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ADAPTIVE MODEL PREDICTIVE CONTROL BASED ON WAVELET NETWORK AND ONLINE SEQUENTIAL EXTREME LEARNING MACHINE FOR NONLINEAR SYSTEMS

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By

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March 2015

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Wavelet networks (WNs) have been introduced as an alternative method of the neural networks for nonlinear system identification and used with model predictive control (MPC) techniques in many applications. Recently, an online sequential extreme learning machine (OSELM) algorithm has been introduced based on extreme learning machine (ELM) theories for single hidden layer feedforward neural networks (SLFN) and has been applied for different online applications. It is well known that SLFN with OSELM (NN-OSELM) is based on random initialization method for the input weights and the hidden layer nodes parameters. This might result in ill-conditioning, hence instability responses in nonlinear system modeling and consequently preventing the model based controller to perform best performances.

In this thesis, the OSELM is introduced with wavelet network (WN-OSELM) and proposed for nonlinear system modeling and control applications. The ability of wavelets for localization in both time and frequency domain will help OSELM to train the WN in both uniform and non-uniform data sets. Moreover, the ability of initialization the hidden nodes parameters using density function and recursive algorithm will help WN-OSELM to perform useful generalization facility and modeling accuracy.

Furthermore, to develop WN-OSELM ability to learn the nonlinear system dynamics minimally, a linear term is added to the WN frame (LWN) so that it is enough to stabilize the open-loop unstable systems in the initial stages. This allowed also learning unmodeled or time-varying dynamics of the system and enhancing the modeling accuracy. An analytical analysis based on ELM theories presented to prove the capability of the LWN to support the OSELM algorithm (LWN-OSELM).

The proposed methods applied with simulations for system identification of different nonlinear systems and had shown well capability of the LWN-OSELM and WN-OSELM over NN-OSELM in terms of modelling accuracy and fast convergence performance.

On the other hand, an adaptive model predictive controller (WNMPC) based on LWN-OSELM modelling method is proposed for nonlinear system control applications. The WNMPC is developed by a proposed algorithm named adaptive updating rule (AUR) used with gradient descent optimization method to minimize a constrained cost function over the prediction and control horizons and to offer a robust control performances.

The AUR is established based on Lyapunov stability theorem to find the limits of the optimization step size that guarantee a stable path on the objective function trajectory. A comparison between the proposed controller and other common related controllers are carried out on different nonlinear systems. The results showed superiority of the proposed controller in both control performance and the robustness tests.

Moreover, the proposed LWN-OSELM and WNMPC applied to a real conveyor-belt grain dryer system for modeling and control applications. The results showed better modeling accuracy and control performance over an existing modelling methods and the simplified adaptive neuro-fuzzy inference system (S-ANFIS) controller respectively. The robustness analysis and validation are carried out to prove the proposed controller reliability.

Abstrak tesis yang dikemukakan kepada Senat Universiti Putra Malaysia sebagai memenuhi keperluan untuk ijazah Doktor Falsafah

MODEL ADAPTIVE KAWALAN RAMALAN BERDASARKAN RANGKAIAN WAVELET DAN ONLINE BERURUTAN MESIN PEMBELAJARAN MELAMPAU

Oleh

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Mac 2015

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Rangkaian Wavelets (WNs) didapati boleh digunakan sebagai alternative untuk Rangkaian Neural (NNs) dan diperkenalkan bersama Kawalan Ramalan Model (MPC) di dalam banyak aplikasi.

Baru-baru ini, berdasarkan melampau mesin pembelajaran (ELM) teori algoritma, berurutan mesin pembelajaran melampau (OSELM) algoritma dalam talian telah diperkenalkan dengan lapisan suap depan tersembunyi tunggal NN dan menunjukkan keupayaan pembelajaran sangat cepat dalam talian untuk aplikasi yang.

Di dalam tesis ini, kaedah diperkenalkan iaitu WN yang berasaskan OSELM (WN-OSELM) dicadang untuk membentuk model bagi sistem yang tidak linear. Keadah ini berkebolehan untuk menangani masalah local minima yang sering dihadapi oleh NNs berasakan OSELM. Pembentukan model ini menunjukkan perbezaan bagi fungsi impulse atau fungsi step di dalam ruang yang sama dan data latihan yang sama.

Keadaan awal bagi pembolehubah WN dibuat menggunakan fungsi ketumpatan dan algoritma recursive di mana maklumat masukan diambil untuk membolehkan transformasi wavelet memproses data latihan secara menyeluruh. Selain itu, kaedah ini boleh juga menyelesaikan ketidakstabilan yang berlaku pada respon NN-OSELM yang disebabkan oleh masalah minima tempatan dan prosedur rawak bagi keadaan awal.

Justeru, untuk meningkatkan tahap prestasi penumpuan WN-OSELM, satu terma linear telah dimasukkan ke dalam rangka WN di mana ia membolehkan satu set persamaan linear diselesaikan melalui kaedah penyelesaian squares.

Sebagai pembuktian, teori analisis berasaskan ELM telah dipersembahkan yang menunjukkan kebolehan linear wavelet Rangkaian (LWN) yang menyokong OSELM algoritma.

Keputusan simulasi menunjukkan tahap yang lebih baik bagi LWN berbanding model WN dan NN dari sudut prestasi best fit, ketepatan dan kebolehan convergence yang pantas, di mana sebab tersebut boleh dirujuk kepada penyelesaian least square secara linear bagi LWN dan pada ketika pemulaan fasa latihan OSELM (LWN-OSELM).

Berdasarkan LWN-OSELM, satu MPC (WNMPC) dicadangkan atau dikemukakan bersama algaritma penambahbaikan dan berasaskan Keturunan kecerunan (GD) method yang mampu untuk menyelesaikan masalah constrained quadratic secara online dan aplikasi secara masa sebenar.

Bagi menjamin kestabilan tracking untuk model rujukan, analisis kestabilan iaitu algoritma Adaptive Kadar Update (AUR) telah dicadangkan untuk menentukan saiz yang paling optimum bagi GD untuk penumpuan yang pantas. Beberapa simulasi telah dilaksanakan bersama beberapa ujikaji untuk menilai tahap alat kawalan yang dikemukakan. Ujikaji menunjukkan tahap yang lebih baik bagi alat kawalan yang dikemukakan berbanding model NN berasaskan alat kawalan jangkaan iaitu dari sudut prestasi indeks ITAE, IAE and ISE. Tambahan pula, ujian robustness menunjukkan kebolehan alat kawalan yang dikemukakan untuk menangani kesan perubahan persekitaran yang boleh berlaku ketika kawalan proses sedang berlangsung.

Kaedah yang dikemukakan telah diaplikasikan kepada sistem Conveyor-Belt Grain Rambut, dan menunjukkan kebolehan untuk menghasilkan model dinamik yang tepat dan menunjukkan prestasi kawalan yang cemerlang di dalam keadaan awal yang berbeza-beza melalui penyingkiran ketidaktentuan dan isyarat gangguan yang mungkin berlaku.

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I would like to extend my special thanks to my passed mother and father. I would not be where I am today if it weren't for your love and support, Oh Allah, make their graveyard paradise. Finally I would like to dedicate this thesis to my lovely wife and daughters! Love you all.

I certify that a Thesis Examination Committee has met on 27 March 2015 to conduct the final examination of Dhiadeen - M - Salih on his thesis entitled "Adaptive Model Predictive Control Based on Wavelet Network and Online Sequential Extreme Learning Machine for Nonlinear Systems" in accordance with the Universities and University Colleges Act 1971 and the Constitution of the Universiti Putra Malaysia [P.U.(A) 106] 15 March 1998. The Committee recommends that the student be awarded the Doctor of Philosophy.

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LIST OF ABBREVIATIONS

WN	Wavelet network, Wavelet neural network
LWN	Linear wavelet network
LLWNN	Local linear wavelet neural network
RWNN	Recurrent wavelet neural network
HWNN	Haar wavelet neural network
FWNN	Fuzzy wavelet neural network
RWNFN	Recurrent wavelet-based neural fuzzy network
NN	Neural network
RNN	Recurrent neural network
RBF	Radial base functions
RAN	Resource allocating network
SLFN	Single hidden layer feedforward neural networks
ELM	Extreme learning machine
NN-ELM	(SLFN) Neural network –ELM
WN-ELM	Wavelet network-ELM
SW-ELM	Sigmoid and wavelet function with ELM
NN-OSELM	Neural network –OSELM
WN-OSELM	Wavelet network-OSELM
LWN-OSELM	Linear wavelet network-OSELM
CFWNN	Composite function wavelet neural networks
LDWNN	Lattice dynamical wavelet neural network
AUR	Adaptive updating rate
GD	Gradient descent
EKF	Extended Kalman filter

NARX	Nonlinear auto regressive with eXternal input
SVM	Support vector machines
WSVR	Wavelet support vector regression
PSO	particle swarm optimization
DE	Differential evolution
PIDBP	PID back-propagation (BP) algorithm
ANAOVA	Analysis of variance
WBFNN	Wavelet basis function neural network
LMS	Least mean square
OLS	Orthogonal least squares
OPP	Orthogonal projection pursuit
ADLA	Annealing dynamical learning algorithm
ART	Adaptive reasoning theory
ERR	Error reduction ratio
BF	Best fit model performance
Waveleons	Wavelet network hidden nodes
FPEC	Final prediction error criteria
SQFS	Sequential forward search
SQP	Sequential quadratic programming
RMSE	Root mean square error
NMSE	Normalized Mean Square Error
PI	Performance index
ISE	Integral square error
IAE	Integral absolute error
ITAE	Integral of time absolute error
SQLA	Sequential learning algorithm

ANFIS	Adaptive neuro-fuzzy inference system
RPROP	Resilient back propagation
BP	Back propagation
MPC	Model predictive control
DMC	Dynamic matrices control
GMP	Generalized predictive control
NGPC	Neural network and generalized predictive control
NMPC	Nonlinear MPC
MRC	Model reference control
WNMPC	LWN-OSELM based Model predictive controller
NNMPC	Neural network based MPC
NARMA-L2	Feedback linearization control
WPSE	Welch Mean-Square Spectrum Estimate
CSTR	Continuous stirred-tank reactor
MagLev	Magnetic Levitation
DAQ	Data acquisition device
MC	Moisture content
FIS	Fuzzy inferred structure
PEM	Prediction error minimization
QFT	Quantitative feedback theory
% OS	Overshoot percentage
S-ANFIS	Simplified ANFIS
St	Settling time
AWGN	Additive white Gaussian noise
SNR	Signal-to-noise ratio

CHAPTER 1

INTRODUCTION

1.1 Introduction

Wavelet neural networks (WNs) have been found in many applications with model predictive control (MPC) during the past years [1], [2], [3]. In general, there are typically two stages involved when using wavelet networks with MPC algorithms, the system identification and the predictive control design. Accordingly this introduction will be discussed in two parts.

1.1.1 System Identifications using Wavelet Network

Wavelet network is a combination of wavelet analysis and neural network (NN), where the wavelet functions are used at the hidden nodes instead of the traditional activation functions of NNs [4]. The architecture of WN can be similar to that of the radial basis functions (RBF) in single hidden layer feedforward neural networks (SLFNs), where both of them showed the capabilities of function learning and nonlinear system identifications [5].

The training methods for WNs commonly are gradient-based with batch-mode learning algorithms. These types of the training algorithms, the data involved through much iteration and the weight matrices are tuned iteratively to minimize the error function. However, these methods faced with many difficulties such as learning rate, number of epochs, stopping criteria, and slow convergences which are usually consume time and memory for large training samples [6].

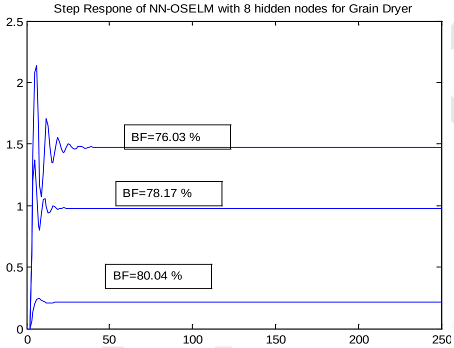
In the past few years, an extreme learning machine (ELM) has been introduced as a batch learning algorithm for SLFNs with RBF or additive activation functions (NN-ELM) and have been considered as a very fast training algorithm that able to estimate the network output weights in a single step without need for any lengthy learning procedure that uses learning rate, epochs, etc. [7]. The input weights, biases, and the hidden nodes parameters of NN-ELM are initialized randomly and assigned within the region [0, 1]. The method has been applied successfully in different applications and has shown a good generalization performance at high learning speed compared to the other well-known batch mode learning algorithms [8].

Recently, a feed forward wavelet networks (WNs) with composite activation functions in a single hidden layer have been presented through ELM (WN-ELM) and showed better generalization performance over NN-ELM [9], [10]. The superiority was due to the time–frequency localization and multi-resolution properties of the wavelet functions. Moreover, the initialization procedure of the WN parameters which takes into account the input-output information of the plant, guarantee the covering of all the trained data by the wavelets properly [4], [9], [10].

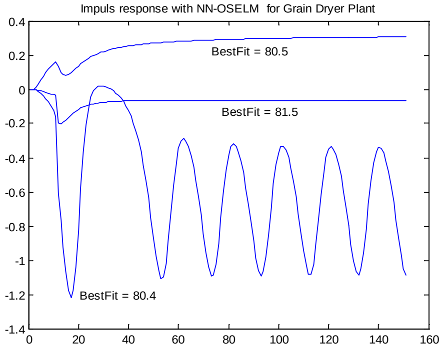
However, in the industrial field there are many applications that online sequential learning algorithms are preferred over batch learning algorithms [11]. The online learning algorithms do not require retraining whenever a new data is received unlike the batch learning method which uses the past data together with the new data, and then implement retraining [12] [13]. Moreover, the reason that online learning is faster than batch learning especially on large training sets, is because online learning takes many steps per epoch which can follow curves in the gradient [14].

Based on ELM theories, an online sequential extreme learning machine (OS-ELM) algorithm was developed for SLFN neural network (NN-OSELM) to deal with data that comes chunk by chunk or one by one [15]. The method, showed better generalization capability, and fast training compared to the other well-known sequential learning algorithms applied on real world benchmarks for regression, classification, and time-series problems [15].

However, investigating NN-OSELM in nonlinear system modeling for control application, it is found that the random initialization of network parameters have instable result on the identified model responses. In another word, there are different impulse and step function responses of the identified model by NN-OSELM after each new training process for same training data. For example Figure 1.1. shows the Grain Dryer identified model open loop impulse and step function responses for three training trials with the same training data, even where the model best fit (BF) performance [16] are close to each other.



(a)



(b)

Figure 1. 1 The step (a) and impulse (b) responses for the NN-OSELM model of the grain dryer plant

The reason possibly can be referred to the random initialization of the NN parameters, which may change the initial start point of the training on the non-convex curve where the learning scheme starts. Therefore, the NN-OSELM in each trial hits different local minima in the same solution space for the same training data which cause different open loop responses. Note that, repeating the training algorithm for several times may hit the global minima coincidently. This procedure is not acceptable in modeling nonlinear systems for control application especially when the system dynamics are involved.

In this regard, WN-OSELM has been proposed using NARX model structure for nonlinear system modeling to overcome the instability of NN-OSELM caused by local minima problems and the random initialization procedure. The WN parameters namely the dilations and translations are initialized using density function and recursive algorithm [4], while the optimal number of the hidden nodes (waveleons) was found using final prediction error criteria (FPEC). In addition, the number of the input regressors (the delayed inputs and outputs) was selected using sequential forward search (SQFS) method [17]. From the simulations results, WN-OSELM was able to overcome the NN-OSELM problems and showed better generalization, and fast training capability.

However, to maintain the initial stability and allowed the nonlinear WN weights to learn unmodeled or time-varying dynamics of the open-loop system, a linear term (nominal linear model) has been added to the WN frame (LWN) and called linear-wavelet networks (LWN) [18]. This will enable a set of linear equations to be solved using least squares solution [19]. In addition, for many open-loops unstable systems, it helps to take the WN to learn dynamics minimally so that enough to stabilize the plant and improve the prediction ability [19] [18]. Moreover, and from control perspective, the use of LWN for predictive control, the linear term at each step will be hired to produce an initial solution for the sequence of control actions [19]. This solution will then be used as a starting point for the optimization algorithm which takes later the entire model into account. The optimizer algorithm with such warm of initialization may potentially save computation time, and allow for a better solution within a stable time frame [18].

The LWN with OS-ELM algorithm was able perform better generalization property and modeling capability where a theoretical analysis based on ELM theories presented to prove the capability of the linear-wavelet network (LWN) to support OSELM algorithm (LWN-OSELM) for online applications. The simulation carried out using different nonlinear systems to validate the proposed methods and compare it with WN-OSELM and NN-OSELM. The performance of LWN-OSELM model was superior in both modeling accuracy and learning performance. The LWN-OSELM evaluated by a real experimental data of the grain drier system and compared the results with the ANFIS model that obtained by Lutfy [20];

1.1.2 Model Predictive Control with Wavelet Network

In most model predictive control (MPC) applications, linear models are used to predicting the process behavior over the prediction horizon [21]. But, because of a wide range of the real nonlinear processes that is not easy to describe the nonlinear dynamic by using linear models or linearization techniques, using the linear models becomes unfeasible. Therefore, the predictive control performance required to be extended to combine the nonlinear models.

A number of researchers successfully applied the WNs as a system identifier for the generalized predictive control (GPC) algorithm to identify and control the real systems [3] [22] [23] [24]. However, the WN-based GPC method that has been used is hard to promise a good performance for controlling the real-time industrial process that data is available in sequential version. Moreover, the optimization methods that they used, didn’t take in consideration the input and output constraints and the system uncertainties with disturbances. Also, the learning algorithms that has been used by the authors in [3], [22], [23], and [24] to train WN was incapable to be use of online so it can update the network weights when the system parameters changes. The weight updating is necessary for adaptive MPC controller algorithm so it can be robust against any sudden changes in the system or any interfering of the input and output disturbances.

Therefore, this work proposed a method for developing an adaptive model predictive control system coupled with WN-OSELM to solve the optimal control problem online with constraint and be robust by keeping the ability to deal efficiently with system uncertainties and the input output disturbances. For the reason of online learning and stochastic gradient descent methods are closely related and interchangeable [25]. An adaptive gradient descent (AGD) method introduced to solve online the optimal control problem with constraints. The conventional gradient descent with online search algorithms has drawbacks of the slow convergence because of the step size values which is updated proportionally to the gradient size not to the gradient direction (mathematically the sign of the gradient) [26].

On this regard, an adaptive updating rate (AUR) algorithm developed to find the optimal step size based on Resilient Back Propagation (RPROP) algorithm. In order to determine the upper and lower limits of the step size, the Lyapunov stability theorem applied to find the conditional limits that grantee a stable path to minimize the objective function.

The proposed wavelet network based model predictive controller (WNMPC) applied to different nonlinear systems and evaluated in terms of control accuracy, generalization ability, and robustness against uncertainties. These evaluations conducted as a comparative study with other common related controllers, namely an NNMPC controller [27] [3] and NARMA-L2 [28].

1.2 Problem Statement and Motivation

In a model predictive control design, the first concern is how to design an accurate control-oriented model for the plant that is able to capture the most significant dynamics of the system. Later on is how to design a proper predictive controller that generates an optimal control signals with robust performance. However, in this regard a list of problems is relevant:

1. The conventional gradient descent based learning algorithms (including BP) that has been used with wavelet networks based MPC approaches are not proper for online learning process, because it may involve many iterations through the updated data sets, and this may be computationally expensive, especially when the inversion of Hessian matrix needed [19].

2. The linearization process on the identified WN model by dividing into several local operating identifiers [3], [22], [29], may lead the prediction for the future process behavior in MPC scheme to be insufficient and causes inaccurate result.

3. Using WN-ELM with MPC as control-oriented plant model may allow facing problems of high memory size when large training samples are involved. That because of its batch training mode, which may impose the nonlinear quadratic programming problem of the MPC to face a real challenge to find an efficient solution online.

4. Despite of fast and accurate facility using NN-OSELM as control-oriented plant model with MPC algorithms may produce an inaccurate open loop responses because of the network initialization procedure as mentioned in the above sections, and this may deranged all the MPC schemes.

5. Moreover, there is a need for an online plant identifier that capable to combine with MPC algorithm and guarantee system stability by solving the optimization problem with constraints online adaptively with better computational time.

1.3 Research Objectives

In general, the aim of this work is to model nonlinear system accurately using a system identification procedure that allows updating its parameters sequentially online in association with adaptive model predictive control scheme for real-time control application. Moreover, the approaches attempt to cover all these objectives;

1. Design LWN-OSELM nonlinear system identifier by first designing WN-OSELM which will be able to perform useful generalization facility and modeling accuracy by using wavelet functions properties and inspective initialization technique. Second by embedding a linear term to the WN-OSELM frame to help identifying both linear and nonlinear characteristics of the nonlinear dynamic systems also to help the learning algorithm to start with a stable beginning using linear weights initially. Furthermore, this may help to produce minimally an initial solution for the sequence of control actions of MPC scheme when the plant has an open loop unstable response.

2. Design an adaptive MPC scheme based on the designed LWN-OSELM model by developing an adaptive updating rule (AUR) algorithm using Lyapunov stability analysis so it guarantees the robustness and optimal performance.

3. To use LWN-OSELM with adaptive modelling predictive controller and apply this method for implementation on laboratory based conveyor-belt type grain dryer system using experimentally collected real data. The expected performance is better accuracy and robust control performances.

1.4 Scope of Study and The contributions

In this work, a WN-OSELM is introduces for nonlinear system modeling and control application to overcome the NN-OSELM problems. The architecture of WN-OSELM is embedded with a linear term to construct LWN-OSELM that enhances the convergence speed and stabilizes the learning algorithm, hence helps the MPC scheme to find initial solution at the beginning of control. The theoretical analysis need to be carried out to prove the adoption of OSELM with WN and LWN architectures.

On the other hand, a constrained quadratic optimization problem needs to be solved by stochastic gradient descent (GD) method adaptively using Lyapunov stability analysis. Therefore, an adaptive AUR algorithm based on stability conditions is designed for optimal step size to guarantee stability and fast convergence. However, utilizing the LWN-OSELM in nonlinear system modeling and then conjoining it with adaptive MPC can construct the proposed WNMPC controller that is able to deal with real time application. In this work, an experimental data for actual nonlinear system namely, conveyor-belt type grain dryer was handled to perform real data modeling using LWN-OSELM and then applying the WNMPC controller to evaluate of the optimal control performance and the capability of dealing with uncertainties robustly.

1.5 Thesis Outline

This thesis is organized according to the following plan; after the general introduction presented in this chapter, Chapter 2 introduces general concepts of two major parts of the work. The first part is on nonlinear system identification techniques using wavelet networks and the second part is on model predictive control schemes based on neural networks and wavelet networks models.

Chapter 3 presents the detailed methodologies of the proposed methods to achieve the objectives of the present work, namely, the WN and LWN based OSELM as well as WNMPC controller. These methods through theoretical analysis and design by driving the control law formulas, the stability analysis of the proposed WNMPC is carried out to develop an adaptive updating rule for the step size of the GD optimization problem.

Chapter 4 presented in two parts, the first is simulations for modeling using WN-OSELM, LWN-OSELM, and NN-OSELM applied on three different types of nonlinear dynamic systems then evaluation the results with model validation tests and learning feasibility using root mean square error.

The second part is the WNMPC controller simulations carried on two nonlinear systems to evaluate the ability of the proposed controller to control different nonlinear systems in terms of control accuracy, generalization ability, and robustness. In addition, a comparison using the performance index criteria are detailed between the proposed controller and other common related controllers, namely an NNMPC controller and NARMA-L2.

Chapter 5 focuses on the 6th objective of this work, which is modeling a laboratory based grain dryer type conveyor-belt using LWN-OSELM with an experimentally collected input output data set. Well after, the WNMPC controller is applied to evaluate the performances of modeling and the robustness of the controller. In particular, this chapter also presents the works related to the cross-flow conveyor-belt type grain dryers with basic information on grain drying system modeling and control. Furthermore, the simulations will perform with a comparative study between the proposed method and both the NN-OSELM and ANFIS models. Moreover, the results of controlling the drying system by the WNMPC introduced and compared with the simplified ANFIS controller.

To finish, Chapter 6 conducted for comparisons and discussion on Chapter 4 and 5 results while Chapter 7 for conclusions and future work.

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