

Stepping Up Theoretical Investigations of Ultrashort and Intense Laser Pulses Interaction with Overdense Plasmas.

Combining Particle-in-Cell Simulations with Machine Learning & Big Data





• **CONTEXT & MOTIVATION**

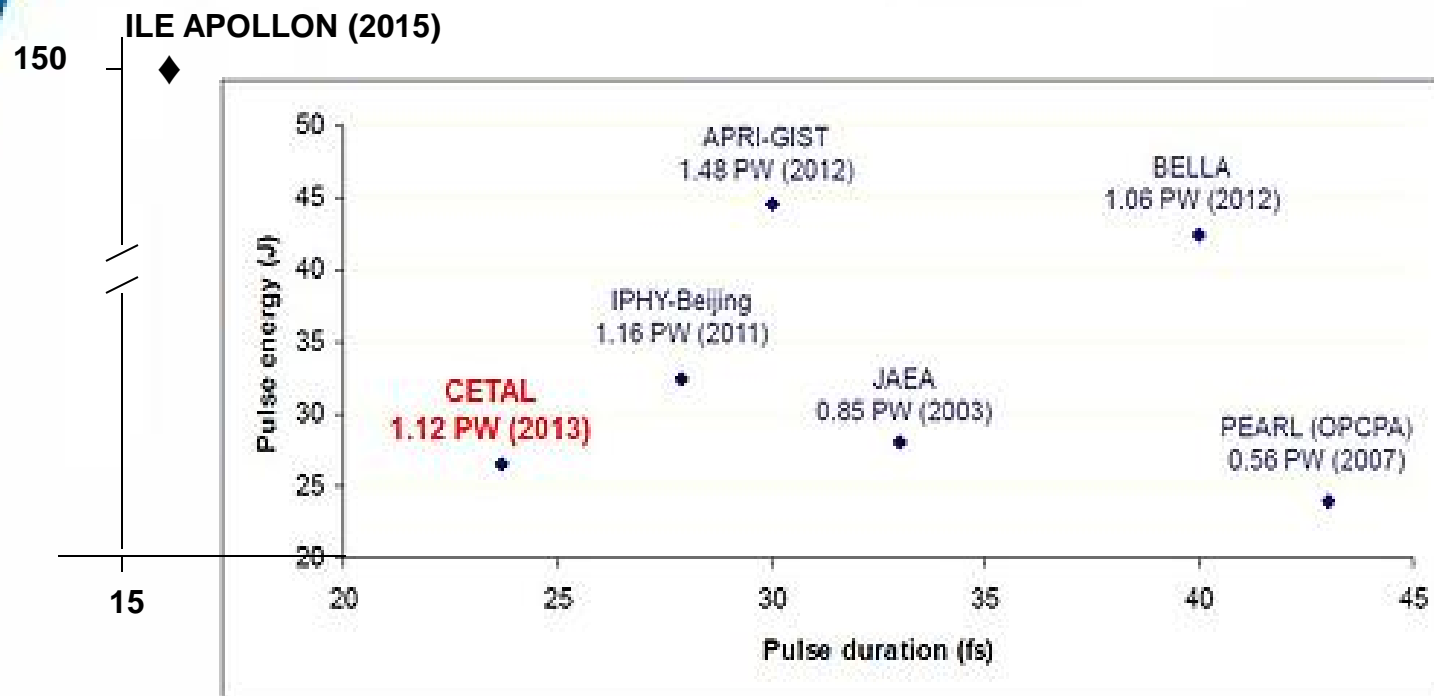
• **BIG DATA & ADVANCED ANALYTICS FOR LASER-PLASMA INTERACTION SCENARIOS.**

• **USING BIG DATA & MACHINE LEARNING FOR PREDICTIVE MODELLING OF HIGH HARMONICS GENERATION.**

• **CONCLUSIONS AND PERSPECTIVES**



High Power Laser Projects- The Global Picture





- The availability of *fs* laser pulses opened opportunities for intense investigations of the rapidly heated matter in extreme conditions.



laser energy transfer to matter

• **Traditionally Modelled with:** Collisionless Vlasov, PIC, Hybrid Codes

- **PIC codes:**
 - used in almost all areas of plasma physics, suitable for analyzing highly transient processes.
 - they are the most intensive computational modelling tool employed in plasma physics
 - have evolved towards improved performances, incorporating physics packages beyond the traditional method & taking advantage of the advent of HPC systems



- PIC codes have evolved towards

- Increased dimensionality
- Full-parallelization
- Fully-relativistic
- Incorporating new diagnostic capabilities
- Improved visualization packages
- Object Orientation
- Migration from Fortran to better performing languages

HOWEVER...

- Statistical noise
- Non-physical instabilities
- Non-conservation
- Numerical heating
- Require considerable computational resources

HOWEVER...

- There is experimental and simulation data already available in the literature
- The advent of cloud technology, Big Data & of platforms like Hadoop

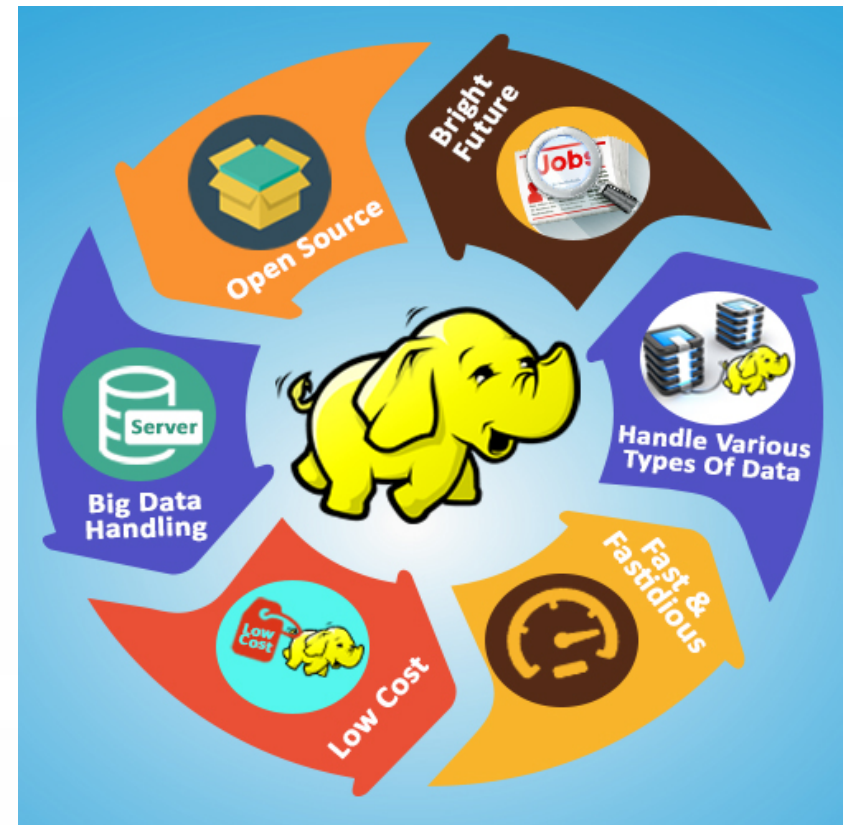
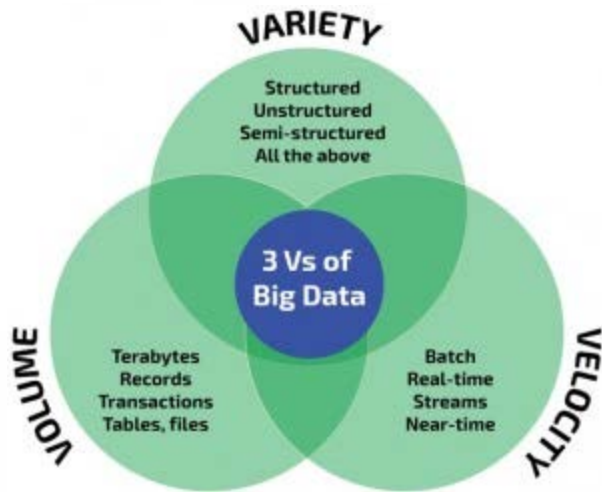


analyzing data is on the verge of becoming trivially inexpensive



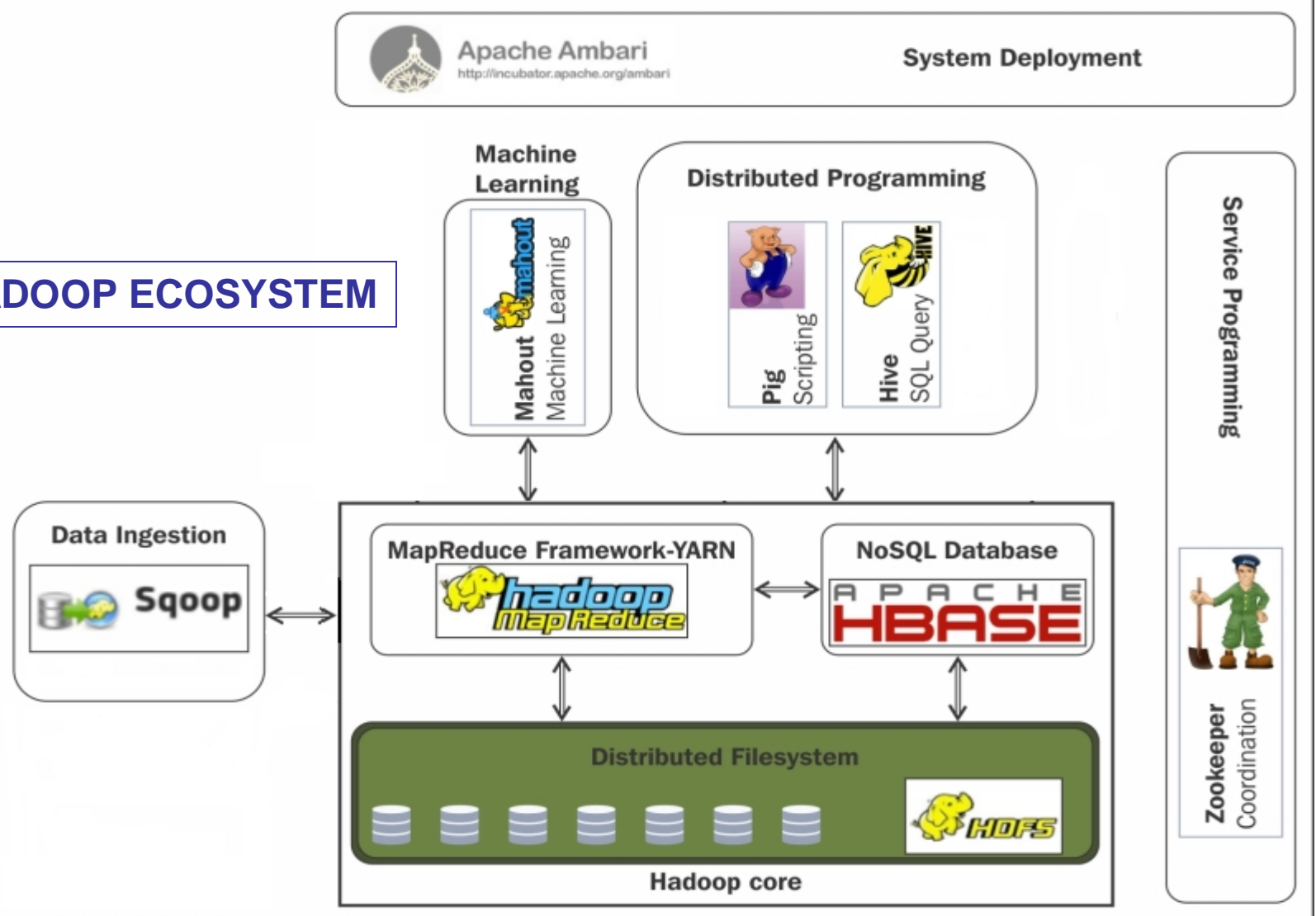
MACHINE LEARNING

BIG DATA & ADVANCED ANALYTICS FOR LASER-PLASMA INTERACTION SCENARIOS.



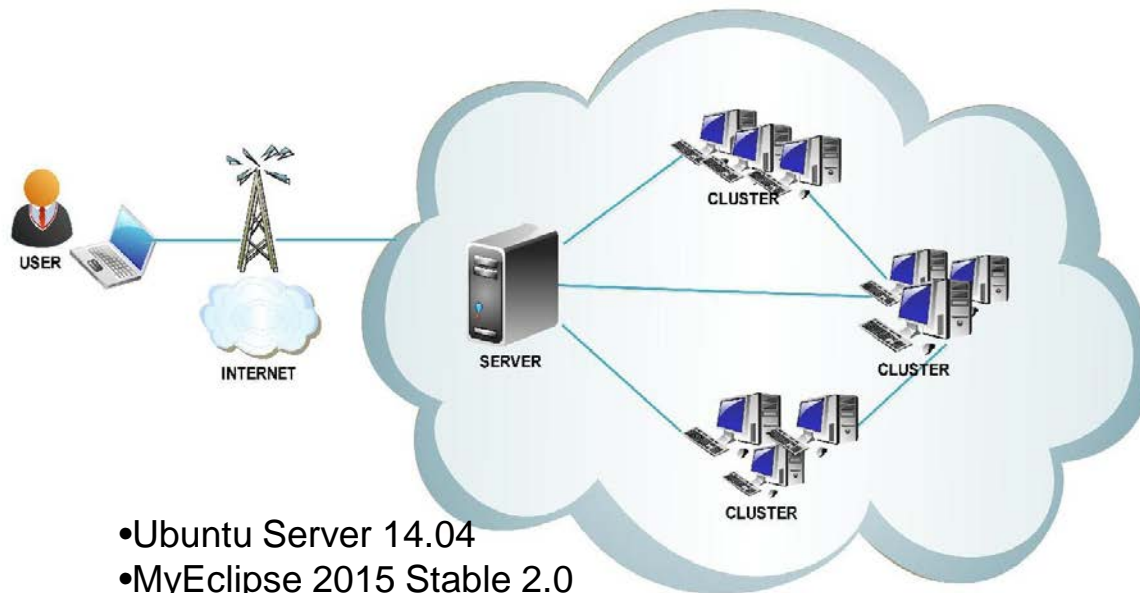
BIG DATA & ADVANCED ANALYTICS FOR LASER-PLASMA INTERACTION SCENARIOS.

HADOOP ECOSYSTEM



BIG DATA & ADVANCED ANALYTICS FOR LASER-PLASMA INTERACTION SCENARIOS.

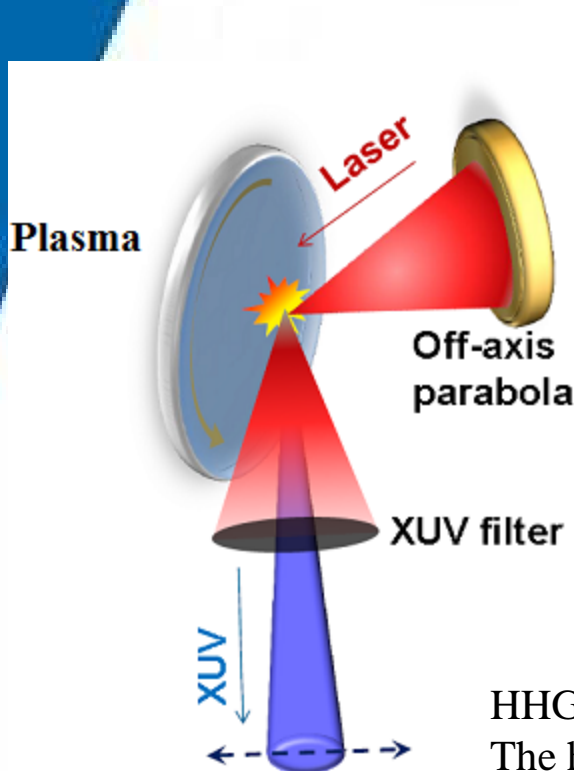
- Communication with users
- User requests
- Manipulation & Treatment of data
- Data Storage



- Ubuntu Server 14.04
- MyEclipse 2015 Stable 2.0
- Tomcat 8.0
- JDK 1.7.0_80
- Hadoop 2.6.0
- Hive 1.2.1

- 1QuadCore CPU
- HDD(500GB,6Gbps, 7200rpm,16MB cache)
- 1000Mbps connectivity card

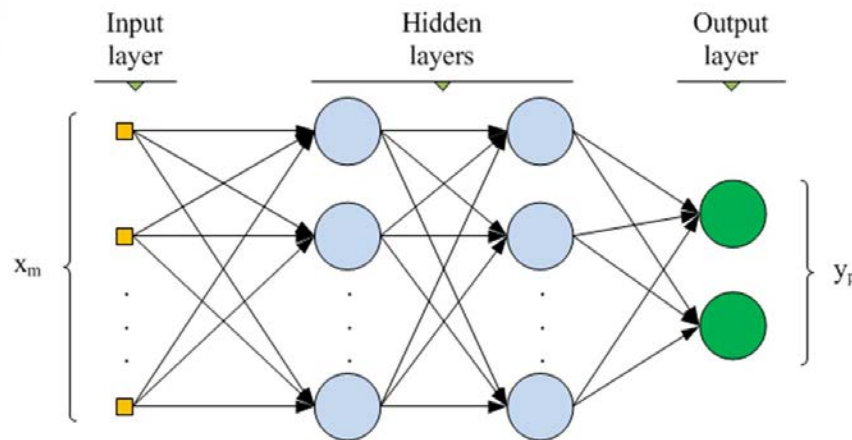
USING BIG DATA & MACHINE LEARNING FOR PREDICTIVE MODELLING OF HIGH HARMONICS GENERATION



- ➔ Higher conversion efficiency than HHG in gases
- ➔ Tunable source of XUV/Soft X rays, typically from 100 to 10 nm but even down to 3 nm
- ➔ No limitation on the intensity of the incident laser
- ➔ Better source from the coherence point of view
- ➔ HH exhibit a very tight angular confinement, sometimes with less divergence than that of the fundamental field and near Gaussian beam profiles

HHG is strongly influenced by the laser-plasma interaction itself. The harmonics are a promising tool for obtaining info on plasma parameters such as the local electron density & on the presence of large electric and magnetic fields, plasma waves, and the electron transport inside the target.

I. Estimating the harmonics order for a particular laser-plasma interaction scenario



- MLP
- Training set

INPUT VECTOR: laser intensity, laser wavelength, pulse duration, polarization, incidence angle, type of plasma, initial plasma density

DESIRED OUTPUT: maximum observable harmonics order, intensity values for different harmonics, harmonic wavelength, harmonics duration, harmonic conversion efficiency

USING BIG DATA & MACHINE LEARNING FOR PREDICTIVE MODELLING OF HIGH HARMONICS GENERATION

- **MLP1 configuration:**

INPUT LAYER: 8 Adaline neurons
HIDDEN LAYERS: 2, all sigmoidal neurons,
12 neurons in each layer.
OUTPUT LAYER: 5 sigmoidal neurons

Batch training, Cost Function
optimized with
Steepest Descent

- **MLP2 configuration:**

INPUT LAYER: 8 Adaline neurons
HIDDEN LAYERS: 3, all sigmoidal neurons,
10 neurons in each layer.
OUTPUT LAYER: 5 sigmoidal neurons

Batch training, Cost Function
optimized with
Resilient BKP

USING BIG DATA & MACHINE LEARNING FOR PREDICTIVE MODELLING OF HIGH HARMONICS GENERATION

Laser: intensity $2 \cdot 10^{18} \text{ W/cm}^2$

$\lambda = 800 \text{ nm}$

pulse duration $\tau = 150 \text{ fs}$

Incidence angle $\alpha = 45$

polarization p

Plasma

$n_e = 4n_c = 6.875 \cdot 10^{21} \text{ cm}^{-3}$

	Highest Observable Harmonic				
	Max. Ord	Intensity W/cm^2	Duration fs	Wavelength nm	Conv. Efficiency
Lit. Data [14]	50	$2 \cdot 10^{11}$	20	16	10^{-7}
PIC Data	58	$2.1 \cdot 10^{11}$	19	13.8	10^{-7}
MLP1	54	10^{11}	21	14.4	10^{-7}
MLP2	56	10^{11}	20	14.8	10^{-7}

II. Estimating electron temperatures within the plasma along with the corresponding fractions of electrons

- **MLP**
- **Training set**

INPUT VECTOR: laser intensity, laser wavelength, pulse duration, polarization, incidence angle, type of plasma, initial plasma density, initial electronic temperature

DESIRED OUTPUT: electron temperatures, corresponding fractions of electrons that have these temperatures, corresponding time moments

- **MLP1 configuration:**

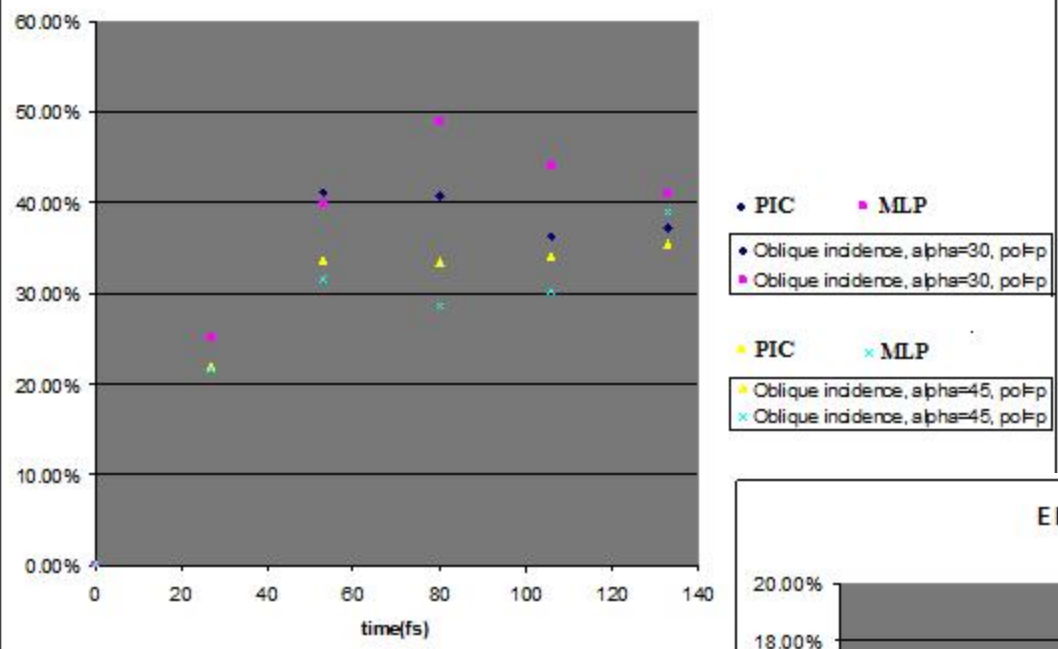
INPUT LAYER: 9 Adaline neurons

HIDDEN LAYERS: 2, all sigmoidal neurons,
11 neurons in each layer.

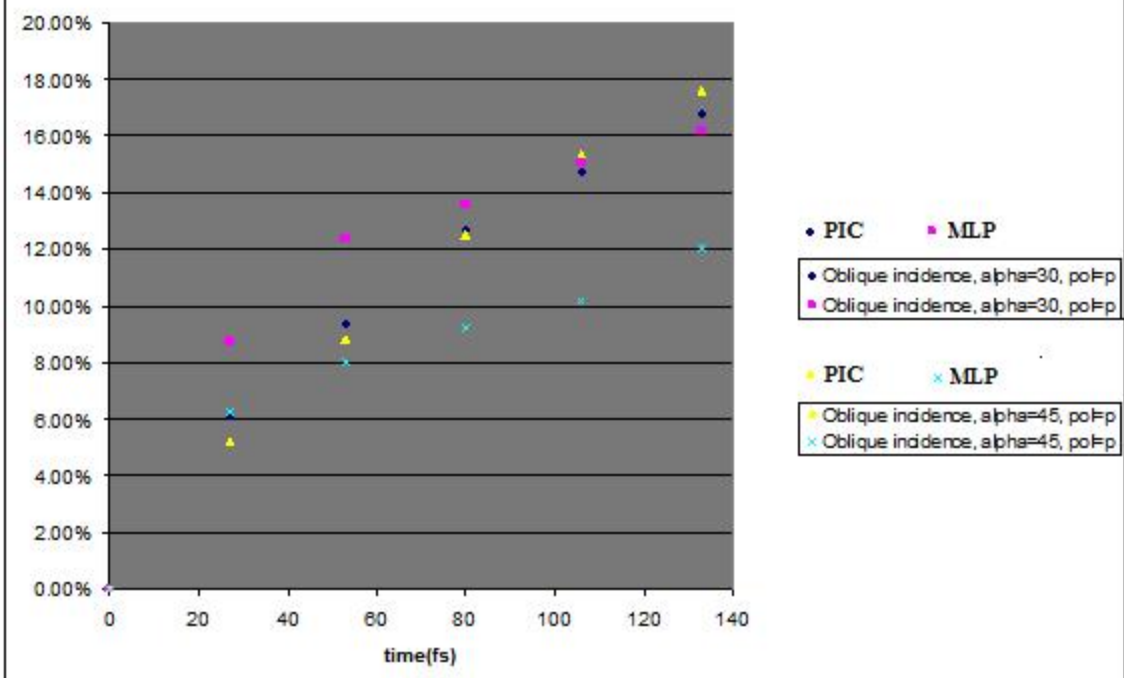
OUTPUT LAYER: 3 sigmoidal neurons

Incremental training, Cost Function
optimized with
Resilient BKP

Electrons with temperature above 10keV



Electrons with temperatures above 100keV



CONCLUSIONS AND PERSPECTIVES

- An alternative to PIC and various plasma kinetics simulations



- the goal is to have a predictor system

- Technologies like cloud, big data and machine learning have tremendous potential of shaping a new face to laser-plasma interaction simulations