X International Conference on Particle-Based Methods, PARTICLES 2027
October 18-20, 2027, Barcelona, Spain

PHYSICAL AI FOR GRANULAR MECHANICS

KRISHNA KUMAR[§], HONGYANG CHENG[†], KONSTANTINOS KARAPIPERIS[*] AND THOMAS LICHTENEGGER[‡]

[§] Oden Institute of Computational Engineering and Sciences, The University of Texas at Austin
301 E. Dean Keeton St., Austin, TX 78712, USA
krishnak@utexas.edu

[†] Faculty of Engineering Technology, University of Twente
Drienerlolaan 5, 7522 NB Enschede, The Netherlands
h.cheng@utwente.nl

[*] Data-Driven Mechanics Laboratory, School of Architecture, Civil and Environmental Engineering, École Polytechnique Fédérale de Lausanne
Station 18, CH-1015 Lausanne, Switzerland
konstantinos.karapiperis@epfl.ch

[‡] Department of Particulate Flow Modelling, Johannes Kepler University, Linz, Austria
thomas.lichtenegger@jku.at

ABSTRACT

Physical AI is a computational pipeline for predicting how a physical system will evolve under an action, with quantities of interest that are physically viable, uncertainty-aware, optimized and actionable. For granular mechanics, the system is a slope, a soil bed, a powder, or a flowing aggregate; the action is loading, excavation, traversal, or deposition; the prediction must support decisions about safety, capital, or autonomy. Numerical methods, such as discrete element and material point methods can produce such predictions, but at a cost that rules out full sensitivity analysis, real-time control, or closed-loop autonomy, often perused by engineering practice. The opportunity is to assemble learned components into a pipeline that answers the same questions end to end.

The pipeline has five stages. *Sensing* recovers the granular state from imagery, in-situ instruments, and sparse measurement. *Constitutive learning* captures material response across solid-like, fluid-like, and gas-like regimes. *Learned surrogates or reduced order models* that predict evolution under intervention. *Conformal prediction and formal verification* carry calibrated guarantees on those predictions. *Planning and shielded control* turn predictions into action. What unifies the stages is not a single architecture but a standard, applicable across settings as different as levee stability, silo flow, autonomous excavation, planetary rover traversal, and additive manufacturing with powders.

The session welcomes contributions to any stage of this pipeline and to work that integrates across stages. Topics of interest include:

1. Constitutive and representation learning for granular media transitioning across solid-like, fluid-like, and gas-like regimes, distilled from heterogeneous DEM, continuum, and experimental data;
2. Operator learning, graph-based simulators, and foundation or world models to query granular dynamics evolution under intervention, with attention to extrapolation across

scales and boundary conditions;

3. Sensing and state estimation that recover physical representations of granular systems from images, sensors, and sparse measurement;
4. Trustworthy machine learning for high-stakes granular tasks, including conformal uncertainty, formal verification of learned constitutive responses, and shielded control under physical constraints;
5. Open benchmarks, datasets, and evaluation protocols that test physical viability rather than visual or statistical fidelity, and that connect simulation packages with experimental facilities.

REFERENCES

[1] Fransen, M., Fürst, A., Tunuguntla, D., Wilke, D. N., Alkin, B., Barreto, D., Brandstetter, J., Cabrera, M. A., Fan, X., Guo, M., Kieskamp, B., Kumar, K., Morrissey, J., Nuttall, J., Ooi, J., Orozco, L., Papanicolopulos, S.-A., Qu, T., Schott, D., Shuku, T., Sun, W., Weinhart, T., Ye, D., & Cheng, H. (2026). Towards scientific machine learning for granular material simulations: Challenges and opportunities. Archives of Computational Methods in Engineering, 33, 789–821.