APPLICATION OF ARTIFICIAL NEURAL NETWORK – GENETIC ALGORITHM IN INFERENTIAL ESTIMATION AND CONTROL OF A DISTILLATION COLUMN

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APPLICATION OF ARTIFICIAL NEURAL NETWORK – GENETIC ALGORITHM IN INFERENTIAL ESTIMATION AND CONTROL OF A DISTILLATION COLUMN

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requirements for the award of the degree of
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To my beloved FATHER and MOTHER, dearest ANN
for their love and support

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ABSTRACT

Adaptation of network weights using Genetic Algorithm (GA) was proposed as a mechanism to improve the performance of Artificial Neural Network (ANN) inferential estimator. This is particularly useful for cases involving changing operating condition as well as highly nonlinear processes. As a case study, a fatty acid distillation process was considered. The ANN model trained using GA, employed as inferential estimator was successful in providing on-line estimates to a reasonable accuracy. Comparisons were also made to the feedforward network model trained using Levenberg-Marquardt (LM) training algorithm as well as Elman network. When implemented on-line, GA-based ANN model was proved to be more efficient. The use of on-line retraining further improved the estimator performances. To avoid drastic changes of network weights, a partial network on-line retraining strategy was introduced. In this case, the estimator model did not undergo on-line retraining, but a newly introduced bias model, attached to the main estimator was used for the fine-tuning purposes. Significant improvements were obtained especially when assessing from the perspective of model generalization. The results obtained in this work confirmed the potential of using model update strategy for neural network process estimator.

ABSTRAK

Penyesuaian pemberat rangkaian dengan menggunakan algoritma genetik (GA) telah dikemukakan sebagai satu mekanisma untuk memperbaiki prestasi penganggar taabir rangkaian saraf buatan (ANN). Ini adalah amat memanfaatkan bagi kes-kes yang melibatkan perubahan keadaan operasi dan juga proses kimia yang mempunyai kelakuan tak linear yang tinggi. Sebagai kes kajian, sebuah proses penyulingan asid lemak telah dipertimbangkan. Model ANN yang dilatih dengan kaedah GA telah digunakan sebagai penganggar taabir, dan berjaya memberikan keputusan anggaran secara dalam talian dengan kejituan yang memuaskan. Perbandingan prestasi turut dibuat antara model rangkaian feedforward dan Elman yang dilatih dengan kaedah Levenberg-Marquardt (LM). Apabila model-model ini diapplikasi secara dalam talian, model rangkaian neural yang berasaskan GA telah dibuktikan lebih berkesan. Penggunaan mekanisma latihan semula secara dalam talian telah memperbaikikan lagi prestasi anggaran. Untuk mengelakkan perubahan mendadak terhadap pemberat rangkaian, strategi latihan semula separa rangkaian telah diperkenalkan. Dalam kes ini, model anggaran tidak mengalami latihan semula secara dalam talian. Sebaliknya, sebuah model sampingan baru yang berhubung dengan model anggaran utama telah diperkenalkan untuk tujuan penyelarasan rapi. Peningkatan yang nayta tercapai terutamanya dari segi generalisasi model. Keputusan yang diperoleh dalam kajian penyelidikan ini telah mengesahkan potensi penggunaan strategi pengemaskinian model dalam anggaran proses rangkaian neural.

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LIST OF ABBREVIATIONS

ANN	Artificial Neural Network
BL	Boltzmann learning
BP	backpropagation
CL	competitive learning
DCS	distributed control system
DDE	dynamic data exchange
EA	Evolutionary Algorithms
ECL	error-correlation learning
ELM	Elman network
EP	Evolutionary Programming
EPNN	Evolutionary Polymorphic Neural Network
ES	Evolutionary Strategies
FF	feedforward network
FPM	first principle model
GA	Genetic Algorithm
GC	gas chromatography
GP	Genetic Programming
HETP	height equivalent theoretical plate
HL	Hebbian learning
LM	Levenberg-Marquardt
MAPE	mean absolute percentage error
MIMO	multi input multi output
MISO	multi input single output
MPC	model predictive control
MSE	mean square error
OLE	objects linking and embedded

PCA	principal component analysis
PCOC	Pan Century Oleochemical Company
PHS	palm hydrogenated stearine
PI	proportional integral
PID	proportional integral derivative
PKFA	palm kernel fatty acid
PKO	palm kernel oil
PLS	partial least squares
PRBS	pseudo-random binary sequence
PSHFA	palm stearine hydrogenated fatty acid
RMSE	root mean square error
SISO	single-input single-output
SSE	sum square error
SVD	singular value decomposition
UNIQUAC	UNIversal QUAsi Chemical

LIST OF SYMBOLS

B	bottom flow
b	internal bias
D	distillate flow
e	error function
f	transfer function
J	Jacobian matrix
K	static gain
K_c	proportion gain
K_T	temperature gain matrix
L	reflux flow
M	manipulated variable
N	total number of data
N_{hdn}	number of hidden nodes
N_{inp}	number of input nodes
N_{out}	number of output nodes
N_{trn}	number of training data
N_{wgh}	total number of weights
P	vapour pressure of the liquid-vapor mixture
p	population size
T	temperature of the liquid-vapor mixture
t	generation counter
t_d	dead time
U	left singular vectors
V	vapor flow
V	right singular vectors
v_i	variables

$v_i^{\max}$	maximum value of variables
$v_i^{\min}$	minimum value of variables
v_i^{norm}	normalize variables
w_{i}	weight factor
x_{i}	neuron input
x_D^{C-12}	mole fraction of C-12 in distillate stream
x_F^{C-12}	mole fraction of C-12 in feed stream
y	neuron output
y	actual composition
$\hat{y}$	estimated composition
y^b	output of the bias model
y^m	output of the main model
Z_i	absolute value of difference between the two *U* vectors

a ?	online evolution tuning parameter
Σ	singular value
l_1	minimum value of interval
l_2	maximum value of interval
t	effective time constant
t_I	integral time constant
t_D	derivative time constant

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CHAPTER 1

INTRODUCTION

1.1 Motivation

Over the years, the application of Artificial Neural Network (ANN) in process industries has been growing in acceptance. This is because ANN is capable of capturing process information in a black box manner. Given sufficient input-output data, ANN is able to approximate any continuous function to arbitrary accuracy. This has been proven in various fields such as pattern recognition, system identification, prediction, signal processing, fault detection and others.

In general, the development of a good ANN model depends on several factors. The first factor is related to the data being used. This is consistent with other black box models where model qualities are strongly influenced by the quality of data used. The second factor is network architecture or model structure. Different network architecture results in different estimation performance. Commonly, multilayer perceptron and its variances are widely used in process estimation. The third factor is the model size and complexity. What is required is a parsimonious model. This is because a small network may not able to represent the real situation due to its limited capability, while a large network may overfit noise in the training data and fail to provide good generalization ability. Finally, the quality of a process model is also strongly dependent on network training. This stage is essentially an identification of model parameters that fits the given data; and is perhaps the most important factor among all.

This work focuses on the last issue. The aim is to improve the estimation capability of ANN regardless of the network architecture. Until today, many researchers still prefer use gradient search method – Backpropagation (BP) in training ANN. Among all the backpropagation methods, Levenberg-Marquardt (LM) algorithms is the most widely used. Some of the advantages of this gradient-based technique include its efficient implementations, good at fine-tuning and faster convergence when compared to other methods. However, these techniques are local search methods and when applied to complex nonlinear optimization problems, can sometimes result in inconsistent and unpredictable performances. One of the main hindrances due to the fact that searching of optimal weights is strongly dependent on initial weights and if they are located near local minima, the algorithm would be trapped.

Several different attempts have been proposed by various researchers to alleviate this training problem. These include imposing constraints on the search space, restarting training at many random points, adjusting training parameter and restructuring the ANN architecture (Sexton *et al.*, 2002). However, some approaches are problem-specific and not well accepted and different researchers tend to prefer different methodologies. Among these, one of the more promising techniques is by introducing adaptation of network training using Genetic Algorithm (GA).

Unlike BP, GA is a global search algorithm based on the principle “survival of fittest”. It simultaneously searches for solutions in several regions, thus increasing the probability of global convergence. Furthermore, since it is impossible to formulate an a priori exact model of the system, a more practical approach is off-line set up a rough model, followed by on-line update of the model using GA. In this way, the merging of GA and ANN will gain adaptability to dynamic environment and lead to significantly better intelligent systems than relying on ANN or GA alone. In other words, the ANN-GA model developed should be more robust to dynamic nonlinearity of the process involved.

In this work, the ANN-GA model is used for inferential estimation and control of product composition in a distillation column. The aim is to address the difficulty in measuring product quality in process plants. Most quality variables in process industries require some kinds of analysis to be carried out. The use of on-line analyzer for product quality variables has been limited due to large measurement delay, the need for frequent maintenance as well as high capital and operating costs. In order to adapt to changing market conditions while maximizing profit, the demand for accurate inferential estimators for controlling the product quality variable becomes paramount. For this reason, this work introduces evolution of connection weights in ANN using GA as means of improving adaptability of the resulting estimators.

1.2 Objective and Scope of Work

The objective of this work was to develop an accurate and robust ANN based estimator by using GA as performance enhancer. The implementation of inferential estimator was extended for chemical product composition control in a fatty acid distillation column. To satisfy the intended objective, the following scope of works was carried out.

1. Analysis of open-loop dynamic and process interaction of the selected distillation column.
2. Development of ANN based inferential estimator for product compositions using other secondary measurements.
3. Development of ANN-GA estimator and comparison with ANN model trained with conventional method.
4. Investigation of the issue of training data and its influence on the accuracy and robustness of the model.
5. Application in inferential control of a fatty acid composition and comparison with temperature control strategy.
6. Attempts in improving the robustness of ANN for control application, including on-line retraining strategy to gain adaptation feature.

1.3 Contribution of This Work

This work has proposed an enhancement to neural network model. Aiming at improving the model robustness, evolution in network connection weights using GA was highlighted. The ANN-GA model was implemented in inferential estimation and control scheme for distillate composition. Investigation on the training data used in model development was carried out and its influence on the robustness of the model was discussed. Based on that, on-line retraining to allow automatic update of network weights was proposed as a strategy to increase adaptability to dynamic environment.

1.4 Layout of the Thesis

Following this introductory chapter is Chapter 2 that elaborates some of the fundamental theory about ANN such as network architecture and training algorithm. Literatures on applications of ANN in chemical engineering are also highlighted. This is followed by the discussion on GA and the motivation to include evolution in ANN modelling using GA. Lastly, the basic concept of inferential estimation and control as well as its application in the process industry is reported.

In Chapter 3, the research methodologies involved are described and the background of the case study in this work is also presented. This is followed by the preparatory works for ANN model development such as sensitivity analyses and model input selection. Subsequently, data generation procedure for model development is described in detail. Procedures of ANN model development also been discussed in briefly. The end of this chapter summarizes the method in performance evaluation for this project.

Chapter 4 commences with the discussion on the description of network architecture specification and training process. This is then followed by the application of inferential estimation using different types of estimator. The implementation of estimators is extended in the inferential control of product composition. Results in regulator and servo control problems are displayed and discussed.

Chapter 5 discusses the investigation on model input data when there exist environment changing. On-line retraining strategy is then proposed to improve model robustness. Finally Chapter 6 summarized the thesis and concludes all the findings. To provide guidance for the prospectus researchers, some recommendations for future works are also listed.

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