Advanced Modeling of Emerging MRAM: From Finite Element Methods to Machine Learning Approaches

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Emerging magnetoresistive random access memories (MRAM) are nonvolatile and offer high speed and endurance. They are promising for stand-alone and embedded applications in the automotive industry, microcontrollers, internet of things, frame buffer memory, and slow SRAM. The MRAM cell usually includes a CoFeB reference layer (RL) and a free magnetic layer (FL), separated by an MgO tunnel barrier (TB). To increase the interface-induced perpendicular magnetic anisotropy, the FL is capped with a second MgO layer. Making the FL composed of several pieces separated by MgO layers further increases the perpendicular anisotropy. To benefit from the shape anisotropy and to increase the perpendicular anisotropy even further, the FL is elongated along the easy axis [1]. This allows to reduce the cell diameter to just 2.3 nm, which makes shape-anisotropy MRAM cells promising for ultra-dense memory applications.

To design ultra-scaled MRAM cells it is necessary to accurately model the torques acting on the textured magnetization in elongated composite magnetic layers with several MgO inclusions between the parts. The magnetization dynamics are then governed by the Landau-Lifshitz-Gilbert (LLG) equation supplemented with the corresponding torques. The torques are determined by the electric current generated nonequilibrium spin accumulation which depends on the magnetization. Therefore, the LLG and the spin-charge transport equations are coupled and must be solved self-consistently. To solve numerically this coupled system of partial differential equations, we use the finite element method (FEM). We implemented the solver with open-source C++ FEM libraries.

The computationally most expensive part is the demagnetizing field calculation which is performed by a hybrid finite element-boundary element method. This restricts the computational domain to ferromagnets only. Advanced compression algorithms for large, dense matrices are used to optimize the performance of the demagnetizing field calculations in complex structures [2]. To evaluate the torques acting on the magnetization, we employ the drift-diffusion approach for coupled spin and charge transport commonly applied in nanoscale metallic spin valves. For the computations of the torques acting in a magnetic tunnel junction (MTJ), an essential part of the cell of modern spin-transfer torque memories, we introduced a magnetization-dependent resistivity of the TB [3]. We investigated the dependence of the resulting torques on system parameters and show that this approach produces the torque magnitude expected in MTJs. We showed that a full three-dimensional solution of the equations is necessary to accurately model the torques acting on the magnetization. The use of a unique set of equations for the whole memory cell, including the FL, RL, contacts, and the TB, constitutes the advantage of our approach to rigorously describe the switching process of nonvolatile spin-transfer torque memories [4]. We also investigated the temperature at the free layer (FL) during switching. To incorporate the temperature increase due to the electric current, we solve the heat transport equation coupled to the electron, spin, and magnetization dynamics, and we demonstrated that the FL temperature is highly inhomogeneous due to a non-uniform magnetization of the FL during switching [5].

Spin-orbit torque (SOT) MRAM is fast-switching and thus well suitable for caches. By means of micromagnetic simulations we demonstrated the purely electrical switching of a perpendicular FL by the SOTs created by two orthogonal short current pulses. The second, reduced current pulse can be applied to many cells in an array, while maintaining deterministic switching [6]. To further optimize the pulse sequence, we used a machine learning approach based on reinforcement learning [7]. We demonstrated that a neural network trained on a fixed material parameter set optimally applies pulses and achieves switching for a wide range of material parameter variations as well as for sub-critical current values of the first pulse and second pulse.

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