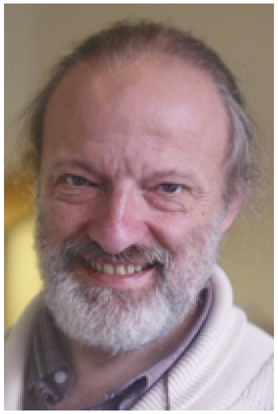
# Intel® Parallel Computing Center at CERN, European Organization for Nuclear Research

Published on December 19, 2014, updated September 25, 2018 Translate

## Principal Investigators:

**Federico Carminati** is a chief innovation officer at [CERN openlab (https://openlab.cern)](https://openlab.cern). After getting his degree in 1981, he worked at Los Alamos National Laboratory and CalTech. He was responsible for the CERN Program Library's standard code for high energy physics (HEP) in the 1980s. In 1994, he worked with Nobel Prize winner Carlo Rubbia in the design of a novel accelerator-driven nuclear power device. In

1998, he was the computing coordinator of the A Large Ion Collider Experiment (ALICE) experiment at the Large Hadron Collider (LHC) facility. From 2103 to 2017, he led the detector simulation activities in the physics department. In 2013, he obtained his physics PhD from the University of Nantes.



## Description:

The ever-increasing need for computing resources has prompted a sustained effort to optimize the high energy physics program library to take advantage of new computing architectures and novel algorithms. This is necessary if we want the HEP code to meet the challenges posed by the ever-increasing requirements of HEP research. After a detailed research and development phase during 2012 and 2013, CERN decided to target simulation as a primary candidate for optimization. Half of the approximately 600,000 cores constituting the World LHC Computing Grid are continuously running simulation programs, and the simulation needs are expected to increase at least tenfold in the near future.

To address this problem, we propose the development of a fast, deep learning-based approach to detector simulation. We plan to develop an automatic, self-adaptive tool to replace a Monte Carlo simulation with a wide variety of detectors, particles, and energies. The simulation process can be treated as black box to be replaced by a deep learning algorithm trained on different particle types, momentum, and positions.

We plan to develop a general interface where a user can specify a physics process and detector type and get back an optimally trained machine learning model that will simulate the detector response. This will be achieved by implementing network meta-optimization and hyperparameter scans: One of the key features of this tool will be its capability of adjusting and tuning the architecture hyperparameters depending on the geometry of the detector being simulated. This kind of approach requires running large hyperparameter scans and algorithmic meta-optimization and therefore an efficient distributed training process.

The results of this project will be highly useful for a far broader range of applications. The problem we want to solve is how to reliably simulate a complex, highly nonlinear system using self-adaptive machine learning techniques. The questions that we are considering are:

- How capable are machine learning models in reproducing a 3D or 4D training set, maintaining proper correlations?
- How robust is the prediction outside of the trained input range?
- How generic these models can be? What are the limits and capability of DNN self-adaptation via hyperparameter scans?

Moreover, apart from being instrumental for HEP, particle transport simulation is relevant well beyond the domain of fundamental research. Radiation transport techniques are extremely important for a wide range of applications:

- Radiation protection in all industrial fields using ionizing radiations (sterilization, imaging, and so on)
- Radiation protection for space flights
- Design and optimization of imaging medical instruments
- Treatment planning for radiation therapy
- Radiation safety for nuclear power and fuel processing plants

All these applications and their respective fields would greatly benefit from an increase in the simulation speed. Beyond the specifics of radiation transport, development of such simulation tools can further benefit any field where a fast assessment of the consequences of a complex set of input parameters is important, such as complex industrial process monitoring, environmental modelling, natural disaster avoidance, simulation of biological systems development (from cancer cells to neurons, and more) and so on.

## Publications:

- Rob Farber, 8/14/2018, CERN Project Sees Orders-of-Magnitude Speedup with AI Approach (https://www.hpcwire.com/2018/08/14/cern-incorporates-ai-into-physics-based-simulations/), HPCWire, Web Article
- Linda Barney, 7/27/2018, Speeding CERN LHC Research with HPC Systems and ALCF Workflow Optimization (https://www.rdmag.com/news/2018/07/speeding-cern-lhc-research-hpc-systems-and-alcf-workflow-optimizations), R&D, Web Article

List of Publications (https://openlab.cern/code-modernisation-fast-simulation)

## Related Websites:

- CERN (http://www.cern.ch/)
- CERN openlab (https://openlab.cern/)

---

For more complete information about compiler optimizations, see our Optimization Notice (/en-us/articles/optimization-notice#opt-en).

- **Hardware Developers**
  - Firmware
  - Modeling & Simulation
  - Resource and Design Center
  - Shop Intel
- **Open Source**
  - 01.org
  - GitHub*
- **Manage Your Tools**
- **Connect**

- Download Center
- Priority Support
- Registration Center

- Forums
- Meet the Experts
- Newsletter
- Recent Updates
- YouTube* Channel

**Get the Newsletter**

**Follow us:**

Terms of Use *Trademarks Privacy Cookies Email preferences