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## DATA DRIVEN MULTISCALE MODELING USING LATTICE MODEL ON THE LOWER SCALE

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Data driven computational mechanics (DDCM) [1] is a generalization of traditional, modeling approach, where material behavior is described with a model,  $\hat{\sigma}(\epsilon)$ . The traditional approach in the computational mechanics considers the formulation of material models whose development relays on the data. Those data are usually collected either through experimental measurements (extensometry, force cells, fullfield kinematic/thermal measurements, etc.) or simulation (different methods, discretization techniques and scales can be considered). While in the 1960s the available data were sparse, at least across certain regimes, nowadays we live in the era of data generation and collection. Thus, before one needed a great deal of intuition and experience to develop a quality model from sometimes scarce input, with the goal to generalize experimental measurements made on simple test. The transition to the data rich era progressively happened in all scientific domains, and as a result we ought to deal with the big-data even in computational mechanics. On the other hand, traditional models were developed in a different context which sometimes makes them incompatible with the data rich environment, finally causing the model with it's assumed properties to downgrade the available data. In other words, traditional fitting of a model to the rich data is often ill-posed and can cause modeling errors which might severely impact the accuracy of the solution. Thus, the basic idea behind DDCM is to use the provided measurements as constitutive data (or big-data) directly in the computation, skipping entirely the modeling step and the usage of the constitutive model. DDCM, introduced in [1], is a reformulation of the boundary value problems aiming to search for the solution in the set of mechanically admissible states,  $A$ , by minimizing the distance to the material data set,  $D$ . In the classical sense, mechanically admissible state is a tuple (strain, stress) which satisfies equilibrium and kinematic relations, as well as boundary conditions. In this context, DD problem is defined with minimization:

$$\min_{\mathbf{y} \in A} \min_{\mathbf{z} \in D} d^2(\mathbf{y}, \mathbf{z})$$

where  $d^2$  is the squared distance in phase space  $(\epsilon, \sigma)$ , and the objective is to find admissible state  $\mathbf{y}$  in  $A$  the closest to the state  $\mathbf{z}$  in  $D$ . To solve DD problem a distance-based solver is introduced to iteratively minimize the distance between  $\mathbf{y}$  and  $\mathbf{z}$ . In each iteration within a staggered solution scheme we are: a) projecting the data state to admissible set which boils down to solving two linear systems resulting from FE discretization, and b) searching the closest point in  $D$  to the previously calculated point in admissible set. From it's introduction the performance of the new 'model-free' computational paradigm was presented in statical [1, 2] and dynamical [3] context. The convergence analysis of the proposed solver is presented for the linear and non-linear [4, 5] elastic behavior. In last five years the model-free approach is emerging as an alternative to model-based computing and was extended to inelasticity [6] and fracture [7].

Current trend in engineering practice is to replace as much as possible expensive and sometimes hardly realizable experiments with virtual test. In line with this trend goes the development of the multiscale (MS) methods aiming to promote the coupling between different scales in virtual testing and increase predictiveness. One of the most developing MS strategies is based on computational homogenization [8] permitting to take into account the influence of the underlying material microstructure

explicitly in the macroscopic constitutive response through the analysis of Representative Volume Elements (RVEs). Thus, the constitutive relation at the macroscale is not a priori required, it is inferred from the RVE homogenization results. In this context one can model a complex microstructure geometry in the expense of often huge computational cost due to the need for homogenized RVE results on-the-fly in each material (integration) point and each iteration.

More importantly the absence of the constitute model on the macro scale opens the possibility to couple standard MS analysis with the previously described DD approach where the macro scale material behaviour is fed by database created from off-line RVE simulations. An example of the DD multi-scale method, with nested boundary value problems treated with finite elements (FE) on both scales, is presented in [9]. However, it is possible to use distinct numerical methods for the solution of either the macro and micro-problems, see [10] for the application related to granular materials simulated with discrete element method.

In this work we explore the possibility of using lattice model [11, 12] on the RVE (micro) scale. In the first place is the problem of generating the data set that will be used for the subsequent data driven predictions with the material data being extracted from lower-scale, lattice simulations. The DD prediction depends entirely on the material data base and it's quality. We focus here firstly on the off-line sampling targeting to generate data base which is sufficient for the chosen examples. More precisely, we impose on the lattice RVE deformational component of the local state and by running an equilibrium RVE simulation we seek a work conjugate, that is, homogenized local stress. In this context, we discuss the optimal sampling of the input strain.

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