



Data-driven correlations for thermohydraulic roughness properties

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Reynolds Analogy: Velocity and Heat



Example: Heat Exchanger



Reynolds analogy

- Heat and momentum transfer are proportional
- Reynolds analogy factor:

$$RA = \frac{2St}{C_f} = \frac{2Nu}{C_f \operatorname{Re} \operatorname{Pr}} \tag{1}$$

Classical application: smooth surfaces

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Reynolds Analogy: Velocity and Heat





Rough surface



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Reynolds Analogy: Velocity and Heat





Question

- → How does the presence of rough surfaces influence velocity and temperature distribution?
- Is everything from the rough surface important? \rightarrow

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Roughness Influence on Channel Flow I



Velocity Augmentation:

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Roughness function (Hama, 1954; Clauser, 1954)

$$\Delta U^{+} = U_{\rm S}^{+} - U_{\rm R}^{+}$$

= $\frac{1}{\kappa} \ln \left(k_{\rm s}^{+} \right) + A - B(k_{\rm s}^{+})$

 $\bullet \ B(\infty) = 8.5$ in fully rough regime \rightarrow only $k_{\rm s}$ necessary for ΔU^+







Roughness Influence on Channel Flow II

Temperature Augmentation:

 Equations following Dipprey and Sabersky (1963), Brutsaert (1975) and Yaglom (1979)

$$\Delta \Theta^{+} = \Theta_{\rm S}^{+} - \Theta_{\rm R}^{+}$$

= $\frac{1}{\kappa_{\theta}} \ln \left(k_{\rm s}^{+}\right) + A_{\theta}(Pr) - g(k_{\rm s}^{+}, Pr)$
= $\frac{1}{\kappa_{\theta}} \ln \left(y_{\rm I}^{+}\right) + A_{\theta}(Pr) - \Theta_{\rm I}^{+}(k_{\rm s}^{+}, Pr)$

Empirical and phenomenological relations



Important

- → Breakdown of Reynolds analogy for flow with rough surfaces (e.g. Hantsis and Piomelli (2024))
- \twoheadrightarrow Predict ΔU^+ and $\Delta \Theta^+$ without detailed simulation

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Procedure:



Data:

- 4200 rough surfaces and 93 high-fidelity simulations ($Re_{\tau} \approx 800, Pr = 0.71$) (Yang et al., 2023)
- External data set for additional testing

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Procedure:



Neural Network:

Data-driven function approximation given powerful statistical measures

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Procedure:



Symbolic Regression:

Convert hidden function in human-understandable symbolic expression

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Procedure:



Exploration:

Use predictive tools on rough surfaces

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Neural Network Prediction





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Neural Network Prediction





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Neural Network Prediction







Neural Network Prediction



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Symbolic Regression



Goal

- → Translate network to correlation using simple statistical properties
- Statistical parameters vs. power spectrum & probability density function
- Genetic Programming
- Python library PySR (Cranmer, 2023)



Exploration

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Results



Correlation	R^2	Result
$k_{\rm r} = \frac{k_{\rm s}}{k_{99}} = ES_x \left(-ES_x + Sk + 2.21 \right) + 0.819$	0.931	exceed references

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Results







→ Selected statistical parameters align with conclusion by Flack and Chung (2022) and other correlations (Chung et al., 2021)

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Results



Correlation	R^2	Result
$k_{\rm r} = \frac{k_{\rm s}}{k_{\rm 99}} = ES_x \left(-ES_x + Sk + 2.21 \right) + 0.819$	0.931	exceed references
$\Delta \Theta^+ = 6.02 \left(k_{\rm s} \left(-0.18 \ Sk \ + \frac{k_{\rm z}}{k_{\rm rms}} \right) \right)^{0.138}$	0.827	less powerful

- → Limited reference data
- → Missing Pr-dependency ($\Delta \Theta^+ = f(Pr)$)

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Explore Symbolic Expression

Velocity Augmentation

Temperature Augmentation



Observation

→ Velocity correlation follows known behaviors (Kuwata et al., 2023); temperature is limited

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Explore Predictive Tools







Explore Predictive Tools



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Summary

Summary

- → Different features of rough surface are important for ΔU^+ and $\Delta \Theta^+$
- Prediction without detailed simulation
- Correlation aligns with literature and simulations
- $\pmb{\times}$ Limitation in generalization for $\Delta\Theta^+$





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