Supplement Material

Unit-aware Multi-objective Genetic Programming for the Prediction of the Stokes Flow around a Sphere

Heiner Zille
Sanaz Mostaghim
Otto von Guericke University Magdeburg
{heiner.zille|sanaz.mostaghim}@ovgu.de

Fabien Evrard
Berend van Wachem
Otto von Guericke University Magdeburg
{fabien.evrard|berend.vanwachem}@ovgu.de

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A TEST INSTANCES

Table 1 shows the six test instances with the corresponding input features and predicted values. In more detail, the instances are composed as follows.

(1) **Instance 1:** Predict $|\vec{u}|$ from u_x and u_y.

$$|\vec{u}| = \sqrt{u_x^2 + u_y^2} \tag{1}$$

(2) **Instance 2:** Predict $|\vec{u}|$ from u_r, u_θ and θ.

$$|\vec{u}| = \sqrt{(u_r \cdot \cos(\theta) - u_\theta \cdot \sin(\theta))^2 + (u_r \cdot \sin(\theta) + u_\theta \cdot \cos(\theta))^2} \tag{2}$$

However, this equation reduces to

$$|\vec{u}| = \sqrt{u_r^2 + u_\theta^2} \tag{3}$$

(3) **Instance 3:** Predict u_x from u_r, u_θ and θ.

$$u_x = u_r \cdot \cos(\theta) - u_\theta \cdot \sin(\theta) \tag{4}$$

(4) **Instance 4:** Predict u_y from u_r, u_θ and θ.

$$u_y = u_r \cdot \sin(\theta) + u_\theta \cdot \cos(\theta) \tag{5}$$

(5) **Instance 5:** Predict u_r from u_∞, θ, a and r.

$$u_r = u_\infty \cdot \cos(\theta) \cdot (1 + \frac{a^3}{2 \cdot r^3} - \frac{3 \cdot a}{2 \cdot r}) \tag{6}$$

(6) **Instance 6:** Predict u_θ from u_∞, θ, a and r.

$$u_\theta = -u_\infty \cdot \sin(\theta) \cdot (1 - \frac{a^3}{4 \cdot r^3} - \frac{3 \cdot a}{4 \cdot r}) \tag{7}$$

B PARAMETER AND EXPERIMENT SETTINGS

For running the GP algorithm, we use the following experimental and parameter settings.

(1) Number of Iterations of the main loop: 20.
(2) Each Iteration consists of 15 generations of a normal GP (Phase 1), followed by 20 generations of a Mutation-only GP (Phase 2)
(3) The reproduction scheme follows the $(\mu + \lambda)$-approach
(4) In phase 1, the crossover-probability is 0.5 and the mutation-probability is 0.5.
(5) In phase 2, the crossover-probability is 0.0 and the mutation-probability is 1.0.
(6) Initial population is created using a half-and-half scheme of growing iterative trees and creating full trees of a certain depth. The maximum depth of the initial solution is 4.
(7) During the experiments, created solutions are restricted to a maximum length of 50 and a maximum height of 17.
(8) The crossovers in Phase 1 are chosen uniformly at random among one-point crossover and a leaf-based one-point crossover with a probability to select leaves (terminals) for the crossover of 0.9.
(9) The mutations in Phase 1 are chosen uniformly at random from uniform mutation, node-replacement mutation, insert mutation and shrink mutation.
(10) The mutations in Phase 2 are chosen among node-replacement with probability of 2/3 and shrink mutation with a probability of 1/3.
(11) The population size is 2000.
(12) A numerically perfect solution is considered if the max absolute fitness (f_1) is smaller than 1e−15.

Instance No.	Predicted Value	Input Features
1	$\vert\vec{u}\vert$	u_x, u_y
2	$\vert\vec{u}\vert$	u_r, u_θ, θ
3	u_x	u_r, u_θ, θ
4	u_y	u_r, u_θ, θ
5	u_r	u_∞, θ, a, r
6	u_θ	u_∞, θ, a, r

Table 1: Configuration of 6 created Test Instances.

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