# ONLINE SYSTEM IDENTIFICATION DEVELOPMENT BASED ON RECURSIVE WEIGHTED LEAST SQUARE NEURAL NETWORKS OF NONLINEAR HAMMERSTEIN AND WIENER MODELS

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To my mother, father's memory, brother, and all family.

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## ABSTRACT

The realistic dynamics mathematical model of a system is very important for analyzing a system. The mathematical system model can be derived by applying physical, thermodynamic, and chemistry laws. But this method has some drawbacks, among which is difficult for complex systems, sometimes is untraceable for nonlinear behavior that almost all systems have in the real world, and requires much knowledge. Another method is system identification which is also called experimental modeling. System identification can be made offline, but this method has a disadvantage because the features of a dynamic system may change over time. The parameters may vary as environmental conditions change. It requires big data and consumes a long time. This research introduces a developed method for online system identification based on the Hammerstein and Wiener nonlinear block-oriented structure with the artificial neural networks (NN) advantages and recursive weighted least squares algorithm for optimizing neural network learning in real-time. The proposed method aimed to obtain a maximally informative mathematical model that can describe the actual dynamic behaviors of a system, using the DC motor as a case study. The goodness of fit validation based on the normalized root-mean-square error (NRMSE) and normalized mean square error, and Theil's inequality coefficient are used to evaluate the performance of models. Based on experimental results, for best Wiener parallel NN model and series-parallel NN model are 93.7% and 89.48%, respectively. Best Hammerstein parallel NN polynomial based model and series-parallel NN polynomial model are 88.75% and 93.9% respectively, for best Hammerstein parallel NN sigmoid based model and series-parallel NN sigmoid based model 78.26% and 95.95% respectively, and for best Hammerstein parallel NN hyperbolic tangent based model and series-parallel NN hyperbolic tangent based model 70.7% and 96.4% respectively. The best model of the developed method outperformed the conventional NARX and NARMAX methods best model by 3.26% in terms of NRMSE goodness of fit.

## ABSTRAK

Model matematik yang dinamik pada sesuatu sistem adalah sangat penting untuk menganalisis sistem tersebut. Sistem model matematik dapat diterbitkan dengan menerapkan hukum fizik, termodinamik dan kimia. Tetapi kaedah ini mempunyai beberapa kelemahan, antaranya sukar untuk sistem yang kompleks, kadangkala tidak dapat dikesan untuk tingkah laku tidak linear yang hampir semua sistem ada di dunia nyata, dan memerlukan banyak pengetahuan. Kaedah lain ialah dengan menggunakan pengenalan sistem, dan ia juga dipanggil pemodelan secara eksperimen. Pengenalpastian sistem boleh dibuat di luar talian, tetapi kaedah ini mempunyai kelemahan kerana ciri sistem dinamik mungkin berubah dari semasa ke semasa. Parameter mungkin berbeza apabila keadaan persekitaran berubah. Ia memerlukan data yang besar dan memakan masa yang lama. Penyelidikan ini memperkenalkan kaedah yang dikembangkan untuk pengenalpastian sistem dalam waktu nyata berdasarkan struktur berorientasikan blok tidak linear Hammerstein dan Wiener dengan kelebihan rangkaian neural tiruan (NN) dan algoritma kuadrat terkecil rekursif untuk mengoptimumkan pembelajaran rangkaian saraf di waktu sebenar. Kaedah yang dicadangkan bertujuan untuk mendapatkan maklumat model matematik maksimum yang dapat menggambarkan tingkah laku dinamik sebenar sesuatu sistem dengan menggunakan DC motor sebagai kajian kes. Pengesahan kebaikan fit berdasarkan ralat punca-punca persegi normal, ralat segiempat sama normal, dan pekali ketaksamaan Theil digunakan untuk menilai prestasi model berbanding dengan keluaran sebenar. Berdasarkan keputusan eksperimen, untuk model NN selari Wiener terbaik dan model NN selari-siri masing-masing ialah 93.7% dan 89.48%. Model berasaskan polinomial NN selari Hammerstein terbaik dan model polinomial NN selari siri masing-masing ialah 88.75% dan 93.9%, untuk model berasaskan sigmoid NN selari Hammerstein terbaik dan model berasaskan sigmoid NN selari siri masing-masing 78.26% dan 95.95%, dan untuk model berasaskan hiperbolik tangen NN selari Hammerstein terbaik dan model berasaskan hiperbolik tangen NN selari siri masing-masing 70.7% dan 96.4%. Model terbaik bagi kaedah yang dibangunkan melebihi model terbaik kaedah NARX dan NARMAX konvensional sebanyak 3.26% dari segi kesesuaian NRMSE.

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## LIST OF ABBREVIATIONS

| | | |
|---|---|---|
| ANN | - | Artificial Neural Networks |
| ARMAX | - | Auto-Regressive Moving Average eXogenous |
| ARX | - | Auto-Regressive eXogenous |
| bemf | - | Back electromotive force (V) |
| CT | - | Continuous time |
| DAQ | - | Data acquisition |
| DC | - | Direct current |
| ELU | - | Exponential Linear Unit function |
| emf | - | Electromotive force |
| GA | - | Genetic Algorithm |
| GND | - | Ground |
| gof | - | Goodness of fit |
| HNN | - | Hammerstein neural network |
| I/P | - | Input |
| LS | - | Least Squares |
| LS-SVM | - | Least-squares support vector |
| LTI | - | Linear time invariant |
| MIMO | - | Multi-Input Multi-Output |
| MISO | - | Multi-Input Single-Output |
| MLP | - | Multilayer-Perceptron |
| MRAN | - | Minimum resource allocation networks |
| MRELS | - | Multi-pace Recursive extended least-squares |
| MSE | - | Mean square error |
| NARMAX | - | Nonlinear autoregressive moving average with exogenous inputs model |

| | | |
|---|---|---|
| NARX | - | Nonlinear autoregressive with exogenous inputs model |
| NMSE | - | Normlized mean square error |
| NN | - | Neural network |
| NRMSE | - | Normalized root-mean-square error |
| O/K | - | Observer/Kalman filter |
| O/P | - | Output |
| OE | - | Output Error |
| PHNN | - | Parallel Hammerstein neural network |
| PLC | - | Poly lactic Acid (plastic filament) |
| PMDC motor | - | Permanent magnet DC motor |
| PReLU | - | Parametric Rectified linear Unit function |
| PWM | - | Pulse width modulation |
| PWNN | - | Parallel Wiener neural network |
| RBF | - | Radial basis function |
| RELS | - | Recursive extended least-squares |
| ReLU | - | Rectified linear Unit function |
| RLS | - | Recursive least squares |
| RNN | - | Recursive Neural Network |
| RWLS | - | Recursive weighted least squares |
| SPHNN | - | Series-parallel Hammerstein neural network |
| SPWNN | - | Series-parallel Wiener neural network |
| SI | - | System identification |
| SISO | - | Single Input Single Output |
| TIC | - | Theil's Inequality Coefficient |
| TDNN | - | Time delay neural network |
| WLS | - | Weighted least squares |
| WNN | - | Wiener neural network |

# LIST OF SYMBOLS

| | | |
|---|---|---|
| $d(t)$ | - | Disturbance signal |
| $F$ | - | Force |
| $F_f$ | - | Friction force |
| $f_n$ | - | The normal force |
| $F_S$ | - | Static friction force |
| $G(q^{-1}), H(q^{-1})$ | - | Transfer function in time-shifting polynomial terms |
| $\mathscr{P}(x)$ | - | Polynomial of $x$ |
| $f(.)$ | - | Function of the variables between the round brackets |
| $i$ | - | Armature current of motor (A) |
| $I$ | - | The current |
| $J$ | - | Associated moment of inertia for motor and load (Kg.m$^2$) |
| $K$ | - | Motor constant (N.m/A) or (V/rad.s$^{-1}$) |
| $L(t)$ | - | Gain array |
| $\ell$ | - | The polynomial order |
| $\mathscr{M}$ | - | Mathematical model |
| $n_e$ | - | The polynomial error order |
| $n_u$ | - | The polynomial input order |
| $n_y$ | - | The polynomial output order |
| $\mathbb{N}$ | - | The set of natural numbers |
| $P(t)$ | - | Covariance matrix |
| $P_e$ | - | Electrical power generated in armature of DC machine |
| $P_m$ | - | Mechanical power |
| $q^{-1}$ | - | Shfting time |

| | | |
|---|---|---|
| $\mathbb{R}$ | - | Real numbers set |
| $R_A$ | - | Armature circuit resistor |
| $S$ | - | Sigmoid function |
| $T$ | - | Torque of DC machine |
| $T_C$ | - | Coulomb friction torque |
| $T_f$ | - | Friction anti-torque |
| $T_L$ | - | Load torque (N.m) |
| $T_m$ | - | The generated motor torque (N.m) |
| $T_v$ | - | Viscous friction |
| $tanh$ | - | Hyperbolic tangent |
| $u$ | - | Input voltage (V) |
| $u(t)$ | - | Traditional input signal symbol |
| $V_i$ | - | Induced voltage in the armature winding |
| $v_S$ | - | Stribeck velocity |
| $y(t)$ | - | Traditional output signal symbol |
| $\gamma$ | - | Parameter of raising static friction |
| $\delta_S$ | - | Decay degree parameter of Stribeck curve |
| $\delta_v$ | - | Geometric viscous coefficient |
| $\hat{\theta}$ | - | Estimated parameters |
| $\lambda$ | - | Weighting factor |
| $\mu$ | - | Coulomb friction anti-torque (N.m) |
| $\mu_o$ | - | Coefficient of friction |
| $\Phi$ | - | Magnetic flux (Weber) or (Volt-second) |
| $\sigma_v$ | - | Viscous friction coefficient |
| $\nu$ | - | Rotational viscosity coefficient (N.m/rad.s$^{-1}$) |
| $\omega_m$ | - | Motor's angular velocity (rad/sec) |
| $\theta, \theta(t)$ | - | Parameters in system model |
| $\Theta$ | - | Vector of parameters |
| $\varphi, \varphi(t)$ | - | Variable array |

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# CHAPTER 1

# INTRODUCTION

## 1.1 Background of the study

System identification is a tool used to construct a mathematical model that defines characteristics of a system (or process's characteristics) by establishing a relationship between its parameters and variables built on finding the relation between the actual input of the system and the related measurable output data [1]. The appropriate model, for a specific system, is determined according to the function which is intended to perform. Therefore, there are many models for the same physical system, each with varying levels of accuracy according to the phenomena under study. The importance of models is emitted from giving a description of a system and making predictions about how a system will behave [2].

The mathematical model for a dynamic system can be derived by applying a first principle modeling method known as the white-box modeling method [3]. It is founded on prior knowledge of the phenomena being represented as well as universal equations that may be used to construct the model. The models of this type are underpinned by the conservation of energy, mass, and momentum principles, e.g., heat and mass transfer rates and chemical or biological processes that are used to develop mathematical formulations for these conservation laws [4]. The general nature of those mathematical relationships is commonly considered. Nevertheless, they are restricted by understanding fundamental concepts, and their mathematical solution methods are often complicated, necessitating simplifying assumptions. Furthermore, the data required is frequently enormous, the model's uncertainties cannot be included, and the environmental error that comes in the system is usually ignored [5, 6].

On the other hand, deriving a mathematical model for a dynamic system from monitored data (input/output data) is named system identification [7], which are not depending on prior knowledge for a specific system, such as data-driven modeling methods known as black-box modeling methods. Or there is a certain amount of prior knowledge but not entirely for a particular system, known as gray-box modeling methods. There are two types of system identification: offline system identification, which can not be used before all system data are accumulated and preprocessed, then divided to be training and validation data sets [8, 9]. However, a dynamic system changes over time, leaving an offline identification technique vulnerable to these changes. The parameters may vary as environmental conditions change; this is the offline method's major drawback [10, 11]. The second type of system identification is online system identification, where the model processes the new input data synchronously with the actual system to predict the output in real-time. Then it takes the actual output to correct the estimated parameters [12–14].

Nowadays, researchers tend to use artificial neural networks (ANN), which are biologically inspired, in the system identification field to solve many system problems like nonlinearity, time-varying, and ambiguity or inaccessibility because of their ability to learn and update the model's parameters from obtained data [15, 16]. The ANN are based on the learning concept, weights that belong to a specific perceptron start with random values, and then these weights are tuned up to be suitable values. The efficacy of the neural networks depends largely on the training method with the network configuration and the type of activation function. However, the sluggish learning pace of a pure ANN with traditional learning methods (such as backpropagation and decent methods) in the online system identification area is the primary drawback of this technique [17]. The recursive regression techniques used as optimization procedures and learning methods are adopted to overcome this drawback in the online system identification. The recursive weighted least squares (RWLS) is a superior optimization and learning method that fulfills online system identification [18, 19].

The system can be modeled as a linear system, which assumes that the system has linear fixed features [20–23]. However, many real-world systems are with outside disturbances or nonlinear function faults because most physical systems are nonlinear [24–28]. A modeling analysis from a nonlinear perspective for system identification is necessary to avoid losing the generality (valid for all inputs) and considering the system's unmeasured inputs, such as disturbances and errors [29–32]. Traditional nonlinear system identification has taken two approaches to this problem: specialized nonlinear models for specific issues based on knowledge of the mapping structure or universal nonlinear models with significant computing restrictions in their implementation [33].

This thesis introduces a systematic and practical system modeling process to develop a nonlinear model starting from principle laws using the input/output data as graybox system identification. The developed nonlinear parametric model structure is based on nonlinear block-oriented multilayer perceptron (MLP) with time-delay neural networks. Hammerstein and Wiener neural networks with RWLS optimization and learning algorithm are used to tackling the drawbacks of traditional methods and offline system identification approach and identify the PMDC motor in real-time as a case study.

## 1.2 Problem statement

Identifying any actual system or process allows scientists and engineers to understand that system or process behavior. Consequently, it provides the ability to control or extend knowledge about that system or process to develop its applications. Linear analysis identification methods are matured over the past decades to cover some nonlinear systems (under linearity assumption) [20–23]. However, from an engineering standpoint, nonlinear systems are extremely important in control and modeling systems. Because, in practice, all systems are nonlinear in nature (including the DC motor, the case study of this research), and applying linearity assumptions to a nonlinear system leads to a deceptive mathematical model and loses the model's generality [34, 35]. This is the primary motivation for considering the nonlinearity of the system in this research.

Offline system identification approaches rely impractically on vast empirical data sets to assess the dynamics of a complicated growing process with a certain accuracy [36]. Another shortcoming of offline system identification methods is that they cannot take into consideration the feedback of the variations that the parameterization generates for the parameterizing process itself [37].

Although if the model is developed as a nonlinear to be more realistic, using the traditional methods for a nonlinear system, to estimate the parameters, is still a complex calculation and not a general solution, i.e., it is for a particular case [38–40]. In addition, Traditional approaches' mathematical models are vulnerable to modeling errors, parameter fluctuation, disturbance, and noise [41].

The ANN techniques already have the ability to overcome the calculation complexity and vulnerability to system error and noise that traditional system identification methods suffer from. In the system identification field, the ANN methods

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## APPENDIX D

## LIST OF PUBLICATIONS

***Publication(s):***

1. A. M. Kwad, D. Hanafi, R. Omar, and H. Abdul Rahman, “Development of system identification from traditional concepts to real-time soft computing based,” IOP Conference Series: Materials Science and Engineering, vol. 767, p. 012050, Mar 2020.
2. A. M. Kwad, D. Hanafi, R. B. Omar, and H. B. A. Rahman, “A real-time nonlinear hammerstein model for bidirectional dc motor based on multi-layer neural networks,” in 2020 IEEE Student Conference on Research and Development (SCOReD). IEEE, 2020, pp. 102–107.
3. A. M. Kwad, D. Hanafi, R. Omar, and H. A. Rahman, “Online nonlinear series–parallel hammerstein model for bi-directional dc motor,” in Pro- ceedings of the 12th National Technical Seminar on Unmanned System Technology 2020. Springer, 2022, pp. 823–838.
4. A. M. Kwad, D. Hanafi, R. Omar, and H. A. Rahman, “A nonlinear model for online identifying a high-speed bidirectional dc motor,” Engineering Journal, vol. 24, no. 5, pp. 245–258, 2020.

***Conference(s):***

1. A. M. Kwad, D. Hanafi, R. Omar, and H. Abdul Rahman, “Development of system identification from traditional concepts to real-time soft computing based,” in 1st International Symposium on Engineering and Technology (ISETECH) 2019 , Kangar, Perlis, Malaysia, 23 December 2019 - Presented.

2. A. M. Kwad, D. Hanafi, R. B. Omar, and H. B. A. Rahman, “A real-time nonlinear hammerstein model for bidirectional dc motor based on multi-layer neural networks,” in 2020 IEEE Student Conference on Research and Development (SCOReD), Universiti Tun Hussein Onn Malaysia (UTHM), Batu Pahat, Johor, Malaysia, 27-29 September 2020 - Presented.
3. A. M. Kwad, D. Hanafi, R. Omar, and H. A. Rahman, “Online nonlinear series–parallel hammerstein model for bi-directional dc motor,” in the 12th National Technical Seminar on Unmanned System Technology 2020 (NUSYS’20), Malaysia, 24- 25 November 2020 - Presented.

## APPENDIX E

## VITA

The author was born in Al-Rusafa, Baghdad, Iraq in 1978. He received the B.S. and M.S. degrees in Mechatronic engineering from the University of Baghdad, Engineering college in 2001 and Al-Khawarizmi Engineering college 2010 successively, and he started the PhD degree journey in Mechatronic, electrical engineering department in University of Tun Hussein Onn Malaysia (UTHM), Malaysia in 2017. From 2013 to 2017, he was a Lecturer Assistant in engineering college, Al-Iraqia University, Baghdad, Iraq. He is the author of Two-axes sun tracking system the theory and design book in 2013. His research interests include control of mechatronic systems, embedded systems and microcontrollers, system identification development and applications, Artificial Intelligence, and Robotics.