Artificial Neural Network Modeling and Optimization of PEM Fuel Cells

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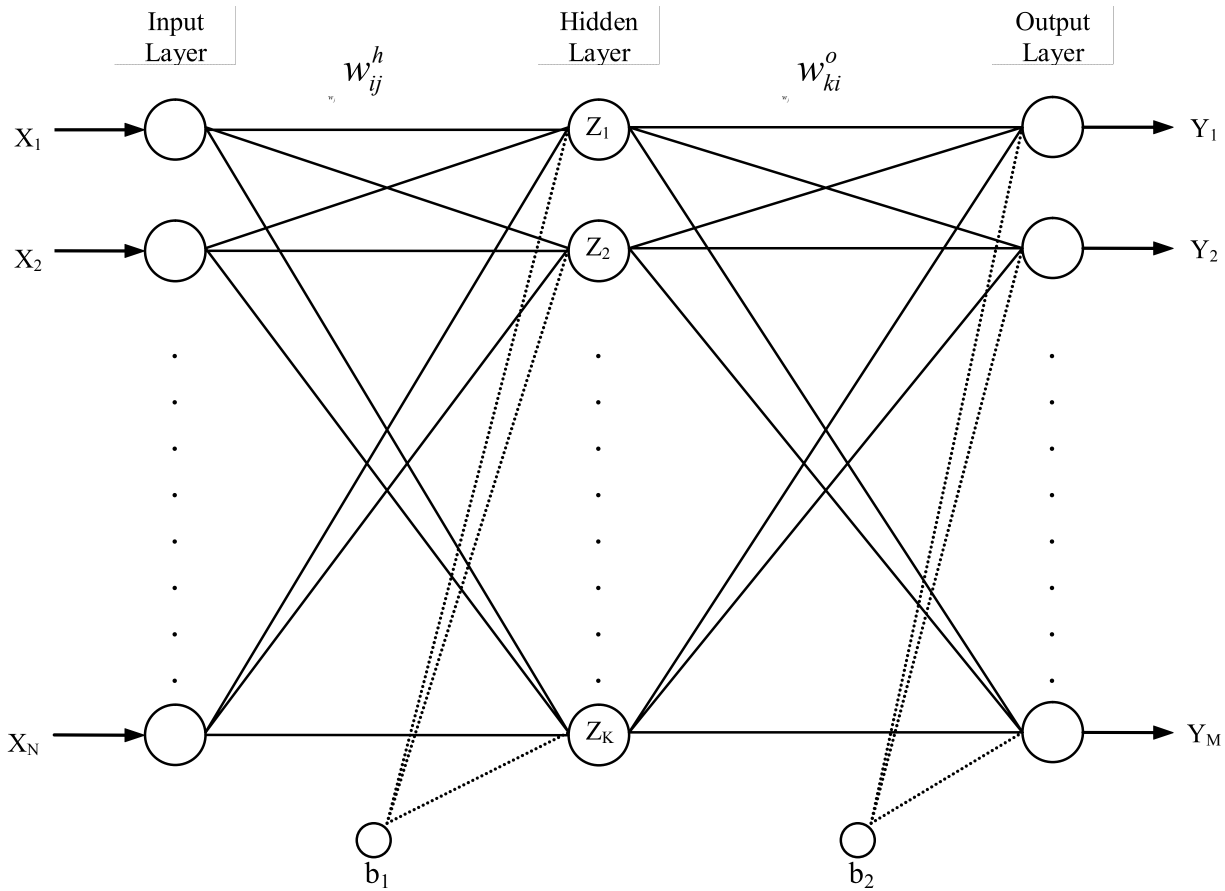
Introduction

Artificial Neural Networks (ANN) are computational paradigms made up of massively interconnected adaptive processing units.

Features:

- Nonlinearity
- High parallelism
- Fault tolerance
- Adaptivity
- Ability to tackle imprecise and fuzzy information

Introduction



A feed-forward multi-layer neural network with a single hidden layer

Introduction

ANN applications:

Artificial Neural Networks Applications	
Information processing	Pattern recognition
	Financial processing
Control	Process control (chemical, environmental and mechanical)
	Electric motor control
	Voltage control
	Robotic control
Power system	Load forecasting
	Fault detection
	Security assessment
Medical system	Medical diagnosis
	Medical signal image processing
Other applications	Signal processing
	Manufacturing production and inspection

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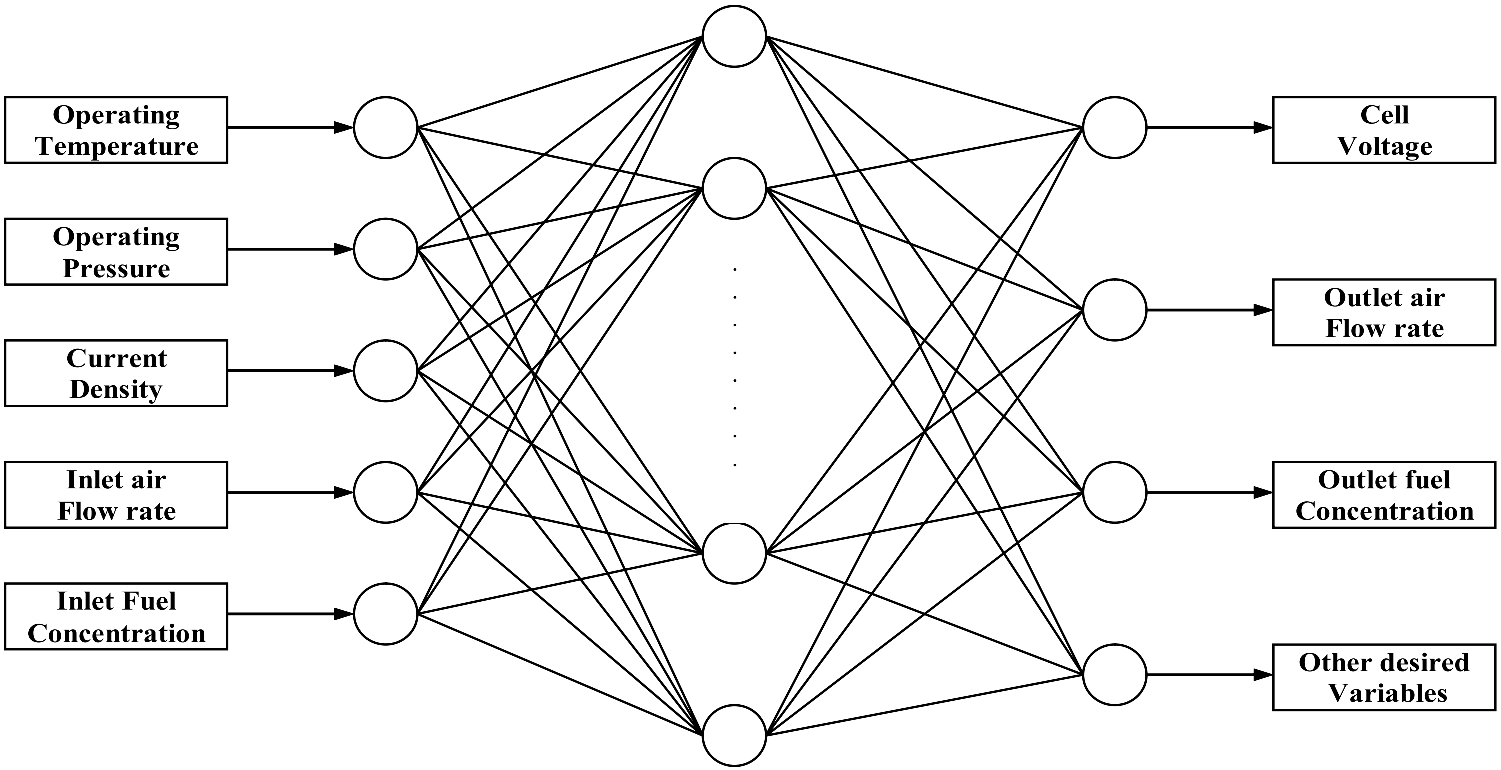
Introduction

Advantages of ANN Modeling of PEM fuel cells:

- Good multiple variables mapping capability (accurate)
- Ease to set up and use
- Computationally fast
- Able to simulate the effects of the parameters that current physical models are unable to address

Introduction

An ANN Model for PEM fuel cells



Background of ANN

Model equation for a feed-forward neural network

$$y_k = \varphi\left(\sum_{i=1}^{K} w_{ki}^{o} z_i + b_i\right) = \varphi\left(\sum_{i=1}^{K} w_{ki}^{o} \varphi\left(\sum_{j=1}^{N} w_{ij}^{h} x_j + b_1\right) + b_2\right)$$

$$\varphi(v) = \frac{1}{1+e^{-av}}$$ **(Sigmoid function)**

Background of ANN

Back-propagation feed-forward network

Algorithm for weight adjusting:

$$\Delta w = -\eta \frac{\partial E(w)}{\partial w}$$

where

$$E(w) = \frac{1}{2} \sum_{j=1}^{N} \sum_{k=1}^{M} \left(e_k^j\right)^2$$

$$e_k^j = y_k^j - t_k^j$$

Background of ANN

Radial basis function (RBF) network

Model equation for RBF network:

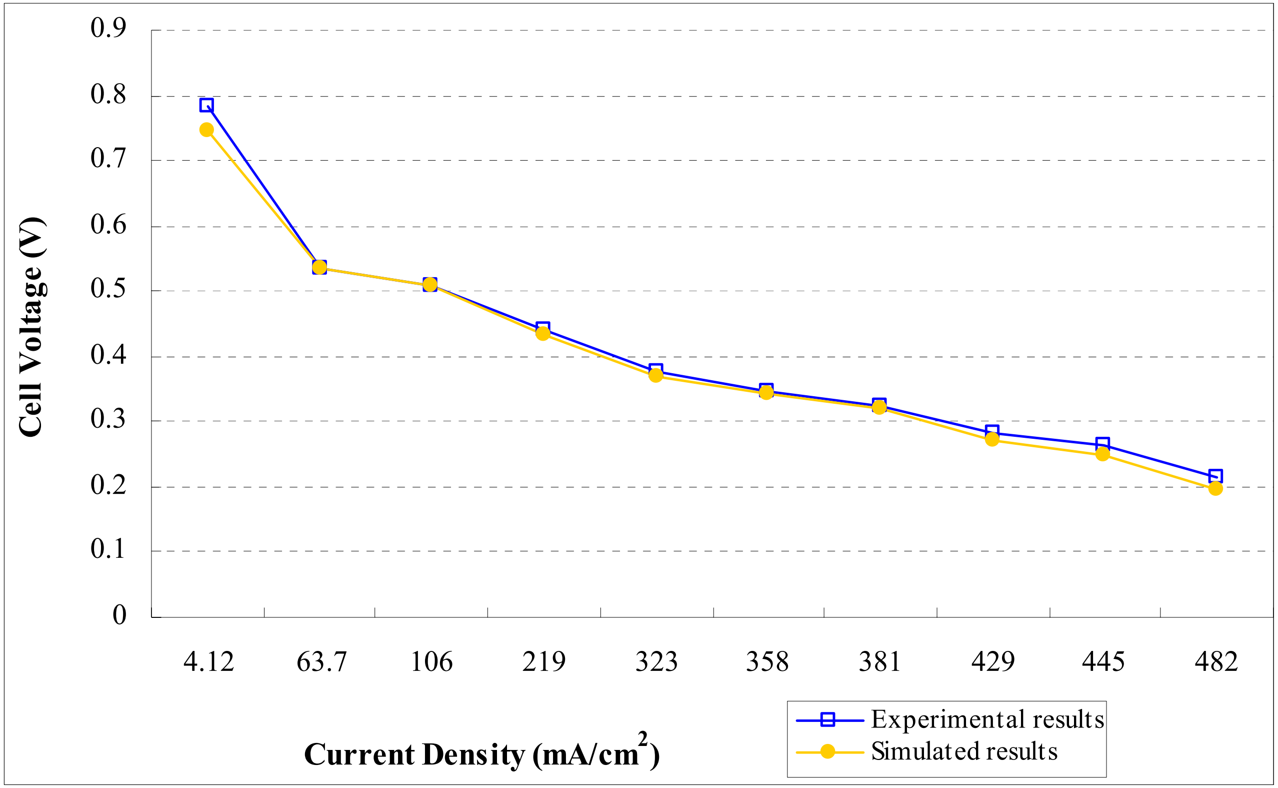
$$y_k(\vec{x}) = \varphi\left(\sum_{j=1}^{K} w_{ki}^{o} h\left(\left|\vec{x} - \vec{t}_j\right|, p_j\right) + b_k\right)$$

$$h\left(q, p_j\right) = e^{-p_j q}$$ **(Gaussian function)**

$$q = \left|\vec{x} - \vec{t}_j\right|^2$$

Results and discussion

Performance curve prediction



Cell performance for a direct methanol fuel cell (methanol solution concentration: 1M, air flow rate: 5ml/min, operating temp: 353K)

Results and discussion

Performance curve prediction

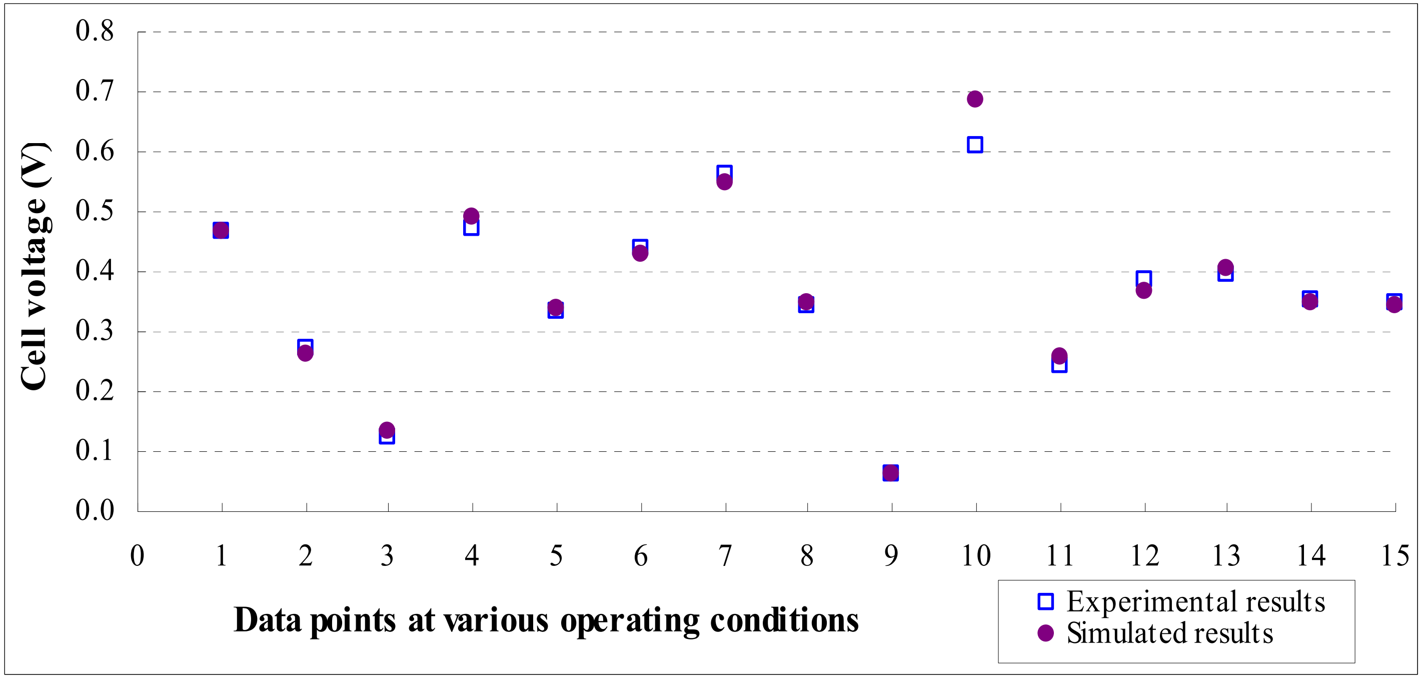
	Concentration	Flow rate	Current density	Bias	Voltage (output)
Hidden 1	1.069	-0.756	-1.494	-1.541	-1.040
Hidden 2	-0.221	-0.060	-1.063	-1.295	0.088
Hidden 3	-1.261	0.068	5.699	-4.416	-5.472
Hidden 4	-0.700	-2.541	1.606	-2.260	2.407
Hidden 5	-5.872	1.918	6.350	-5.099	3.115
Hidden 6	0.236	-0.119	-14.53	-1.724	7.142
Voltage (output)	N/A	N/A	N/A	0.320	N/A

Values of weights and bias in the neural network

Results and discussion

Cell Voltage Prediction

Input variables: current density, methanol solution concentration and flow rate

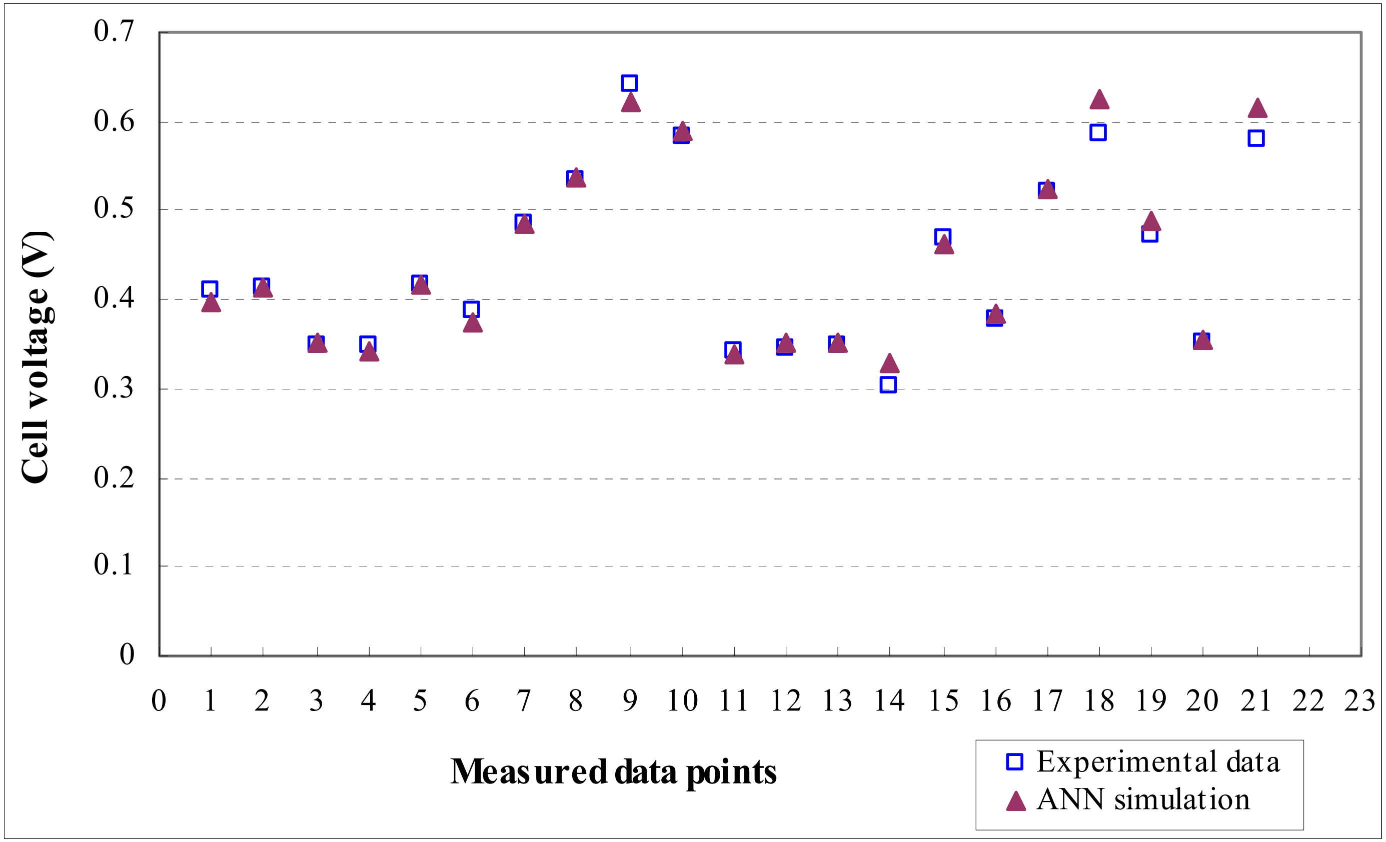


Experimental and simulated cell voltages for a DMFC running at various operating conditions at 333.15K

Results and discussion

Comparison with experimental results from CGFCC Ginar system

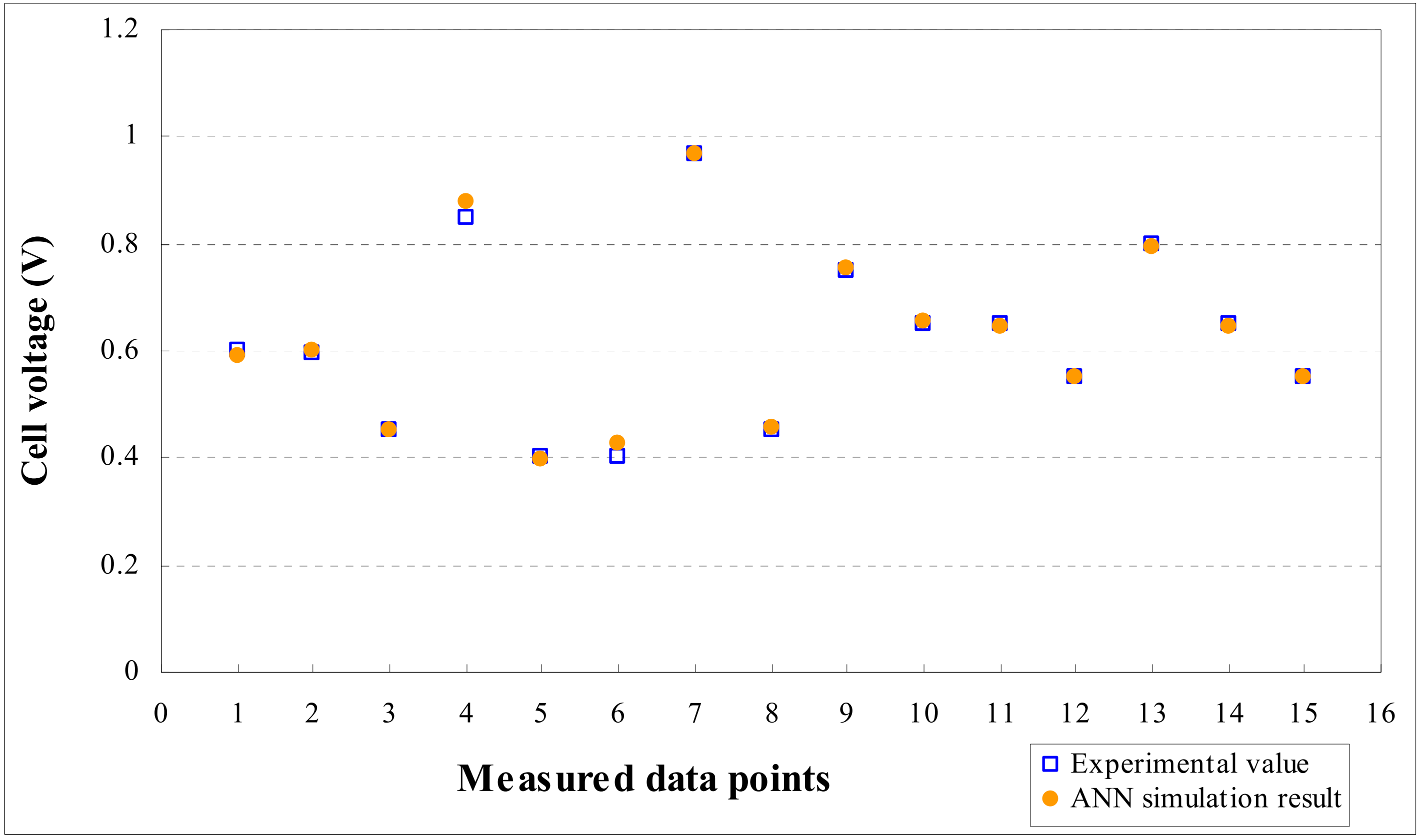
Temperature effect on cell performance



Results and discussion

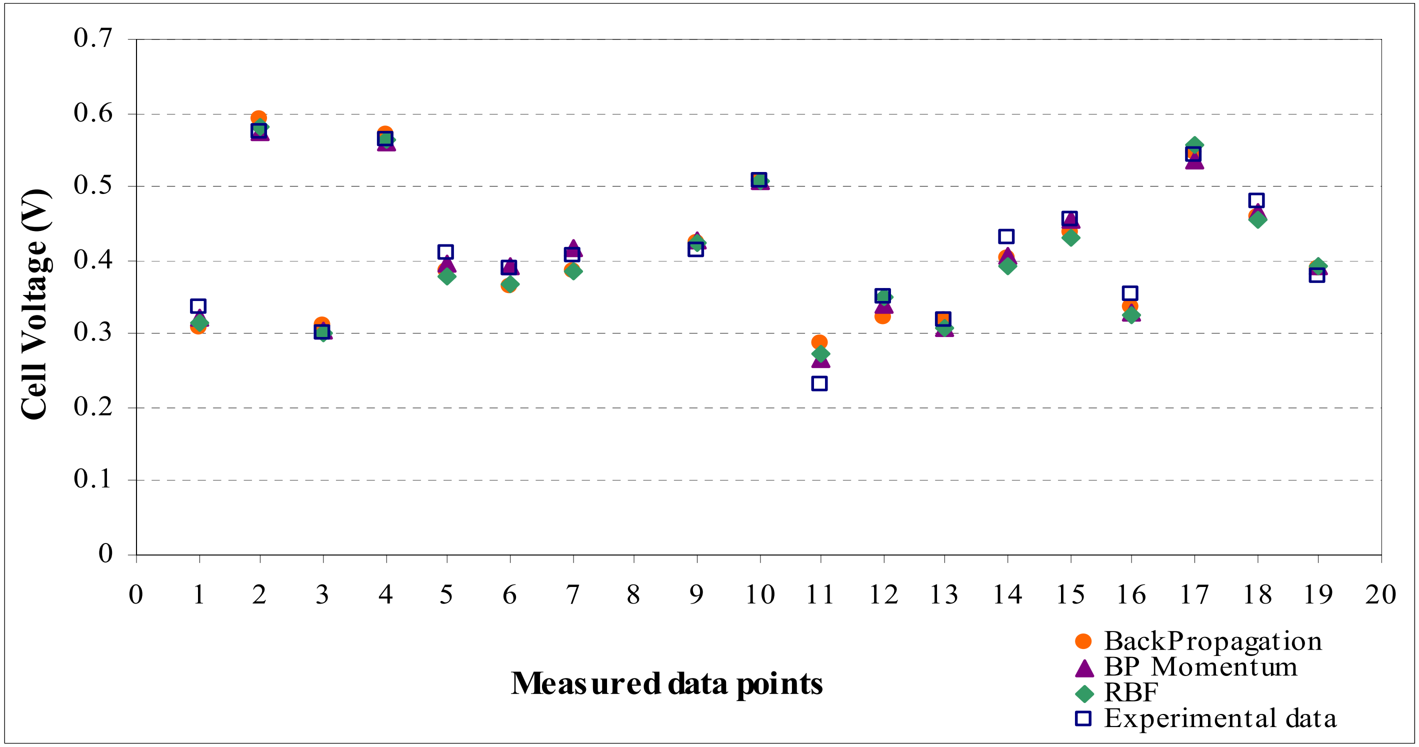
Pt-loading effect on cell performance

Input variables: Pt-loading, Pt/C, temperature, current density



Results and discussion

Performance Comparison of different ANN approaches



Method	Average MSE(10^{-3})
Back-Propagation	1.5
BP momentum	1.0
RBF	1.4

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Optimization based on ANN model

Framework of optimization model

$$\min_{d} J(d)$$

$$subject\ to$$

$$Model(d)=0$$

$$g(d)\leq 0$$

d = *independent process variables*

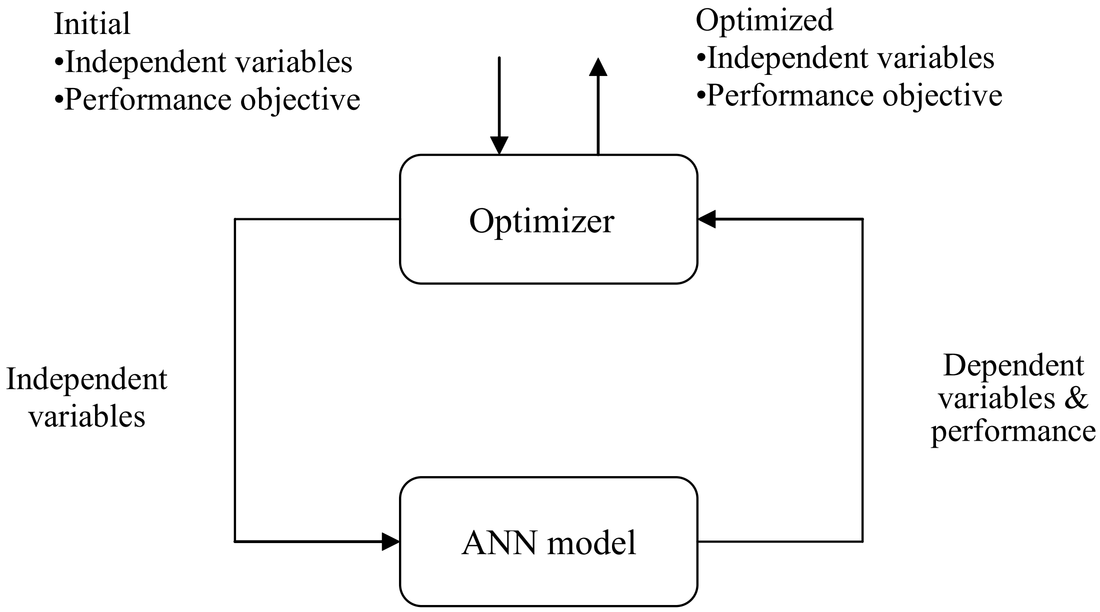
J(d) = *performance measure*

Model(d) = *ANN model*

g(d) = *process constraints*

Optimization based on ANN model

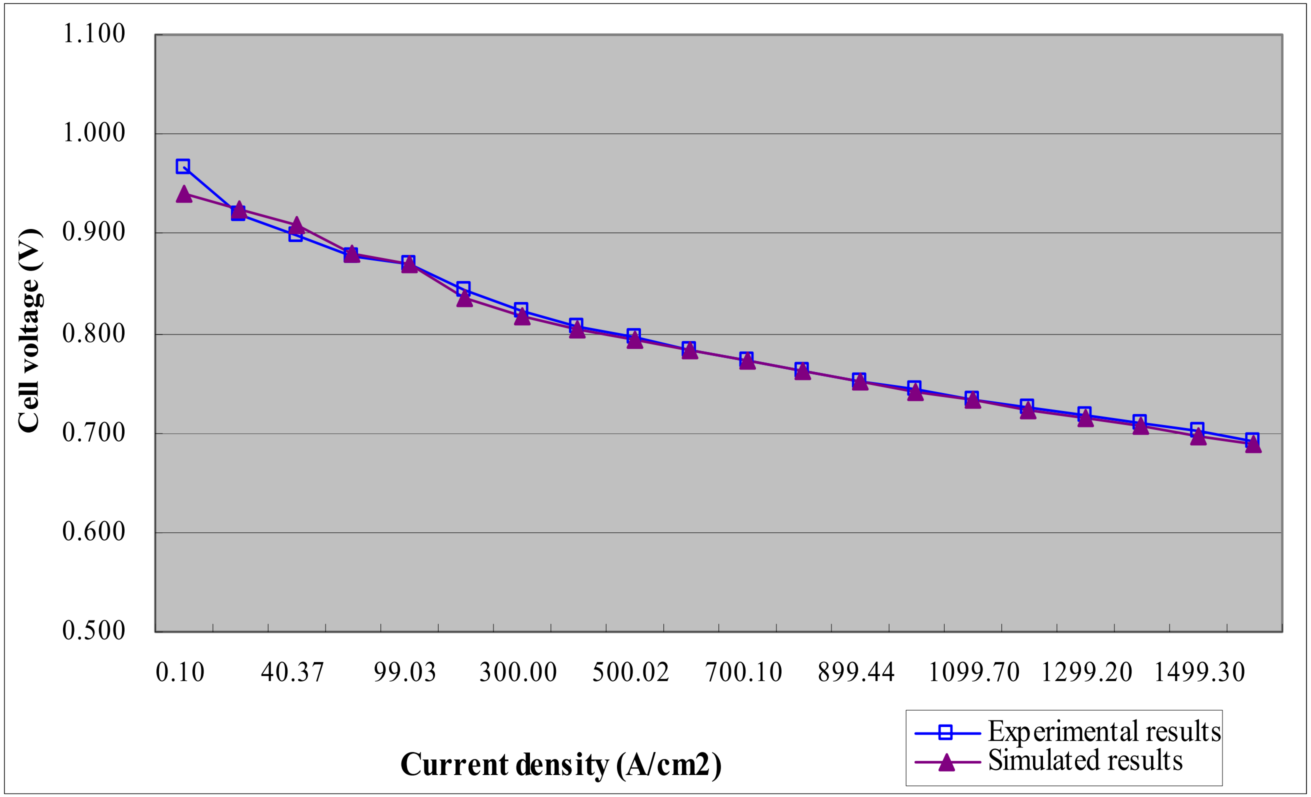
Schematic diagram



Schematic diagram of the optimization solution

Optimization based on ANN model

ANN model validation



Results comparison for hydrogen feed PEM fuel cell (Operating conditions: 323K, 1.5 atm)

Optimization based on ANN model

Preliminary results and discussion

Constrains are limited to the bounds of design variables

The optimal operating conditions and optimized value of objective function (within the range of our dataset):

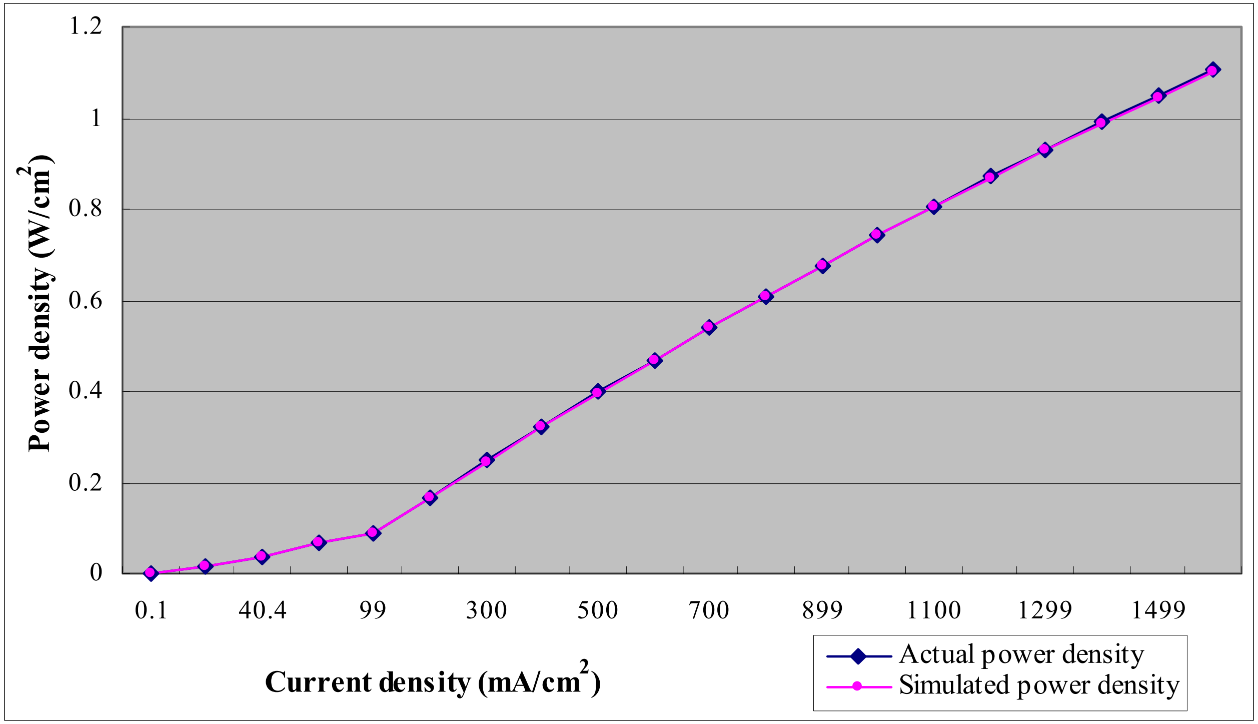
Temperature: 353 K Pressure: 2.5 atm Current density: 1600 mA/cm^2

Power density: 1.193 W/cm^2

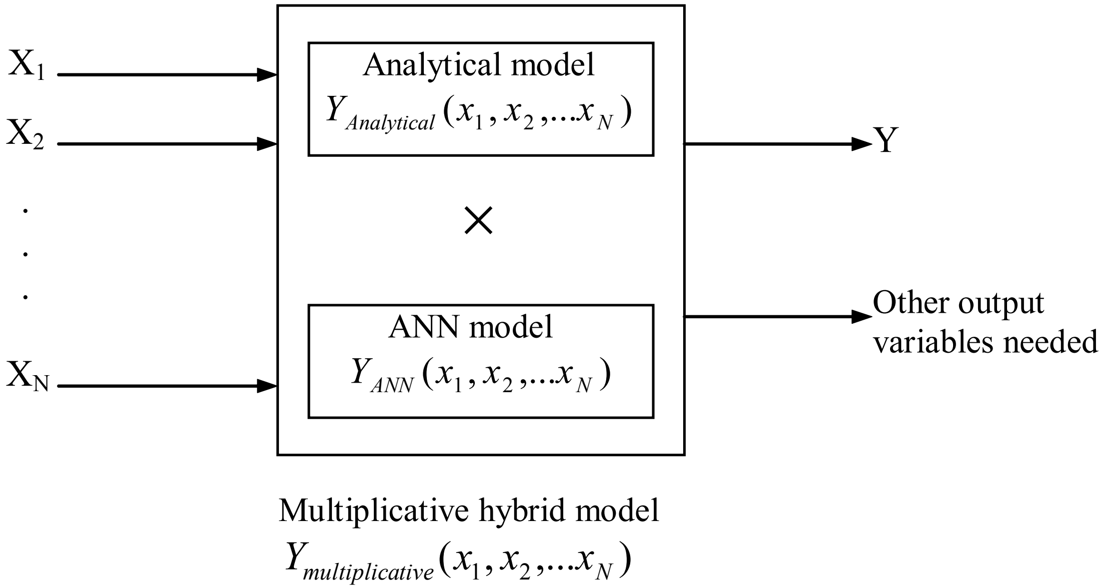
Ability of finding optimal values for design variables within a certain range of operating conditions

Optimization based on ANN model

Preliminary results and discussion



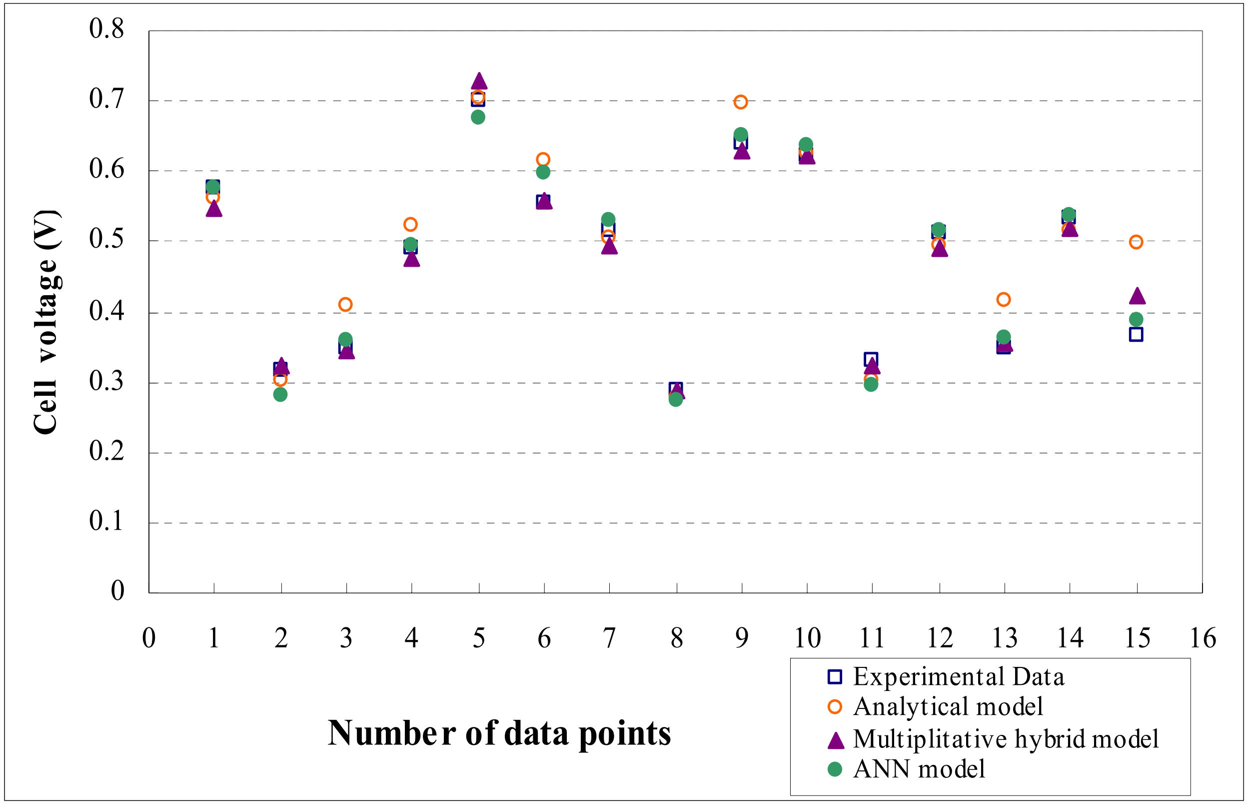
Hybrid Model



The schematic of multiplicative hybrid model

Hybrid Model

Results comparison for multiplicative hybrid model



Model	MSE(10^{-3})
Analytical	2.40
ANN	0.46
Multiplicative Hybrid	0.42

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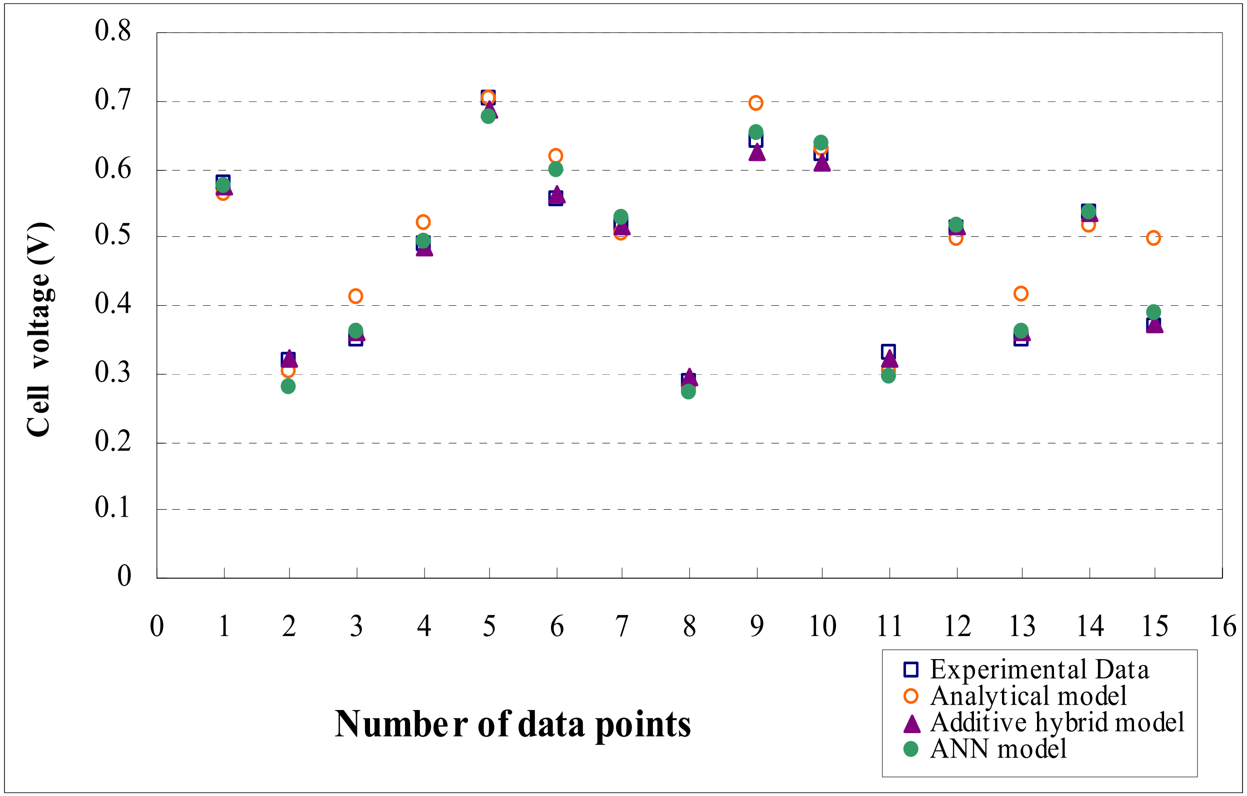
Hybrid Model

Results comparison for additive hybrid model



Model	MSE(10^{-3})
Analytical	2.40
ANN	0.46
Additive Hybrid	0.07

Summary

ANN shows good modeling ability for PEM fuel cells

- Accurate
- Easy to set up and use
- Able to handle parameters physically unaddressed

Back-propagation with momentum term showed better performance in our tests

Optimization model based on ANN model has been developed; preliminary tests showed its ability of finding optimal operating point

The hybrid model is more accurate than the analytical model, so that it can be a useful tool in applications that require good model accuracy

Acknowledgement

- ***CGFCC for financial support of this research,***
- ***Dr. Raymond England and Hui Xu for providing experimental data***

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Thank You