Data science meets computational mechanics

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1. Overview

The integration of Machine Learning (ML) with (computational) mechanics is referred to as *data-driven computational mechanics* and *fourth pillar of scientific investigation* which is expected to overcome the limitations of the standard engineering approaches. Two aspects for the integration of Artificial Neural Networks (ANNs), as a robust tool in ML, with mechanics can be imagined.

- ANNs complementing the standard computational approaches such as Finite Element (FE) method making them more "intelligent".
- ANNs as an independent computational mechanics tool respecting the physics laws (PINNs).

Intelligent Finite Element Method (IFEM)

- **Application:** Predictive analysis of complex Multiscale and Multiphysics problems (poroelastic phenomena).
- **Problems:**
  1. Complex strong interdependencies between different scales and phases.
  2. High number of parameters to be identified for governing PDEs.
  3. Time-consuming nested procedures such as homogenisation.
  4. Highly nonlinear response from different sources.
- **The limit:** Standard computational approaches embrace dramatic simplifying assumptions acceptable only in few real-world cases.
- **Methodology:**
  1. Design and development of fast and accurate ANN-aided homogenisation and localisation tool.
  2. Integration of the latter into FE package FEniCS creating an IFEM.
- **Achievements:**
  1. Two models have been developed able to consider different complex aspects of poroelastic media.
  2. Two scientific articles have been published applying the models into different scenarios of interest from soil mechanics to tumor and brain tissue.
  3. Significant scientific results are achieved.

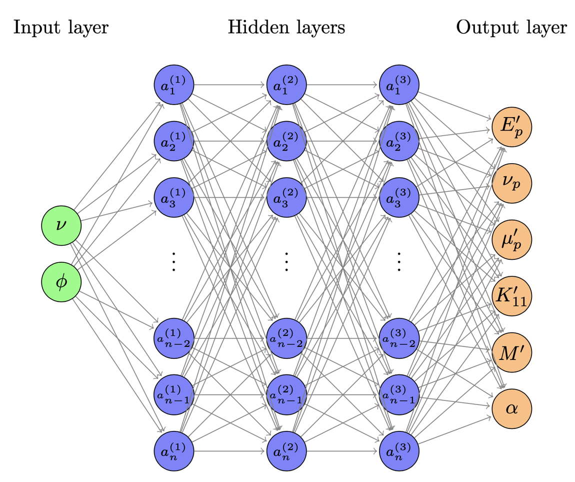
IFEM for spatially dependent material properties

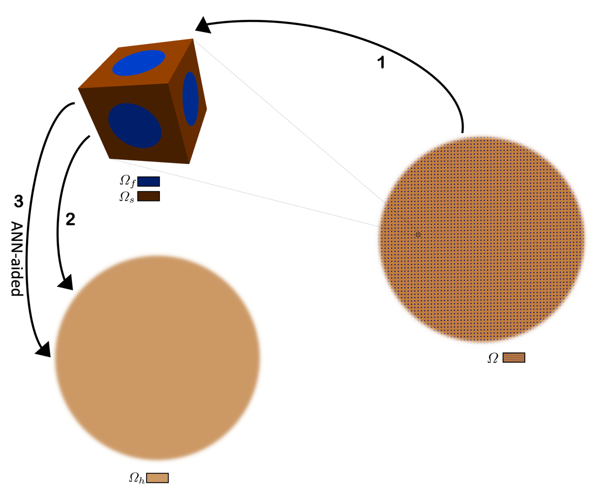
Poroelastic model parameter identification using artificial neural networks: on the effects of heterogeneous porosity and solid matrix Poisson ratio [1]

- An ANN is designed to deliver non-dimensional effective properties based on non-dimensional bounded microscopic properties.

$$ANN(\nu, \phi) = (E'_p, \nu_p, \mu'_p, K'_{11}, M', \alpha) \qquad (1)$$

- The acquired ANN is integrated into FEniCS creating an IFEM.
- The model applied in soil mechanics and biomechanics real-world scenarios to show its robustness.
- Important results are achieved highlighting the advantage of the provided ANN-supported framework.

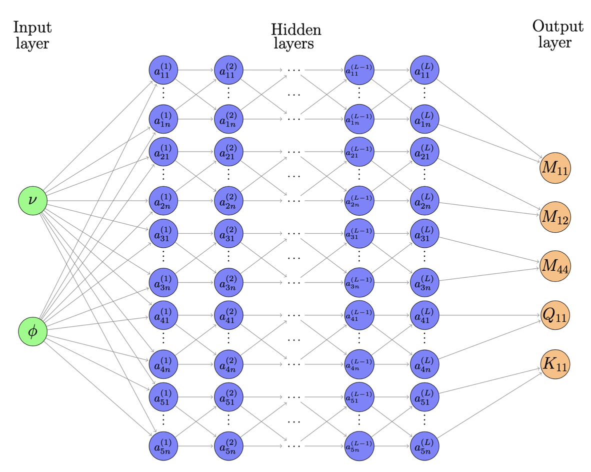


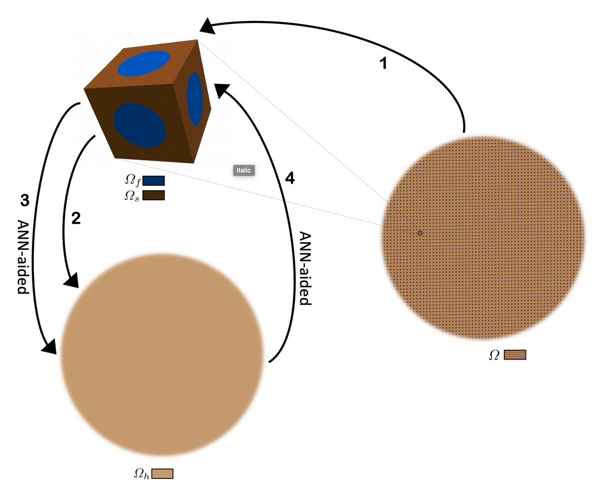


IFEM for finite strain poroelasticity and remodelling

ANN-aided, multiscale, remodelling-based incremental numerical approach for finite strain poroelasticity: On the interaction between the two-scales, nonlinear deviation from Darcy's law, and brain tissue deformation

- The results in Article A are valid only under infinitesimal deformation.
- Under **finite (large) deformation** the **real-time effects** of macroscale response on microscale properties rearrangement must be considered.
- Incremental FE (in time) is used to consider the latter during the analysis.
- Parallel ANNs provides fast and accurate homogenisation and localisation at each increment.

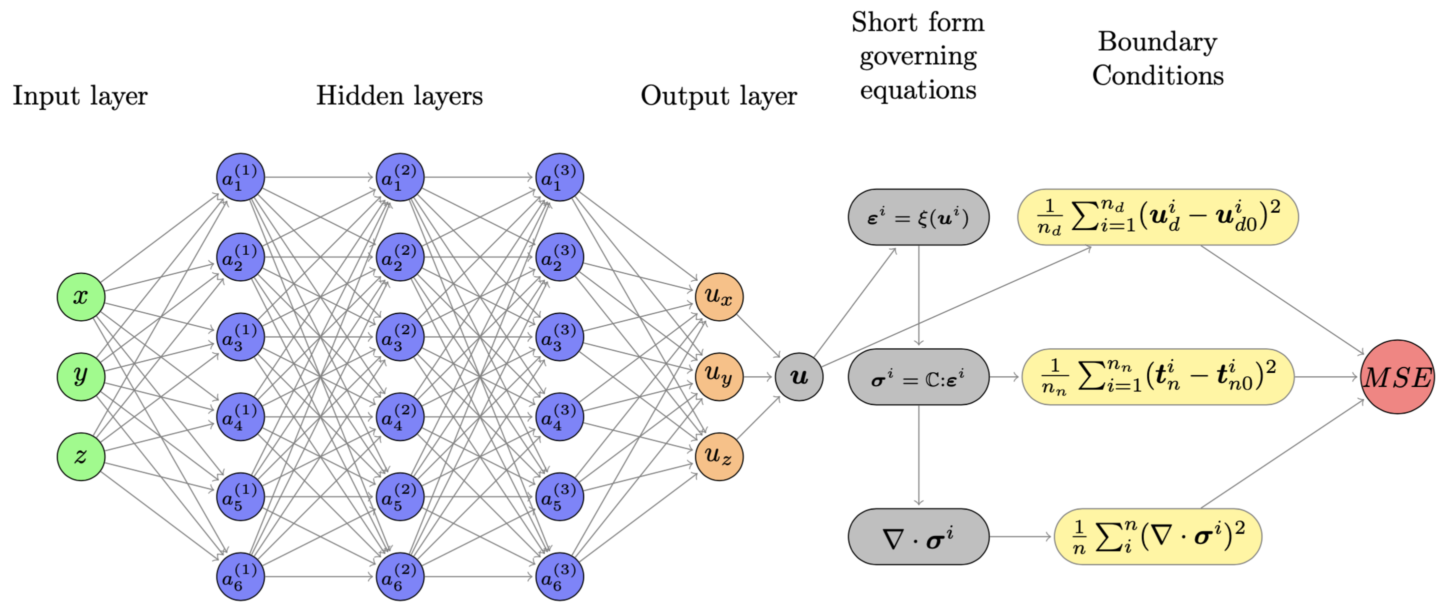




- Material properties rearrangement during consolidation yielded important results.
- Nonlinear fluid flow is captured agreeing with experimental data.
- Hysteresis, preconditioning and Mullins effects are captured simulating the brain tissue under cyclic loading agreeing with experimental data.

ANNs as independent computational tools

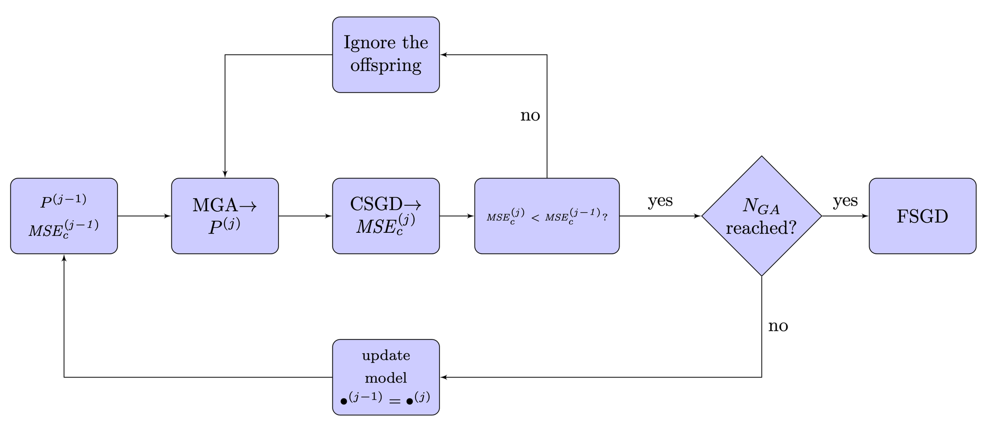
- **Physics Informed Neural Networks (PINNs)** allows to solve mechanical problems using ANNs.
- The distance function to be minimised is constructed based on the strong-form of the governing system of PDEs (The physical laws).



- **Advantages:**
  1. No need to reconstruct the physical field throughout the computational domain to predict mechanical response at a specific point (mesh-free).
  2. Continuous solution and straight forward gradient computation.
  3. Less complex implementation of the Boundary Conditions
- **Problems:**
  1. Third order gradients of outputs w.r.t inputs are required to train the network.
  2. Error explosion happens more frequently.
  3. Time-consuming training procedure.

PINNs for solving linear elliptic PDEs

- **A hybrid MGA-MSGD ANN training approach for approximate solution of linear elliptic PDEs**[2]
- **MGA:** Modified Genetic Algorithm. **MSGD:** Multi-level Stochastic Gradient Descent.



- Linear elastic mechanical problems are solved in 3D via PINNs for the first time.
- The method is compared with standard SGD and Adam optimisers.
- The efficiency of the training procedure is considerably improved and it is less sensitive to the non-mechanical properties and random initial learnable parameters.
- More accurate mesh-free mechanical response is achieved.

In progress and future works

- Taking the full advantage of IFEM to address, accurately, complex real-world issues and introduce it to the industry.
- Improving the hybrid training approach for PINNs to solve more complex non-linear problems.
- Promote the methods and achievements to interested communities and companies.
- Designing educational courses.

6. References

[1] Hamidreza Dehghani and Andreas Zilian. Poroelastic model parameter identification using artificial neural networks: on the effects of heterogeneous porosity and solid matrix poisson ratio. *Computational Mechanics*, 2020.

[2] Hamidreza Dehghani and Andreas Zilian. A hybrid mga-msgd ann training approach for approximate solution of linear elliptic pdes, 2020.