Prediction of Heat Transfer Coefficient of Pool Boiling Using Back propagation Neural Network

Dr. Salih Abdul Jabbar
Engineering College, University of Al-Qadisyi /Al-Dewania
Abbas Jawad Sultan
Chemical Engineering Department, University of Technology/ Baghdad
Email: ajshw@mst.edu
Hayder Alaa Maabad
Engineering College, University of Al-Qadisyi /Al-Dewania

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ABSTRACT

Artificial neural network (ANN), in comparison with empirical correlations, has recently received more attention. The present paper includes predictive modeling of heat transfer coefficient for binary mixtures in pool boiling for hydrocarbon compounds, using **Back propagation** techniques through **Multilayer Perceptron**, one of the types of the **artificial neural networks**. To train and learn the system, predictive neural network was found, which is capable of understanding and predicting the preset output which is heat transfer coefficient. The principle operation of such neural networks is based on the experimental data collected from some researchers [1-4]. A new ANN model is proposed using five inputs (mole fraction, temperature difference, heat flux, density and viscosity) to predict the heat transfer coefficient. The prediction using ANN shows 0.0026 AARE (Absolute Average Relative Error) with most widely known correlations namely those of Calus, Fujita and Thome which have given 0.086, 0.066 and 0.038 respectively.

Keywords: Pool boiling, neural network and Heat transfer coefficient.

التنبؤ بمعامل انتقال الحرارة في الغليان الحوضي باستخدام شبكة الانتشار العكسي(ANN)

الخلاصة

لاقت الشبكات العصبية الاصطناعية مقارنة بالمعادلات العملية مؤخرا مزيدا من الاهتمام. ويشمل هذا البحث النمذجة التنبؤية لمعامل انتقال الحرارة لمخاليط ثنائية التركيب للمركبات الهيدروكربونية في الغليان الحوضي، باستخدام تقنية التوالد العكسي في الإدراك الحسي المتعدد الطبقات ، احد انواع الشبكات العصبية الاصطناعية. لتدريب النظام في هذا الظرف، وبأستخدام التنبؤ باستخدام الشبكة العصبية،لتكوين شبكة قادرة على الفهم والتعلم والتعلم بالمتغير الخارج. إن مبدأ تشغيل هذه الشبكات العصبية يستند على بيانات جمعت من تجربة بعض الباحثين(1-4). تم تكوين نموذج جديد يقترح استخدام مدخلات خمس(فرق درجات الحرارة، والكسر المولي و كمية الحرارة و اللزوجة والكثافة) لتوقع معامل انتقال الحرارة. وقد تبين ان التنبؤ باستخدام الشبكات العصبية الاصطناعية يعطي نسبة

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2412-0758/University of Technology-Iraq, Baghdad, Iraq

خطأ (AARE) تساوي 0.0026 اما بالنسبة الى المعادلات العملية الأكثر شيوعا وهـــي Fujita وCallus, Thome ، فكانت 0.086، 0.066 و 0.038 تباعا.

INTRODUCTION

Nucleate boiling has been utilized extensively in industry because it is one of the most efficient modes of heat transfer, particularly in high-energy-density systems such as nuclear reactors, power plants, electronic packaging and the like. Scientific research into boiling and the industrial usage spans over several past decades. Starting from the pioneering paper of Nukiyama (1934) [5], widespread data have accumulated from experimental studies dealing with a diverse array of conditions.

Heat transfer in boiling is one of the most challenging fields of contemporary heat transfer research. Despite extensive research, a complete understanding of boiling is still lacking, even for many simple cases. This may be due to the fact that, in addition to the thermo-physical properties of the fluid, many parameters such as surface condition, mass transfer effect, presence of impurities and deposition of foreign materials on the heat transfer surface are inherent factors that influence bubble generation (Jamialahmadi et al, 2008)[6].

Boiling of pure components has been well established, while the boiling of mixtures has been studied in fewer details, especially in organic and inorganic mixtures, which has considerable practical significance.

Nucleate pool boiling of liquid mixtures finds many applications in chemical and petrochemical process industries, principally the processes involving the boiling of multi-component liquid mixtures. Recent interest in these as working fluids in thermal power plants and refrigeration systems is growing because of their potential to reduce available energy loss in heat exchanges (Fujita and Bai, 1997) [2].

Boiling of binary and multi-component mixtures constitutes an important process in chemical process, air separation, refrigeration and many other industrial applications. Reboilers feeding the vapors to distillation columns and flooded evaporators generally employ pool boiling, while the tube evaporation process involves flow boiling. Although the multi-component boiling is of greater interest from a process standpoint, fundamental understanding of the mechanism can be obtained first with binary mixtures. [7].

The present work is directed toward reviewing the existing correlations on pool boiling heat transfer with binary mixtures and using ANNs (artificial neural network) to predict the heat transfer coefficient of binary pool boiling mixtures which have been widely utilized in many fields of science and engineering [8–10].

The main advantages of the ANN models are: (1) no particular knowledge is needed about the system being modeled, unknown effects could be involved through a proper design of the input–output patterns; (2) relative simplicity of neural network

architecture; (3) high ability of the ANNs to reproduce stochastic signals. In this work, using the Neural Network Toolbox of Statistica 8 [11] an ANN was employed to predict heat transfer coefficient.

NUCLEATE BOILING STUDIES FOR MIXTURES

Since the complexity of mixture boiling was recognized some years ago, a wealth of data giving nucleate boiling superheats and transfer coefficients has been published. According to Grigorjev (1962) [12], the reduction in heat transfer is due to the increase of the bubble radial in equilibrium with the mixture, resulting in a smaller bubble population at the same degree of wall superheating.

Stephan and Korner (1970) [13] found that the reversible isothermal work for a single bubble in equilibrium in mixture is greater than that needed for a pure component of the same physical properties.

Calus and Leonidopoulos (1974) [4] showed results that approved the decrease in heat transfer coefficient up on the addition of n- propanol to water, but an improvement in the heat transfer coefficient was recorded up on the addition of water to pure n-propanol.

PREDICTION OF HEAT TRANSFER COEFFICIENT OF BINARY MIXTURES IN POOL BOILING BY USING ARTIFICIAL NEURAL NETWORK (ANN)

ANNs (artificial neural network) have been widely utilized in many fields of science and engineering [8–10]. The main advantages of the ANN models are: (1) no particular knowledge is needed about the system being modeled, unknown effects could be involved through a proper design of the input–output patterns; (2) relative simplicity of neural network architecture; (3) high ability of the ANNs to reproduce stochastic signals.

In this work, using the Neural Network Toolbox of Statistica 8 [10] an ANN was employed to predict heat transfer coefficient. The input layer of the network consisted of mole fraction, temperature deference, heat flux, density and viscosity of the liquids. The output layer of the network corresponded to the heat transfer coefficient.

ANNs are applied to estimate desired output parameters when sufficient experimental data is provided. Therefore, ANNs allow for the modeling of physical phenomena in complex systems without requiring explicit mathematical representations. Thus, ANN can be used as a predictor of heat transfer coefficient based solely on instances of input–output relationships due to its black box characteristics.

Many researchers use ANN in their search like Ertunc H. M who use ANN to predict the critical heat flux in pool boiling for dielectric liquids under a variety of operating conditions [14] and many others.

DATA COLLECTION

Data were collected from different recourses for different researchers (1-4); Table (1) shows number of points that were extracted from each researcher.

RESULTS AND DISCUSSION

The neural network model which was developed using Statistica® 8 (2009) software (Figure 1 & 2) involved five input and five neurons in the hidden layer [36 weights] to predict heat transfer coefficient values for the pool boiling. Using Automated Neural network option in the main bar of Statistica® 8 to train and test the data collected using back propagation techniques and the result are listed for 200 maximum iteration showed in Table (2) using Quasi-Newton method, and it is obvious that neural NO. 2 in the table is the optimum one due to low error gain 0.000022.

Figure (3) shows the architectural building of the neural which results from the regression work.

Figure (4) represents the relation between predicted and experimental heat transfer coefficient and mole fraction which shows congruent between predicted and experimental for ethanol-n-butanol mixture. Figure (5) represents the relation between predicted and experimental heat transfer coefficient and temperature difference which shows decreasing in heat transfer coefficient with increasing in temperature difference for ethanol-n-butanol mixture.

In addition Figure (6) shows relation between predicted and experimental heat transfer coefficient and density for ethanol-n-butanol mixture, which shows identical in curves of experiential and predicted heat transfer coefficient related to density.

From all above it can see that the use neural network is an ideal method to predicate the heat transfer coefficient for the case of pool boiling depending on the variables such as density, mole fraction, temperature deference and heat flux. Table (3) shows the weight of neurons that result from predication process which can be used to continue predication and continue learning and training of the ANN. Figure (7) shows comparison between predicted and experimental heat transfer coefficient which explain uniform distribution around 45^{o} lines.

ANN COMPARISONS WITH ANOTHER EMPIRICAL MODEL

The comparison was done using AARE (Table 4), which shows that there are differences between ANN model and the three empirical models (Calus, Fujita and Thome) knowing that:

- $AARE = \frac{1}{N}\sum\left|\frac{y_{pred}-y_{exp}}{y_{exp}}\right|$
- Heat transfer coefficient derived by Calus and Leonidopoulos(4) was:

$$\frac{h_I}{h}=\frac{\Delta T}{\Delta T_I}=\left[1+\left|y_1^{*}-x_1\right|\left(\frac{\alpha}{D}\right)^{0.5}\left(\frac{C_{pl}}{\Delta h_{LG}}\right)\left(\frac{dT}{dx_1}\right)\right]=\frac{1}{Sn}$$

- Heat transfer coefficient derived by Thome (3) was:

$$\frac{h_I}{h}=1+\frac{h_I}{q^{"}}\Delta T_{BP}\left[1-\exp.\left(\frac{-B_0 q^{"}}{\rho_l \beta_l \Delta h_{LG}}\right)\right]$$

- Heat transfer coefficient derived by Fujita et al (2) was:

$$h=\frac{h_I}{1+K_s\left(\frac{\Delta T_{Bp}}{\Delta T_I}\right)}$$

$$K_s=\left[1-\exp.\left(\frac{-2.8\Delta T_I}{\Delta T_{sat.1-2}}\right)\right]$$

Where

$$\Delta T_I = x_1\Delta T_1 + x_2\Delta T_2$$

$$D\mathbf{T_{sat.1-2}} = \mathbf{T_{sat.1}}\big|_{p} - \mathbf{T_{sat.2}}\big|_{\mathbf{P}}$$

$$h_I = \frac{h_1 h_2}{x_1 h_2 + x_2 h_1}$$

CONCLUSIONS

From above work, the using of Multilayer Perceptron for predicting the heat transfer coefficient for pool boiling for binary mixture give good result with less error comparing with empirical correlation which used 5-5-1 model Multilayer Perceptron. The ANN model tolerates a wide range of data, while other models apply for small range of data, and using STATISTICA 8 simplify the analysis and bring the errors to its smallest values.

NOMENCLATURE

C_P	Specific heat, (J/kg.K).
D	Mass diffusivity, (m^2/s).

g	Parameter defined as ,$g=(x_1-x_{1,s})/(y_{1,s}-x_{1,s})$,.(-).
h	Heat transfer coefficient,($W/m^2.K$).
k	Thermal Conductivity,(W/m.K)
M	Molecular weight,(kg/kmol)
q"	Heat flux ,(W/m^2)
Sn	Scriven number,(-)
T	Temperature, (K).
T_{Sat}	Saturated temperature,(K).
T_W	Wall temperature,(K).
x	Mole fraction of the more volatile component,(-)
y^*	Equilibrium vapor mole fraction,(-)
H.T.C Pred.	Heat transfer coefficient predict ($W/m^2.K$)
H.T.C Exp.	Heat transfer coefficient experimental ($W/m^2.K$)

GREEK SYMBOLS

α	Thermal diffusivity
Δh_{LG}	Latent heat of vaporization
ΔT_{bp}	Boiling range
ΔT_{eff}	Effective superheat
ΔT_{sat}	Wall superheat [$T_w - T_{sat}$]
ΔT_1, ΔT_2	Wall superheat for component (1) and (2) in pool boiling
μ	Viscosity
ρ	Density
σ	Surface tension

ABBREVIATIONS

- AARE :Absolute Average Relative Error
- BFGS: (or Quasi-Newton) is a powerful second order training algorithm with very fast convergence but high memory requirements due to storing the Hessian matrix.
- Hyperbolic tangent (Tanh): is a symmetric S-shaped (sigmoid) function, sometimes used as an alternative to logistic functions.
- SOS: sum-of-squares (SOS) which is an error function used in neural network. SOS can be used for both classification and regression tasks.

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Table (1) Data collected

Researcher	No. of points	System
Abbas J.Sultan (2006) (1).	**246**	**Ethanol-N-Butanol Acetone-N-Butanol Acetone-Ethanol Hexane-Benzene Hexane-Heptane Methanol-Water**
Fujita et al. (1997) (2).	**35**	**Ethanol / water Ethanol / n-butan ol Methanol / benzene Benzene / n-heptane Water / ethylene glycol**
Thome and Shakir (1987) (3).	**35**	**Ethanol / water Acetone / water Ethanol / benzene Nitrogen / argon Nitrogen / oxygen Nitrogen /methane**
Calus and Leonidopoulos (1974) (4).	**35**	**N- Propanol / water Isopropanol with water and acetone**

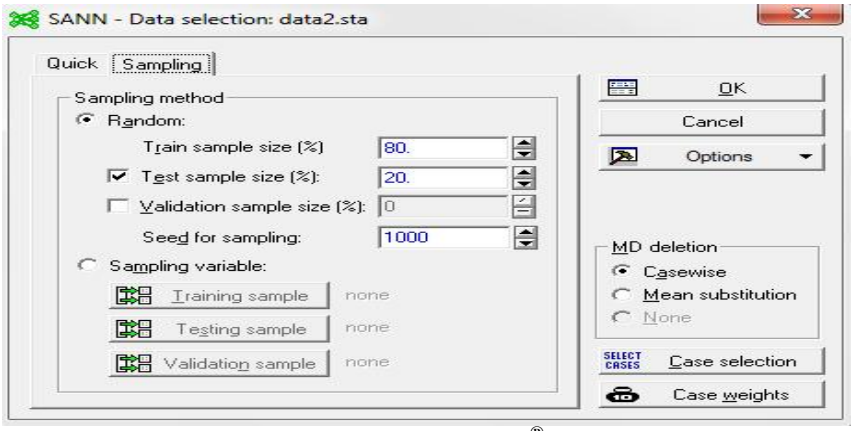

Figure (1) Statistica® 8 (2009)

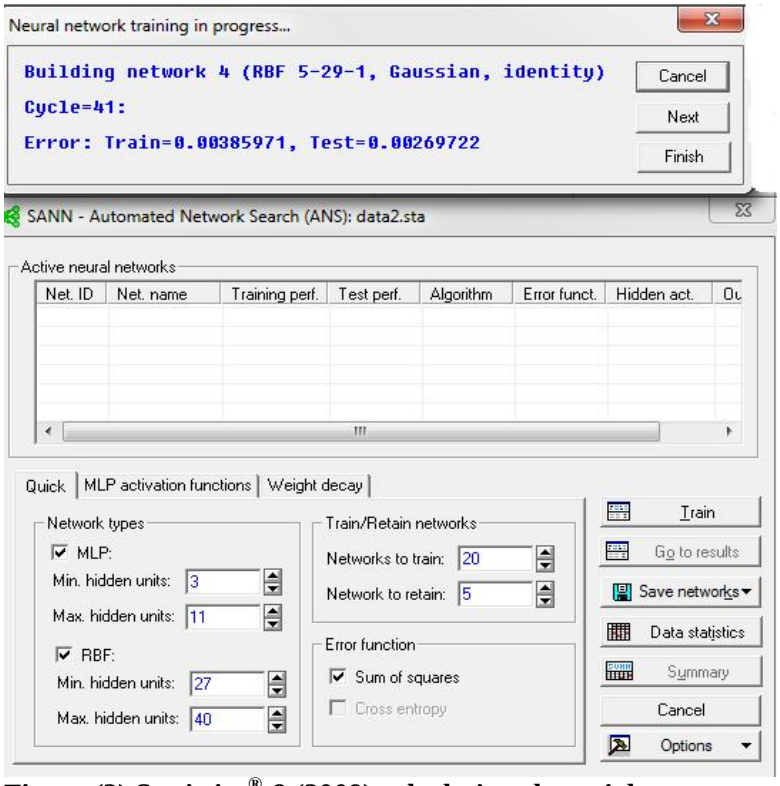

Figure (2) Statistica® 8 (2009) calculating the weights.

Table (2) neural models obtained

Index	Net. name	Training perf.	Test perf.	Training error	Test error	Training algorithm	Error function	Hidden activation	Output activation
1	MLP 5-5-1	0.999586	0.999327	0.000023	0.000030	BFGS 73	SOS	Exponential	Exponential
2	MLP 5-5-1	0.999607	0.999351	0.000022	0.000030	BFGS 84	SOS	Tanh	Exponential
3	MLP 5-10-1	0.999409	0.999745	0.000033	0.000014	BFGS 63	SOS	Logistic	Tanh
4	MLP 5-10-1	0.999409	0.999175	0.000034	0.000037	BFGS 58	SOS	Tanh	Logistic
5	MLP 5-3-1	0.999248	0.999499	0.000042	0.000024	BFGS 92	SOS	Tanh	Tanh

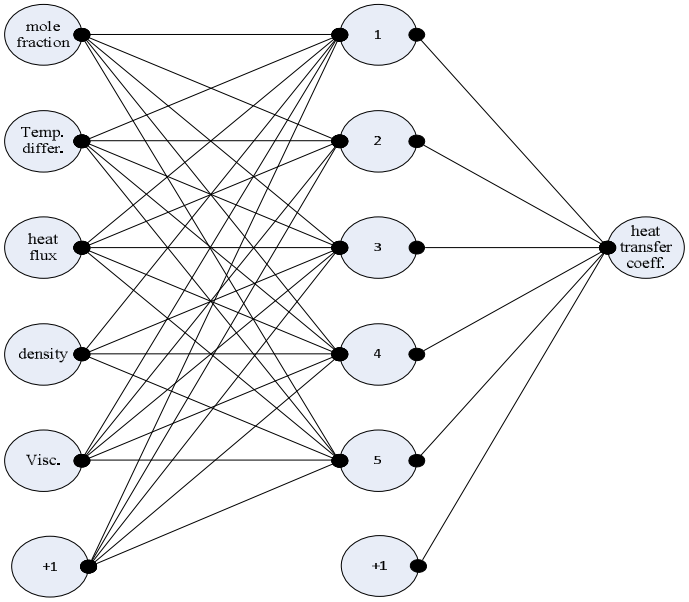

Figure (3) architectural building of the neural 5-5-1

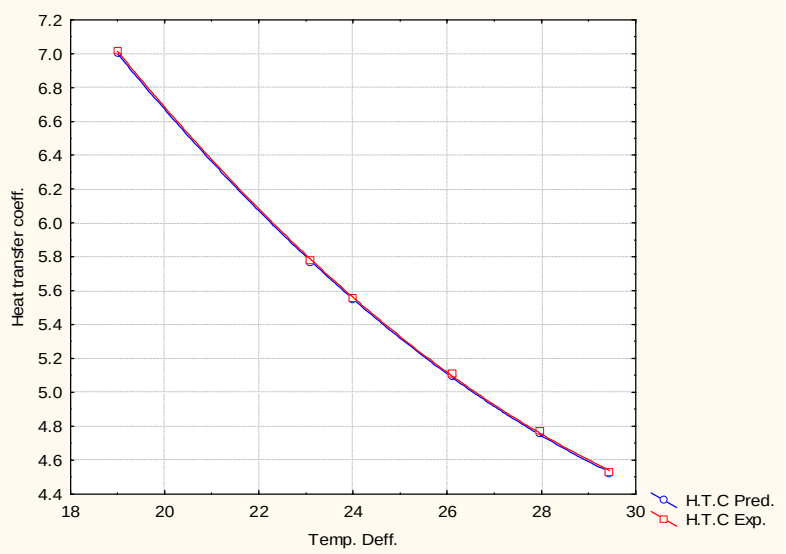

Figure (4) Relation between mole fraction and heat transfer coefficient

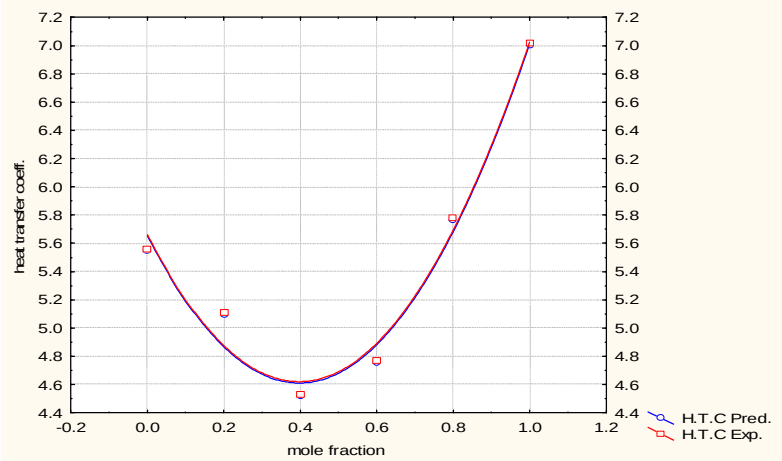

Figure (5) Relation between temperatures difference and heat transfer coefficient.

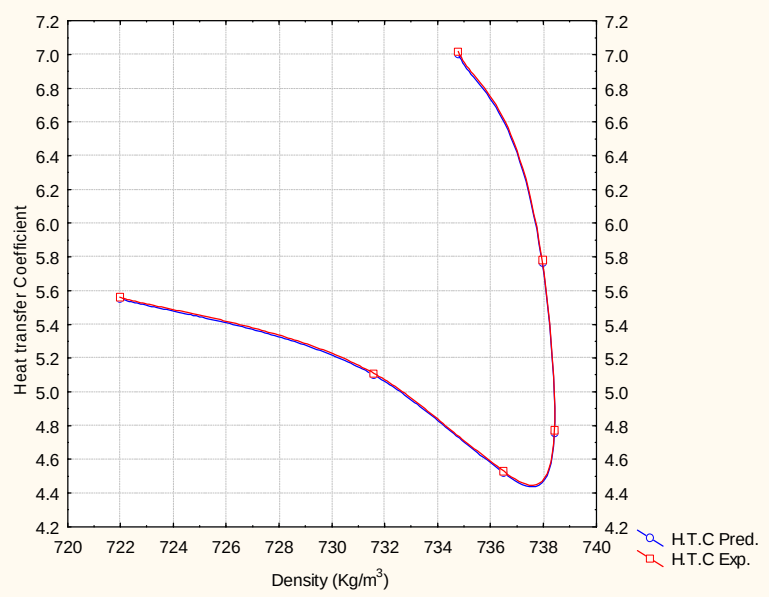

Figure (6) Relation between density and heat transfer coefficient.

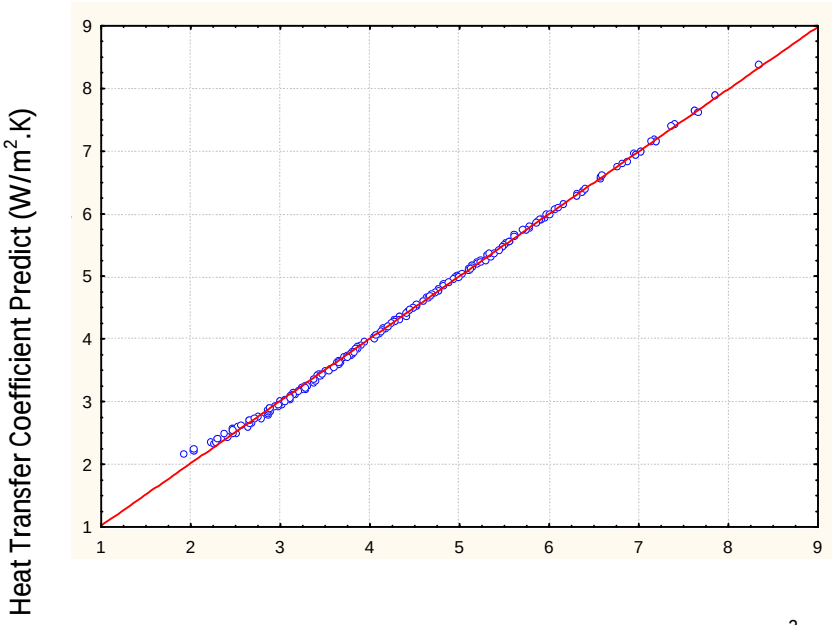

Figure (7) Comparison between experimental and predicted heat transfer coefficient.

Table (3) weight of neurons.

Connections	Weight values
mole fraction X --> hidden neuron 1	-0.00075
mole fraction X --> hidden neuron 2	-0.94872
mole fraction X --> hidden neuron 3	0.22692
mole fraction X --> hidden neuron 4	0.01180
mole fraction X --> hidden neuron 5	-0.03194
Temp Deffr. --> hidden neuron 1	0.04930
Temp Deffr. --> hidden neuron 2	-3.04160
Temp Deffr. --> hidden neuron 3	5.20498
Temp Deffr. --> hidden neuron 4	0.03232
Temp Deffr. --> hidden neuron 5	-0.07582
H eat Flux (q) --> hidden neuron 1	-0.02423
H eat Flux (q) --> hidden neuron 2	1.33423
H eat Flux (q) --> hidden neuron 3	-1.95501
H eat Flux (q) --> hidden neuron 4	-0.03035
H eat Flux (q) --> hidden neuron 5	-0.07712
dencity mix. --> hidden neuron 1	0.11506
dencity mix. --> hidden neuron 2	0.41873
dencity mix. --> hidden neuron 3	-1.15293
dencity mix. --> hidden neuron 4	0.18331

dencity mix. --> hidden neuron 5	-0.05110
viscosity mix. --> hidden neuron 1	0.55726
viscosity mix. --> hidden neuron 2	-2.07237
viscosity mix. --> hidden neuron 3	-3.77494
viscosity mix. --> hidden neuron 4	0.17653
viscosity mix. --> hidden neuron 5	0.04606
input bias --> hidden neuron 1	-0.50952
input bias --> hidden neuron 2	0.54824
input bias --> hidden neuron 3	0.57909
input bias --> hidden neuron 4	-0.27277
input bias --> hidden neuron 5	1.86622

Table (4) ARRE for different model

Model	AARE
Calus (1974)	0.086
Thome (1987)	0.066
Fujita (1997)	0.038
ANN (now)	0.0026