出國報告（出國類別：國際會議）

運用 NNARX 方法於質子交換膜燃料電池非線性建模

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摘要

2015 年「系統科學與工程國際研討會」(International Conference on Systems Science and Engineering, ICSSE 2015)，於 104 年 5 月 28 日至 29 日在日本東京成田東武機場酒店(Narita Tobu Hotel Airport)舉行，本人投稿該研討會論文乙篇，論文題目：運用 NNARX 方法於質子交換膜燃料電池非線性建模，因榮獲刊登及大會議程邀請於 5 月 28 日上午 0800-1015 場次進行口頭發表，故於 5 月 27 日搭機前往與會。當日該場次會議中，計有來至台灣、加拿大、匈牙利、土耳其及拉脫維亞等十篇論文發表，期間發表人均詳細報告其研究成果，報告完後，台下與台上學者討論熱絡，彼此交流受益良多。

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壹、目的：

2015 年「系統科學與工程國際研討會」(International Conference on Systems Science and Engineering, ICSSE 2015)，由主辦單位 WASET 於 104 年 5 月 28 日至 29 日假日本東京成田東武機場酒店舉行，該研討會主要探討的主題為：系統科學(Systems Science)與工程(Engineering)等新興科技領域，其屬於探討現今新興科技於系統工程應用之國際學術研討會，而本次參與發表之專家學者，計有來至日、韓、台灣、馬來西亞、捷克、印度、法國、加拿大及泰國等各國學者專家，合計發表論文達 300 餘篇。藉由參加本次國際研討會的互相討論，除了平日鑽研研究與查閱期刊論文所得知識，更能開闊自身眼界，瞭解國際研究趨勢與脈動，因而增進研究動力與方向。此外，本會議所投稿之論文均經由國際相關領域之學者、專家審查，因此一旦獲得大會收錄刊登，亦將大幅增加本院的能見度及學術地位。

貳、過程：

會議議程

Session V, May 28, 2015, Room A: 08:00 – 10:15

Chair: Sunantha Teyarachakul, Alan Lin

本人發表之論文名稱：

Nonlinear modeling of the PEMFC based on NNARX approach

作者：

Shan-Jen Cheng, Te-Jen Chang, Kuang-Hsiung Tan (談光雄), and Shou-Ling Kuo

(Chung Cheng Institute of Technology, National Defense University, ROC)

本次赴日本東京參加國際研討會，因舉辦地點近及國人赴日本免簽證之因素，故僅委託旅行社代訂來回機票，而相關住宿則自行決定愛德蒙大都市東京飯店(Hotel Metropolitan Edmont)住宿三晚，雖然下榻飯店離研討會舉辦地點稍有距離，但考量東京地鐵的便利性及住宿費用便宜，因而決定市區之飯店以節省開支。研討會舉行時間為 104 年 5 月 28 日至 29 日，故由旅行社代訂 5 月 27 日上午 08 時 50 分搭乘長榮航空班機赴日本成田機場，抵達日本成田機場時已逾當地時間 13 時 15 分(台灣時間 12 時 15 分)，辦好出關手續，即自行搭乘京成鐵路抵達日幕里車站，再轉 JR 東日本國鐵山手線及中央線抵達飯田橋車站，步行 5 分鐘後抵達下榻飯店，此時已逾 16 時 40 分，由於發表之場次為 28 日上午，故 27 日當天晚上在飯店稍作休息及準備。5 月 28 日當日早上 07:40 到達會場 Narita Tobu Hotel Airport 並順利完成報到手續，會議一開始，由會議主持人(Session Chair) Prof. Alan Lin 主持議程並由發表人逐一開始報告，本會議共發表十篇論文，分別由台灣科技大學、加拿大麥科文大學(MacEwan University)、土耳其薩卡里亞大學(Sakarya University)、匈牙利布達佩斯經濟和技術大學(Budapest University of Technology and Economic)、拉脫維亞里佳技術大學(Riga Technical University)、土耳其阿塔圖爾克大學(Ataturk University)、及台灣成功大學等教授及學者輪流發表，發表人均詳細報告其研究成果，報告完後，主持人亦提供時間給在場與會學者、專家提問，由於所研究之領域具相關性，因此台下與台上學者討論相當熱絡，導致會議主持人為控管時間而打斷討論，也因而會議延遲結束。本人發表之論文為第 8 順位，論文發表完後，主持人及台下學者亦提出見解及寶貴建議，對於本次參加國際研討會，使自身眼界更開闊及瞭解國際研究趨勢與脈動，因此對於未來研究與方向將產生更大的動力。

本人所發表之論文為 Nonlinear modeling of the PEMFC based on NNARX approach，內容報告摘要如下：質子交換膜膜燃料電池是一個時間變化的非線性動態系統，傳統的線性建模方法是很難評估正確 PEMFC 系統結構，由於這個原因，本文提出了 PEMFC 採用神經網路與外部輸入（NNARX）方法自回歸模型非線性建模。此外，多層感知器（MLP）網路被廣泛應用在評估 PEMFC 的 NNARX 模型結構。NNARX 模型的有效性和準確性可由相關的輸出電壓與輸入電流從 PEMFC 的測定實驗步驟進行測試。因此，由實驗結果證明，所得到的非線性 NNARX 模型能有效近似 PEMFC、模型輸出和系統量測的動態模

式一致。相關收錄論文如附件。

5 月 28 日，當日其他學者、專家發表議題，摘錄如下：

(1) Symbiotic Organism Search (SOS) for Solving the Capacitated Vehicle Routing Problem：

本文介紹一共生有機體搜索（SOS）方法解決車輛途程問題（CVRP）。 SOS 是共通啟發式演算法領域的一個新方法，且從未用於解決離散問題。本文提出一個應用基本共生有機體搜索（SOS）架構的複雜編碼方法來處理在 CVRP 離散問題。該方法將與目前已知的最佳解決方式作性能比較與評估。由計算結果證明，本文所提的方法能產生較佳的解決方案以作為初步測試。此外，由結果證明所提出的 SOS 可作為解決車輛路徑問題的替代方法。

(2) Predicting Medical Check-Up Patient Re-Coming Using Sequential Pattern Mining and Association Rules：

隨著體檢概念的普及，現今儲存相關體檢數據的大型資料庫，已經日益不堪負荷。而這些體檢數據資料，如果正確地探索它，其實是可以有效地做為醫學科技參考依據。另外，患者的身體狀況是不可預測，且由於現有醫療設施的限制以致於醫院無法提供最大健康檢查服務項目。為了解決這個問題，本研究採用相關體檢數據來預測病人身體狀況及可能發生之疾病。本文選擇序列模式挖掘（SPM）和關聯規則法來進行預測，因這些方法利用體檢數據之判斷模式，進而成為最適用於預測患者可能發生之疾病。首先，根據患者個人體檢數據被分組為數組，然後分析判別檢查各組顯著的差異。其次，對於每組利用 SPM 法產生頻繁模式。第三，根據各組的頻繁模式，對變數利用關聯規則以獲得預測患者身體健康。

(3) A Strategic Performance Control System for Municipal Organization：

策略性能控制是一個顯著的管理過程。目前有許多各種方法來改善此過程。本研究提出一個訊息系統開發市政管理績效性能評估。該系統將有效應用市政流程之改善。

(4) Eliminating Cutter-Path Deviation For Five-Axis Nc Machining：

本研究提出了一種偏差控制方法來增加插補點到五軸加工編碼的數值控制（NC），以達到所需的加工精度。本文具體研究的問題包括：（1）切割位置和數值控制之間的加工數據轉換，（2）計算偏離路徑和直線路徑間之偏差值，（3）找到內插點，（4）確定工具插補點位置與方向。藉由系統與實際應用例子執行相關測試，由測試結果可之，所提的偏差控制法可有效達到加工之精度。

(5) Cyclostationary Gaussian Linearization for Analyzing Nonlinear System Response Under Sinusoidal Signal and White Noise Excitation：

循環高斯線性化法，主要是用來研究非線性系統在正弦信號和白噪音下的時間平均響應。噪聲的循環平均值、方差、均值振幅譜和功率譜密度等量測數值，被用來分析。本文針對隨機跳躍和交叉定性響應進行研究與探討。而目前普遍的方法係利用蒙特卡羅模擬方式驗證與預測定性和定量響應，此法不需強加限制性條件就可以直接求解非線性代數方程式，並可解出杜芬系統中承受正弦信號和白噪音的平均值和噪聲響應，進而達

到可靠的定量與定性預測。

5 月 29 日，當日會議旁聽其他學者、專家發表議題，摘錄如下：

(1) Fast Algorithm to Determine Initial Tsunami Wave Shape at Source：

現今海嘯建模無法有效建立的問題是主要缺乏浪頭的初始資料。因此，目前皆直接將壓力紀錄器裝置在深水底部以量測海嘯相關數據。在本文中，作者提出了一種新方法，來建置海平面及海嘯源頭之初始位置，此方法是透過測量信號（marigram）近似與預先計算合成 marigrams 的線性組合來重建初期海面位移之海嘯源頭。此方法已經驗證其具有良好的精度和高性能。相關數學模型和數值試驗結果也在本文呈現。

(2) Forecasting of Grape Juice Flavor by Using Support Vector Regression：

果汁品質與甜度預測之研究已成為各國研究主題。由於經濟的快速增長，許多不同種類的果汁已經在市場推出。如果一家飲料公司可以更瞭解客戶的喜好，則該公司的產品將更具吸引力。因此，本研究利用基於支持向量回歸（SVR）的基本理論和計算過程來預測果汁之品質。利用 SVR，BPN 和 LR 的預測，將實現果汁品質與甜度數據化，最後由結果證明，SVR 能有效地預測。

(3) Development of Intelligent Smart Multi Tracking Agent System to Support of Logistics Safety：

現今，通過使用 GPS 和無線通信技術，使貨物位置定位變得更方便。透過物聯網技術和追踪系統的發展使我們能夠在所有的工業和社會臨時性環境下，仍可以確認物品位置。此外，我們也能夠運用 IT 技術在管理層面。然而，使用該系統時仍存在許多限制，例如:即時定位訊息確認問題等。為了將相關物流產業之追踪系統全球化，因此，亟需進行相關研究，以解決上述問題。因此，本文設計並開發了利用物聯網和智慧即時定位追蹤多重代理系統，該方法將對於物流產業提供更安全，準確，及可靠運輸。

(4) Automatic Music Score Recognition System Using Digital Image Processing：

音樂一直是人類日常生活中不可或缺的一部分。但是，對於大多數人來說，讀一本樂譜，並把它變成旋律其實是一件不容易的事。本研究的目的主要開發使用數位影像處理來讀取和自動分析樂譜的自動樂譜識別系統。該技術方法包括：（1）五線譜區域分割;（2）圖像預處理;（3）注意識別;（4）臨時符號和休止符認定。數位影像處理技術（例如，水平/垂直投影，連結區域標記，形態學處理，樣板匹配等）主要是根據音符與記號來做處理。由研究結果知，作者提出的自動樂譜識別系統可以達到 96.3%和 91.7%的檢測和識別率。此外，自動樂譜識別系統也可以放置在一個系統中與媒體播放器播放指定的樂譜圖像音樂與歌曲。

參、心得報告：

本次赴日本東京拜參加國際研討會，不僅是在學術方面，擴張自己研究知識，而在國際觀上，對當地生活習慣及科技發展也有新的體認與見解。在學術上藉由本次研討會，可以看到其他專家學者對於自己所專研領域具有一套特殊見解，也充分運用自身專業解決當今工程問題，例如:有學者提出如何利用現今科技針對海洋來建模，以利預測海嘯的發生等。因此，甚有所感體會到，一篇研究論文，即使是 SCI 等級，如果對當今社會毫無實質改善或增進科技進步，那也只是一篇毫無用處的文章而已。另外，在國際觀上，因本次研討會在東京舉行，其交通相當便利，因此在研討會期間利用搭乘該地區的各式鐵路系統前往會場，沿途景觀可以充分感受到日本首都的繁榮與進步，且由於地鐵的四通八達，道路上並不會看到太多車子，然而或許是地鐵的發達，造成各式列車的型式規格不一，進而發現列車與月台的間隙竟高達 30 公分寬，對於印象中重視安全的日本感覺好像有很大落差!此外，在 5 月 30 日晚上，要搭乘班機返國時，當正排隊準備登機時，突然機場發出一則緊急廣播，內容大致說明:「…日本氣象廳預測接下來三分鐘內將會發生強烈地震，請所有人員做好準備…」。當廣播結束後，登機閘口也暫停登機，正當半信半疑時，果真發生有感地震，原來這是日本研發的地震預警系統，準度也確實相當精確，這也讓我充分見識到日本的國力，甚為驚嘆。最後，參加國際研討會是一項很有意義的學術活動，也非常感謝科技部研的經費提供，校院部各級長官的協助，使得此次研討會能順利成行。

肆、參考資料：

圖片為研討會內外場、大會出席證明、會議現場及市區導覽等

研討會地點指示牌

註冊報到

研討會場外


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This certificate is awarded to
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in oral and technical presentation, recognition and appreciation of research contributions to ICSSE 2015 : 17th International Conference on Systems Science and Engineering

INTERNATIONAL SCIENTIFIC RESEARCH AND EXPERIMENTAL DEVELOPMENT

TOKYO, JAPAN

Authorized Signature

MAY 28-29, 2015

大會頒發出席證明

研討會會議進行(1)

研討會會議進行(2)

研討會會議進行(3)

研討會會議進行(4)

伍、建議事項：

對於參加國際研討會，將可增進學術交流亦可開闊自己國際觀，利用參加國際學術研討會，使各國瞭解我們的學術成就。所謂學術無國界，藉由各國的專家學者互相研討，彼此激勵出火花，對於學術而言也是一項寶貴收穫，因此，在經費有限的情況下，期許能鼓勵老師們能多出去走走，瞭解目前各國學術研究方向，增進學校能見度，以提升自己本職學能。最後，感謝科技部研的經費提供，校院部各級長官的協助，使得此研討會能順利成行。

陸、會議資料：

收錄論文光碟片(論文電子檔 345 篇)

Nonlinear modeling of the PEMFC based on NNARX approach

Shan-Jen Cheng, Te-Jen Chang, Kuang-Hsiung Tan, Shou-Ling Kuo

Abstract—Polymer Electrolyte Membrane Fuel Cell (PEMFC) is such a time-vary nonlinear dynamic system. The traditional linear modeling approach is hard to estimate structure correctly of PEMFC system. From this reason, this paper presents a nonlinear modeling of the PEMFC using Neural Network Auto-regressive model with eXogenous inputs (NNARX) approach. The multilayer perception (MLP) network is applied to evaluate the structure of the NNARX model of PEMFC. The validity and accuracy of NNARX model are tested by one step ahead relating output voltage to input current from measured experimental of PEMFC. The results show that the obtained nonlinear NNARX model can efficiently approximate the dynamic mode of the PEMFC and model output and system measured output consistently.

Keywords— PEMFC, neural network, nonlinear identification, NNARX.

I. INTRODUCTION

FUEL CELL (FC) technologies development and commercialization motivation is concerned with increasing environment and resource issues. Polymer Electrolyte Membrane Fuel Cell (PEMFC), as a renewable energy source, is one of the most promising fuel cells due to their compact modular, high efficiently and good stability. Because of its advantage, PEMFC is demanded as a dependable power sources for many application such as distributed power generation and automobile [1-2].

PEMFC is an extremely complex nonlinear multi-input and multi-output and coupled dynamic system. The performance of PEMFC can be represented by a current-voltage relation that is influenced by levels of internal influential parameters such as gas flow channel design, relative humidity ratio, operation temperature or pressure, stoichiometric flow rate, and others. All these parameters have strong impacts on PEMFC performance, and are related to each other by nonlinear behaviors. The inner working processes are accompanied with liquid, vapor, gas-mixed transportation, heat conduction and electrochemical dynamic reaction. For such kind of nonlinear system of PEMFC, yet there is no standardized procedure neither to estimate a matching mode structure not to select a suitable types of models. During the last several decades, various mechanism models of PEMFC, based on mass, energy and momentum conservation laws, has received much attention in an attempt to better understand the phenomena occurring within the cell, and a variety of mechanism models have been established in previous research [3-4]. In open literatures, these models characteristics focused on FC operating condition such as temperature effects, reaction gas transportation phenomena, heat management, etc. Each parameter with according to the operating conditions will exert different effects to improve the performance and define quantitative determination whether the effects of operating factors are necessary on the PEMFC. These models are very useful for analyzing the transient characteristic, but they are too complicated to be used for control system design.

For the purpose of dynamic control of real system in future work, precise dynamic characteristic model of the PEMFC are necessary. However, no matter what kind of models, there must be some errors between the models and real performance of the PEMFC because assumptions and approximations are made in modeling for computing simplify. In order to improve the accuracy of mechanism models and make the models reflect the actual PEMFC performance better, it is necessary to mode the structure of the models using nonlinear model approach. Most dynamic systems can be better described by nonlinear models, which are able to present the whole behavior of the system during the all operating condition [5-7]. Motivated by this need, an attention has been paid to identification of nonlinear dynamical systems. The nonlinear dynamic systems behavior has made the employ of Artificial Neural Network (ANN) for the modeling task in recent decades [8-9]. In addition, all the numerical studies have proven the multilayer perceptron (MLP) neural networks match very well for nonlinear system identification.

In this work, a nonlinear model approach, consisting of a Neural Network Auto-regressive model with eXogenous inputs (NNARX) approach is adopted to model the nonlinear dynamic of the PEMFC. The paper organized as follows: Section II gives a description of NNARX model approach. Section III presents the results of modeling of PEMFC based on NNARX approach. Section IIII is the conclusion. The proposed nonlinear modeling of the PEMFC based NNARX approach procedure is graphically summarized in Fig. 1.

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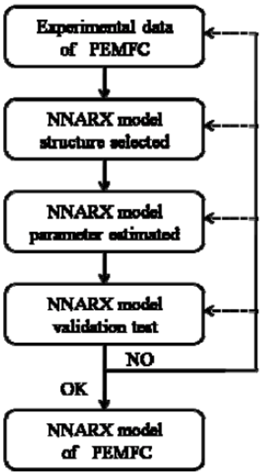

Fig. 1 Nonlinear model of PEMFC procedure

II. Neural Network Auto-regressive model with exogenous inputs (NNARX) modeling approach

Modeling is an important issue in the process of parameter estimation. Auto-regressive eXogenous models have been employed extensively to represent the relationship of the system output with the system input in the present of noise in many linear systems. In the process of parameters estimation, the Levenberg-Marquardt (LM) algorithm is usually used in neural networks (NN) method. In order to meet a closer approximation to the real system, nonlinear ARX models are used, which are modeled by means of NN. The Multilayer perceptron (MLP) network is one of the most studied members in the NN. The primary of MLP neural network reason is its ability to model simple as well as complex functional relationships. The LM algorithm minimizes the mean-square error of the prediction errors for the nonlinear ARX model, which is as particular case of a nonlinear neural network ARX model (NNARX), as described in after[10,13].

A. NNARMAX model

A general linear system ARX empirical model can be described by the following equation:

$$A(q^{-1})y(k) = B(q^{-1})u(k) + e(k) \tag{1}$$

where $y(k)$ denotes the system output or autoregressive (AR) factor; $u(k)$ is the system input or exogenous (X) factor, e is the white noise or disturbance and q^{-1} negative shift operator. The polynomials $A(q)$ and $B(q)$ are given by:

$$\begin{aligned} A(q) &= 1 + a_1 q^{-1} + \cdots + a_{na} q^{-na} \\ B(q) &= b_0 + b_1 q^{-1} + \cdots + b_{nb} q^{-nb} \end{aligned} \tag{2}$$

The model of system corresponding predictor:

$$\begin{aligned} \hat{y}(k|\theta) = &-a_1 y(k-1) - \cdots a_{n_a} y(k-n_a) + \\ &b_1 u(k-n_k) + \cdots + b_{n_b} u(k-n_k-n_b+1) \end{aligned} \tag{3}$$

is thus based regression vector:

$$\begin{aligned} \vartheta(k) = [&y(k-1)\ldots y(k-n_a)u(k-n_k)\ldots \\ &u(k-n_k-n_b+1)] \end{aligned} \tag{4}$$

where n_a is number of output poles; n_b is the number of input zeros and n_k is the system time delay. In order to estimate the parameter of nonlinear ARX model structure, the NN can be done. The neural network version of ARX model structure is defined as Neural Network ARX (NNARX).The NNARX model structure is presented in the Fig. 2. The relationship between input-output structures of NNARX mode can be shown by

$$y(k) = g[\varphi(k), \theta] + e(k) \tag{5}$$

The one-step-ahead (OSA) prediction of the NNARX model structure is defined by

$$\hat{y}(k|\theta) = g[\varphi(k), \theta] \tag{6}$$

where g is the function realized by the multilayer perceptron neural network method.

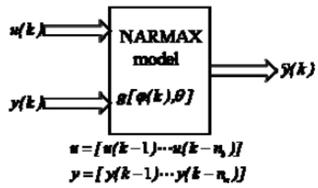

Fig. 2 NNARX model structure approach.

B. Multilayer perceptron (MLP)network

The multilayer perceptron (MLP) network is one of most used of the NN family; because of its enable simply represent complex function. The class of MLP NN meted with three layers: an input, an output and hidden layer. In the hidden layer (j) of each neuron, the sums up of input data x_i after weighting them with strengths of the respective connections w_{ji} from the input layer and computed output y_j as a function of the sum:

$$y_j = f\left(\sum_{i=1}^{q} w_{ji} X_i\right) \tag{7}$$

where the function $f(\cdot)$ can be linear, threshold, sigmoid, hyperbolic tangent and radial basis. In this paper, hyperbolic tangent functions are considered for the neurons in the hidden layer and linear function for the output layer neurons, respectively. The output of the MLP presented:

$$\hat{y}_i(w, W) = F_i\left(\sum_{j=1}^{q} W_{ij} \cdot f_j\left(\sum_{i=1}^{m} w_{ji} X_i + w_{j0}\right) + W_{i0}\right) \tag{8}$$

where q is hidden neurons, w_{ji} between input and hidden neuron weighting, w_{ij} between hidden neuron and output weighting and m is input number. The weighting w and W of are the adjustable parameter of the network and determine through the training process. The sets of training inputs data $u(t)$ and corresponding outputs $y(t)$ defined

$$Z^N = \{[u(k), y(k)]\, k = 1, \cdots, N\} \tag{9}$$

The goal of training is to meet a mapping from the training data set to the set of possible weights $Z^N \to \hat{\theta}$, so that the network will produce the close to the true outputs *y(k)*. The prediction error measurement is often described by a function required as the loss function. The general form can be depicted as

$$P_N(\theta, Z^N) = \frac{1}{2N}\sum_{k=1}^{N} \varepsilon^2(k,\theta) \tag{10}$$

In (10) is used to simplify differentiation when minimizing residual $\varepsilon(k,\theta) = y(k) - \hat{y}(k,\theta)$. Z^N is mean the training data set. The minimizing solution implements the Levenberg-Marquardt (LM) algorithm, due to its rapid convergence properties and robustness.

C. The Levenberg-Marquardt (LM) algorithm

The LM algorithm is the iterative numerical process in realizing solution. In this paper, NNARX model of PEMFC is obtained by LM algorithm. For minimal of sum of the squares $\varepsilon(k,\theta)$, the LM algorithm is used in optimizing the parameter vector θ. The linear approximation to the i_{th} residual of the LM algorithm at iteration is given by:

$$\tilde{\varepsilon}(k,\theta) = \varepsilon(k,\theta^i) + [\varepsilon'(k,\theta^i)](\theta - \theta^i) \tag{11}$$

and the criterion id given by

$$L^i(\theta) = \frac{1}{2N}\sum_{k=1}^{N} \tilde{\varepsilon}^2(k,\theta) \approx P_N(\theta, Z^N) \tag{12}$$

The gradient and Hessian for $\theta = \theta^i$ are given by:

$$\begin{aligned} G(\theta^i) &= (L^i(\theta))' \\ R(\theta^i) &= (L^i(\theta))'' \end{aligned} \tag{13}$$

The next iteration parameter vector is defined $\theta^{i+1} = \theta^i + f^i$. The search direction f^i is computed by

$$[R(\theta^i) + \lambda^i I] f^i = -G(\theta^i) \tag{14}$$

That damping factor λ is computed at each iteration. The reduction of $P_N(\theta, Z^N)$ is determined based on the ratio:

$$r^i = \frac{P_N(\theta^i, Z^N) - P_N(\theta^i + f^i, Z^N)}{P_N(\theta^i, Z^N) - L^i(\theta^i + f^i)} \tag{15}$$

The stopped criterion in iterative compute process of LM algorithm is satisfied convergence value.

III. Result and Discussion

In these work, the identification process was presented by the widespread mathematical software package MATLAB, provided by the MathWorks Inc. [14] The steady output voltage of power source of PEMFC is an important. PEMFC experimental data was recorded during various step load of current. The data were divided into two sets, one for training and remaining for validation. The input-output data is presented in Fig .3.

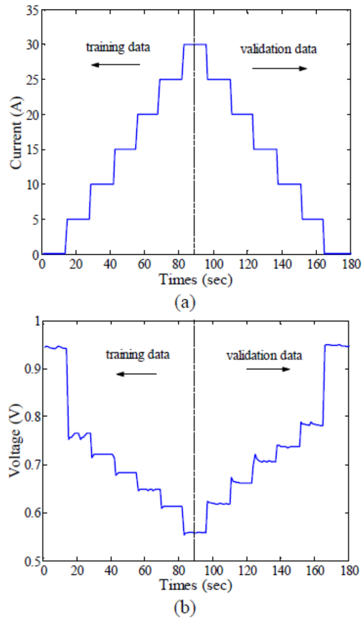

Fig. 3 Input and output experimental data of PEMFC

The NNARX model of PEMFC was employed for divided set data and it shows the modeling of second order nonlinear dynamic system of PEMFC. In order to model a good structure of PEMFC, the model structure parameter selection of system which we wish to employ is done firstly. In the process of model structure selection of NNARX model consists of two sun problems: a regressor parameter selection and MLP network architecture selection. As regressor structure selection is used two past inputs (n_b) and two past outputs (n_a) in this work as shown in Fig. 4.

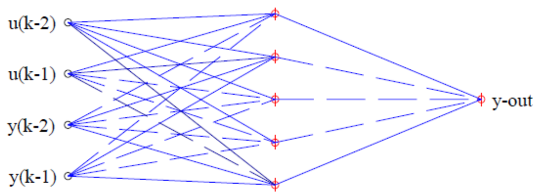

Fig. 4 Network architecture of NNARX model of PEMFC

Furthermore, the MLP architecture was selected five tannhypberbolic (tanh) neurons in hidden layer, and a single linear neuron in output layer. Fig . 5 is the results of iteration criterion NNARX modeling which demonstrated a good training convergence value. The comparison of experimental data of PEMFC and NNARX model over training set data of patterns are presented in Fig. 6. From the residual plot in training process, the trained NNARX model output OSA is in good agreement with the experimental output of PEMFC.

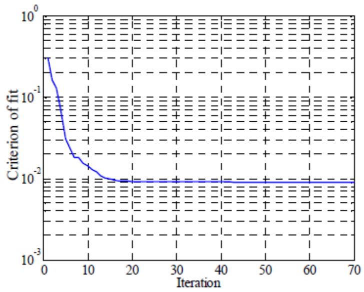

Fig.5 Iterative criterion of fit with training process

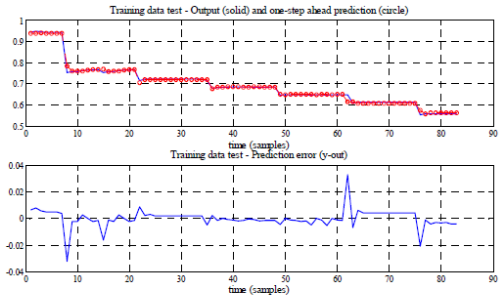

Fig. 6 Training test of NNARX model

Fig. 7 shows the experimental data of PEMFC and NNARX model OSA in validation procedure, the NNARX approach has ability to mode the real system data. The residual shows that mode prediction and experimental output is closer.

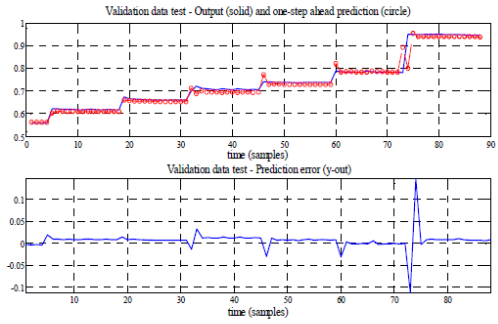

Fig. 7 Validation test of NNARX model

The residuals of autocorrelation and cross correlation with NNARX validation process plot in Fig. 8. The results show the residual pass the correlated coefficient of 95% confidence limited in autocorrelation process; the signification correlation between the input and residual was completely modeled in cross correlation process. That indicated NNARX model approach can fit accuracy of the PEMFC system.

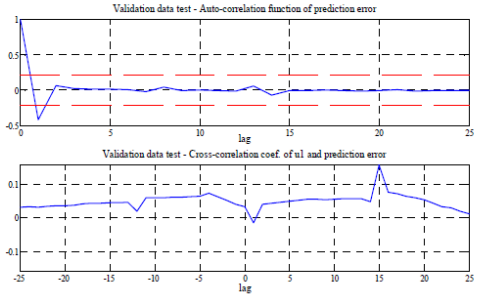

Fig. 8 Auto and cross correlation function of output prediction error.

IV. Conclusion

In this paper, the nonlinear modeling of PEMFC is applied via Neural Network Auto-regressive model with eXogenous inputs (NNARX) approach. From the results of training process, the LM algorithm of MLP neural network can fit training iteration criterion convenience. In NNARX mode with small network architecture was founded to be adequate to model the PEMFC dynamic system. Applying the validation tests, the NNARX model could pass the residual test and cross correlation tests. This work demonstrates that the nonlinear modeling approach, employing the NNARX model, provides a very simple and yet highly accurate model of the PEMFC system.

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