

Comparison of Different Correlating Methods for the Single-Phase Heat Transfer Data in Laminar and Turbulent Flow Regions

by

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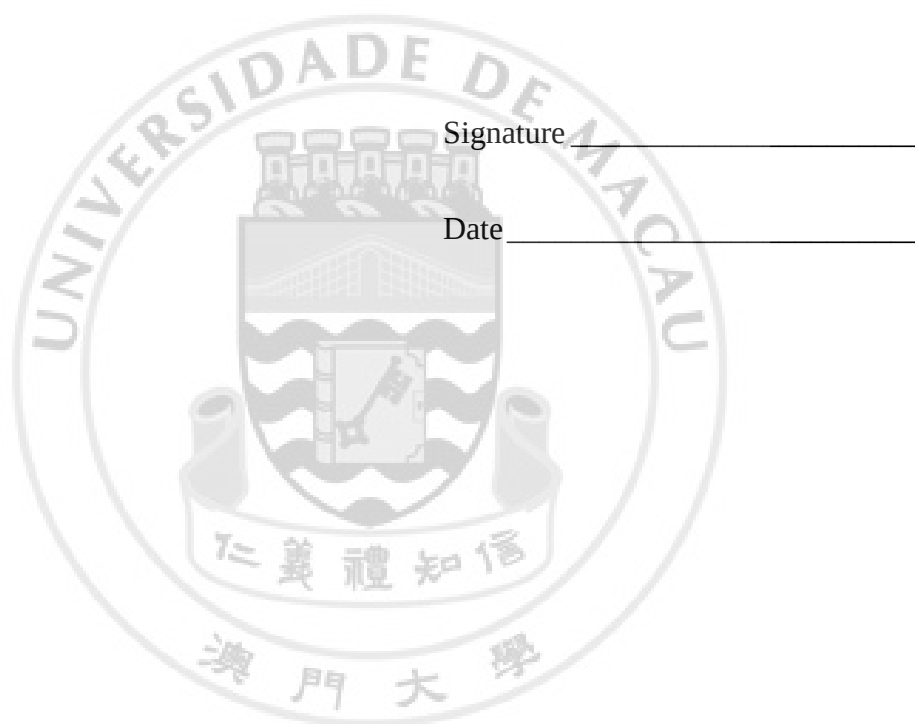
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Abstract

COMPARISON OF DIFFERENT CORRELATING METHODS FOR THE
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TURBULENT FLOW REGIONS

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Experimental approach is one of the methods in heat transfer engineering research. The experimental heat transfer results, typically expressed as Nusselt number, are usually put in the form of an empirical correlation. Different correlating methods can be used to establish the correlation, such as the traditional least-squares method, artificial neural networks (ANN), and symbolic regression, to name a few. Ghajar and his co-workers (1994) have applied the three-layer ANN for the complicated heat transfer problem. The ANN-type correlation can predict the heat transfer data in good accuracy. However, the relationship between the input and output variables cannot be visually inspected from the matrix-form correlation. In recent studies of Tam and Ghajar (2008), the optimized correlation form was found out by the symbolic regression. The global combination of input variables was determined by the genetic programming of Tam and Ghajar (2006). The symbolic-type correlation may give out not only the accurate predictive power, but also the explicit correlation format. Therefore, the input-output relationship, such as the importance of input variables, can be seen directly from the correlation. In this study, the traditional least-squares method, ANN and symbolic regression will be compared. Correlations for the basic single-phase heat transfer data of Tam and Ghajar (2004) (546 data points for laminar region and 604

data points turbulent region) were developed with these methods. The traditional correlation predicts the laminar data with a deviation range of -16.9% and +15.4% and the turbulent data with a deviation range of -10.3% and +10.5%. Majority of the experimental data (86% of the laminar data and 93% of the turbulent data) were predicted within the $\pm 10\%$ range. For developing the new correlations, 90% of the total data were used for training. The new correlations developed by ANN and symbolic regression can both predict all of the heat transfer data in laminar and turbulent regions within $\pm 15\%$ range. Over 90% of the data points, which includes the unused data, can be predicted by those correlations within the $\pm 10\%$ deviation. The accuracy of those new correlations are comparable to that of the traditional least-squares method. For visual inspection of the symbolic-type correlation, the importance of each term can be examined directly. Therefore, the symbolic regression is more superior to the ANN method.

Keywords: Heat Transfer Correlation, Laminar Flow, Turbulent Flow, Artificial Neural Networks (ANN), Symbolic Regression

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NOMENCLATURE

a	output vector
A	Cross sectional area, ft ² or m ²
b	bias matrix
cp	specific heat at constant pressure, kJ/(kg·K)
D	inside diameter of the tube, m
f	activation (or transfer) function
g	acceleration of gravity, m/s ²
Gr	local bulk Grashof number ($= g\beta\rho^2D^3(T_w-T_b)/\mu_b^2$)
Gz	local Graetz number ($= RePrD/x$)
h	local peripheral heat transfer coefficient, W/(m ² ·K)
h _b	h _b local peripheral heat transfer coefficient at the bottom of tube, W/(m ² ·K)
h _t	local peripheral heat transfer coefficient at the top of tube, W/(m ² ·K)
k	thermal conductivity, W/(m ² ·K)
Nu	local average or fully developed peripheral Nusselt number ($= hD/k$)
Nu _l	local average or fully developed peripheral laminar Nusselt number
Nu _t	local average or fully developed peripheral turbulent Nusselt number
p	input vector
P _j	contribution of the jth independent variable p _j
Pr	local bulk Prandtl number ($= c_p\mu_b/k$)
Q _k	contribution of the kth neuron output to the ANN model
Ra	local bulk Rayleigh number ($= GrPr$)
Re	local bulk Reynolds number ($= \rho VD/\mu_b$)
T _b	local bulk temperature, °C
T _w	local wall temperature, °C
V	average velocity in the test section, m/s

W	weight matrix
x	local distance along the test section from the inlet, m

<i>Subscripts</i>	
i	dummy parameter
j	j^{th} input variable
k	k^{th} hidden neuron
max	maximum value
min	minimum value
R	number of inputs
S	number of hidden neurons

<i>Greek Symbols</i>	
β	local bulk coefficient of thermal expansion, K^{-1}
μ_b	local bulk dynamic viscosity, Pa·s
μ_w	local wall dynamic viscosity, Pa·s
ρ	local bulk density, kg/m^3

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