Empowering Engineering Organizations with Deep Learning: Applications to a faster transition towards electrification for Automotive OEMs and Suppliers - Heat Exchanger optimization

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1. Frontloading simulation with Deep Learning

In the evolving landscape of engineering, there's a growing need for enhanced capabilities, especially in optimizing the use of computational resources.

Traditional simulation tools, owing to their historical development, may sometimes face challenges in rapidly changing design and production environments. However, these tools have been instrumental in providing foundational insights for design teams.Integrating Deep Learning technologies can offer a way to seamlessly combine the strengths of simulation and design optimization tools, facilitating a more collaborative approach between design engineers and simulation experts.

While traditional design tools have been pivotal in shaping engineering solutions, there's room for further innovation. These tools have often been employed to select optimal configurations based on predefined parameters or to make incremental adjustments to existing designs. The future of engineering design could benefit from a more expansive, computer-driven exploration approach. In this context, Deep Learning can play a complementary role, enhancing the capabilities of traditional simulations and broadening the horizons of design possibilities.

In this talk, we explain how recent algorithms based on Geometric Deep Learning, allow shortcutting any simulation chain through a predictive model that outputs post processed simulation results and optimization suggestions, right from the CAD design. These models are being used in engineering companies to simplify processes and to emulate the expertise of simulation engineers in the hands of product or design engineers early in the development process. Thus, the number of iterations between teams are reduced while accelerating the design activities.

These new capabilities are being adopted by a growing number of leading players, especially in the Automotive industry, who have achieved:

- 2x reduction of lead time to deliver new vehicle or parts programs
- Product performance improvement resulting in 50% more successes in tender processes.

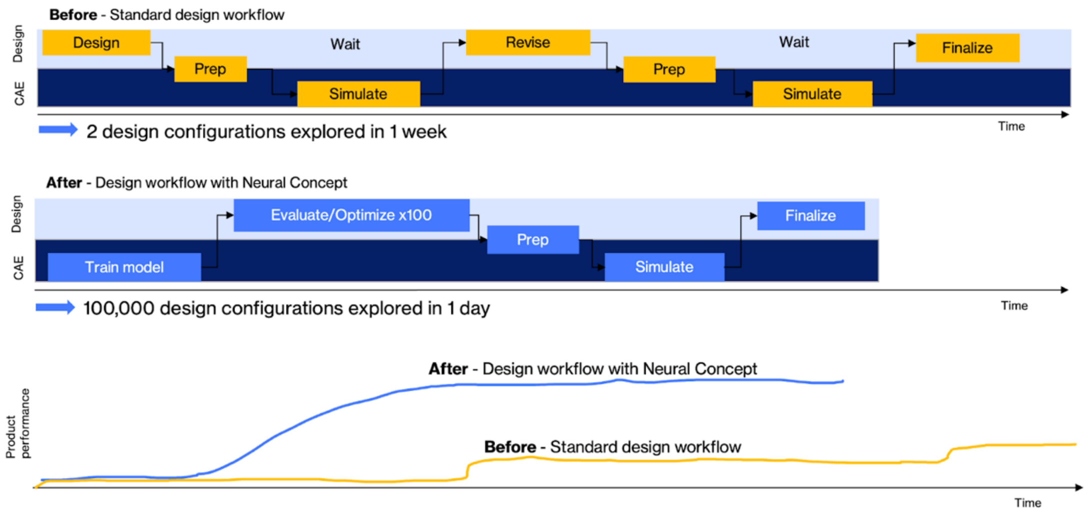

Figure 1: design workflows comparison

2. Geometric Convolutional Neural Networks

With traditional approaches, the models are trained on a specific parametric representation of the design space. Thus, any modification in the design space or in the boundary conditions will require generating a new dataset of simulations and training an independent model. In many industries, including automotive and aerospace sectors, each project involves many changes in the description of the parametric space or in the external conditions. Moreover, most engineering teams work on improving or redesigning variants of the same class of devices. Either way, the necessity to generate a completely new dataset at each iteration, without being able to leverage simulations collected during previous iterations, is underwhelming for the engineer.

At the same time, Geometric Convolutional Neural Networks can be used to build surrogate models of numerical solvers, like other learning-based methods, while also being agnostic to the shape parameters as it directly processes the mesh representation of the design. Hence, a single predictor can be trained with a large amount of data and can be used for numerous optimization tasks and the engineer does not have to choose and stick to a specific parametrization from the beginning to the end of experiments. Furthermore, it can leverage on transfer learning abilities of Deep models to blend simulations from multiple sources and with multiple fidelities.

Geometric Neural Networks can also provide more decisive accuracy gains by learning based on multiple data outputs and using the correlations between quantities to obtain the best result. Secondly, the convolutions used in Geometric Neural Networks are particularly suited to the accurate prediction of complex local field quantities, such as deformation, temperature, or pressure. Moreover, using the physical space as a reference for learning makes it possible to exploit any raw, unprocessed data source for training a model. Therefore, one can exploit an existing database of simulations or reuse data across design iterations, across projects or across multiple teams. This is a key enabler to improve performance of approximation models, while generating an order of magnitude fewer simulations in the long term. This new approach is breaking silos between projects to allow a unified model to be built and used once and for all.

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3. Deployment on HPC systems

Practical solutions are already available for teams who want to access such tools. For instance, Neural Concept Shape (NCS) is a software platform that allows engineers, at all levels of expertise, to implement the latest Deep Learning based engineering practices into their development processes. Using Neural Networks, simulation engineers and the design engineers can collaborate more efficiently and save costly iterations between teams.

Since NCS exploits directly the results of traditional simulations, the integration of HPC clusters with Kubernetes distributed training on multiple GPUs and the efficient exchange of large volumes of data is a force-multiplier for AI. Therefore, NCS has been built to leverage the flexibility and power of cloud HPC services (such as Microsoft Azure) that provide seamless integration with large volumes of simulation results, access to heterogeneous computing platforms and the ability to deploy trained models in a secure environment for remote engineering and design teams working in different locations. In short, the association of GCNNs with cloud-based HPC is breaking a new barrier in terms of possibilities, performance and convenience for deploying AI-based design optimization at large organizations and provides significant reduction of design times thanks to high performance in simulation, training and inference.

4. Heat exchanger application case

To illustrate the practical capabilities of Deep Learning, we use an example in Heat Exchanger design optimization. Heat Exchanger design and optimization is a critical topic with the electrification of vehicles, and more specifically for battery cooling applications, but also for other electronic components inside the vehicle. It is a major driver in the vehicle efficiency and its durability. Hence, a well established and efficient design process is a key competitive advantage within the automotive industry.

Heat Exchanger design is a complex task: the engineer has to make a lot of important design decisions to select the right concept (fins/pins heat exchanger, plate with dimples, channel structure…). Most of these decisions are based on best practices and rely on the experience of the team in charge of the development of the product. Moreover, within a single heat exchanger concept, the design freedom is significant, and small design changes could lead to drastic performance variations. Most of the time, the engineers and design teams can only afford to explore a few variations from a given concept, due to the complexity of the CAD/CFD workflow.

We conducted a study using Heat Exchanger internal CFD simulations, where we show how the AI model can be used to run a non-parametric optimization, leading to drastic performance improvements compared to a standard parametric study. Moreover, the predictive model can be made accessible to the design team through a simplified graphical interface. Ultimately, this leads to shorter lead times, especially critical for the RFQ phase in the automotive industry, together with better product performances.

In this application, we used the generative design capabilities of NCS models (NC Design Module) to create an initial, non-parametric dataset, used to train the predictive model. An integration with Ansys Fluent is then available, allowing to automatically simulate the created designs. Over a couple of days, a dataset of 100 geometries and corresponding simulations was created.

Leveraging this dataset, a predictive model was trained. The predictive model has proven to be highly accurate, capturing complex flow phenomenon such as recirculation, across different topologies.

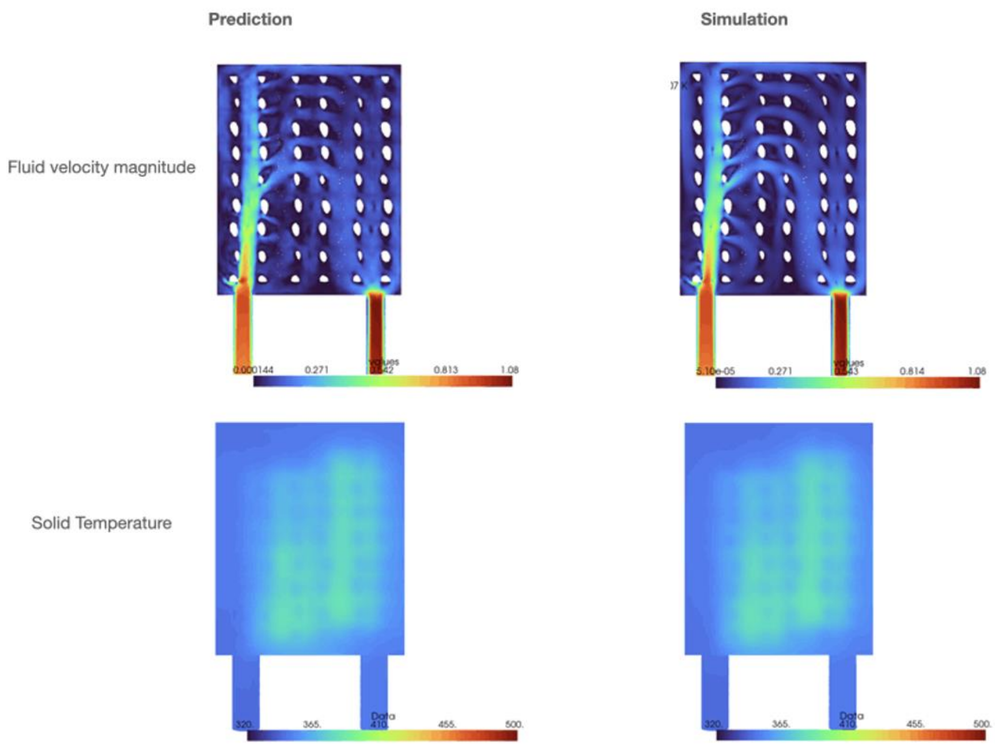

Figure 2: Comparison between a NCS model prediction (left), and the corresponding Ansys Fluent CFD simulation (right)

Once the predictive model was validated, it allowed to run a large optimization campaign, leveraging both the NC Design module for geometry generation, and the predictive model. With the goal to minimize pressure drop and maximum temperature, the optimization loop allows to explore hundreds of innovative designs very rapidly, ultimately converging to designs outperforming the original baseline. Validation through CFD simulation showed a 20% improvement of pressure drop at constant max temperature and manufacturing costs. These results largely outperform any parametric optimization, which could be started from a given heat exchanger topology.

As a summary, this end-to-end workflow shows how we can leverage Geometric Deep Learning based predictive models, coupled with the corresponding design generation capabilities, even without any historical data. The non-parametric nature of this optimization workflow allows the exploration of innovative design and concepts, across topologies, removing some key limitations of standard CAD/CAE based workflows.

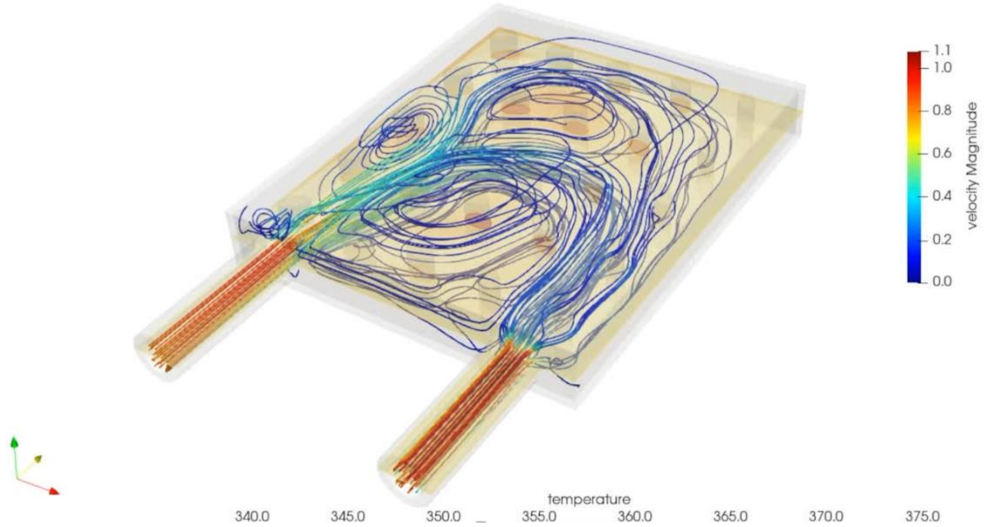

Figure 3: Example of a design explored during the optimization process, with the corresponding performance prediction from the AI model