General shower simulation MetaHEP in key4hep framework

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```
Detector-specific
         Generic
def ML4FastSim(particle(energy,angle,type),detector):
    return f(shower|particle(energy,angle,type),detector)
```

1 . Introduction

We present MetaHEP a **generalizable** and **reusable** solution based on **meta learning** to accelerate shower simulation in different calorimeters using very high granular data. We show its application using a calorimeter proposed for the **Future Circular Collider (FCC-ee)**.

2 . Datasets

Idealised, cylindrical detectors (SiW, SciPb, PBWO4) used in this study are simulated with the **ParO4 example of Geant4.**

Full simulation dataset is available on Zenedo and is part of the CaloChallenge

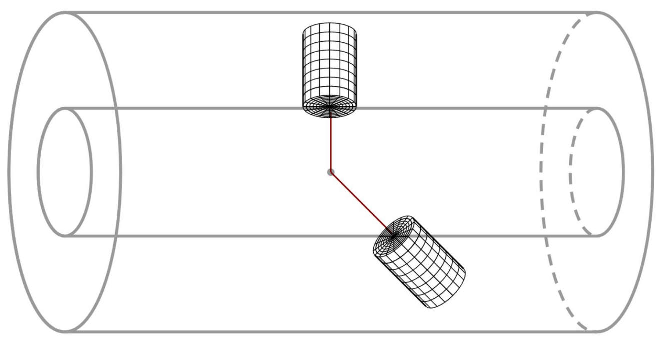
Full simulation of **FCC-ee** detector is performed with the **FCCSW**, a common software for all FCC experiments using the turnkey software stack called **key4hep**.

Energy range : 1GeV-1TeV (discrete values in powers of 2)

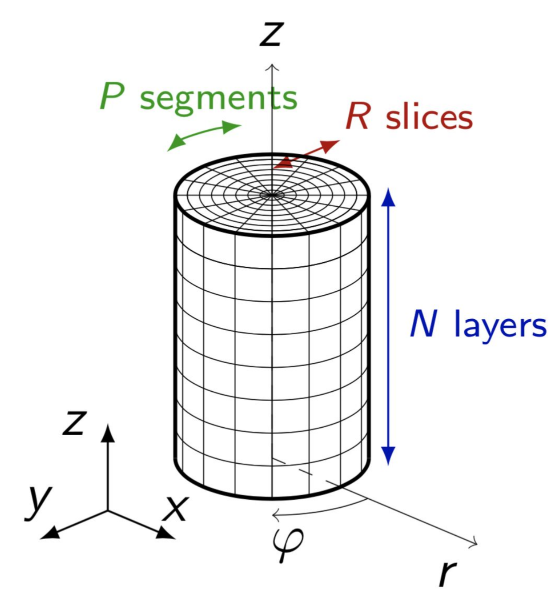
Incident angle : 50-90^0 (step of 10^0)

Detector	1st material thickness (mm)	2nd material thickness (mm)	Number of layers	R	P	N	Δr (mm)	Δz (mm)
SiW cylinders	0.3 mm	1.4 mm	90	18	50	45	2.3	3.4
SciPb cylinders	1.2 mm	4.4 mm	45	18	50	45	4	5.6
$PbWO_4$ cylinders	200.25 mm	-	1	18	50	45	4.9	4.5
SiW FCC-ee	0.5 mm	1.8 mm	40	18	50	45	4.9	5.05

Dimensions of the physical layout of the detector: thickness and number of layers, and of the dynamic mesh readout for four studied detectors



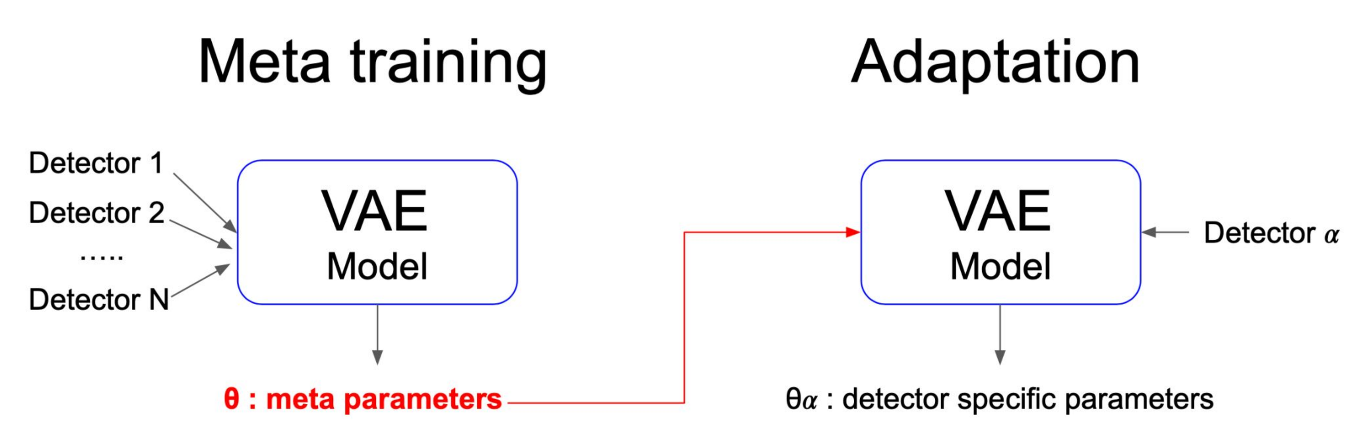
Energy deposits are scored in cylindrical readout around particle momentum. Top cylinder is scoring energy of particle that enters the calorimeter at incident angle of 90^0



Cylindrical (r,ϕ,z) segmentation.

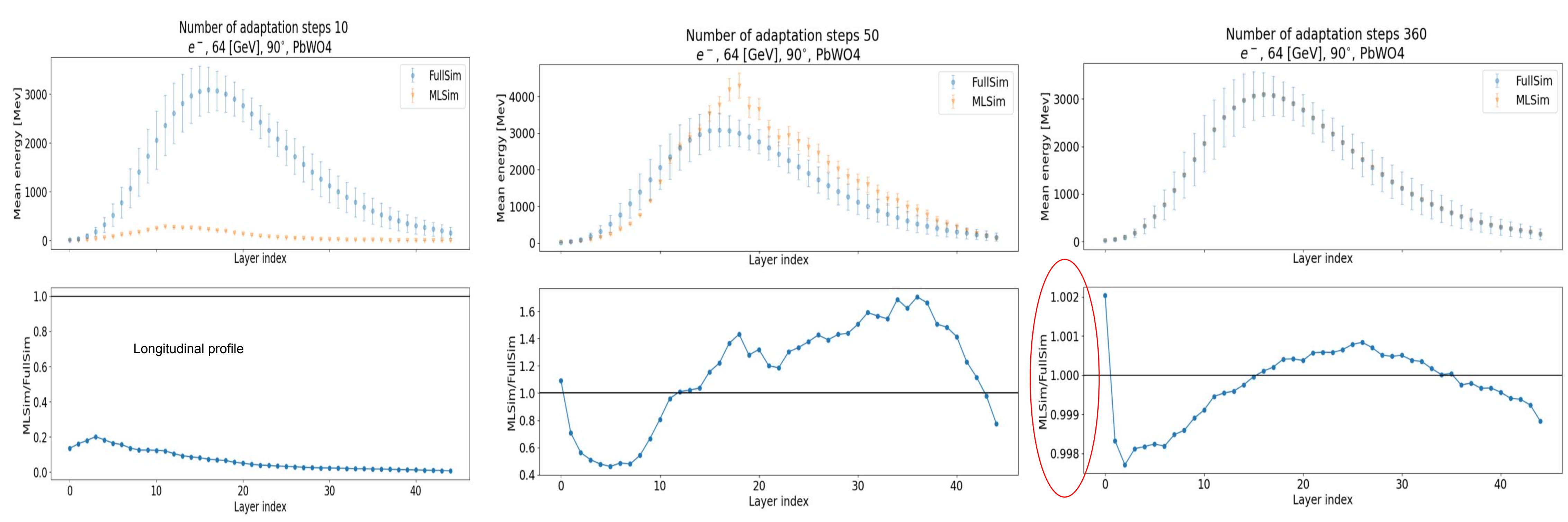
3 . Meta learning for fast shower simulation

The key idea behind the **meta-learning** approach is that instead of starting the training process from scratch on every new geometry, we can use the **meta-knowledge** learned during the meta training step for a **faster and more data-efficient adaptation**.



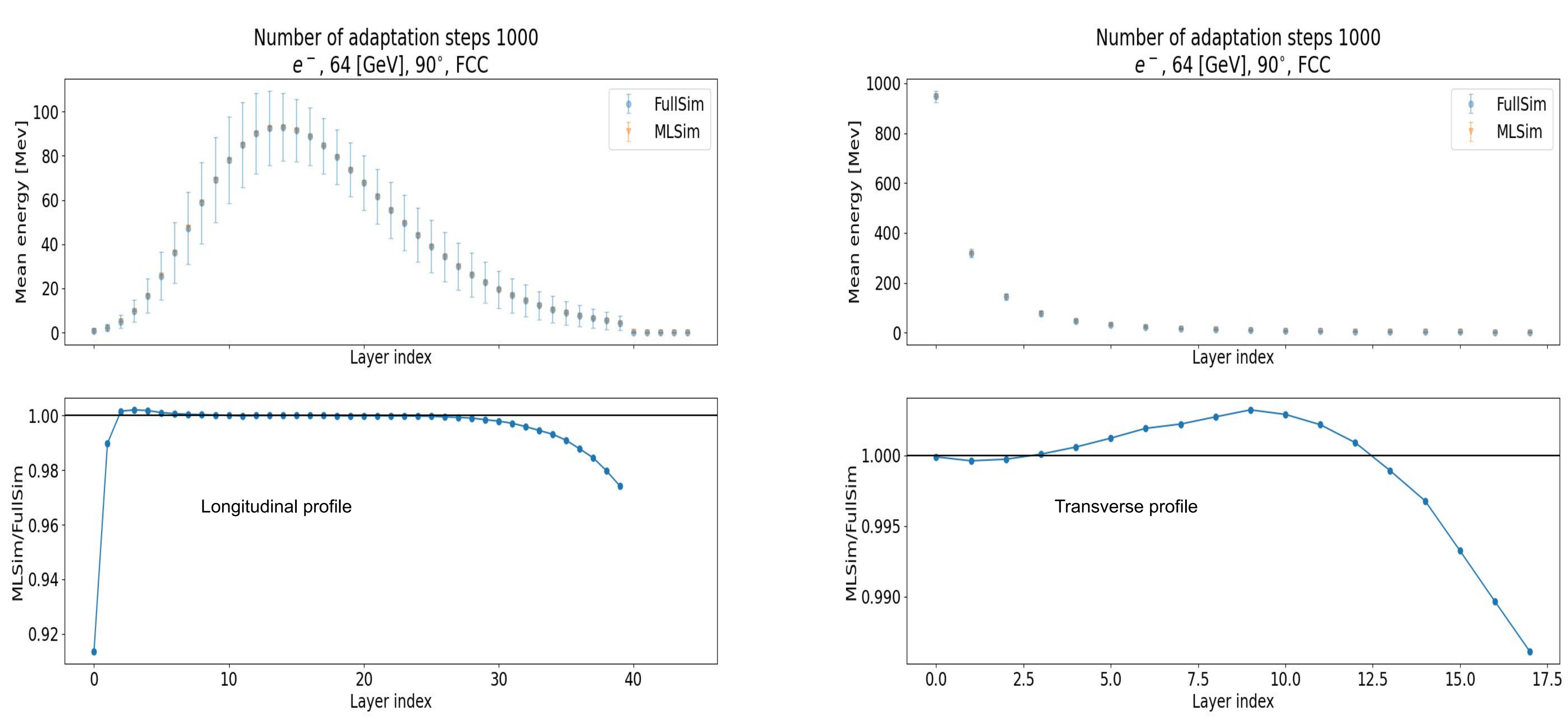
3.1 Fast adaptation with a simplified calorimeter geometry

To test the adaptation on a new detector, full simulation samples of PBWO4 cylindrical geometry are used. The weights of the model are first initialized with the meta-knowledge and the adaptation step is tested every 10 steps up to 1000 adaptation steps.



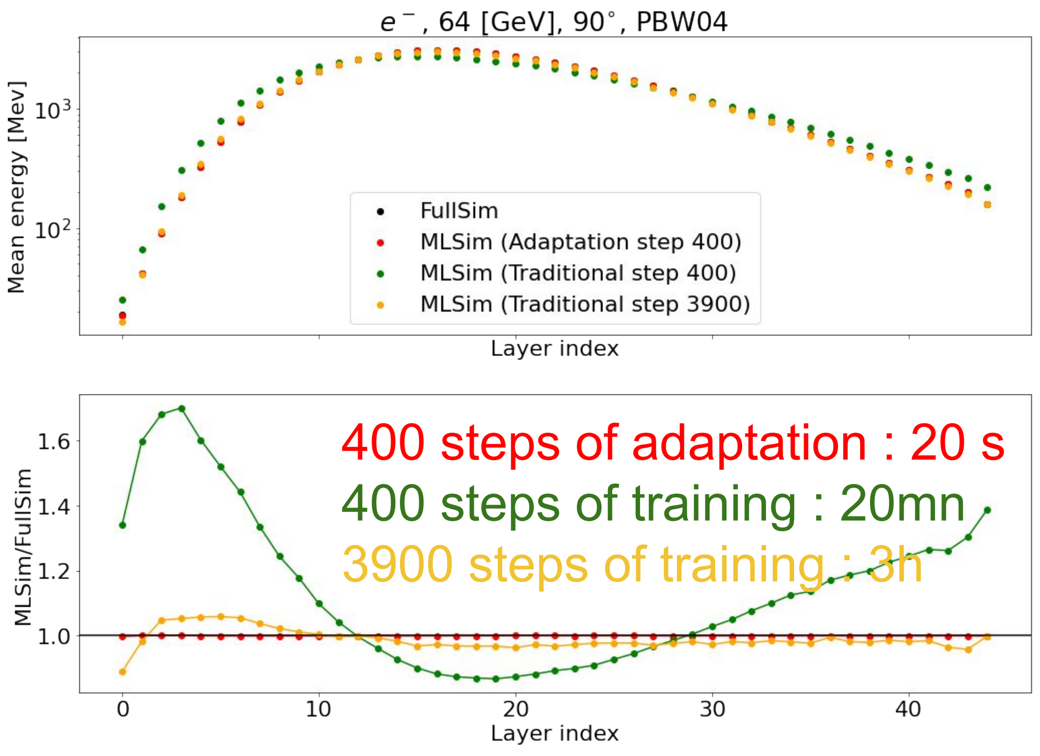
3.2 Fast adaptation with a real calorimeter geometry

The second test is done on the **SiW FCC-ee detector,** which is very different from the other three detectors considered so far. As it is a detector with realistic layout, it is much more complicated, and more importantly further from the detectors that were used in the training. The adaptation is tested every 10 steps up to 2000 adaptation steps. Compared to the idealised PbWO4 cylindrical calorimeter, the number of adaptation steps to get a very good agreement with the full simulation is almost 3 times higher. The main origin of this difference is justified by the fact that it is a more complex geometry, and further from the detectors used for training, therefore more steps are needed.



Meta learning - Adaptation vs traditional training

Meta learning - Adaptation Traditional training



4 . Conclusion

We presented MetaHEP: a generalizable and reusable solution for fast shower simulation using meta learning. First results on the tested detectors show very promising results. MetaHEP provides a solution to tackle many conventional challenges of fast shower simulation with deep learning. Moreover, if shower energy is scored in the proposed cylindrical mesh, MetaHEP provides generalization power by learning parameter initialization that can be fine-tuned quickly on a new geometry.

MLFastSim: https://g4fastsim.web.cern.ch/, https://github.com/DalilaSalamani/MLFastSim