## EXPERTISE models, EXperiments and high PERformance computing for Turbine mechanical Integrity and Structural dynamics in Europe

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## Predictive Modeling Supported Collective I/O Auto-tuning Ayse Bagbaba



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## **Performance Model Evaluation Predictive Modeling Motivation and Objectives** Actual performance bandwidth Consider a modeling approach that can model the I/O performance • Motivation: Predicted bandwidth in terms of the application and file system configuration • Effective parallel I/O is a nontrivial job due to the .... • parameters such as number of processes (n), number of bytes •• . .

complex interdependencies between the layers of I/O stack;

- the correct combination of a number of tunable parameters depends on diverse applications and HPC platforms,
- engineers and scientists might not be capable of tuning their applications to the optimal level,
- the default settings are often leading to poor I/O efficiency,
- predicting the resulting performance is difficult.
- **Objectives**:
- An auto-tuning solution for optimizing collective I/ O requests and providing system administrators or engineers the statistic information,
- Performance modeling including the architecture and software stack to analyze I/O requests.

**Optimization Approach** 

identifying configurations' searching scope

choosing the best configuration parameters

(n\_bytes), collective buffering (status), number of collective *buffering nodes* (n\_cb\_nodes), Lustre *striping factor* (s\_factor), Lustre *striping unit* (s\_unit) for "single file, collective clients" I/O access pattern.



- $\phi = f(\alpha, \zeta, \omega),$
- $-\alpha$ : a set of observable parameters that describe application characteristics (I/O pattern, I/O operation, benchmark)
- $-\zeta$ : a set of observable parameters that describe file system and/or I/O characteristics (Lustre parameters)
- $-\omega$ : uncontrolled non-observable parameters
- Aim: to understand the relationship between  $\phi$  and the parameters  $(\alpha, \zeta)$ .



Random forest regression performance model with max depth = 4, Accuracy: 90.52 % on dataset including configuration parameters and achieved I/O bandwidth to be used in training and validation of the performance model (Training set size is 2153, test set size is 539). The performance model is extracted based on 100 iterations. Time taken to build model is 3.19 seconds.

max_depth	Prediction errors under different depths		
	Accuracy	MAE	RMSE
3	82.16 %	495.86	963.36
4	90.52 %	287.92	576.51
5	95.15 %	147.25	325.94
7	98.87 %	46.27	180.32
10	99.68 %	24.85	167.20

Prediction errors in MB/s for training sets under different depth of each tree in the random forest algorithm (MAE: Mean Absolute Error, RMSE: Root





Architecture Overall the Auto-tuning of Approach with the following modules; *IO\_Tracer*, *IO\_Tuner, IO\_Optimizer, IO\_Analyzer.* 

Development of an predictive modeling supported auto-tuning solution to improve collective I/O performance; • implemented upon widely used MPI-IO library,

• approachable for engineers/administrators with little knowledge of parallel I/O,

• compatible with MPI based scientific and engineering applications, portable to different HPC platforms,

• has a success varies between 50-130% at scale in the parametrization's I/O bandwidth gain,

• supports and informs the system administrators if performance anomaly is detected,

• will be tested on engineering applications in different professional areas.

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