

## Introduction

### Motivation:

Lossy compressors (e.g. SZ [2] and ZFP [9]) are increasing in ubiquity as they are more compress floating-point data better.

As scientific simulations become more complex and create more data, more energy will be spent in compressing data due to runtime increases [4].

Understanding how variables such as CPU frequency, error bound, and data size affect power will increase the ability to save energy.

### Contributions:

- We present a characterization of nodal energy consumption for SZ compression and decompression.
- We provide a predictive model for system power given CPU frequency and, minimum frequency power.
- We produce recommendations for optimizing energy consumption using the gathered results from the energy model.

## Making a Power Approximation

$$P_{avg} = \frac{E_{total}}{t_{SZ}}$$

Eqn. 1 Average power relation

No significant difference between PSNR or Application in profile

Model computed from datasets in Table 1.

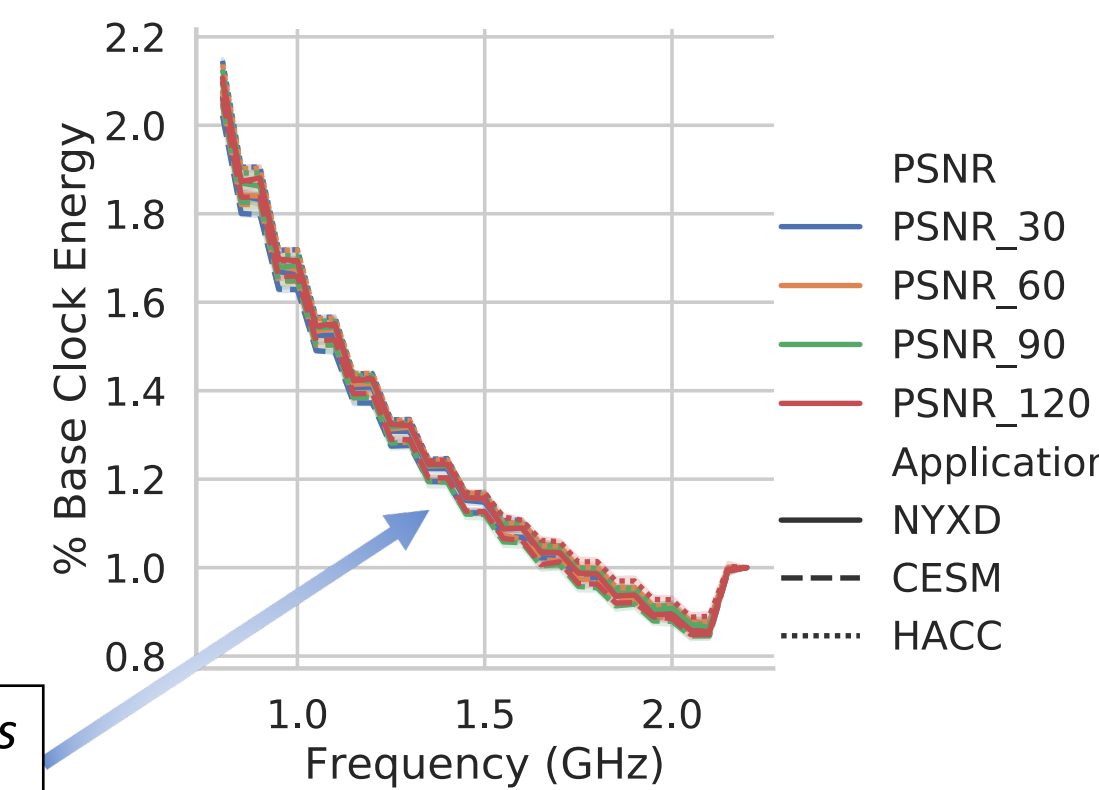


Fig. 2 SZ Energy

CESM, HACC, NYX curves indistinguishable

CESM, HACC, NYX curves overlapping

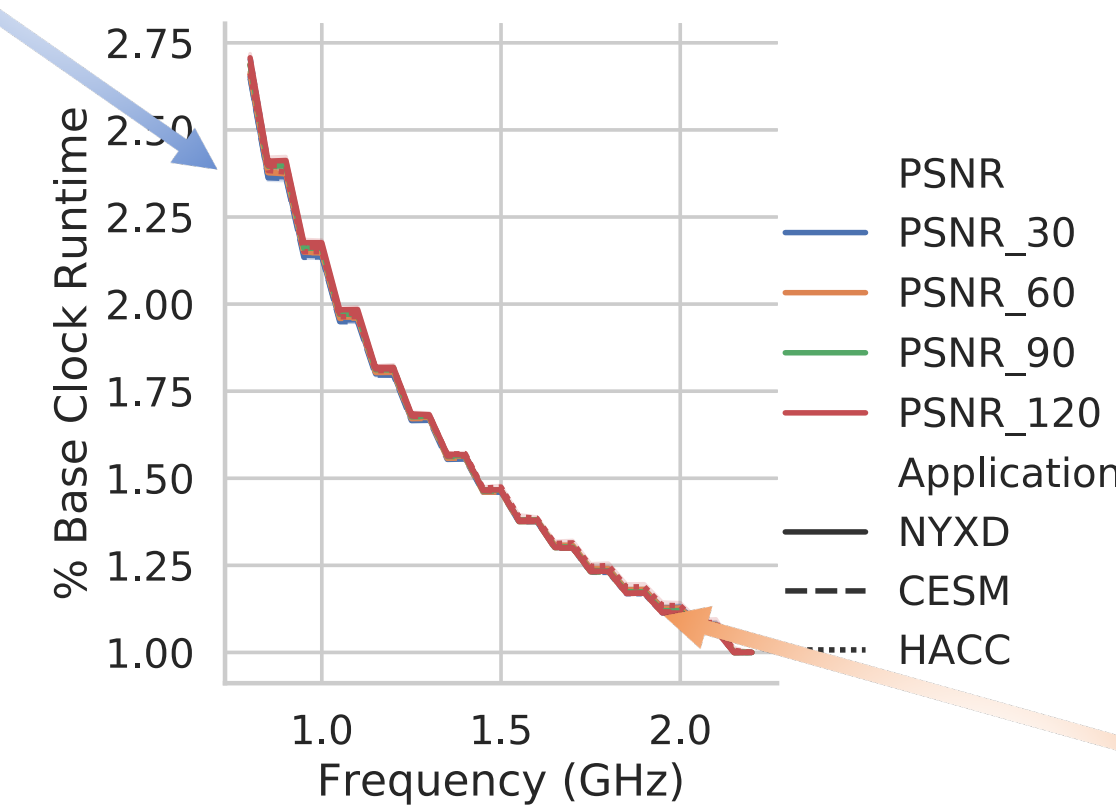


Fig. 3 SZ Runtime

Small time tradeoff: +5%  
Large Power Save: -15%

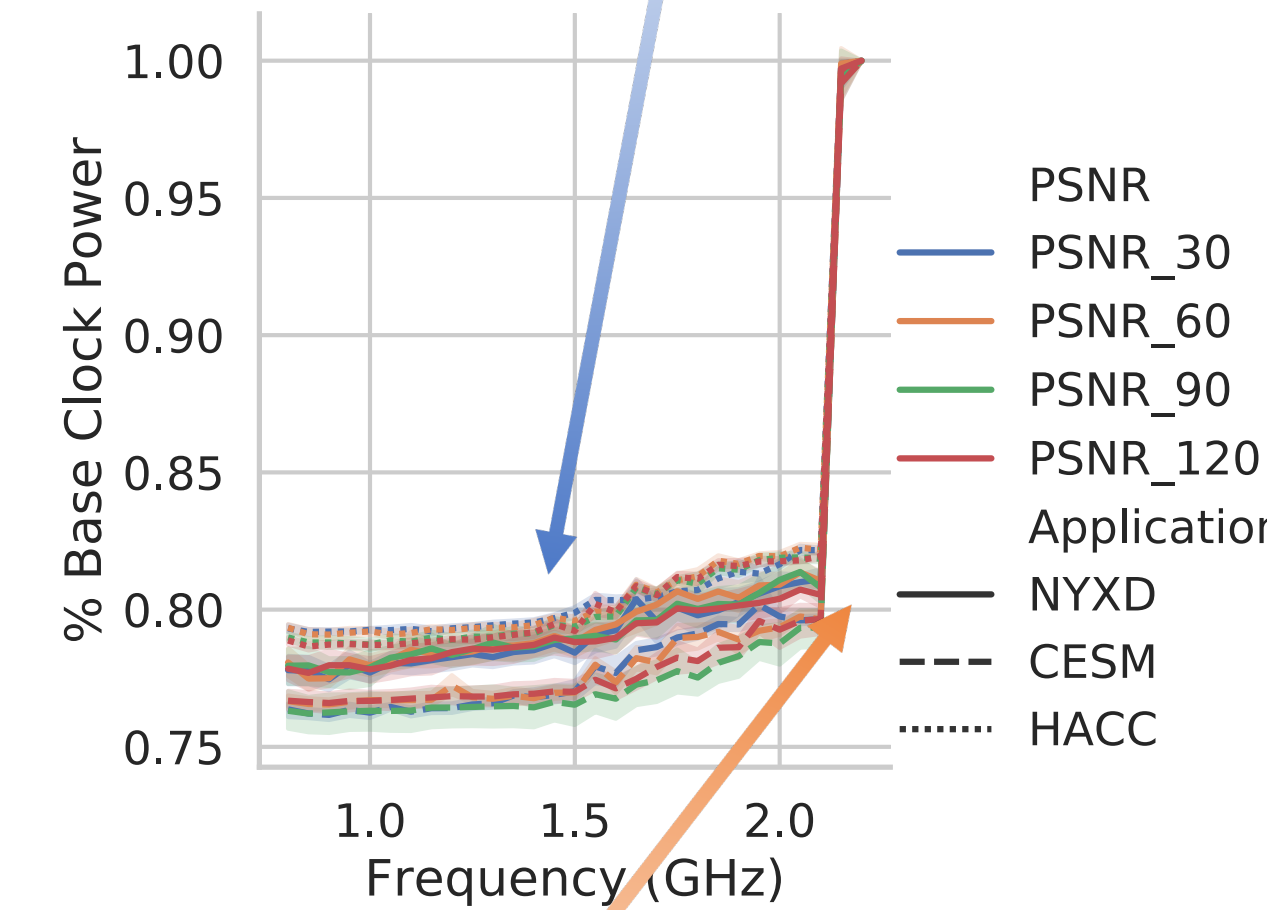


Fig. 4 Power curve to be fit

## Applications of Energy Processing

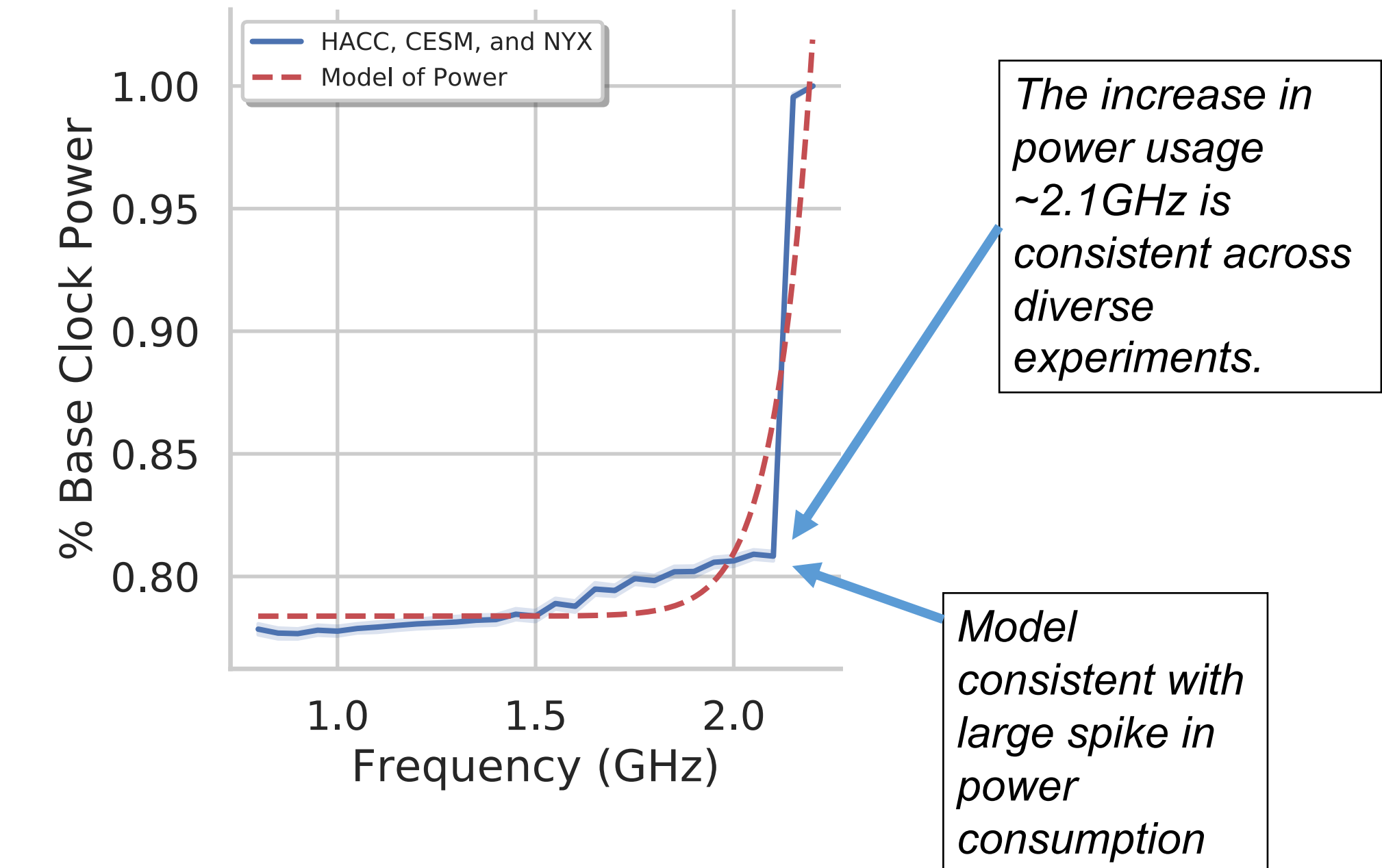


Fig. 5 Black-box model for the power of SZ

The increase in power usage ~2.1GHz is consistent across diverse experiments.

Model consistent with large spike in power consumption

Metric	Power Model Statistic
$R^2$	0.8296
Adjusted $R^2$	0.8295
SSE	2.188
RMSE	0.0229

Table 4 relates the goodness of fit for the black-box model.

Table 4. Goodness of fit metrics, relating the model from Fig. 6

## Experimental Setup

Application	Dimensions	Size of Fields	Fields Considered
CESM-ATM [6, 8]	26 × 1800 × 3600	673.9MB	CLOUD, CMFDT, ICLDTWP, QC, T, VU
HACC [5, 8]	1 × 280953867	1046.9MB	$v_x, v_y, v_z, x, y, z$
NYX [7, 8]	512 × 512 × 512	563.9MB	b_dens, dm_dens, temp, $v_x, v_y, v_z$

Table 1. Datasets used in SZ power monitoring

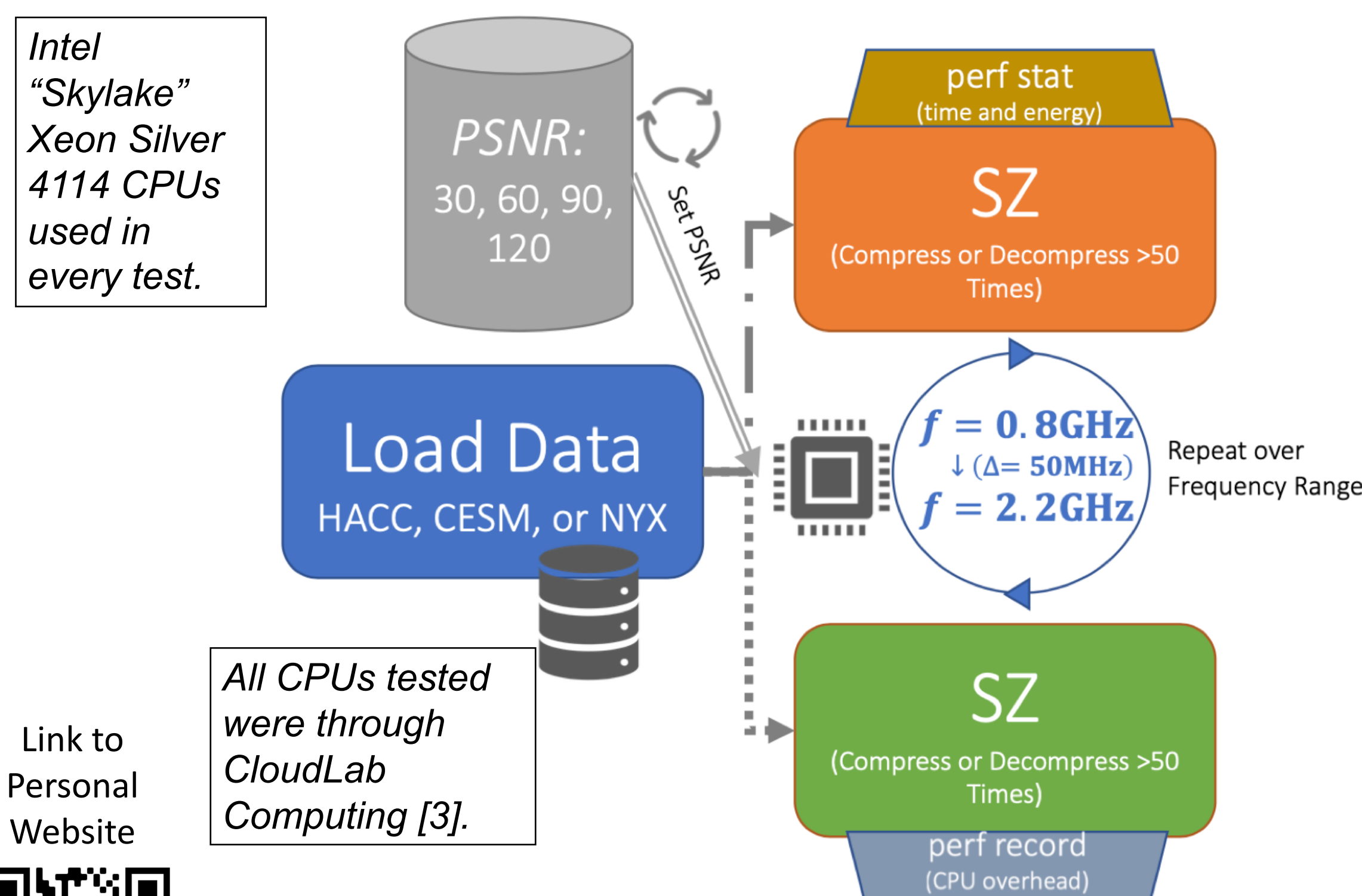


Fig. 1 Experimental process for SZ monitoring

## Fitting the Theoretical Model

### Model Fitting:

We fit a model for  $P_{SZ}(f, P_{base})$  a function that models power usage in terms of CPU frequency and a constant,  $P_{base}$ , base power.

Model	Model Equation $P_{SZ}$	Sum of Squared Error	Root-Mean Squared Error
Linear	$P_{base}(af + b)$	0.0451	8.488
Quadratic	$P_{base}(af^2 + bf + c)$	0.03694	5.694
Cubic	$P_{base}(af^3 + bf^2 + cf + d)$	0.03062	3.911
Exponential	$P_{base}(ae^{bf})$	0.04475	8.36
Power	$P_{base}(af^b + c)$	0.0229	2.188

Table 2. Model fitting for SZ power function

$$P_{SZ}(f, P_{base}) \approx P_{base}(af^b + c)$$

$a, b, \text{ and } c \text{ in Table 3.}$

Eqn. 2 Form of best-fit black-box model

Parameter	Value
$a$	2.237E - 9
$b$	23.44
$c$	0.7833

Table 3. Eqn. 2 fit parameters

## Conclusions and Future Studies

### Conclusions:

We conclude that power usage can be reduced by ~15% with a 5% time tradeoff.

The predictive model produced accurately depicts power usage for SZ compression and decompression, using CPU frequency.

### Future Study Goals:

- Expand to other compressors (e.g. ZFP).
- Test on other CPU architectures.
- Improve model accuracy by quantizing error bound and compressibility.

## References

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