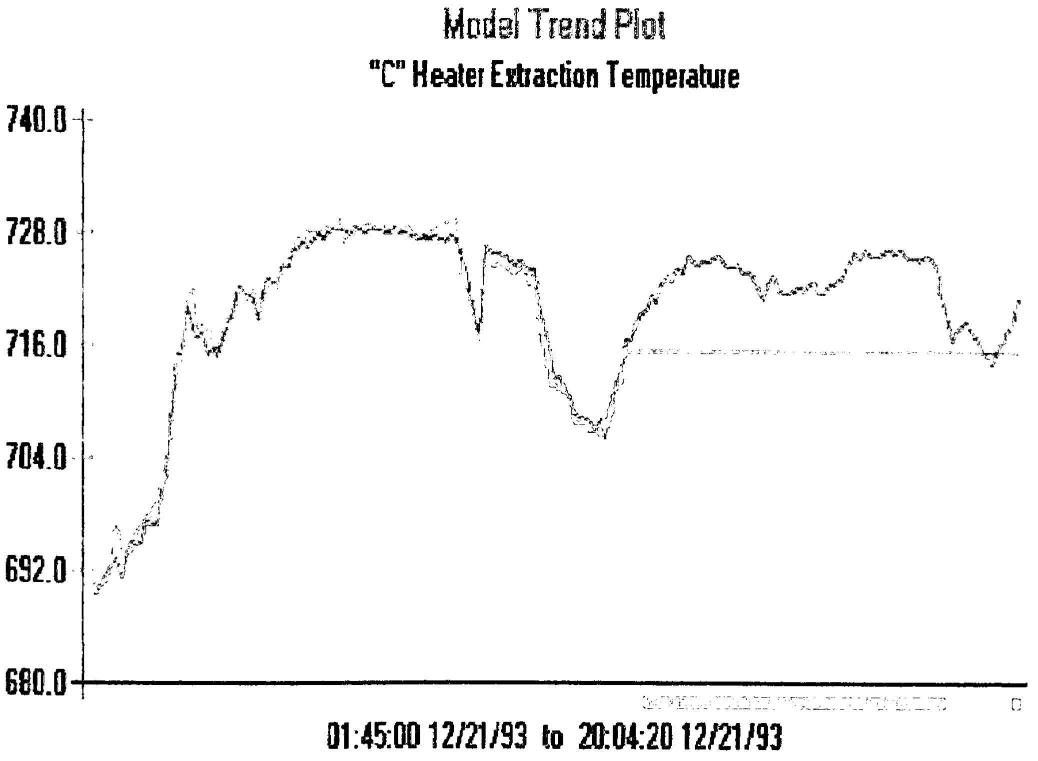
從圖中可以觀察到,當量測值跨越動態警示限值時ACM系統會出現紅色橫線警訊,並且即使量測值已經發生漂移(Drifting)現象,準確的ACM溫度預測值可被當成原量測值的替代值來使用。



圖四. ACM 的動態警示

■ ACM處理走平的訊號

對於走平的訊號可觀察出來是有明顯的儀測問題，雖然可以要求儀控人員解決，但總是需要一些時間進行修復及必需動作將正確的數值再回存至熱功性能監測系統及控制系統，如圖五所示的例子中：第C飼水加熱器其抽汽溫度(the heater extraction temperature)為汽機橫跨管的溫度(the crossover temperature)將對效率計算結果產生不良衝擊，譬如中壓汽機效率(IP turbine efficiency)、低壓汽機效率(LP turbine efficiency)、第C飼水加熱器抽汽流量，及鍋爐飼水泵汽機效能(BFPT performance)等等計算皆產生誤差，又如果儀控問題並無法及時修正，則這期間許多關鍵性的熱功性能連線監測計算亦無法發揮正常的功能。

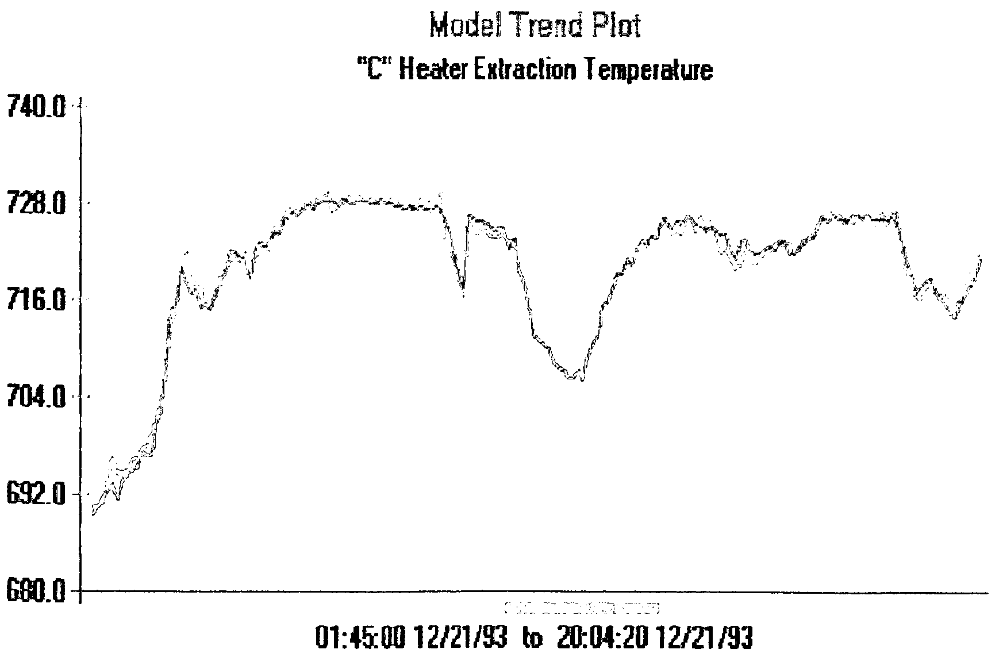


圖五. ACM處理走平的訊號

上述的困境當使用了ACM系統便可以順利的解決，ACM系統不僅可以確認出有問題的儀測也同時為這些有問題的儀測訊號提供了高準確度的替代值，因此能夠十分可靠地供給熱功性能監測系統、控制系統以及運轉人員及時應用。

■ ACM處理丟失的訊號

如圖六所示，另一種在電廠常發生的儀測問題為丟失一段訊號，同樣地ACM系統可以確認出儀測問題，並對有問題的儀測提供一高準確度的替代值，再次可靠地供給熱功性能監測系統、控制系統以及運轉人員及時應用，由於ACM系統提供有標準差的計算，將同時可以掌握替代值的準確度。



圖六. ACM處理丟失的訊號

二、 運轉最佳化技術

火力電廠發電鍋爐運轉的最佳化,為在程序上設法改善包括:運轉或控制參數及鍋爐的各項設備設定以進而達成一組預定的最佳化目標;在某些案例中,輸送燃用空氣及(或)燃料的硬體設備可能被變動或加以更新,以便對於輸送燃用空氣及(或)燃料的分佈,以及對於粉煤粒子大小的分佈等允許有更好的控制能力;系統的調整及最佳化通常的進行步驟為:

- 先建立效能基準線
- 迅速調整以反應修訂的運轉目標(Ex:降低 NOx 排放目標優於降低熱耗率目標)
- 以診斷式測試確認所有的鍋爐設備處於良好的運作
- 選擇透過進行參數測試及數據分析或者透過特定最佳化軟體的應用施行效能最佳化。

在此心得報告討論之對象為主要偏重於以特定工具軟體的應用來施行鍋爐運轉效能最佳化,分別就(1)鍋爐運轉最佳化之概念(Basic Concept)、(2)已商業化的最佳化產品(Available Product)及其(3)在發電鍋爐之應用實績(Utility Experience)來說明:

(1) 鍋爐運轉最佳化之概念

在此說明鍋爐運轉最佳化技術的應用概念時,有必要對於會密切影響最佳化施行範圍、投入成本及最後最佳化結果之

各構成要素先加以定義，完整的敘述應包括有下列四項：

- 最佳化施行之目標(The objectives.)
- 施行前之基準狀況(The baseline conditions.)
- 施行時所做的改變(The changes being made .)
- 所使用的工具或方法(The methods or tools used.)

a. 最佳化施行之目標

通常鍋爐運轉最佳化的應用會鎖定包括所列目標中某一項或多項--例如降低氮氧化物(NOx)、改善熱耗率(Heat Rate)、降低燒失量(LOI)，一氧化碳(CO)及透明度(Opacity)等等。

b. 施行前之基準狀況

發電鍋爐於進行調整及最佳化之前的機組基準狀態，會對於改善的潛能(尤其是 NOx)及改進的難易度有明顯的衝擊，此基準狀態意指鍋爐尚未嘗試過降低 NOx 的調整，也沒有花費額外努力以降低熱耗率(Heat rate)的狀況下，並假定運轉員的操作方式皆依循以往的操作經驗或源自於原設備製造廠家(OEM)所提供之運轉標準程序書。

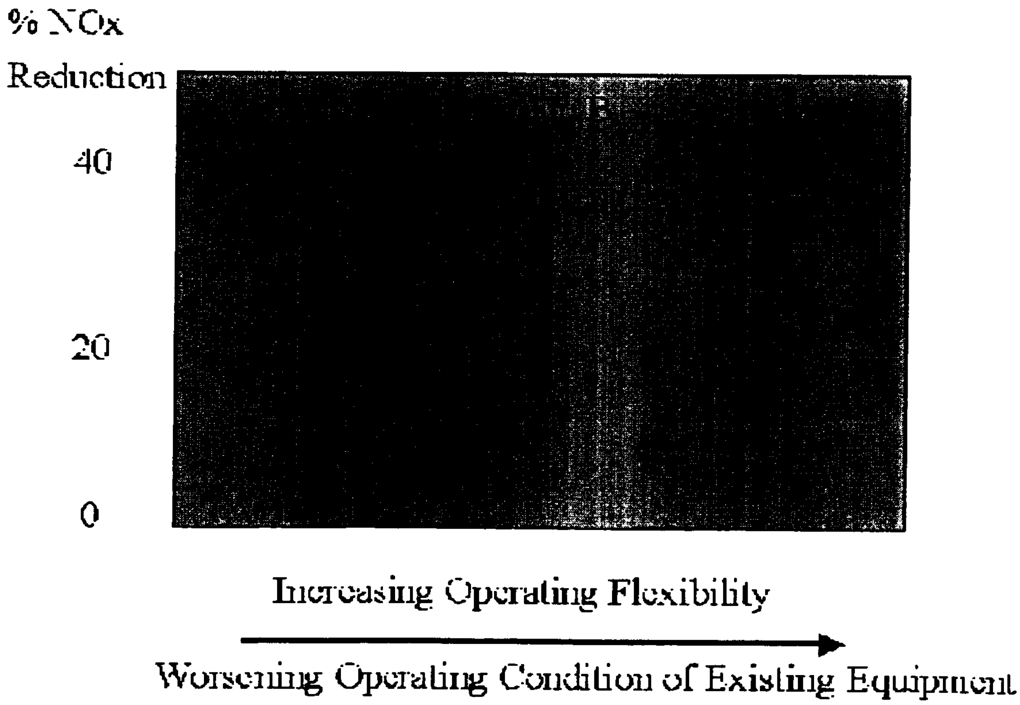
c. 施行時所做的改變

鍋爐施行最佳化應用過程所做的改變，由所允許變動的程度之不同可劃分為狀況一. 控制參數改變(Changes in control variables)、狀況二. 設備設定改變(Changes in equipment settings)及狀況三. 修改硬體(Hardware modifications)等層次。

比例值、燃燒器傾斜角度、二次空氣空調、過剩空氣"等控制參數作某種程度的改變，即只作有限的燃用空氣調整但不涉及燃煤流量的調整。

在狀況二.設備設定改變：除保有狀況一，尚可作燃用空氣與燃煤流量的調整、改變燃燒系統中燃燒器及過火空氣的設定(不一定從控制室內)、改變粉煤機的設定：如粉煤粒度篩選器/軸頸彈簧壓力/空氣洩漏量等。

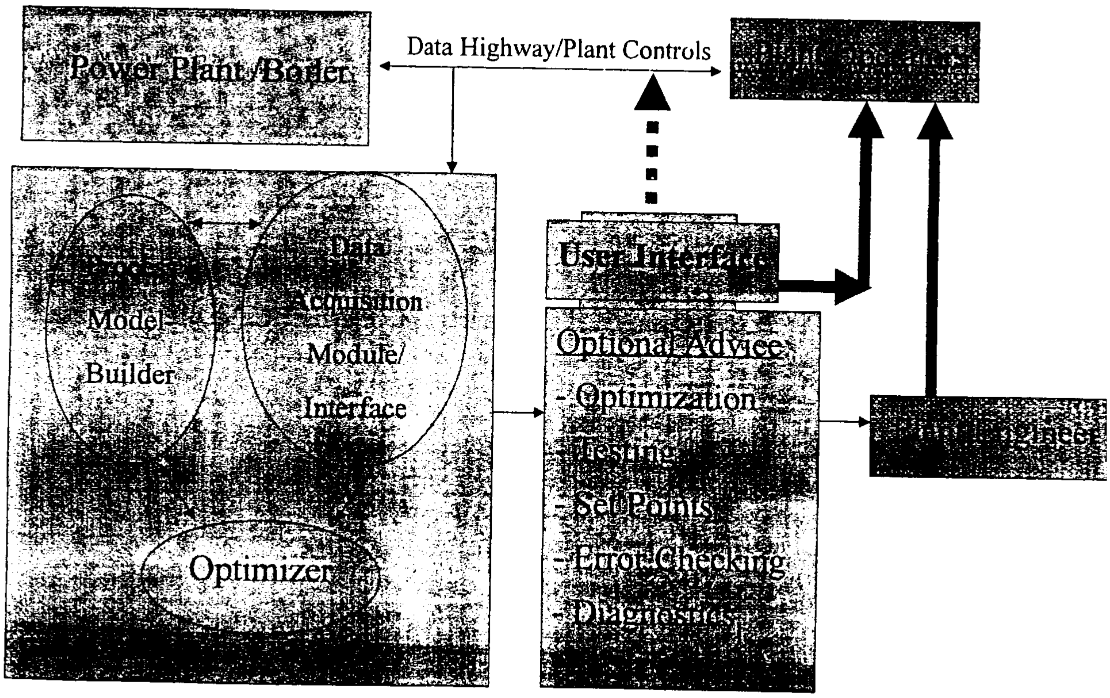
在狀況三.修改硬體：除保有狀況二，尚可在機組滿載下停用一臺粉煤機的操作藉以模擬過火空氣的運轉模式、作一些硬體設備方面的修改，如加裝粉煤粒度篩選器/飼煤管節流/以分流擋板改善空氣分佈等。當施行前之基準狀況配合不同狀況之施行時所做的改變，將對降低 NOx 產生不同的效果，如下列圖七.所示：Group A 為狀況一、 Group B 為狀況二、Group C 為狀況三。



d. 所使用的工具或方法

通常鍋爐運轉最佳化系統的內建最佳化機制不外乎為使用類神經網路(Neural net)、統計分析(Statistical Analysis)及人工智慧(A.I. Techniques)等技術,在使用型態上可依應用功能劃分成離線/單次型(Off-line/one-time)、線上/諮詢型(On-line/advisory)、密閉迴路型(Closed-loop)等三類,其與電廠設備之連線介面關係則如圖八.鍋爐最佳化系統的型態所示。

離線/單次型係由電廠工程師依階段性需求在某一時間點進行最佳化分析並將結果提供給運轉員參考;線上/諮詢型則為以連線方式自動進行最佳化分析,並即時將結果輸送至控制室螢幕供給運轉員作為操作之參考;密閉迴路型為以連線方式自動進行最佳化分析,並即時將結果供給機組控制系統。



圖八.鍋爐最佳化系統的型態

(2) 已商業化的最佳化產品(Available Product)

以下從"鍋爐最佳化產品安裝之案例"及"鍋爐最佳化產品主要特色"兩項,來討論市場上可應用之鍋爐最佳化產品:

a. 鍋爐最佳化產品安裝之案例

綜合相關的產品資訊及報告,比較鍋爐最佳化產品以往完成安裝之案例狀況,詳如表一.所示為各產品名稱--廠家名稱--1996年底以前--已完成安裝之案例數目,及*1997年當年度--完成安裝之案例數目等。從表格內可以明顯看到,其中(a)1996年底以前--完成安裝之案例數目,及(b)1997年當年度--完成安裝之案例數目之中,市場佔有率最高的前三位,分別為:

(a) Before 1996-- ULTRAMAX-53, GNOCIS-4, NeuSIGHT-3

(b) As 1997 ----- ULTRAMAX- 7, GNOCIS-8, NeuSIGHT-4

表一. 鍋爐最佳化產品安裝之案例

Product Name	Developer	Before 1996	*In 1997
01. ULTRAMAX	Ultramax&EPRI	53	*7
02. GNOCIS	PowerGEN&EPRI	4	*8
03. NeuSIGHT	Pegasus Technologies Corp.	3	*4
04. PECOS	Praxis Engineer Inc.	NA	*2
05. Boiler OP	Lehigh University	4	
06. TOPAZ	NYSEG	2	
07. InEC	Lockheed Martin	2	
08. Power Insights	Pavilion	NA	

b. 鍋爐最佳化產品主要特色

從比較上節鍋爐最佳化產品以往完成安裝之案例，將市場佔有率最高的前三種具代表性產品的主要特色相互比較，結果如表二.和表三.所示：

ULTRAMAX, GNOCIS, NeuSIGHT 三種產品各採用了不同的最佳化技術(分別為 Sequential Opt, Neural Net, AI techniques 等)，於實際應用時依鍋爐設計類型及燃料種類及燒用模式各有其優勢,而三種最佳化系統之功能皆已跨入線上型(On-line)之應用形態。

最佳化目標皆普遍以降低氮氧化物 (NOx) 排放量及降低鍋爐熱耗率 (Heat Rate)為主;系統之諮詢特色以超出級距(Out of range)為主;所需匹配的電腦系統類型為市場上一般通用的 IBM/PC, UNIX, DEC 等。

表二. 鍋爐最佳化產品主要特色(1)

Product Name	Process Model & Optimizer	Capability Closed/	Advisory/	Off-line
01. ULTRAMAX	Sequential Opt	No	Yes	Yes
02. GNOCIS	Neural Net	Yes	Yes	No
03. NeuSIGHT	AI techniques	Yes	Yes	Yes

表三. 鍋爐最佳化產品主要特色(2)

Product Name	Advisory Feature	Optimization Objective	Computer Hardware
01. ULTRAMAX	(Out)	NOx + HR	IBM/PC, UNIX
02. GNOCIS	(Out)	NOx + HR	IBM/PC, UNIX, DEC
03. NeuSIGHT	(Out)	NOx + HR	IBM/Risk, SUN, DEC

(3)在發電鍋爐之應用實績(Utility Experience)

a. 發電鍋爐設計及燃料類型

截至1996年年底,有68座發電鍋爐安裝使用最佳化系統,其中有62座鍋爐為燃煤機組(佔全數的91%),另4座鍋爐為燃油機組、2座鍋爐為燃氣機組;設計類型則切線式鍋爐(Tangentially-fired)及對火式鍋爐(wall-fired)幾乎各佔了50%。

b. 使用的最佳化系統類型

截至1996年年底,68座發電鍋爐安裝使用最佳化系統,其中僅有11座鍋爐的最佳化系統類型屬於線上/諮詢型、密閉迴路型(Closed loop or On-line/Advisory type),佔全數的16%。

但隨著個人電腦性能的大幅提昇及最佳化系統產品之競爭,在隔年1997當年度內有21座鍋爐安裝使用最佳化系統,其中則已有19座鍋爐的最佳化系統類型屬於線上/諮詢型或密閉迴路型(Closed loop or On-line/Advisory type),佔了全數的90%。

c. 效能改善之主要成果

從相關報告之統計得知安裝使用最佳化系統鍋爐數量之成長，於 1996 年年底之前共 68 座,於 1997 當年度內新增安裝最佳化系統有 21 座,1998 當年度內又新增加了 41 座,即數量上截至 1998 年年底為止共有 130 座發電鍋爐使用最佳化系統來改善舊有機組的效能，相關報告並提出對發電鍋爐之效能改善普遍地能夠達成下列兩項主要成果:

- 降低氮氧化物 (NO_x) 排放量 5% -- 40%
- 降低鍋爐熱耗率 (Heat Rate) 0.5% -- 1.5%

第 參 章　建議事項

一.　燃煤機組為本公司火力發電之主力,由於多樣煤源及採用爐膛共燒模式(Co-fired)加以燃煤本身複雜的燃燒行為,使得在維持環保限值(90 年)的要求下,期望能兼顧達成鍋爐更有效率的運轉將是一件充滿挑戰的課題,建議公司及早引進可行之鍋爐最佳化技術及升級相關輔助設備,以協助運轉人員努力達成目標。

二.　電廠儀測校準監視系統等,係應用型態辨識技術強化整廠儀測訊號,提供應用系統(或機組控制系統)可靠的儀測輸入,可監視整廠的儀測狀態掌握有問題之儀測,作合理有效的儀測校準,為本公司各電廠強化決策及運轉效能時值得即時引進之應用技術。

三.　鍋爐最佳化系統(PPO)的應用技術對舊有發電鍋爐效能改善於 1998 年之前已有(130 座鍋爐)普遍性的成功案例,能夠降低氮氧化物排放量 5% -- 40%以及改善鍋爐熱耗率 0.5% -- 1.5%,為本公司舊有燃煤鍋爐值得考慮積極引進應用。

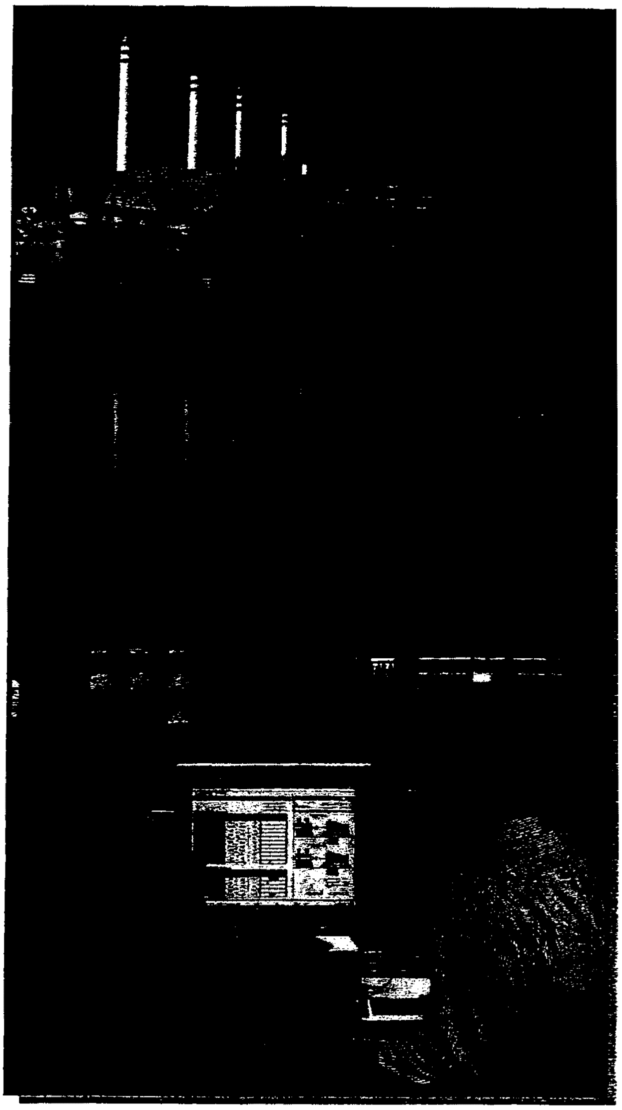
四.　關於規劃鍋爐最佳化系統(PPO)搭配電廠儀測校準監視系統在電廠的實際應用施行,建議先期以 2-3 座不同的燃煤鍋爐進行示範研究案(Demonstration Projects),經由該系統在電廠的實際安裝工作/應用管理/維護負擔等全程實務經驗的累積,建立專案管理的能力,以進一步掌握該技術在本公司之推廣應用。

附 錄 一、B&V公司的"熱功性能連線監測系統"

BLACK & VEATCH ON-LINE PERFORMANCE MONITORING SYSTEM

OPM

Many standard calculational modules and custom configuration services are available to provide comprehensive monitoring capabilities for all types of plants.



CALCULATIONAL MODULES

- Overall Plant Performance
- Controllable Losses
- Boiler Cleanliness
- Sootblowing Optimization
- Boiler Performance
- Air Heater Performance
- Steam Turbine Performance
- Pump Performance
- Fan Performance
- Feedwater Heater Performance
- Condenser Performance
- Cooling Tower Performance
- Combustion Turbine Performance
- HRSG Performance

CUSTOMIZATION SERVICES

- Windows NT system configuration
- Excel-based on-line calculations configuration
- Excel-based reports configuration
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- Total plant predictive modeling
- Turnkey system implementation

In addition to on-line analyses, OPM provides predictive modeling for "what if" analyses of plant operations. This allows for possible changes to equipment or operations to be more accurately considered before implementation.

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about the Black & Veatch OPM system, call 913-458-4(OPM), or e-mail opm_info@bv.com

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ON-LINE PERFORMANCE
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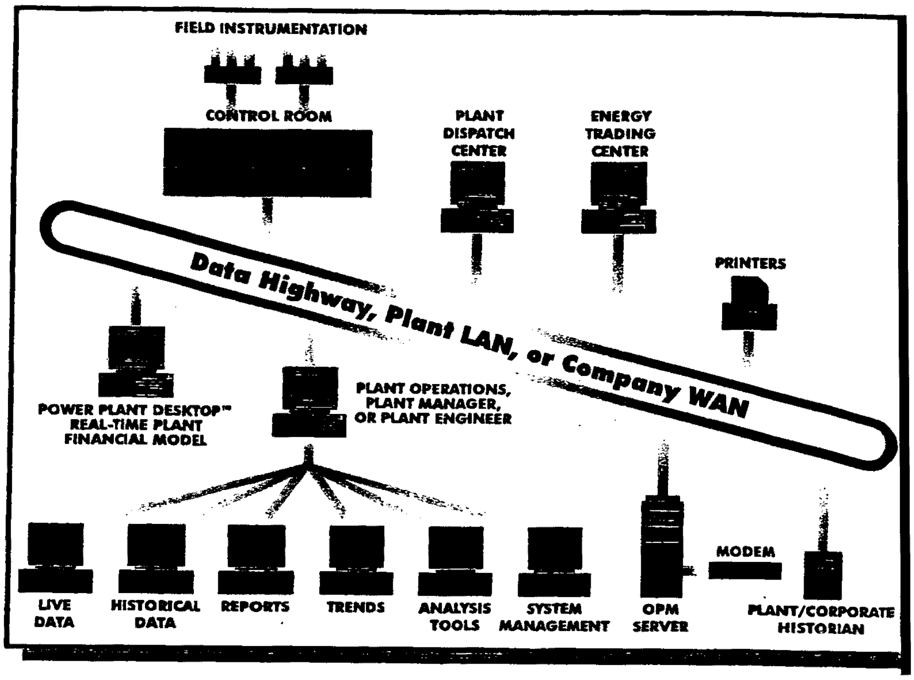
OPM is a toolbox for optimizing your plant operations. It consists of flexible computer software applications designed to help you reduce your operating costs, identify capacity limitations/opportunities and improve plant profitability. "Live" and historical data, as well as the tools to analyze that data, are provided to all types of plant personnel. OPM operates under the Windows NT operating system.



OPM - REDUCING YOUR COSTS

For more than a decade, Black & Veatch's OPM system has helped customers reduce costs through:

Improved Operations

"Live" data and performance calculations, displayed to plant operators, highlight off-target operations to encourage quick response by operators to improve plant performance..

Manpower Savings

OPM performs labor-intensive functions such as data retrieval, analysis, data storage, equipment testing, and reporting.

Precise Information

Information on equipment performance and degradation, energy use, and other process data is at your fingertips to support decision making at all levels.

THE INDUSTRY LEADER

As a leader in process plant design and construction, Black & Veatch can put its expertise to work for you. Today, OPM is in use worldwide – helping users monitor, control, and reduce costs. The firm will provide a turnkey system custom configured to meet your needs. Our expertise remains available to you after implementation through maintenance and support services.

Black & Veatch On-Line Performance Monitoring (1997 – Current)

Customer, Plant	Location	Units	MW, ea	Plant Type	OPM Das/DCS Interface	Comments
AEM						
Cassano	Cassano, Italy	1				
AES Corporation						
Barber's Point Cogeneration Plant	Ewa Beach, HI	1	198	CFB	Westinghouse WDPF	
Ameren						
Coffeen Power Station	Coffeen, IL	1	358	Coal	PI	Reorganizing performance strategies after CIPS and UE purchases.
		2	560	Coal	PI	
Labadie Power Station	Labadie, MO	1-4	600	Coal	PI	
Meredosia Power Station	Meredosia, IL	1	225	Coal	PI	
Newton Power Station	Newton, IL	1			PI	
British Columbia Hydro						
Burrard Power Station		6	162	CC	Foxboro	
Calpine/Utilicorp						
Aries Power Station	Belton, MO	1	600	2on1 CC		
City Utilities of Springfield						
James River Power Station	Springfield, MO	3,4	40	Coal	PI	
			60	Coal	PI	
Southwest Power Station	Springfield, MO	1	190	Coal	PI	
Dynegy Midwest Generating						
Hennepin Power Station	Hennepin, IL	1	80	Coal	Honeywell	
		2	220	Coal	Honeywell	
Great River Energy						
Coal Creek Station	Underwood, ND	1,2	570	Coal	Honeywell TDC 3000	
Owensboro Municipal Power						
Elmer Smith	Owensboro, KY	1	156	Coal	PI/MAX Controls	
		2	282	Coal	PI/MAX Controls	
Ottertail Power						
Big Stone Power Plant	Big Stone City, SD	1	460	Coal	Honeywell TPH	
Coyote Station	Beulah, ND	1	460	Coal	Honeywell PHD	

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Black & Veatch On-Line Performance Monitoring (1997 - Current) (continued)

Customer, Plant	Location	Units	MW, ea	Plant Type	OPM Das/DCS Interface	Comments
PGE National Energy Group						
Cedar Bay	Jacksonville, FL	1,2		CFB	Westinghouse WDPF	
PSEG Fossil						
Mercer Generating Station	Trenton, NJ	1,2	320	Coal	PI	
Reliant Energy						
Titus Station	Reading, PA	1,2,3	80	Coal	Westinghouse	
Salt River Project						
Navajo Station	Page, AZ	1,2,3	800	Coal	Foxboro I/A	
Tenaga Nasional Berhad (TNB)						
SSAAPS	Port Klang, Malaysia	1,2	500	Coal		
Texaco/Edison Mission Energy						
Tri-Energy	Ratchburi, Thailand	1	720	CC	Bailey Infi90	
Union Camp						
Paper Mill	Franklin, VA	1	50	CC	Bailey Infi 90	
Union Fenosa						OPM Value Added Reseller.
Anllares	Madrid, Spain	1	350	Coal	Bailey	
La Robla	Madrid, Spain	2	350	Coal	Intellution FIX32	
Meirama	Madrid, Spain	1	550	Coal	Sainco	
Narcea	Madrid, Spain	3	350	Coal	Intellusion FIX32	
Western Farmers Electric Cooperative						
Hugo	Fort Towson, OK	1	450	Coal		
Western Kentucky Energy						
Coleman Station	Hawesville, KY	1,2,3	150	Coal	Molytek/Bailey Infi 90	
Reid/Green Station	Sebree, KY	1,2	210	Coal	Molytek	
Henderson Municipal Power & Light	Henderson, KY	1,2	60	Coal	Westinghouse WDPF	

Black & Veatch On-Line Performance Monitoring (1990 – 1996)

Customer, Plant	Location	Units	MW, ea	Plant Type	OPM Das/DCS Interface	Comments
American Electric Power						
Barney Davis Station	Corpus Christi, TX	1	350	Gas	L&N MAX 1	Failed system-wide co-development effort. Some residual feelings, especially at corporate level.
Coleto Creek Power Plant	Fannin, TX	1	550	Coal	Westinghouse WEStation	
Comanche Station	Lawton, OK	1	260	CC Gas	Triconics 3000 DAS	
Conesville Plant	Conesville, OH	4	720	Coal	Westinghouse WDPF	
		5,6	375	Coal	Westinghouse WDPF	
Flint Creek Power Station	Gebtry, AR	1	550	Coal	Foxboro I/A	
James M. Gavin Plant	Cheshire, OH	1,2	1300	Coal	POPS, Diamond Power BOS	
Northeastern Station	Oologah, OK	3,4	460	Coal	Acurex 10/60	
Southwestern Station	Washita, OK	3	300	Gas	Forney	
Tanner's Creek Plant	Lawrenceburg, IN	1,2	145	Coal	Bailey Net90, Westronics Recorders, PI	
		3	205	Coal	Bailey Net90, Westronics Recorders, PI	
		4	500	Coal	Bailey Net90, Westronics Recorders, PI	
Welsh Power Station	Pittsburg, TX	1,2,3	550	Coal	Foxboro I/A	
AES Corporation						
Medway Power Station	Kent, United Kingdom	1	660	CC Gas	Bailey Infi90	
Basin Electric Power Cooperative						
Antelope Valley Station	Beulah, ND	1,2	450	Coal	Honeywell TDC 3000	
Laramie River Station	Wheatland, WY	1,2,3	550	Coal	Foxboro I/A	
Leland Olds Station	Stanton, ND	1	200	Coal	Bailey Infi90	
		2	440	Coal	Bailey Net90	
City of Grand Island						
Platte Generating Station	Grand Island, NE	1	180	Coal	Bailey Infi90	
Consolidated Edison						Systems no longer in service.
74th Street Power Plant	New York, NY	1	28	Gas	Transition Technologies DAS	
Arthur Kill Station	Staten Island, NY	2	380	Gas	Genesis DAS	

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Black & Veatch On-Line Performance Monitoring (1990 – 1996) (continued)

Customer, Plant	Location	Units	MW, ea	Plant Type	OPM Das/DCS Interface	Comments
KJC Operating Company						
SEGS	Boron, CA	6,7	35	Solar/Gas	Westinghouse WDPF	
Louisiana Generating Company						
Big Cajun II	New Roads, LA	1,2,3	580	Coal	Foxboro I/A	
Minnesota Power						
Boswell Energy Center	Cohasset, MN	1,2	74	Coal	Foxboro I/A	
		3	360	Coal	Foxboro I/A	
		4	510	Coal	Foxboro I/A	
Ocean State Power						
Ocean State Power	Harrisville, RI	1,2	250	CC Gas	Bailey Infi90	
Reliant Energy						
W. A. Parish Generating Station	Thompsons, TX	5,6	650	Coal	Honeywell 4500	

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Black & Veatch On-Line Performance Monitoring (1985 – 1990)

Customer, Plant	Location	Units	MW, ea	Plant Type	OPM Das/DCS Interface	Comments
Alliant Energy						Systems no longer supported.
Columbia Generating Station	Portage, WI	1	527	Coal	Westinghouse WDPF	
		2	527	Coal	Westinghouse WDPF	
Nelson Dewey Generating Station	Cassville, WI	1,2	100	Coal	Bailey Net90/L&N Recorders	
Rock River Generating Station	Beloit, WI	1,2	75	Coal	Molytek/Westronics	
AES Corporation						Systems no longer supported.
Thames Power Plant	Uncasville, CT	1	198	Coal	Westinghouse WDPF	
Atlantic Electric						Systems no longer supported.
B. L. England	Beesley's Point, NJ	1,2	160	Oil	Bailey Infi90	
		3	160	Oil	Bailey Infi90	
Deepwater Station	Pennsville, NJ	6,8	85	Oil	Westinghouse WDPF	
Board of Public Utilities						Systems no longer supported.
Quindaro	Kansas City, KS	1	87	Coal	Bailey Infi90	
		2	152	Coal	Bailey Infi90	
Duquesne Power & Light Company						Systems no longer supported.
Cheswick	Cheswick, PN	1	525	Coal	Westinghouse WDPF	
Illinois Power						Systems no longer supported.
Baldwin Power Station	Decatur, IL	1	600	Coal	Westinghouse WDPF	
Nebraska Public Power District						Systems no longer supported.
Gerald Gentleman Generating Station	Sutherland, NE	1,2	650	Coal	Honeywell TDC 3000	
New York State Electric & Gas						Systems no longer supported.
Milliken	Binghampton, NY	1,2	170	Coal	Westinghouse WDPF	

Black & Veatch On-Line Performance Monitoring (1985 – 1990)

(continued)

Customer, Plant	Location	Units	MW, ea	Plant Type	OPM Das/DCS Interface	Comments
Oklahoma Gas & Electric						Systems no longer supported.
Horseshoe Lake Generating Station	Oklahoma City, OK	6	170	Gas/Oil	Bailey Infi90	
		7	225	Gas/Oil	Bailey Infi90	
		8	410	Gas/Oil	L&N Micro Max	
Muskogee Generating Station	Fort Gibson, OK	3	170	Gas	Honeywell 4500	
		4,5	550	Coal	Westinghouse WDPF	
		6	550	Coal	Westinghouse WDPF	
Mustang Generating Station	Oklahoma City, OK	3	100	Gas/Oil	Bailey Infi90	
		4	250	Gas/Oil	Bailey Infi90	
Seminole Generating Station	Konawa, OK	1	510	Gas	Honeywell 4500	
		2	505	Gas	Honeywell 4500	
		3	505	Gas/Oil	Honeywell 4500	
Sooner Power Station	Red Rock, OK	1,2	568	Coal	Honeywell 4500	
Reliant Energy						Systems no longer supported.
Limestone Generating Station	Jewitt, TX	1,2	750	Coal	Honeywell 4500	
W. A. Parish Generating Station	Thompsons, TX	7,8	570	Coal	Honeywell 4500	
West Texas Utilities Company						Systems no longer supported.
Oklaunion Power Station	Vernon, TX	1	664	Coal	Westinghouse WDPF	
Weyerhauser Paper Company						Systems no longer supported.
Valliant Mill	Valliant, OK	1		Paper Mill	Bailey Infi90	
Wisconsin Electric Power Company						Systems no longer supported.
Pleasant Prairie	Kenosha, WI	1,2	580	Coal	Fluke Helios	

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附 錄 二、ACM Concepts and Theory

ACM Concepts and Theory

Goal: The goal of this section is to provide new ACM users with a detailed understanding of the concepts required to apply ACM in many applications, including data validation, calibration monitoring, and plant health monitoring. In addition, an overview of the advanced pattern recognition theory embedded in ACM will be provided.

Objective: On completion of this section participants will have an understanding of the differences between classical modeling methods and advanced pattern recognition modeling methods. Participants will also have knowledge of the underling theory of ACM, which will better enable the configuration and maintenance of ACM models.

Terminology:

Plant Health Monitoring
Dependent Variables
Independent Variables
Interdependent Variables
System Performance Curve (Surface)
Data Record
Point Value
Similarity
Reference Data Record
Input Data Record
Nearest Neighbor Record
Output Data Record
Fault Tolerance
Localized Modeling
Correlation
Auto Correlation

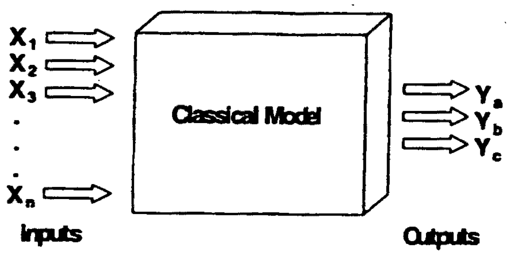
Modeling Basics

There are many different types of mathematical models. A model can be a set of simple equations, a set of complex equations, a power plant simulator, a performance monitoring system, a control system, or a neural network. What all of these models have in common is that they are mathematical representations of physical systems or phenomenon, and the models are created to provide information about the physical system.

Most of the classical models that we are accustomed to using have some common assumptions built in. Some of these assumptions are:

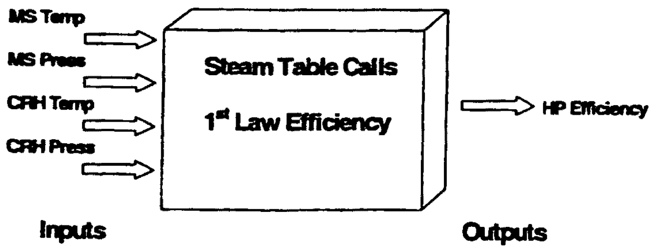
- Output parameters are a function of input parameters.
- Outputs, or dependent variables, are separated from inputs, or independent variables.
- All inputs are fully independent of each other.
- Outputs are completely determined by the values of the inputs.

In addition, in most classical modeling methods there are more inputs than outputs. Figure 2-1 depicts the classical approach to modeling, with dependent and independent variables.



Schematic of Classical Model

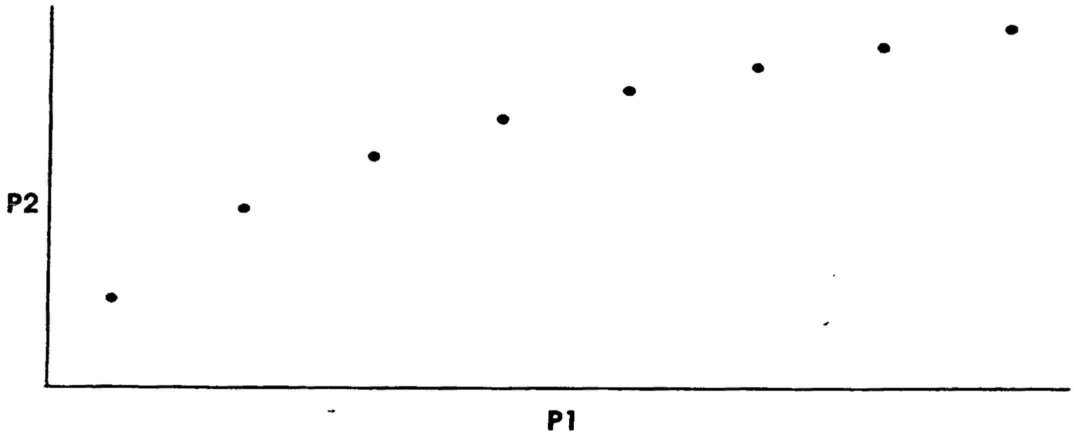
Another characteristic of classical models is that if the quality of input data is poor, the quality of the outputs, or results, will be poor. As an example, let's look at a model that calculates the efficiency of a high pressure steam turbine. In this case the model includes the First Law efficiency equation and steam table equations. The inputs will be the measured pressures and temperatures at the high pressure turbine inlet and outlet, and the output will be the high pressure turbine efficiency. So the schematic for this model will look like Figure 2-2.



Schematic of High Pressure Turbine Efficiency Model

But in a model of this type, what happens to the outputs if there is a problem with one of the inputs? In the case of the example in Figure 3-2, if there is an error in any one of the four inputs, the output will be in error. In the worst case, if the error in one of the inputs is large enough, the modeling calculation might fail. If the calculation fails, we know something is wrong, but we really can't tell what is wrong. This is an inherent flaw in all classical modeling techniques. In the most technical terms this is called the "garbage in = garbage out" syndrome.

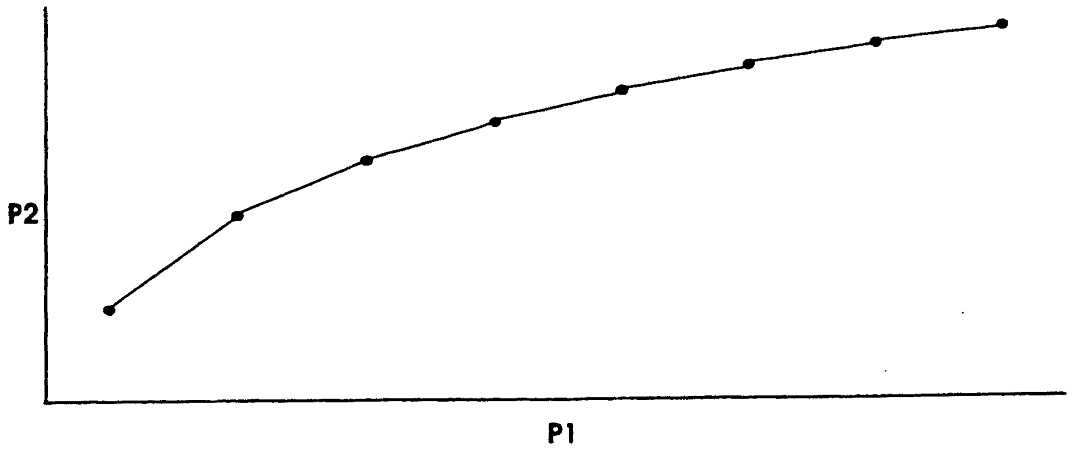
To understand how ACM and advanced pattern recognition is different, we will look at a simple example. First, ACM treats any process or system as a set of numeric data values. For example, a power plant is viewed as a list of pressure, temperature, and flow values rather than an assemblage of turbines, pipes, and heat exchangers. Let's consider a hypothetical system that has just two significant measurable parameters, P1 and P2. Data for this simple process can be collected through a series of tests and a graph can be constructed showing one parameter versus the other.



Plotting Process Parameters

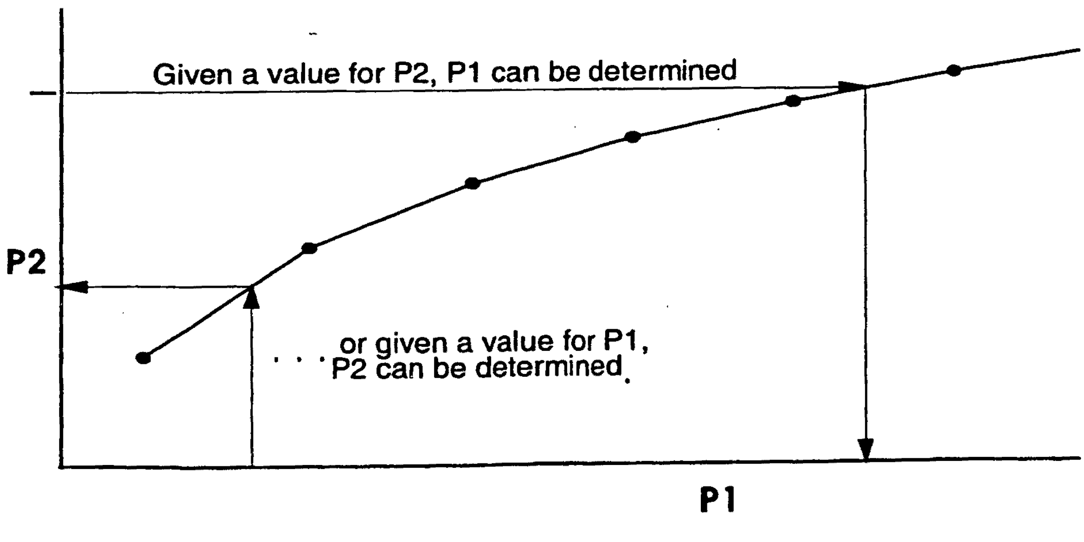
The individual points in Figure 3-3 represent discrete operating conditions for a simple process. That is, each point represents a unique characteristic condition of the process. In order to accurately describe a single process state at any given time, the values of all the system parameters must be known (two in this case).

The process can then be generalized to estimate behavior at operating states for which no discrete data values have been collected by placing a continuous curve through the plotted points (Figure 3-4). This curve represents known normal operation and can be referred to as the "system performance curve." It should be noted that, when using pattern recognition techniques, these points are considered to be interrelated and are not separated into input and output (independent and dependent) categories.



Generalizing Process Behavior

This modest procedure can lead to some very useful results. For example, if at a later time the value of one of the parameters is known, the value for the other can be readily estimated (Figure 3-5). In addition, the generalized plot could be used to determine whether or not the process is currently operating in a manner consistent with past operation (Figure 3-6).



Determining Unknowns

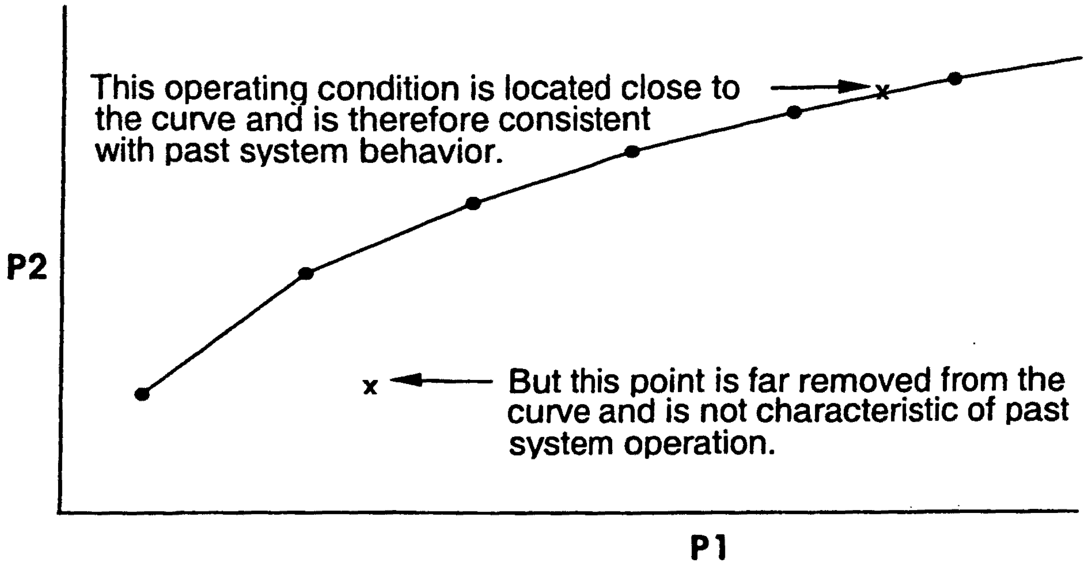
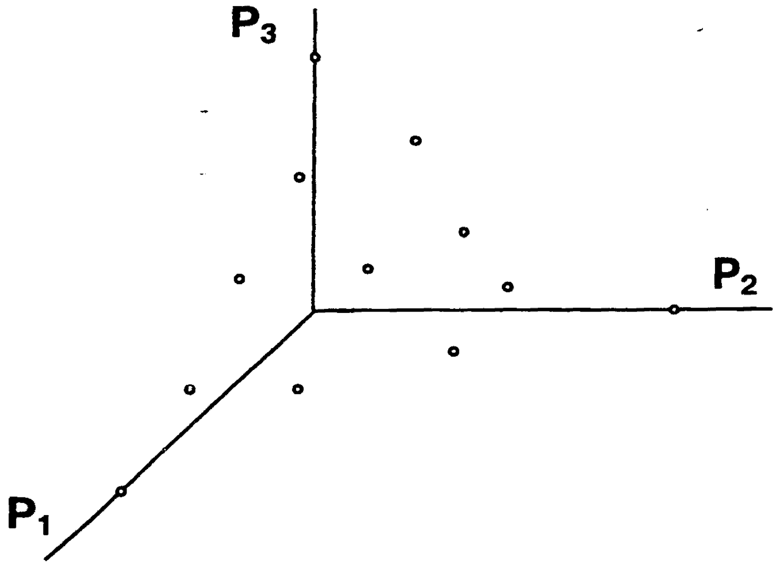
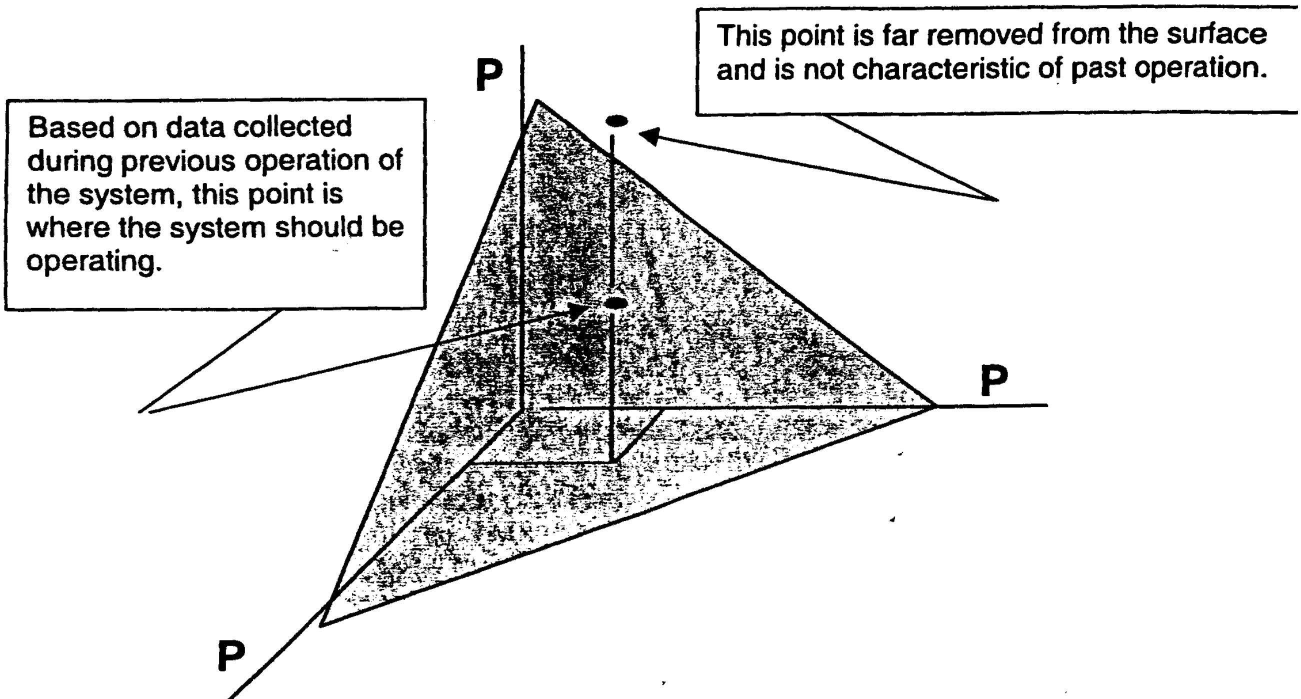


Figure 3-6 Assessing Process Operation



Plotting Process Parameters – 3 Dimensional System

Now, we can expand this process to a system with three parameters, or a three-dimensional system. As in our two parameter system, the first step is to collect a set of data over the operating range of the system for the three parameters in our system, P1, P2 and P3. Second, we plot the data, as shown in Figure 3-7. Third, we need to generalize the plotted data. Instead of a line, as in the two parameter system, generalization of the three-dimensional system yields a performance surface. Again, this generalized plot could be used to determine if the process is



currently operating in a manner consistent with past operation, as illustrated in Figure 3-8.

Assessing Process Operation – 3 Dimensional System

Although the examples above are presented graphically, similar results can be obtained numerically. However, most processes cannot be characterized sufficiently with just two or three parameters. For example, a complex process such as a power plant requires the measurement of many different parameters to describe plant conditions completely. Furthermore, most of the parameters associated with a complex process are interrelated and cannot be assessed simply as pairs of variables isolated from the rest of the system. So with most real-world processes it is necessary to examine many different parameters simultaneously rather than grouping them in twos or threes.

Instead of the simple case of P1 vs. P2 for two parameters, if we look at a system with four or five or *n* parameters, we now have a more complicated situation of P1 vs. P2 vs. P3 vs. P4 vs. . . . P*n* for *n* different parameters associated with a complex process. Although a graph showing all parameters plotted simultaneously for a complex process is not feasible, numerical methods analogous to the concepts presented graphically above can be employed. In other words, numerical techniques can be applied that utilize historical data values collected from a complex process to form the numerical equivalent of a "system performance surface."

ACM Modeling Principles

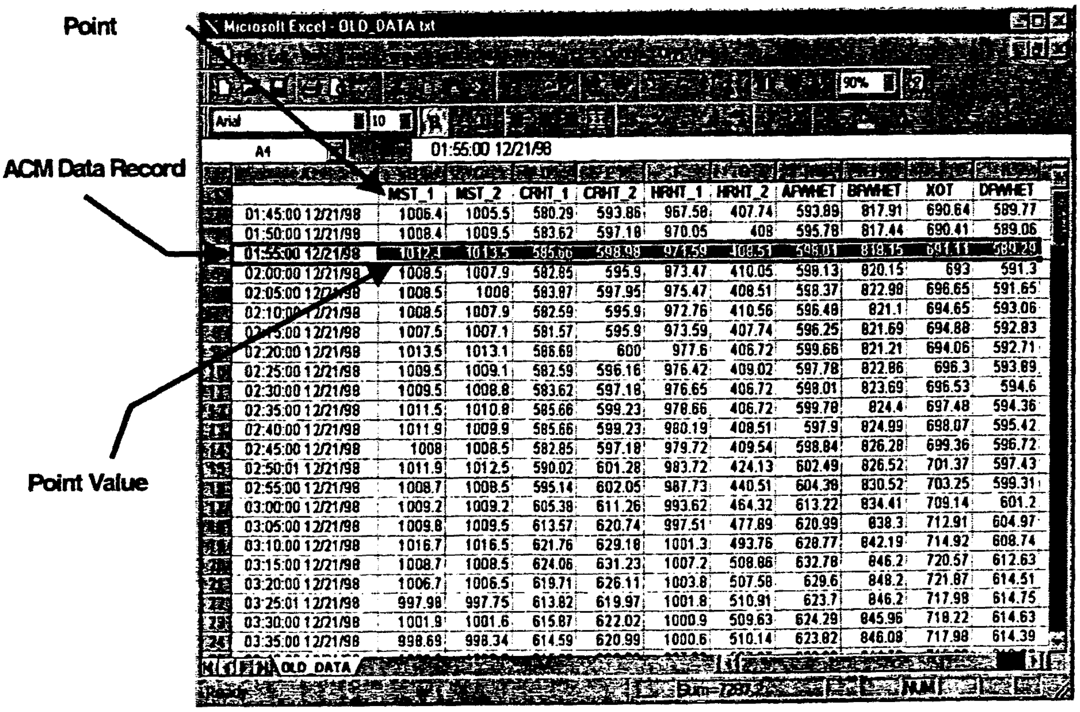
We have discussed two simple systems that can be represented graphically or mathematically, however, as you might suspect, the mathematics associated with larger systems can be a bit intimidating. Fortunately, ACM bears the burden of the mathematics, and with an understanding of the concepts discussed previously, you can use ACM quite effectively.

A good part of our understanding of a system like a power plant comes from observing the behavior of the system and relating our current observations to past experience. Any conclusions we draw about plant operating conditions depend largely on the experience we have with the system. ACM works in a similar manner by observing a process and making judgments based on past experience. It does this by creating a mathematical model of the plant using archived plant data values that represent past operating characteristics.

ACM views a system as a set of numerical data values -- main steam temperature, condenser pressure, plant heat rate, and so forth. These values are grouped together in arrays called **data records**. A data record is simply a snapshot of plant data values for a single instant in time. The individual items associated with a data record are called **points** and their related values are called **point values**. Figure 3-8 illustrates these concepts.

ACM analysis is performed by quantifying the "similarity" between any two data records that are being compared for purposes of creating modeled estimates and other essential functions. Computed similarities are scalar values that range between zero and one. A similarity value of one indicates the two plant conditions being compared are identical (e.g., each temperature, pressure, and flow value is exactly the same in both data records). A similarity value of zero indicates that the two conditions are completely different from each other (e.g., plant conditions at full power compared to plant conditions at zero power).

Prior to analyzing a system with ACM, a number of data records spanning a range of plant operating conditions are collected and stored in a file. These records are called **reference data records** and their purpose is to act as a knowledge base characterizing normal plant behavior.



ACM Data File Terminology

After the reference data records have been obtained, a new set of snapshots are collected and saved in a different file for assessment by ACM. These newer snapshots of plant data are called **input data records**. 1In other words, ACM provides a <u>computed</u> point value corresponding to each of the input point values. The computed point values are collectively known as the **output data record**. Figure 3-8 summarizes this procedure.

it may be compared with the input record for further data manipulations. Again, it should be noted that the ACM approach calculates an output point value for each and every input point (Figure 3-10). The significance of any differences between the input and output values is generally viewed in the context of the specific application (e.g., indication of a signal failure, calibration drift, abnormal system operation, etc.).

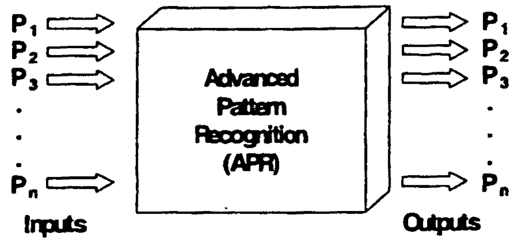


Figure 3-10 An Output for Every Input

ACM uses the computed output values to provide dynamic alarm limits for detecting plant abnormalities and instrument drift. The alarm limits for a given instrument are set by placing user-specified bounds above and below the output values. Recorded instrument values that lie outside of the dynamic alarm limits are flagged as needing attention by an operator or engineer. In a practical sense, the type of information required by ACM to assess the health and validity of plant data values includes the following:

- A set of modeling specifications defining general calculational options.
- A listing of the points to be assessed and any associated options such as criteria for testing the validity of the plant data.
- A reference data file containing plant data values spanning a range of operating conditions.
-

Given this information, ACM provides the following:

- Graphical output displaying information concerning the status of the process points.
- Summary reports listing computational results, data file statistics, and user specifications.

In addition, ACM stores the output values from the modeling computations to be used for any desired purpose. Table 3-1 presents a partial set of descriptions, inputs and outputs from an ACM data validation calculation.

Partial ACM Data Validation Results

Plant Parameter	Input Values	Output Values
Main Steam Temperature	1004.0	1003.2
Main Steam Pressure	2459.3	2456.8
First Stage Pressure	1915.0	1912.4
Cold Reheat Pressure	591.5	590.2
Cold Reheat Temperature	636.1	636.9
"A" Htr. Extr Pressure	586.9	585.8
"A" Htr. Extr. Temperature	636.6	636.0
Hot Reheat Temperature	1007.3	1007.0
Hot Reheat Pressure	553.4	552.4
"B" Htr. Extr. Pressure	288.4	288.7
"B" Htr. Extr. Temperature	554.5	553.9
Etc.	---	---

Advanced Pattern Recognition (APR) Characteristics

The APR technology embedded in ACM has several important characteristics:

Fault Tolerance: ACM minimizes the effects of incorrect or missing plant measurements. This is due to the fact that it treats all monitored parameters as being interrelated. ACM uses all parameters simultaneously to determine all of the predicted values so the impact of individual defects is minimized.

Localized Modeling: ACM forms a local model for every new input data record. Because it does not operate using a single set of coefficients, complex non-linear systems can be modeled more accurately and with fewer examples than are required with other techniques. In addition, localized modeling automatically takes into account changes in a system as it progresses through different operating conditions.

No Iterative Training Phase: ACM does not require an iterative training phase. Because no iterative training phase is involved, the reference data can be changed as often as desired allowing immediate adaptation to new information.

High Dimensionality: ACM is unrestricted in the number of plant parameters that it can handle in a single model, however, extremely large systems should often be broken down into multiple, smaller models based on point relationships identified using ACM tools. These smaller models enhance model accuracy and fault tolerance.

Advanced Pattern Recognition Theory

ACM utilizes advanced pattern recognition techniques to identify the current operating state of the system being monitored, then predicts a value for each data point being analyzed. The only information needed for an ACM model is a reference data set and an observed or input data set. The ACM calculations result in an equation for which there is one unique solution, unlike iterative empirical methods.

The training or learning process involves loading samples of reference data which represent good operating practice and well calibrated instrumentation into a reference library. Input data samples are then compared with those in the reference library for similarity. A group of the most similar reference data samples that bound the input sample are selected for the analysis process. These selected samples, referred to as the nearest neighbors, are manipulated to develop a mathematical representation of the system for the current operating conditions. When this mathematical representation is combined with the input data set, a prediction for each point value is calculated.

The equation used to calculate the predicted point value is:

$$\mathbf{P} = \underline{\underline{\mathbf{N}}} \bullet [(\underline{\underline{\mathbf{N}}}^T \otimes \underline{\underline{\mathbf{N}}})^{-1} \bullet (\underline{\underline{\mathbf{N}}}^T \otimes \mathbf{A})]_{norm}$$

Where:
P represents the predicted data record (an n-dimensional vector),
$\underline{\underline{\mathbf{N}}}$ represents the nearest neighbor matrix,
$\otimes$ represents the similarity operator, and
A represents the input data sample (an n-dimensional vector).

The similarity between the ACM equations presented above and the equation for a matrix-based least squares fit calculation will probably be very quickly recognized. In fact, the primary difference between the ACM calculations and a least squares fit analysis lies in the similarity operator. The similarity operator determines the similarity between the input data record and the nearest neighbor data records.

One key item found in ACM that will not be true with most statistical analysis techniques is that the matrix produced by the ($\underline{\underline{\mathbf{N}}}^T \otimes \underline{\underline{\mathbf{N}}}$) process can always be inverted. This represents a very significant advantage over least squares fit type analyses because the matrix inversion process in least square fit matrix calculations can frequently be impossible, resulting in a failed calculation. In addition, it can be seen from this process that the data samples used in the analysis that are most similar to the input sample will have the highest contribution to the ACM estimation. The reference data samples that were selected for inclusion in the analysis based on an erroneous signal value will have very little impact on the estimations, as opposed to a least squares fit prediction in which all reference data samples would have equal impact on the results. In other words, ACM works on the basis of maximizing similarity rather than minimizing difference. This is the reason that ACM can still provide very accurate signal value estimations even when a large percentage of the input signals have failed. This is responsible for ACM's localized modeling, resulting in a more accurate prediction compared with other methods that attempt to represent all operating conditions with a single set of coefficients.

ACM must have a reference data set that contains system data samples that represent "normal" operation and accurate instrumentation. Remember, "normal" operation is defined as any operating condition that is considered acceptable. For example, if a plant removes the high pressure feedwater heater from service to meet peak load demands, operation with the feedwater heater out of service would be considered "normal" and the reference data set should include samples of this mode of operation. The reference data set represents ACM's entire knowledge base for subsequent analyses. Therefore, it should include data samples that bound the entire range of expected operation for the monitored system, because ACM will not extrapolate beyond the point values available in the reference data file. Because of this, the selection of a representative reference data file is essential for accurate modeling.

Correlation and Auto Correlation

Even though ACM treats all points in a data record as if they are interrelated, certain points will be more strongly related than others. For example, a change in condenser pressure will have a strong effect on hot well temperature, but will have an un-measurable effect on main steam pressure. To improve the accuracy of the ACM predictions, ACM models can be constructed of smaller groups of closely related data points. In some cases, the relationship between points will be obvious from prior knowledge of the system. In other cases, the relationships might not be so obvious. In these less obvious cases, ACM can be used to determine the strength of the correlation between groups of points.

In some cases, a data point will appear to belong in an ACM model, but if that point is not available as input, the prediction for that point will degrade significantly. If this happens, the point is said to be auto correlated, or strongly related only to itself in the data record.