Parametric CFD-based surrogate model for pressure loss in tortuous paths of drip emitters

2.29 Final Project

Julia Sokol

Motivation

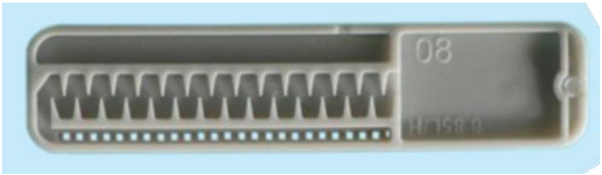
- Drip irrigation is an underutilized method that can reduce water consumption and increase crop yields
- Used on only 6% of irrigated land
- Main barrier: high capital cost, especially off-grid systems
  - Reducing system pressure can reduce the overall system cost significantly
- We can reduce system pressure by redesigning the drip emitter

Inline drip irrigation (source)

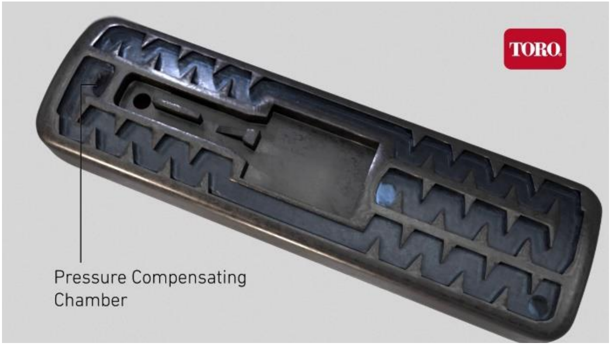
Goal

- Lab is developing theory to analytically model emitter behavior, and use it to optimize design
- One constraint to a flexible analytical model is the complex flow in the tortuous path, which can only be modeled numerically
  - All inline emitters have this feature
- Proposed solution: **develop a quick surrogate model based on parametric CFD simulations**
  - Main concern: pressure loss

Netafim



Jain



Toro

Surrogate model development steps

1. Run CFD model with the base path geometry
    1. Select appropriate turbulence model
    2. Estimate discretization error
2. Parametrize path geometry
3. Sample parameter values using DOE
4. Run CFD simulations for all samples
5. Use results to generate regression model for pressure loss coefficient as a function of parameters
6. Validate model on test geometries

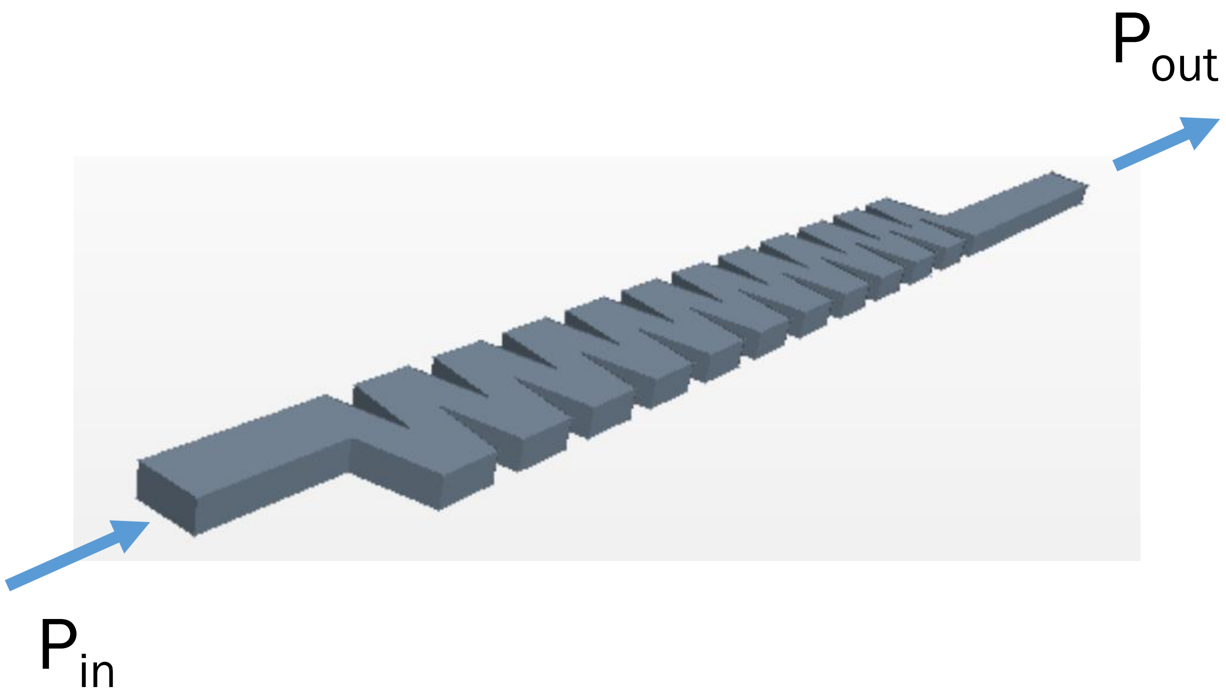
Pressure loss coefficient (K)

$$\Delta P = \frac{1}{2}\rho\bar{u}^2 K$$

P_{out} - P_{in}

mean outlet velocity (Q/A)

$$\boxed{K = \frac{2\Delta P}{\rho\bar{u}^2}}$$



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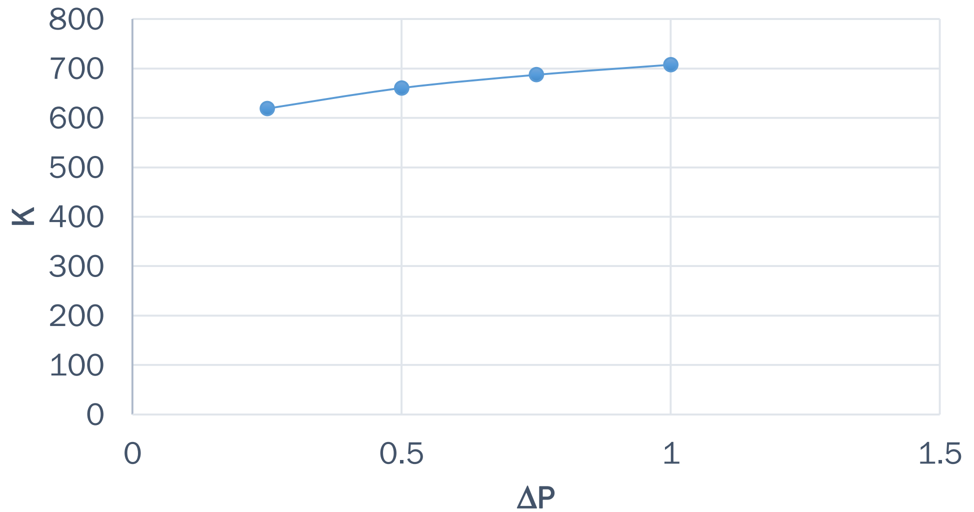
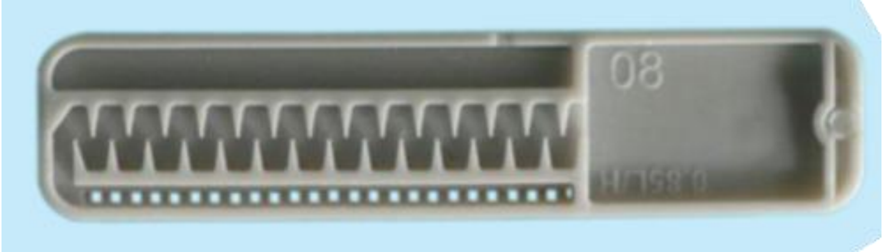


Plot of K versus ΔP for base path geometry

- K varies little with ΔP in emitter operating range (0.5-1 bar)
- All simulations run at 0.5 bar

1. Set up CFD model with base geometry

- Base path geometry from commercial emitter (Jain Turbo Excel Plus 1.6 Lph)
- Simulated in STAR-CCM+ (Siemens)
- Flow expected to be turbulent, even at low Re < 2000 [1,2,3,4]
- RANS (k-epsilon) turbulence models
- Pressure inlet & outlet boundary conditions



Full emitter.


Geometry of CFD model for tortuous path.

[1] Al-Muhammad, J., Tomas, S., & Anselmet, F. (2016)
[2] Wei, Z., Cao, M., Liu, X., Tang, Y., & Lu, B. (2012)
[3] Wu, D., Li, Y., Liu, H., Yang, P., Sun, H., & Liu, Y. (2013)
[4] Zhang, L., Wu, P., Zhu, D., & Zheng, C. (2016)

Meshing of CFD model

- Unstructured polyhedral
- Small fillets and mesh refinement at sharp corners
- Turbulence models that resolve boundary layer down to the viscous sublayer (low-y+/all y+)
- 10 prism layers, with first cell layer at y+ ≤ 1

Mesh detail.

1a. Select appropriate turbulence model

- Standard k-ε does not account for anisotropy of turbulence
- Standard k-ε with quadratic constitutive relation or realizable k-ε are recommended for flow with rotation, separation and recirculation
- Elliptic blending k-ε adds third equation and is meant to improve on realizable model in near-wall region
- Laminar for comparison

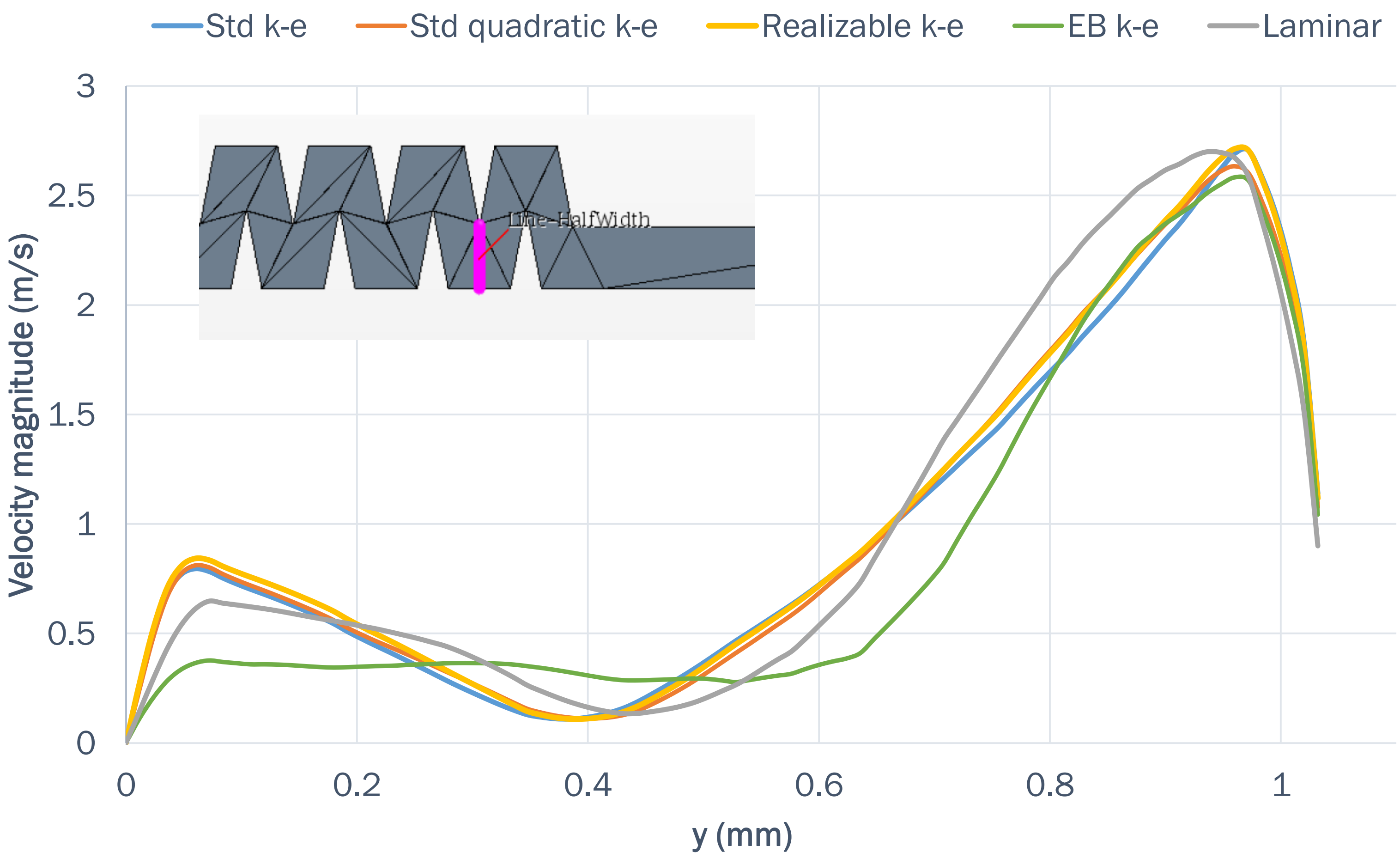
Model	Flow Rate (L/h)	K
Standard k-ε	0.714	636.8
Standard k-ε, quadratic	0.699	665.8
Realizable k-ε	0.701	660.5
Elliptic blending k-ε	0.710	644.8
Laminar	0.697	669.0
Mean	0.704	655.4
Std Dev	0.008	14.0

Model comparison.

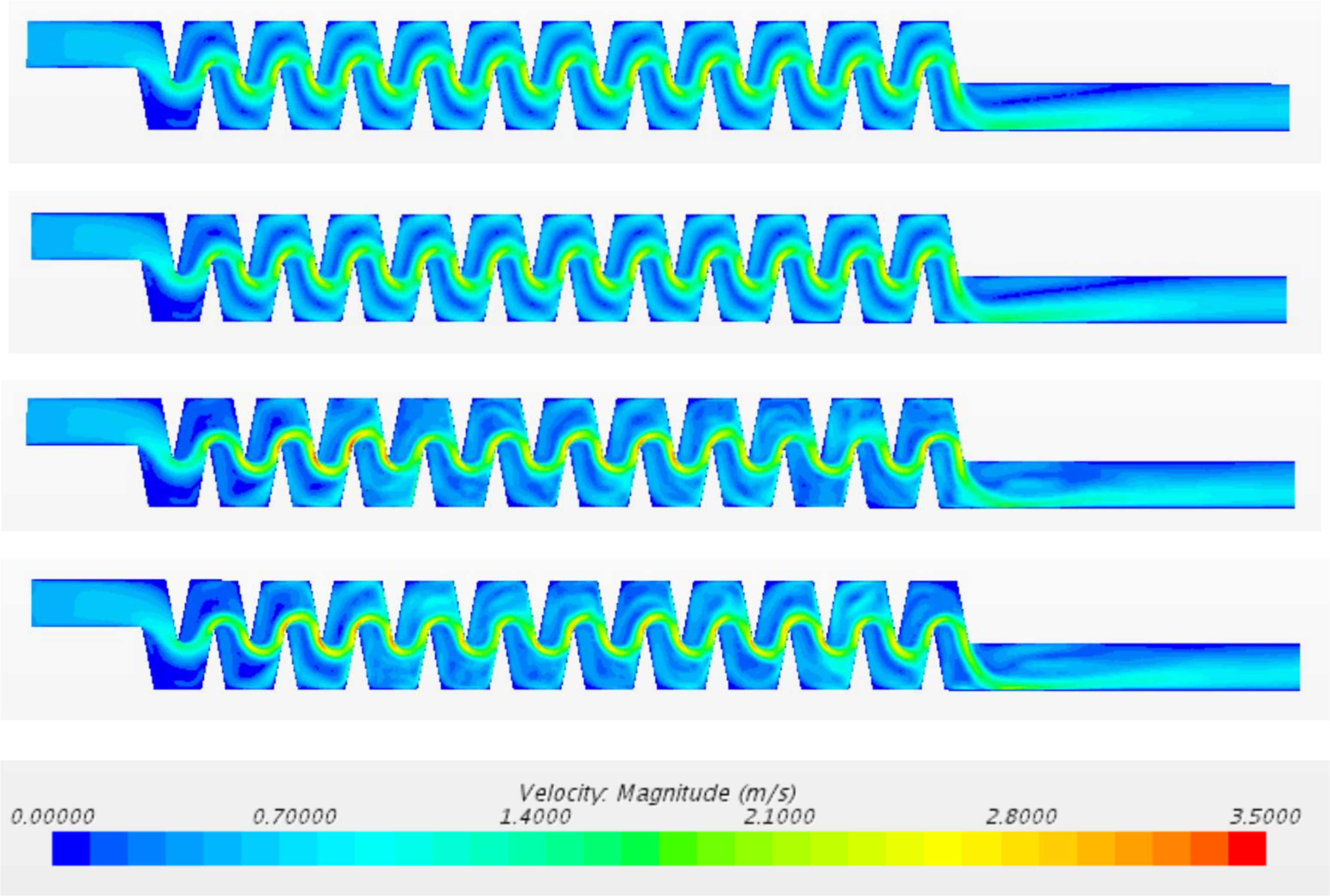
Velocity magnitude profile across path

- Standard, quadratic and realizable k-ε profiles almost identical

- Elliptic blending k-ε showed poor convergence



Velocity magnitude (center plane)



Standard k-ε

Realizable k-ε

Elliptic blending k-ε

Laminar

1a. Select appropriate turbulence model

- All models predict similar flow rate and K values

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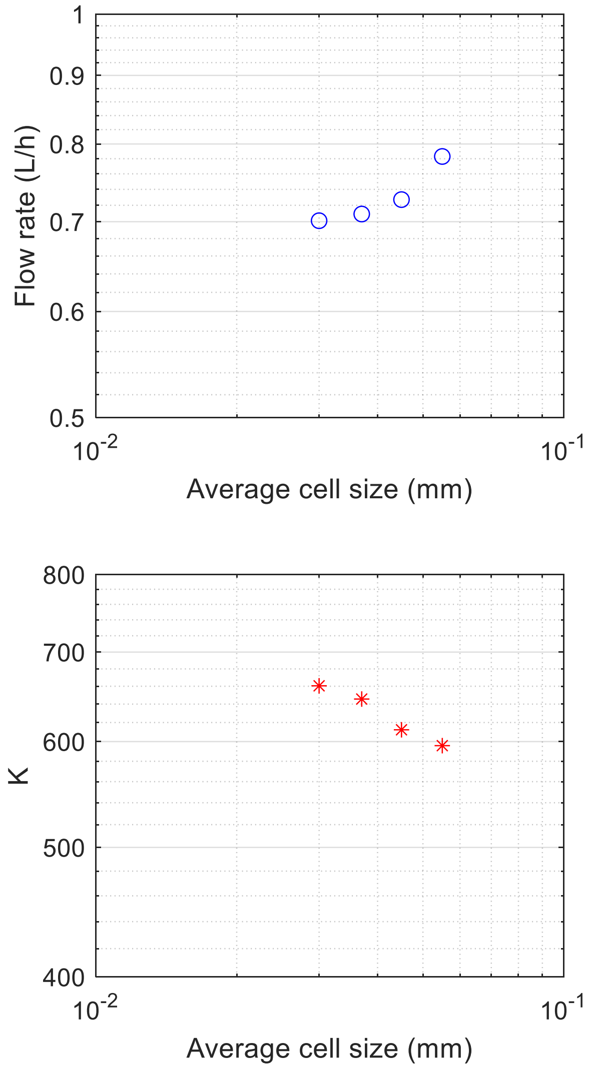
Model comparison.

1b. Estimate discretization error

Grid convergence using 4 mesh sizes

					Discretization error			
					Absolute		Relative	
Num Cells	Avg cell size (mm)	Ratio	Flow (L/h)	K	Flow (L/h)	K	Flow (L/h)	K
123078	0.055		0.738	595.8	0.044	77.0	6.3%	11.4%
227053	0.045	1.23	0.727	612.3	0.033	60.4	4.7%	9.0%
413458	0.037	1.22	0.709	645.6	0.015	27.2	2.1%	4.0%
757342	0.030	1.22	0.701	660.5	0.007	12.2	1.0%	1.8%
		Extrapolated value	**0.694**	**672.8**				
		Order of convergence p =	3.90	3.96				



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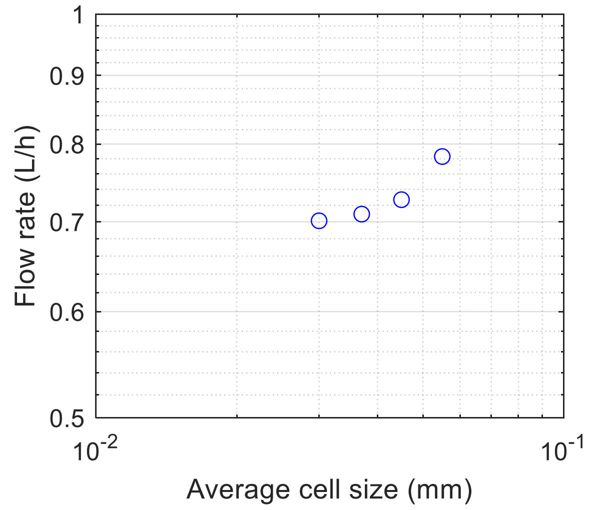
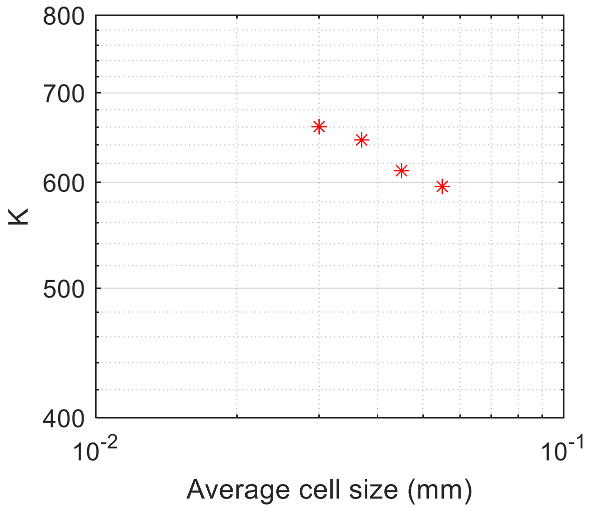
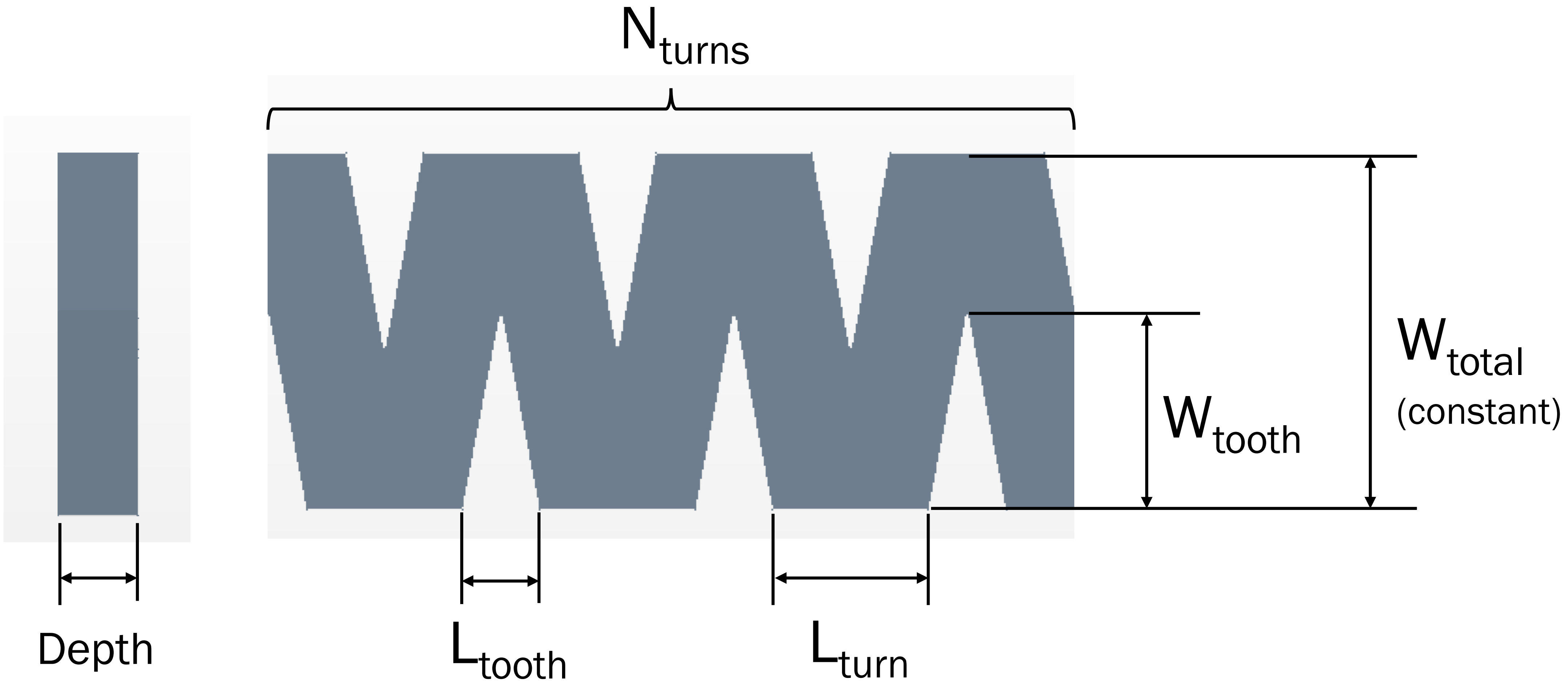




2. Parametrize path geometry



2. Parametrize path geometry

Parameter limits (generally, base value ± 50%)

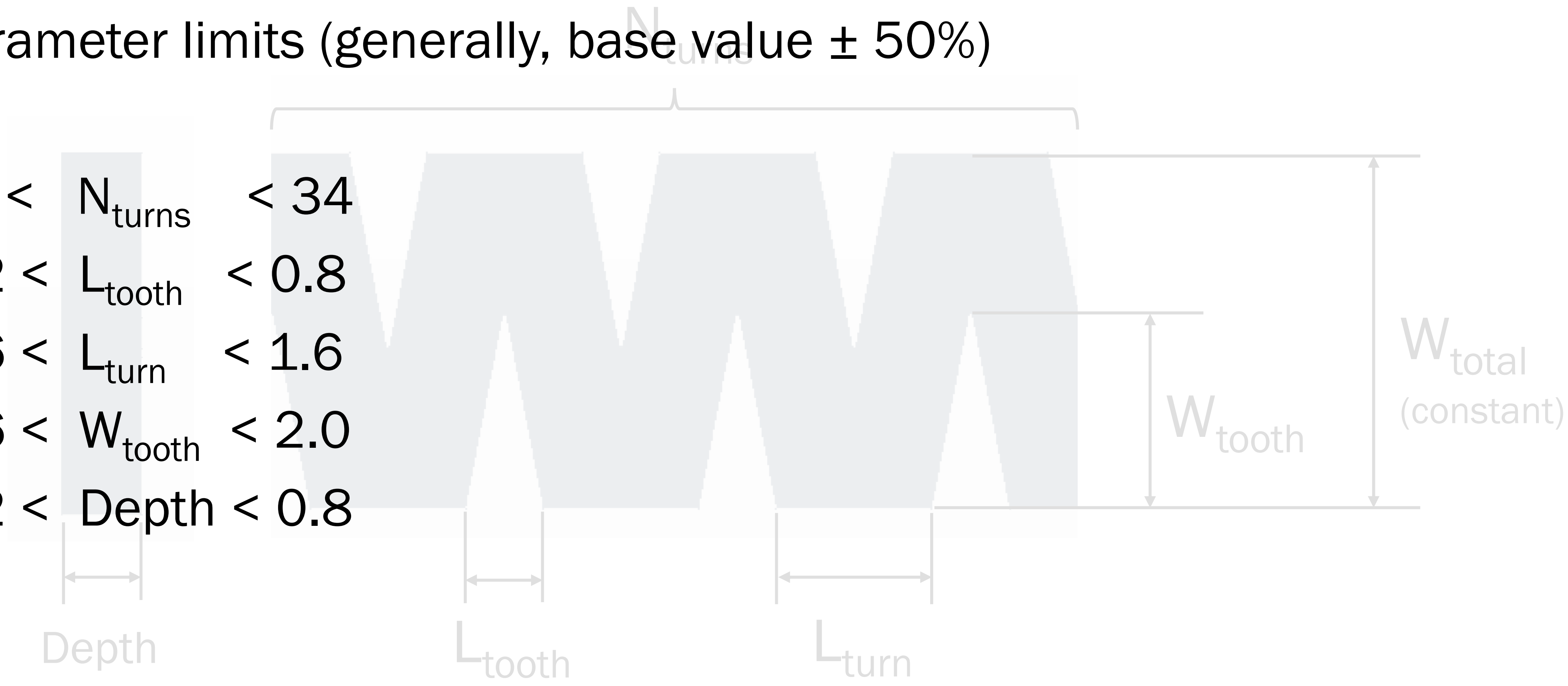
$10 < N_{turns} < 34$

$0.2 < L_{tooth} < 0.8$

$0.6 < L_{turn} < 1.6$

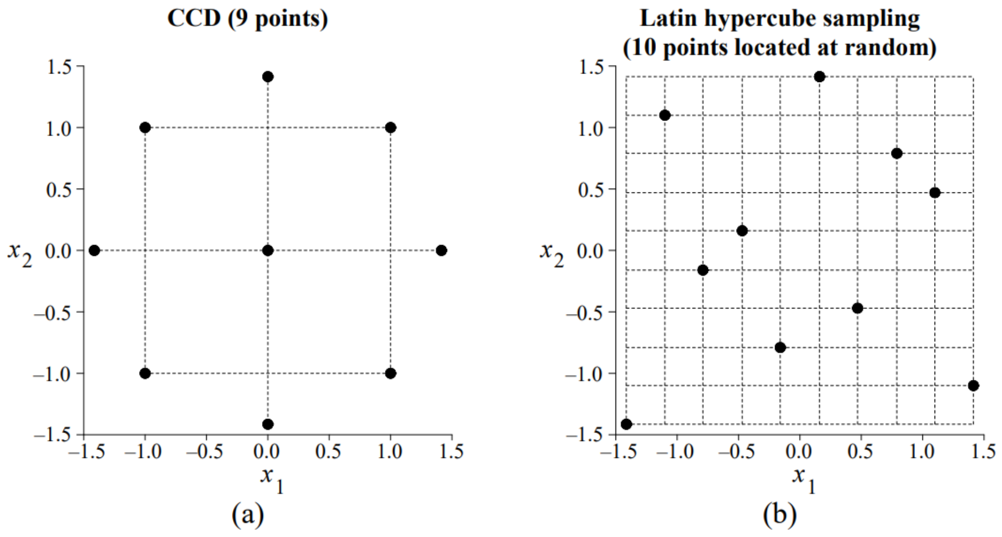
$0.6 < W_{tooth} < 2.0$

$0.2 < \text{Depth} < 0.8$



3. Sample parameter values using DOE

- Used Central Composite Design to sample parameter space
  - 5 parameters
  - 5 levels for each parameter
  - 27 samples
- After analyzing data from first 18 runs, modified the last 8 runs to sample most influential parameters at additional levels



Illustrations of two sampling methods for 2 parameters, (a) Central composite design, (b) Latin hypercube sampling.

(*image source*)

4. Run CFD simulations for all samples

Simulation	N_turns	L_tooth	L_turn	Depth	W_tooth
0	22	0.5	1	0.5	1.3
1	22	0.5	1	0.5	2.0
2	22	0.5	1	0.5	0.6
3	22	0.5	1	0.8	1.3
4	22	0.5	1	0.2	1.3
5	22	0.5	1.6	0.5	1.3
6	22	0.5	0.6	0.5	1.3
7	22	0.8	1	0.5	1.3
8	22	0.2	1	0.5	1.3
9	34	0.5	1	0.5	1.3
10	10	0.5	1	0.5	1.3
11	22	0.57	1.14	0.57	1.48
12	22	0.57	1.14	0.43	1.12
13	22	0.57	0.90	0.57	1.12
14	22	0.57	0.90	0.43	1.48
15	22	0.43	1.14	0.57	1.12
16	22	0.43	1.14	0.43	1.48
17	22	0.43	0.90	0.57	1.48
18	22	0.43	0.90	0.43	1.12
19	16	0.64	1.28	0.64	0.94
20	16	0.64	1.28	0.36	1.66
21	16	0.64	0.8	0.64	1.66
22	16	0.64	0.8	0.36	0.94
23	16	0.36	1.28	0.64	1.66
24	16	0.36	1.28	0.36	0.94
25	16	0.36	0.8	0.64	0.94
26	16	0.36	0.8	0.36	1.66

Samples of parameters for all simulation runs.

→ **K value**

for each run

5. Generate regression model for K

$$K \sim -2751 + 867L_{turn} + 106N_{turns} - 477L_{tooth} + 2527W_{tooth} - 67L_{turn}N_{turns} - 843W_{tooth}^2$$

	Estimate	SE	tStat	pValue
(Intercept)	-2751.1	770.27	-3.5717	0.00191
LTurn	855.78	688.13	1.2436	0.22802
NTurns	106.29	35.73	2.9749	0.007487
LTooth	-476.62	177.49	-2.6854	0.014226
WTooth	2526.6	442.69	5.7074	1.38E-05
LTurn:NTurns	-67.443	34.964	-1.9289	0.068055
WTooth^2	-842.99	167.97	-5.0185	6.59E-05

Number of observations: 27, Error degrees of freedom: 20
Root Mean Squared Error: 109
R-squared: 0.882, Adjusted R-Squared 0.846
F-statistic vs. constant model: 24.9, p-value = 2.81e-08

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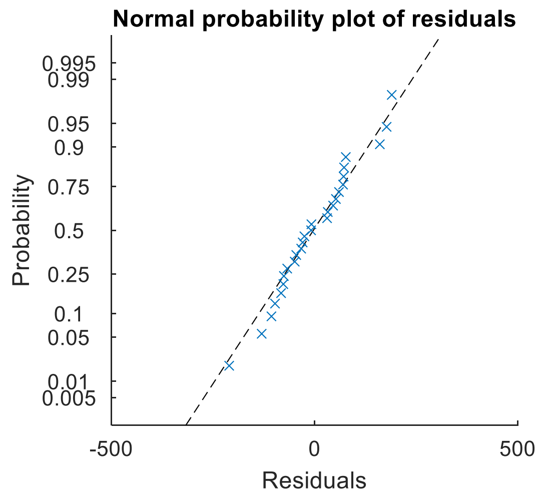

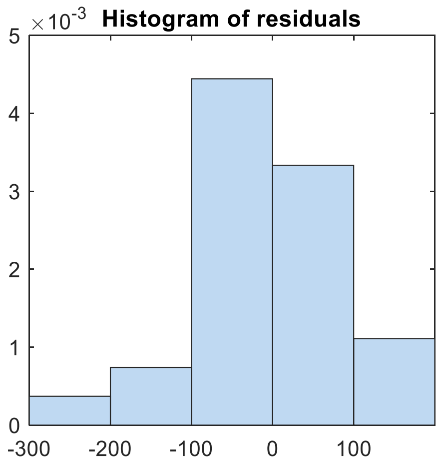

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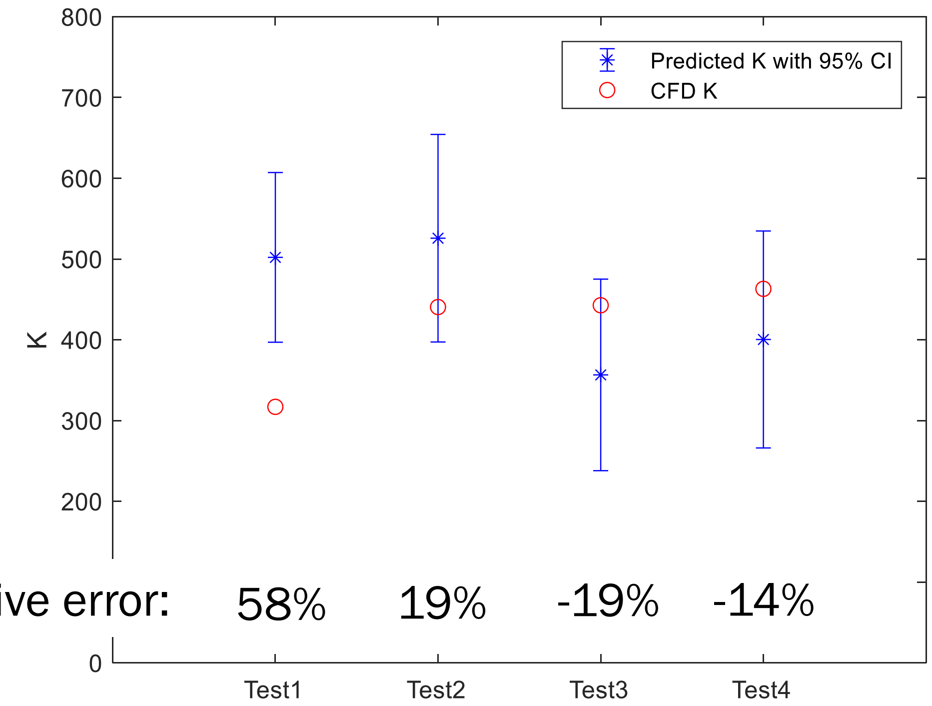
- Standard errors very large
- Model very sensitive to training data set
  - Removing 1 out of 27 runs changes model & its predictions significantly

6. Validate model on test geometries



Relative error: 58% 19% -19% -14%

4 new geometries within parameter range

Test 1

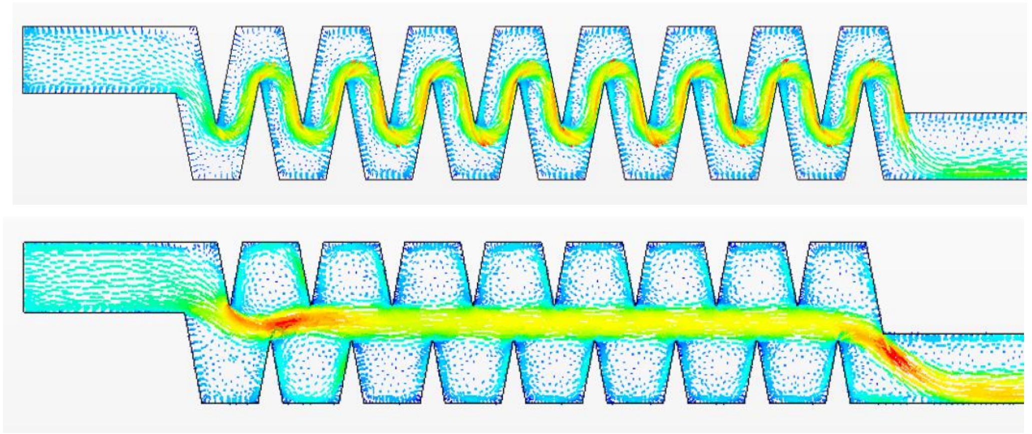
Test 2

Test 3

Test 4

Potential improvements

- Larger training set; different sampling method
- Separate into models for 2 different regimes (gap and no gap)
  - Not enough CFD runs to test this
- Use physical reasoning to make combinations of variables
  - E.g., hydraulic diameter, effective path length, etc.
  - With hydraulic diameter as extra variable: model has R^2=0.997 but still low predictive accuracy



Two different flow regimes, with gap and no gap between teeth.

Conclusions

- Goals: develop quick way to model pressure loss in tortuous path
  - Integrate into more general analytical models of drip emitter behavior
  - Designing emitters with desired features (given a desired pressure loss, output path geometry)
- Developed a surrogate linear regression model to predict pressure loss coefficient in tortuous paths based on geometry alone
  - Simple regression model has low predictive accuracy and is highly sensitive to training dataset
  - Could potentially be improved by separation into models for two (or more) flow regimes and using physical variables
  - This is not a trivial flow to model (large variation in flow patterns due to small geometric changes)

Further work

- Altering surrogate model formulation based on physical reasoning
- If successful, addition of more parameters to model (total path width, corner radius, asymmetry)
- Experimental validation