

การใช้ข่ายงานนิเวศชนิดป้อนไปข้างหน้าแบบหลายชั้น
สำหรับการระบุระบบ การประมาณค่าฟังก์ชัน และการควบคุมขั้นสูง

นางสาวจุฑาทิพย์ เพชรเชิดศักดิ์



สถาบันวิทยบริการ
วิทยานิพนธ์นี้เป็นส่วนหนึ่งของการศึกษาตามหลักสูตรปริญญาวิศวกรรมศาสตรมหาบัณฑิต
สาขาวิชาวิศวกรรมเคมี ภาควิชาวิศวกรรมเคมี
บัณฑิตวิทยาลัย จุฬาลงกรณ์มหาวิทยาลัย

ปีการศึกษา 2542

ISBN 974-333-147-6

ลิขสิทธิ์ของบัณฑิตวิทยาลัย จุฬาลงกรณ์มหาวิทยาลัย

**USE OF MULTILAYER FEEDFORWARD NETWORKS FOR
SYSTEM IDENTIFICATION, FUNCTION APPROXIMATION,
AND ADVANCED CONTROL**



Miss Jutatip Petcherdsak

สถาบันวิทยบริการ
จุฬาลงกรณ์มหาวิทยาลัย

**A Thesis Submitted in Partial Fulfillment of the Requirements
for the Degree of Master of Engineering in Chemical Engineering**

Department of Chemical Engineering

Graduate school

Chulalongkorn University

Academic Year 1999


ISBN 974-333-147-6

Thesis Title Use of Multilayer Feedforward Networks for System
 Identification, Function Approximation, and Advanced Control
By Miss Jutatip Petcherdsak
Department Chemical Engineering
Thesis Advisor Assist. Prof. Paisan Kittisupakorn

Accepted by the Graduate School, Chulalongkorn University in Partial
Fulfillment of the Requirements for the Master's Degree


..... Dean of Graduate School
(Associate Professor Suchada Kiranandana, Ph.D.)

THESIS COMMITTEE


..... Chairman
(Associate Professor Ura Pancharoen, D.Eng.Sc.)


..... Thesis Advisor
(Assistant Professor Paisan Kittisupakorn, Ph.D.)


..... Member
(Assistant Professor Tawatchai Charinpanitkul, D.Eng.)


..... Member
(Dr. Hathaichanok Duriyabunfeng, Ph.D.)

จุทาทิพย์ เพชรเชิดศักดิ์: การใช้ข่ายงานนิวรัลชนิดป้อนไปข้างหน้าแบบหลายชั้นสำหรับการระบุระบบ การประมาณค่าฟังก์ชัน และการควบคุมขั้นสูง (USE OF MULTILAYER FEEDFORWARD NETWORKS FOR SYSTEM IDENTIFICATION, FUNCTION APPROXIMATION, AND ADVANCED CONTROL) อ. ที่ปรึกษา : ผศ. ดร. ไพศาล กิตติคุณกร ; 194 หน้า.

ISBN 974-333-147-6

ข่ายงานนิวรัลชนิดป้อนไปข้างหน้าแบบหลายชั้นสำหรับการระบุระบบ การประมาณค่าฟังก์ชัน และการควบคุมขั้นสูงได้นำมาศึกษาในมานวิจัยนี้ อัลกอริธึมการกระจายค่าความผิดพลาดย้อนกลับ และอัลกอริธึมเลเวนเบอร์-มาร์ควอดท์ได้นำมาใช้เพื่อฝึกข่ายงานนิวรัล

สำหรับการระบุระบบ ข่ายงานนิวรัลได้ถูกฝึกด้วยข้อมูลอินพุท-เอาท์พุทจริงของโรงงาน เพื่อเรียนรู้ไดนามิกของระบบอะเซทิลีนไฮโดรจิเนชันแบบพรอนท์-เอนด์ทางอุตสาหกรรม พบว่า ข่ายงานนิวรัลที่ถูกฝึกแล้ว ให้ผลการทำนายที่ดีที่สุดในชุดข้อมูลที่ใช้ในการฝึกและการทดสอบ โดยมีค่าความผิดพลาดสัมพัทธ์เฉลี่ยสูงสุด 8 เปอร์เซ็นต์

สำหรับการประมาณค่าฟังก์ชัน ข่ายงานนิวรัลได้ถูกฝึกด้วยข้อมูลที่ได้จากการเลียนแบบของเครื่องปฏิกรณ์ถังกวนแบบต่อเนื่อง (ซีเอสทีอาร์) เพื่อที่จะประมาณค่าฟังก์ชันในอัลกอริธึมการควบคุมแบบเงินเนอริกโมเดล (จีเอ็มซี) โดยอยู่บนพื้นฐานของอุณหภูมิของสารหล่อเย็น และอุณหภูมิของถังปฏิกรณ์ จะเห็นได้ว่า การใช้ตัวประมาณข่ายงานนิวรัลในจีเอ็มซีสามารถปรับปรุงสมรรถนะการควบคุมของจีเอ็มซี ภายใต้การทดสอบในการติดตามเซ็ทพอยท์และการกำจัดตัวรบกวนระบบ ในสภาวะปกติและมีความไม่สอดคล้องกันของแบบจำลองของโรงงานและแบบจำลองที่นำมาศึกษา

สำหรับการควบคุมขั้นสูง ข่ายงานนิวรัลได้ถูกฝึกให้เรียนรู้แบบจำลองไปข้างหน้า และแบบจำลองย้อนกลับของซีเอสทีอาร์ แบบจำลองแรกถูกใช้เพื่อเลียนแบบแบบจำลองของกระบวนการ ส่วนแบบจำลองอีกแบบได้ถูกใช้เป็นตัวควบคุมในอัลกอริธึมการควบคุมแบบมีแบบจำลองภายในไม่เชิงเส้น (เอ็นไอเอ็มซี) จะเห็นได้ว่า ตัวควบคุมข่ายงานนิวรัลที่อยู่บนพื้นฐานของแบบจำลองย้อนกลับ สามารถควบคุมอุณหภูมิของเครื่องปฏิกรณ์ที่เซ็ทพอยท์ในกรณีที่ระบบได้ถูกทดสอบในการติดตามเซ็ทพอยท์ อย่างไรก็ตาม ตัวควบคุมข่ายงานนิวรัลให้ออฟเซตเมื่อระบบถูกทดสอบในการกำจัดตัวรบกวนระบบ ดังนั้นตัวควบคุมแบบพีไอได้นำมาใช้เข้าไปในลูฟการควบคุมเพื่อที่จะกำจัดออฟเซต ด้วยเหตุนี้จึงได้รับสมรรถนะการควบคุมแบบปราศจากออฟเซต

ภาควิชา วิศวกรรมเคมี

สาขาวิชา วิศวกรรมเคมี

ปีการศึกษา 2542

ลายมือชื่อนิสิต จุทาทิพย์ เพชรเชิดศักดิ์

ลายมือชื่ออาจารย์ที่ปรึกษา ไพศาล กิตติคุณกร

ลายมือชื่ออาจารย์ที่ปรึกษาร่วม

3970308521 : MAJOR CHEMICAL ENGINEERING

KEY WORD: NEURAL NETWORKS / BACKPROPAGATION / LEVENBERGE-MARQUARDT / ADVANCED CONTROL

JUTATIP PETCHERDSAK: USE OF MULTILAYERED FEEDFORWARD NETWORKS FOR SYSTEM IDENTIFICATION, FUNCTION APPROXIMATION, AND ADVANCED CONTROL.

THESIS ADVISOR: ASSIST. PROF. PAISAN KITTISUPAKORN, Ph.D. 194 pp.
ISBN 974-333-147-6

Multilayer feedforward networks for system identification, function approximation, and advanced control are studied in this research. Error backpropagation and Levenberge-Marquardt algorithms have been employed to train the neural networks.

For system identification, the neural networks are trained with actual plant input-output data to learn the plant dynamics of an industrial front-end acetylene hydrogenation system. It can be seen that the trained neural networks give good prediction results in both training data set and testing data set with maximum average relative error of 8%.

For function approximation, the neural networks are trained with simulated data of a Continuous Stirred Tank Reactor (CSTR) in order to approximate a function in the Generic Model Control (GMC) algorithm based on the coolant temperature and the reactor temperature. It can be seen that the incorporation of neural network approximator in the GMC can improve the GMC control performance under the disturbance rejection and set point tracking tests in a nominal condition and the presence of plant-model mismatches.

For advanced control, the neural networks are trained to learn the forward model and the inverse model of the CSTR. The first one is used to simulate the process model and the other one is used as a controller in the Nonlinear Internal Model Control (NIMC) algorithm. It can be seen that the neural network controller based on the inverse model can control the reactor temperature at its set point when the system is tested with set point tracking. However, it produces some offsets when the system is tested with disturbance rejection. Consequently, the PI controller is added into the NIMC control loop in order to get rid of the offsets. As the results, offset-free control performances are obtained.

สถาบันวิทยบริการ
จุฬาลงกรณ์มหาวิทยาลัย

ภาควิชา.....วิศวกรรมเคมี.....

สาขาวิชา.....วิศวกรรมเคมี.....

ปีการศึกษา..... 2542.....

ลายมือชื่อนิสิต..... จุตาทิพ เพ็ชรเดชา.....

ลายมือชื่ออาจารย์ที่ปรึกษา..... ทัศนัย กิตติสุภกรณ์.....

ลายมือชื่ออาจารย์ที่ปรึกษาร่วม..... -.....

Acknowledgements



I would take this opportunity to express my affection and high regard for all of those individuals who have, in various ways, contributed to this thesis.

First, I wish to gratefully acknowledge the Thai Olefin Company, Map Ta Phut Industrial Estate, Rayong, especially Dr. Kongkrapan Intarajang, Miss Pornwanchalee Thongyai and all staff in the Research and Development Department, for their information support.

I would like to sincerely thank Assistant Professor Paisan Kittisupakorn, my advisor, for providing me valuable guidance and directions for the completion of this research and thesis as well as giving me a chance to research at the University of Malaya, Kuala Lumpur, Malaysia. I am profoundly thankful for his support and his exceptional advice. Additionally, he has devoted his valuable time to correct my thesis.

I would like to express my special appreciation to the other three members of my committee, Associate Professor Ura Pancharoen, Assistant Professor Tawatchai Charinpanitkul, and Dr. Hathaichanok Duriyabunleng for serving on my thesis committee and providing valuable recommendations for the improvement of this thesis.

For the recommendations about the neural networks, I wish to thank Dr. Mohamed Azlan Hussain, for his supervision and recommendation while I was researching at the University of Malaya. His advice, particularly about the neural networks, is very beneficial to my research works. Moreover, I wish to thank Assistant Professor Karlene A. Hoo, Department of Chemical Engineering, University of South Carolina, Columbia, for her useful recommendations. She has given her valuable time to immediately reply me all questions I mailed to her. And I wish to thank Mr. Santi Limpornchaicharoen, my senior friend for his useful advice about neural network programming.

I would like to thank my friends, colleagues and all staff, in the Department of Chemical Engineering, University of Malaya and Chulalongkorn University for their help and friendliness.

Finally, the most special and important persons I deeply would like to be grateful and thankful are my parents who love me, guide me, encourage me, and support me in any way they can do and also my beloved friends.

Jutatip Petcherdsak

Table of Contents

	Page
Abstract in Thai	iv
Abstract in English	v
Acknowledgements	vi
Table of Contents	viii
List of Figures	xii
List of Tables	xvii
Nomenclature	xviii
Chapter 1 Introduction	1
1.1 Artificial Neural Networks.....	2
1.2 Modeling Approaches.....	3
1.3 Control Systems.....	4
1.4 Research Objectives.....	5
1.5 Scope of the Work.....	5
1.6 Organization of the Thesis.....	6
Chapter 2 Literature Review	8
2.1 Types of Artificial Neural Networks.....	8
2.2 Chemical Process Modeling and Identification with Neural Networks.....	11
2.2.1 Black-box Modeling Approach.....	11
2.2.2 Gray-box Modeling Approach.....	16
2.3 Neural Network Applications in Control Systems.....	20

2.3.1 Model Predictive Control Technique.....	22
2.3.2 Inverse-Model-Based Technique.....	28
2.3.3 Adaptive Control Technique.....	35
2.3.4 Neural Network Applications in Other Control Techniques.....	40
2.4 Other Applications of Neural Networks in Chemical Engineering.....	41
Chapter 3 Neural Network Fundamentals	43
3.1 Origin and Development of Neural Networks.....	43
3.2 Types of Neural Networks.....	45
3.2.1 Structural Categorization.....	45
3.2.2 Learning Algorithm Categorization.....	46
3.3 Multilayer Feedforward Networks.....	48
3.3.1 Feedforward Network Architecture.....	48
3.3.2 Functions of a Neuron.....	50
3.4 Backpropagation Algorithm.....	52
Chapter 4 System Identification with Neural Networks	58
4.1 Introduction.....	58
4.2 Identification.....	59
4.2.1 Forward Modeling.....	59
4.2.2 Inverse Modeling.....	62
4.3 System Identification Steps.....	66
4.3.1 Model Structure and Size.....	66
4.3.2 Data Set.....	66
4.3.3 Input Excitation.....	67
4.3.4 Input and Output Data.....	67
4.3.5 Weight Initialization.....	68
4.3.6 Training Methodology.....	68
4.3.7 Model Validation.....	69

Chapter 5	Neural Network Modeling of an Acetylene Hydrogenation System	72
5.1	Introduction.....	72
5.2	Ethylene Manufacturing.....	73
5.3	Types of Acetylene Hydrogenation Systems.....	75
5.3.1	Front-end Type.....	76
5.3.2	Tailed-end Type.....	77
5.4	Literature Review on Acetylene Hydrogenation Systems.....	79
5.5	Neural Network Modeling of an Acetylene Hydrogenation System.....	80
5.5.1	Process Description.....	80
5.5.2	Plant Data Used.....	81
5.5.3	Neural Network Modeling.....	82
5.5.4	Results and Discussions.....	92
Chapter 6	Neural Networks as a Function Approximator in Generic Model Control	93
6.1	Introduction.....	93
6.2	Generic Model Control Formulation.....	94
6.3	Continuous Stirred Tank Reactor.....	95
6.4	Results and Discussions.....	114
Chapter 7	Neural Network Model and Controller in Nonlinear Internal Model Control	117
7.1	Nonlinear Internal Model Control.....	117
7.2	Neural Network Forward Modeling.....	118
7.3	Neural Network Inverse Modeling.....	121
7.4	Results and Discussions.....	146
Chapter 8	Conclusions and Recommendations for Future Work	151
8.1	Summary	151
8.2	Conclusions.....	153
8.3	Recommendations for Future Work.....	154

References	156
Appendix A Neural Network Toolbox	171
A.1 Neural Network Toolbox.....	172
A.2 Training Functions.....	172
A.3 Speed and Memory Comparison of Training Function.....	179
Appendix B Backpropagation Algorithm	181
B.1 Conclusion of Backpropagation Algorithm.....	181
B.2 Example of Calculation.....	183
Appendix C Signal Processing and Data Filtering	186
C.1 Analog Filters.....	186
C.2 Digital Filters.....	187
C.2.1 Exponential Filter.....	187
C.2.2 Double Exponential Filter.....	188
C.2.3 Moving Average Filter.....	189
C.2.4 Noise-Spike Filter.....	190
Appendix D Tuning of Generic Model Controller	192
Vita	194

List of Figures

		Page
2.1	Multilayer feedforward network architecture with one hidden layer.....	9
2.2	Recurrent neural network architecture.....	10
2.3	Radial basis function network architecture.....	11
2.4	Neural networks in general model predictive control strategy.....	21
2.5	Neural networks in internal-model-control strategy.....	28
2.6	Direct adaptive control.....	35
2.7	Indirect adaptive control.....	36
3.1	General structure of feedforward network with one hidden layer.....	49
3.2	Functions of a neuron.....	51
3.3	Sigmoid function.....	52
3.4	Forward flow of information or data (arrows) and backward flow of error (dashed lines) in a backpropagation type of neural network.....	57
4.1	Identification.....	60
4.2	Series-parallel identification structure.....	61
4.3	Parallel identification structure.....	62
4.4	Direct inverse modeling.....	63
4.5	Specialized inverse modeling.....	65
4.6	Basic steps - Neural network system identification.....	71
5.1	Ethylene plant diagram with front-end acetylene hydrogenation system.....	74
5.2	Front-end acetylene hydrogenation system layout.....	75
5.3	Ethylene plant diagram with tail-end acetylene hydrogenation system.....	78
5.4	Tail-end acetylene hydrogenation system layout.....	79
5.5	Acetylene hydrogenation system.....	82
5.6	Neural network architecture representing forward model: First bed.....	83
5.7	Neural network modeling of the first bed: Training results.....	84
5.8	Neural network modeling of the first bed: Testing results.....	85
5.9	Neural network architecture representing forward model: Second bed.....	86
5.10	Neural network modeling of the second bed: Training results.....	87

5.11	Neural network modeling of the second bed: Testing results.....	88
5.12	Neural network architecture representing forward model: Third bed.....	89
5.13	Neural network modeling of the third bed: Training results.....	90
5.14	Neural network modeling of the third bed: Testing results.....	91
6.1	A schematic of continuous stirred tank reactor.....	95
6.2	Open-loop response of CSTR for +/-15% change of coolant temperature.....	97
6.3	GMC configuration with an estimator.....	98
6.4	The network implementation in GMC configuration.....	99
6.5	Neural network structure representing function approximator.....	100
6.6	Disturbance rejection test with GMC and GMC-NN. Response to 10% load disturbance in the measured feed temperature.....	102
6.7	Disturbance rejection test with GMC and GMC-NN. Response to 10% load disturbance in the unmeasured feed concentration...	103
6.8	Disturbance rejection and robustness tests with GMC and GMC-NN. Response to 10% load disturbance in the measured feed temperature and 20% model error in the pre-exponential constant.....	104
6.9	Disturbance rejection and robustness tests with GMC and GMC-NN. Response to 10% load disturbance in the unmeasured feed concentration and 20% model error in the pre-exponential constant.....	105
6.10	Disturbance rejection and robustness tests with GMC and GMC-NN. Response to 10% load disturbance in the measured feed temperature and -50% model error in the heat transfer coefficient.....	106
6.11	Disturbance rejection and robustness tests with GMC and GMC-NN. Response to 10% load disturbance in the unmeasured feed concentration and -50% model error in the heat transfer coefficient.....	107
6.12	Disturbance rejection and robustness tests with GMC and GMC-NN. Response to 10% load disturbance in the measured feed temperature and 10% model error in the heat of reaction.....	108
6.13	Disturbance rejection and robustness tests with GMC and GMC-NN. Response to 10% load disturbance in the unmeasured feed concentration and 10% model error in the heat of reaction.....	109
6.14	Set point tracking and robustness tests with GMC and GMC-NN.	

	Response to set point change from 440.2 K to 450 K	110
6.15	Set point tracking and robustness tests with GMC and GMC-NN. Response to set point change from 440.2 K to 450 K and 20% model error in the pre-exponential.....	111
6.16	Set point tracking and robustness tests with GMC and GMC-NN. Response to set point change from 440.2 K to 450 K and –50% model error in heat transfer coefficient.....	112
6.17	Set point tracking performance test with GMC and GMC-NN. Response to set point change from 440.2 K to 450 K and 10% model error in heat of reaction	113
7.1	Neural network architecture representing the forward model of the CSTR...	119
7.2	Neural network forward modeling of CSTR: Training result.....	120
7.3	Neural network forward modeling of CSTR: Cross validation result.....	120
7.4	Neural network forward modeling of CSTR: Testing result.....	121
7.5	Neural network architecture representing the inverse model of the CSTR...	122
7.6	Neural network inverse modeling of CSTR: Training result.....	123
7.7	Neural network inverse modeling of CSTR: Cross validation result.....	123
7.8	Neural network inverse modeling of CSTR: Testing result.....	124
7.9	Nonlinear internal model control configuration.....	125
7.10	Proposed nonlinear internal model configuration.....	125
7.11	Disturbance rejection test with NIMC. Response to 10% load disturbance of the measured feed temperature.....	127
7.12	Disturbance rejection test with NIMC. Response to 10% load disturbance of the unmeasured feed concentration	128
7.13	Disturbance rejection and robustness tests with NIMC. Response to 10% load disturbance in the measured feed temperature and 20% model error in the pre-exponential constant.....	129
7.14	Disturbance rejection and robustness tests with NIMC. Response to 10% load disturbance in the unmeasured feed concentration and 20% model error in the pre-exponential constant.....	130
7.15	Disturbance rejection and robustness tests with NIMC. Response to	

	10% load disturbance in the measured feed temperature and -50% model error in the heat transfer coefficient.....	131
7.16	Disturbance rejection and robustness tests with NIMC. Response to 10% load disturbance in the unmeasured feed concentration and -50% model error in the heat transfer coefficient.....	132
7.17	Disturbance rejection and robustness tests with NIMC. Response to 10% load disturbance in the measured feed temperature and 10% model error in the heat of reaction.....	133
7.18	Disturbance rejection and robustness tests with NIMC. Response to 10% load disturbance in the unmeasured feed concentration and 10% model error in the heat of reaction.....	134
7.19	Set point tracking test with NIMC Response to set point change from 440.2 K to 450 K.....	135
7.20	Set point tracking and robustness tests with NIMC Response to set point change from 440.2 K to 450 K and 20% model error in the pre-exponential constant.....	136
7.21	Set point tracking and robustness tests with NIMC Response to set point change from 440.2 K to 450 K and -50% model error in the heat transfer coefficient.....	137
7.22	Set point tracking and robustness tests with NIMC Response to set point change from 440.2 K to 450 K and 10% model error in the heat of reaction	138
7.23	Control performance of the GMC-NN, NIMC, and PI control Response to 10% load disturbance in the measured feed temperature.....	139
7.24	Control performance of the GMC-NN, NIMC, and PI control. Response to 10% load disturbance in the unmeasured feed concentration...	140
7.25	Control performance of the GMC-NN, NIMC, and PI control. Response to 20% model error in the pre-exponential constant and (upper) 10% load disturbance in the measured feed temperature (lower) 10% load disturbance in the unmeasured feed concentration.....	141
7.26	Control performance of the GMC-NN, NIMC, and PI control. Response to -50% model error in the heat transfer coefficient and	

	(upper) 10% load disturbance in the measured feed temperature	
	(lower) 10% load disturbance in the unmeasured feed concentration.....	142
7.27	Control performance of the GMC-NN, NIMC, and PI control.	
	Response to 10% model error in the heat of reaction and	
	(upper) 10% load disturbance in the measured feed temperature	
	(lower) 10% load disturbance in the unmeasured feed concentration.....	143
7.28	Control performance of the GMC-NN, NIMC, and PI control.	
	Response to set point change from 440.2 K to 450 K and	
	(upper) nominal case and	
	(lower) 20% model error in the pre-exponential constant.....	144
7.29	Control performance of the GMC-NN, NIMC, and PI control.	
	Response to set point change from 440.2 K to 450 K and	
	(upper) -50% model error in the heat transfer coefficient	
	(lower) 10% model error in the heat of reaction.....	145
B.1	A backpropagation network for learning the exclusive-or function.....	183
D.1	Generalized GMC profile specification.....	193

List of Tables

		Page
2.1	Description of abbreviations.....	18
2.2	Neural networks applications in simulated process modeling with black-box approach.....	19
2.3	Neural networks applications in real process modeling with black-box approach.....	20
2.4	Neural networks applications in chemical process modeling with gray-box approach.....	20
2.5	Neural network applications in predictive control techniques - simulation implementation.....	27
2.6	Neural network applications in predictive control techniques - online implementation.....	27
2.7	Neural network applications in inverse-model-based control techniques - simulation implementation.....	33
2.8	Neural network applications in inverse-model-based control techniques - online implementation.....	34
2.9	Neural network applications in adaptive control techniques - simulation implementation.....	39
2.10	Neural network applications in adaptive control techniques - online implementation.....	39
2.11	Neural networks in other applications of chemical engineering.....	42
6.1	Nominal operating condition of the continuous stirred tank reactor.....	96
6.2	Performance and robustness tests on the GMC with mass balance estimator (GMC) and the GMC with neural network approximator (GMC-NN).....	100
6.3	Comparison of the GMC and the GMC-NN control performance.....	101
7.1	Comparison of the GMC-NN, the NIMC-PI, and the PI control performance.....	126
A.1	Speed and memory comparison of training functions.....	180

Nomenclature

A	Area
C	Concentration
C_p	Heat capacity
E	Activation energy
h	Heat transfer coefficient for CSTR
$-\Delta H$	Heat of reaction
IAE	Integral absolute error
K_1, K_2	GMC tuning parameters
k_o	Arrhenius pre-exponential constant
q	Flow rate
R	Gas constant
SSE	Sum-squared error
T	Reactor temperature
V	Volume

Subscripts

A	Reactant
c	Coolant
f	Feed

Greek letters

η	Learning rate
α	Momentum parameter