

Modelling Fault Dependencies when Execution Time Budgets are Exceeded

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Introduction

- When we test out analyses, we make a lot of assumptions
 - We have representative data (Statistical methods)
 - A uniform distribution represents all possible inputs (Scheduling algorithms)
- Mostly, these assumptions are OK
 - Pragmatic assumptions which simplify our problems from impossible to doable

Introduction

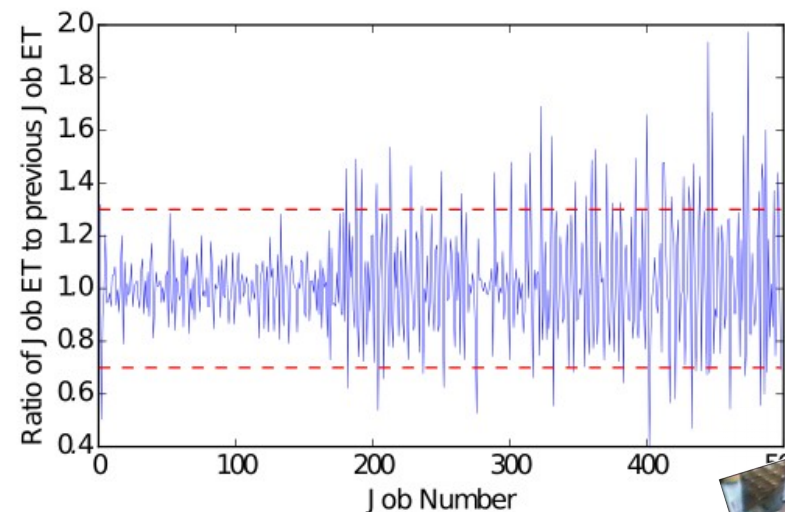
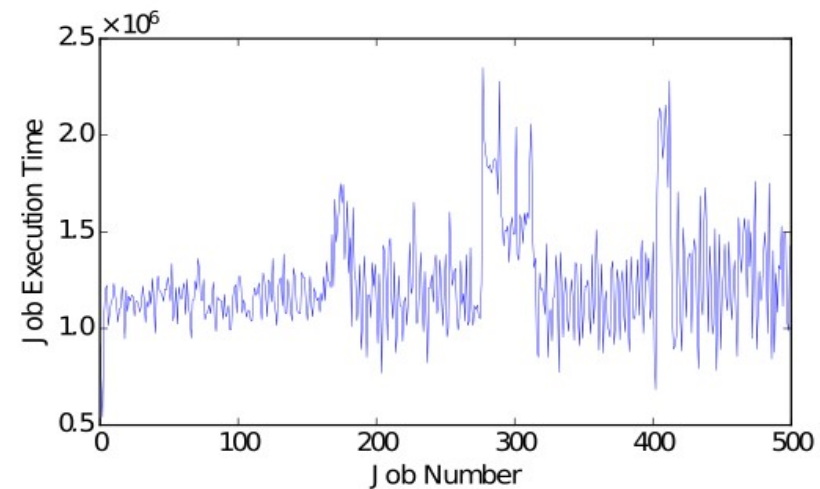
- But what about this one?
 - Job Execution Times are Independent
- It's made in a lot of places
 - Testing scheduling, early versions of MBPTA
- Problem:
 - It is completely unrealistic

Dependencies of Job Execution Times

- Regardless of any intelligent processor design, the job still performs a task
- Presumably, the inputs to the job effect what the job will do
- So if there are dependencies in Job inputs, there are also dependencies in Job execution times
- Is there any realistic system where Job inputs are I.I.D random variables?

Dependencies of Job Execution Times

- FFMPEG Decoding video frames under Valgrind
 - FFMPEG provides a lot of 'real world' data
 - Valgrind instruction counts give exact instrumentation
- Inputs – Video frame data, current decoder state
- Very good indicator of job execution time is previous job execution time



Dependencies of Job Failures

- Given that Job execution times are dependent, Job failures due to budget overruns are also dependent
- Which means that they are definitely not I.I.D.

Is this a problem?

- Potentially – a lot of places make the assumption that execution times are independent
- For example, mixed criticality systems – how do these fare if overall the low-crit failure rate is 10^{-4} , but all those failures happen one after the other?
- Not something that has been tested currently

Problems

- Can't directly model failure durations
- Why?
 - Deadline overrun failures are rare events by definition
 - Won't get enough data
- Need to predict failure durations from data gathered in testing

Solution

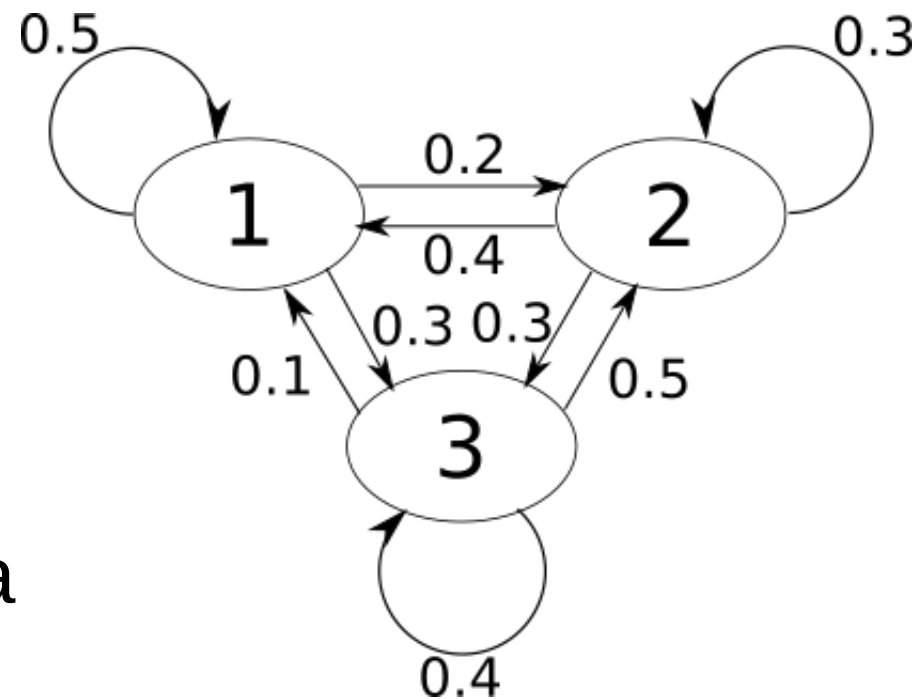
- Forecasting
- Take data from normal case, generate a model, use model to predict behaviour under extreme circumstances
 - Works around scarcity of actual data

Solution (Part 2)

- How to do forecasting?
- For this case, using Model Extrapolation
- Given a set of models with the same structure, fit curves to the model parameters and extrapolate
- To get models, using Markov Chains and Lossy Compression

Markov Chain Models

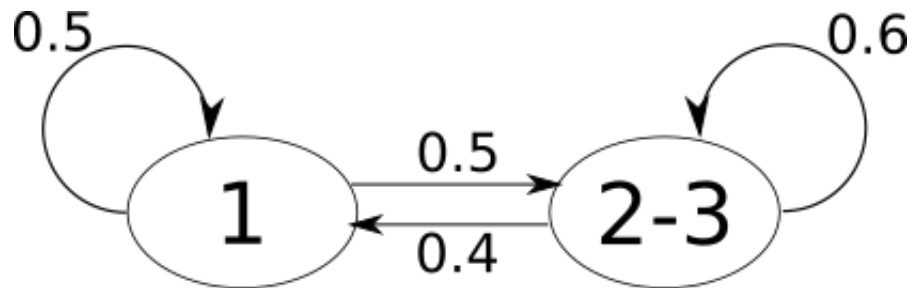
- Set of states corresponding to duration of overruns
- Each state has probability to change to any other state
- Simply trained on test data
 - Other ways to generate models being explored



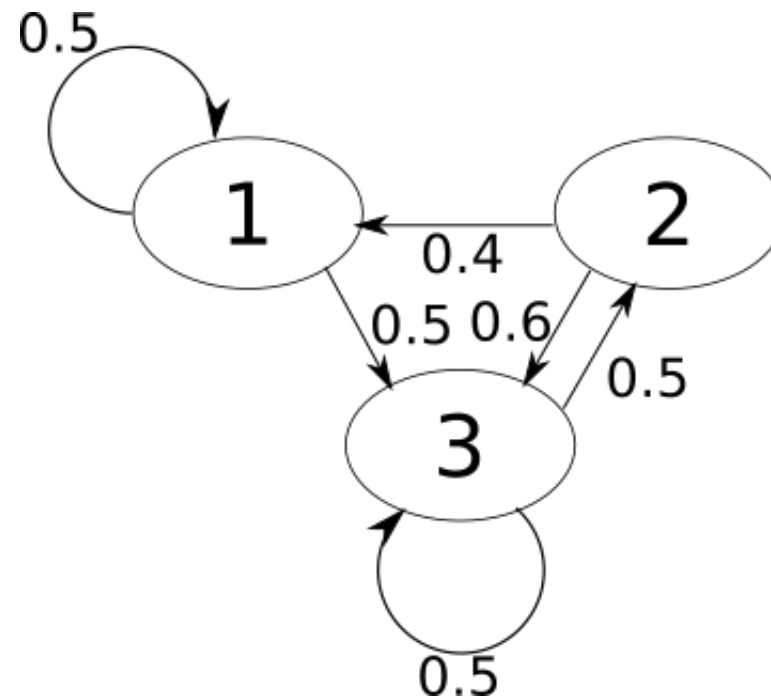
Compressed Markov Models

- Don't want to accept models which don't have enough data to back up each point
- Solution is to permit compressing the model
- Compression combines states/transitions which have a low amount of data behind each point
- Various methods of compression

Compressed Markov Models

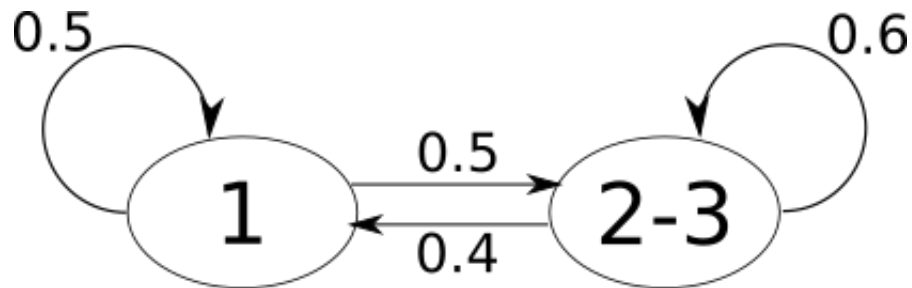


Combine States



Combine Transitions

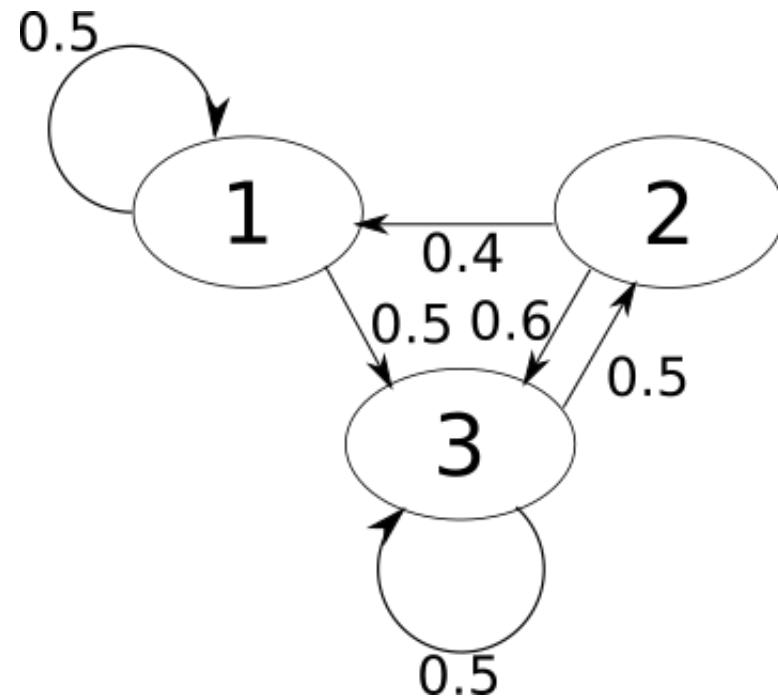
Compressed Markov Models



Combine States



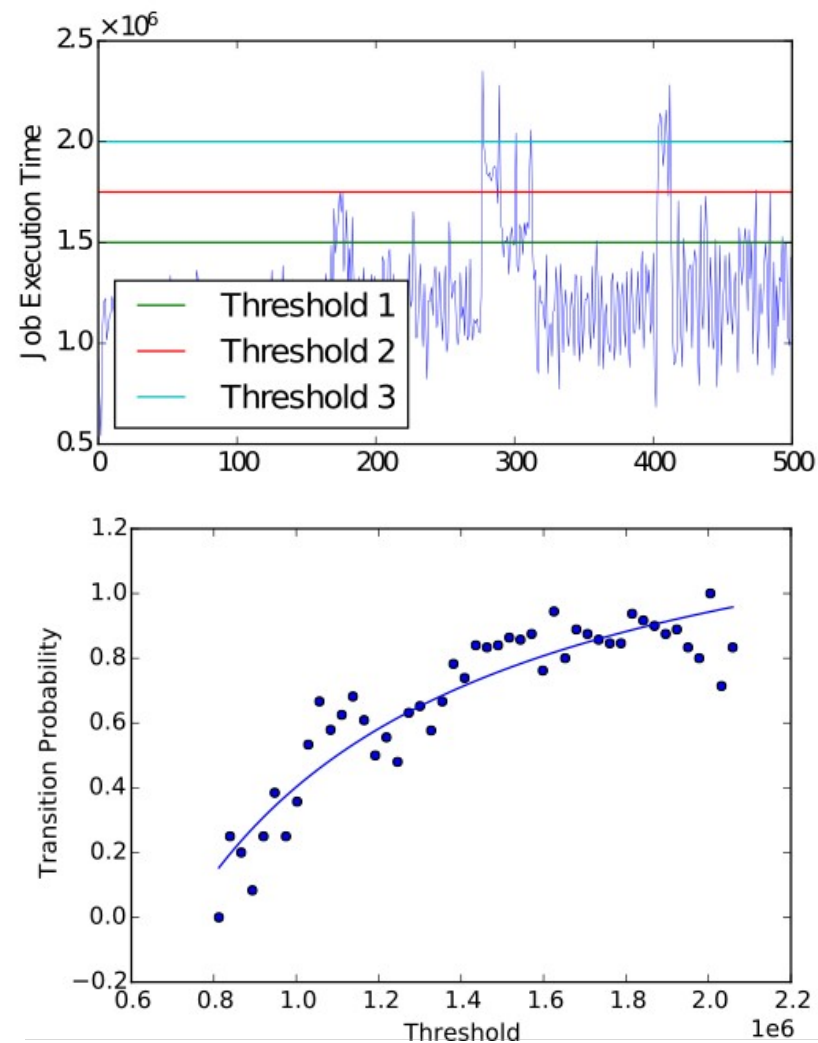
One catch: Will want the user to tell us what intervals we're interested in



Combine Transitions

Forecasting

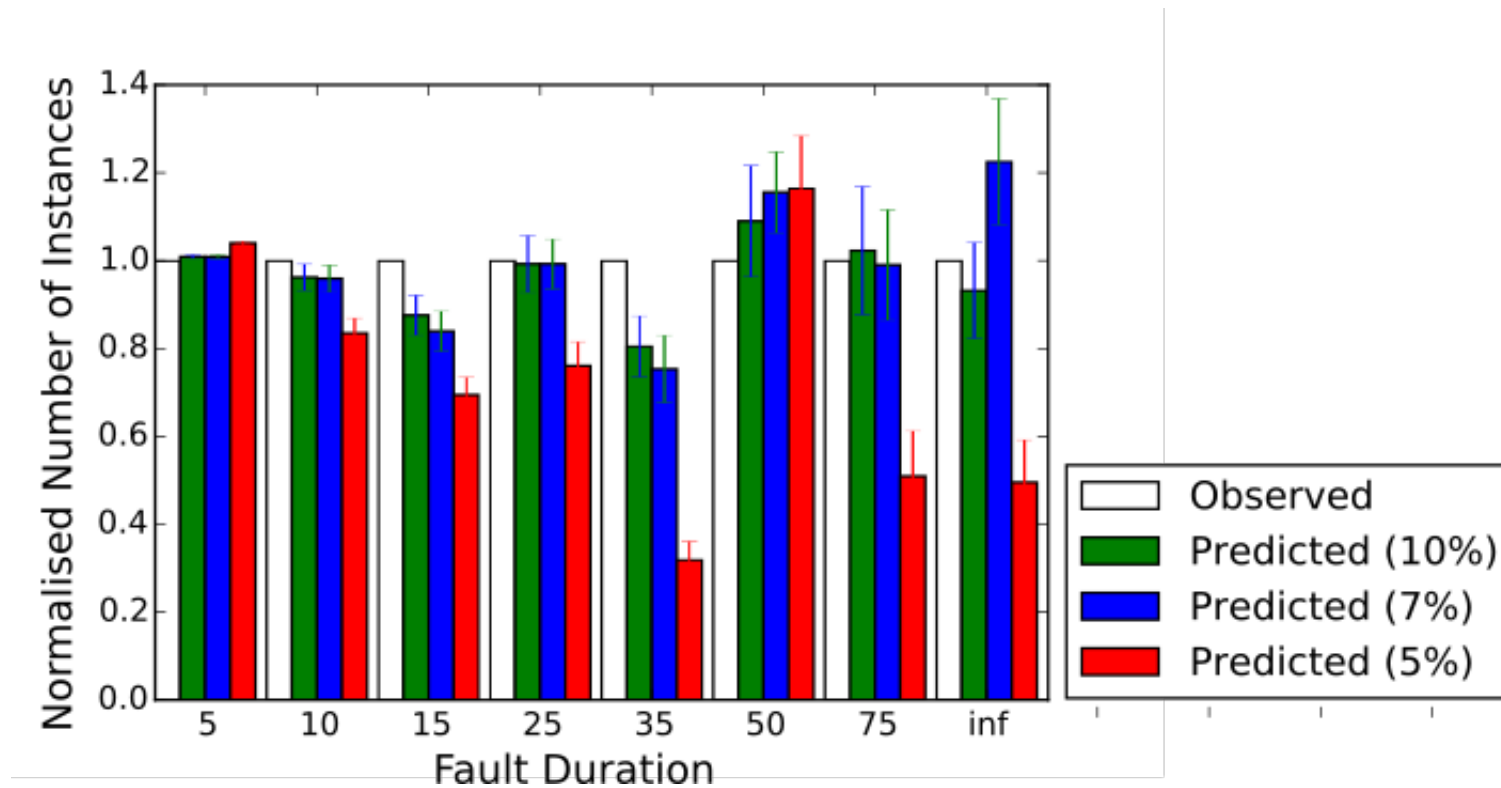
- Outline of method
 - Set multiple exceedance thresholds where there is sufficient data
 - Create models, using compression as needed
 - Find the most common shape of compressed model
 - Fit curves and extrapolate to the desired failure rate



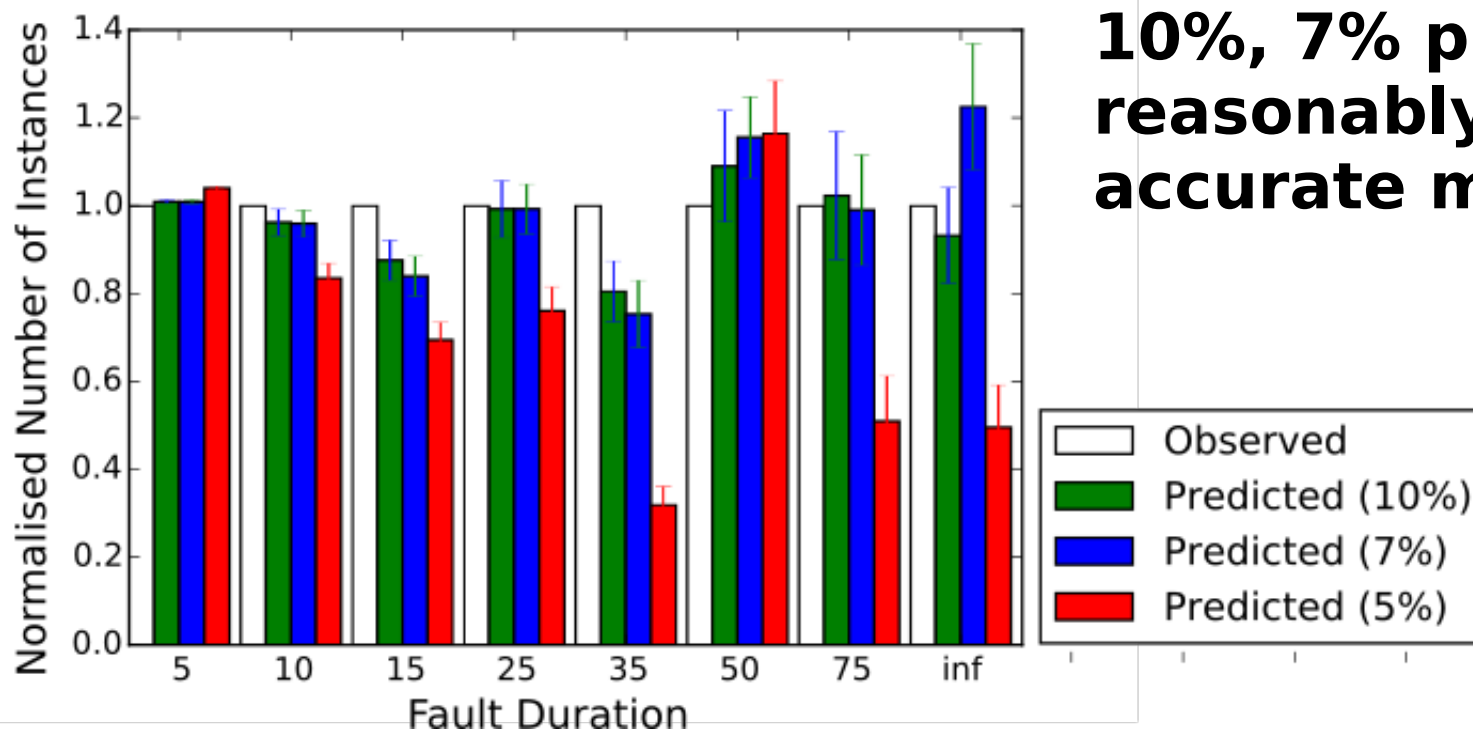
Evaluation

- Method
- Get a large amount of data from target system
 - FFMPEG decoding videos under Valgrind
- Create a forecast model based on a subset of the data
 - Subset of data does not have enough data to reliably model at desired confidence levels
- Compare results from forecast model with what actually happened

Results

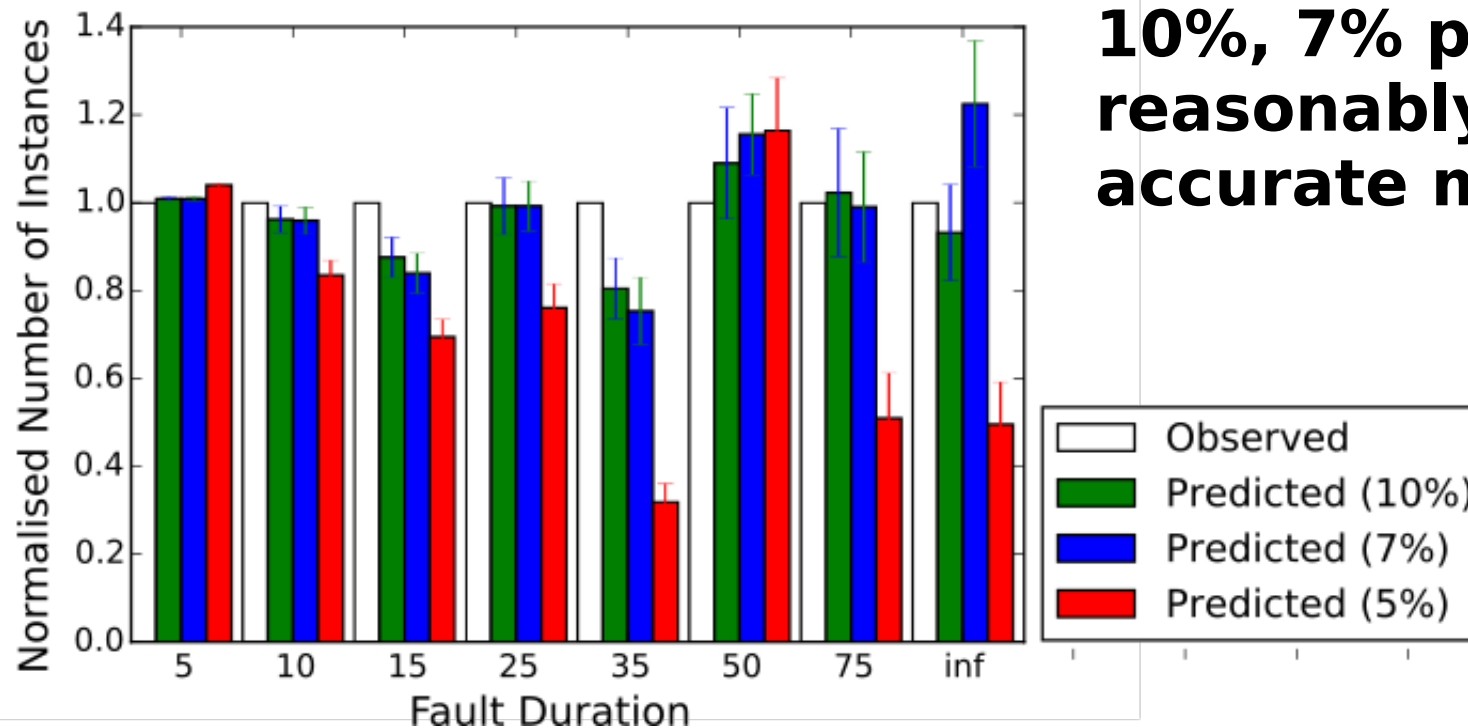


Results



10%, 7% produce reasonably accurate models

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5% has very low accuracy, but first 5% of input data is not representative

DepET – A dependent execution time generator

- Have a way to generate exceedance durations at an arbitrary threshold
- DepET is an algorithm to utilise this to generate dependent execution times
- So as UUniFast generates a useful spread of realistic task utilisations, DepET generates realistic task execution times

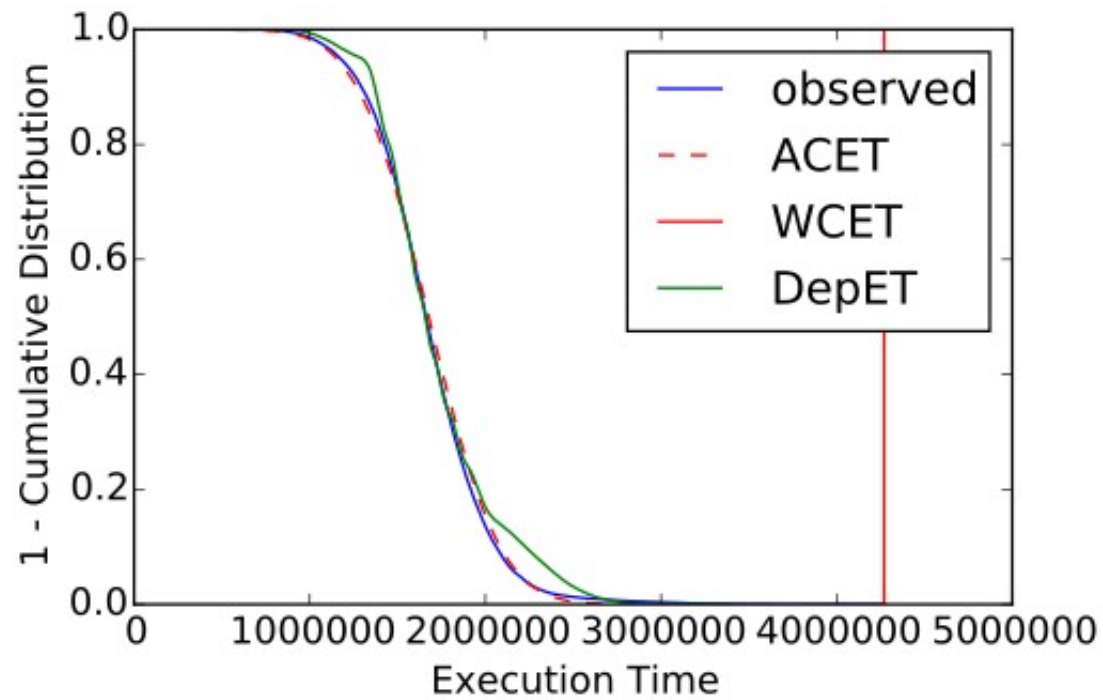
DepET Algorithm

- Divide execution time into a series of bands
- Each invocation has a probability of exceeding it's current band
- An exceedance model governs the duration of this exceedance
- Otherwise, randomly move about inside the band

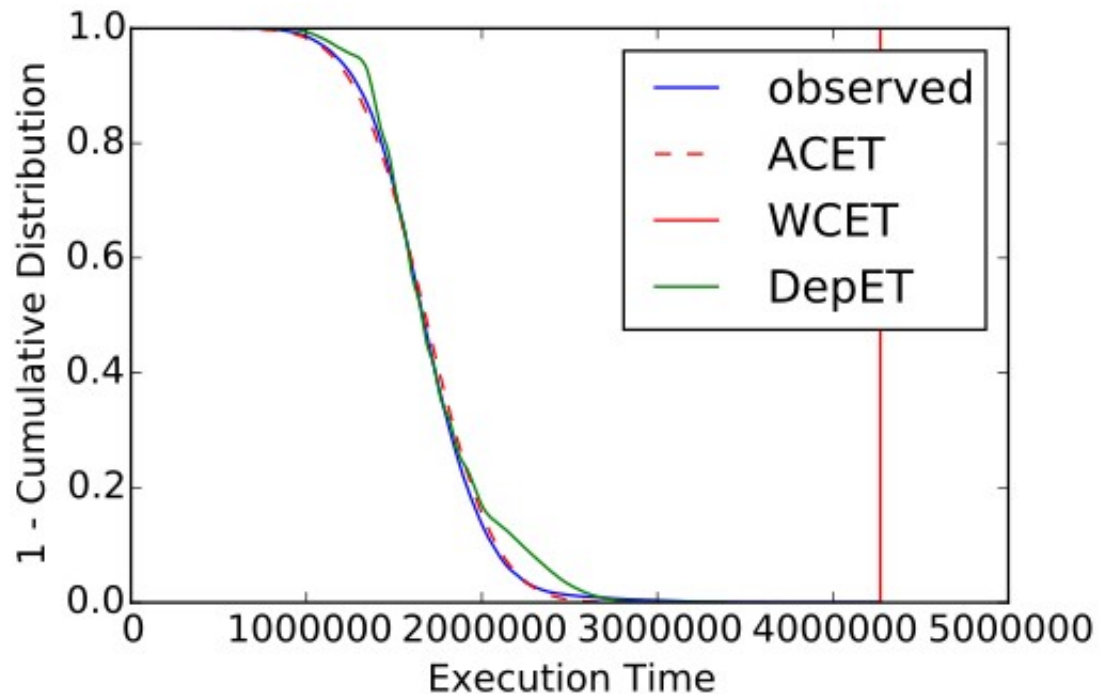
DepET Evaluation

- Compared against SimSO ACET method and observations
- SimSO ACET method implemented as normal distribution with parameters derived from training data
- Useful comparison as it attempts to be realistic
- Note: Other methods of execution time generation are few in number, and may not be trying to be realistic to compare against
 - e.g. SimSO WCET method

DepET Overall Distribution

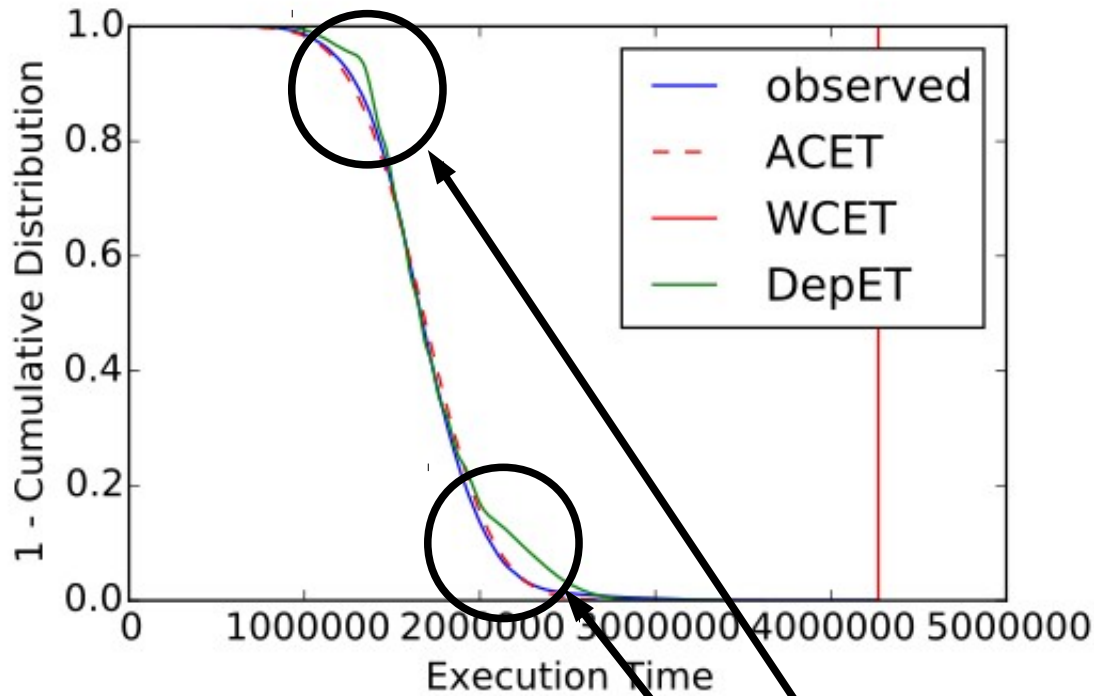


DepET Overall Distribution



Both methods give a good overall fit

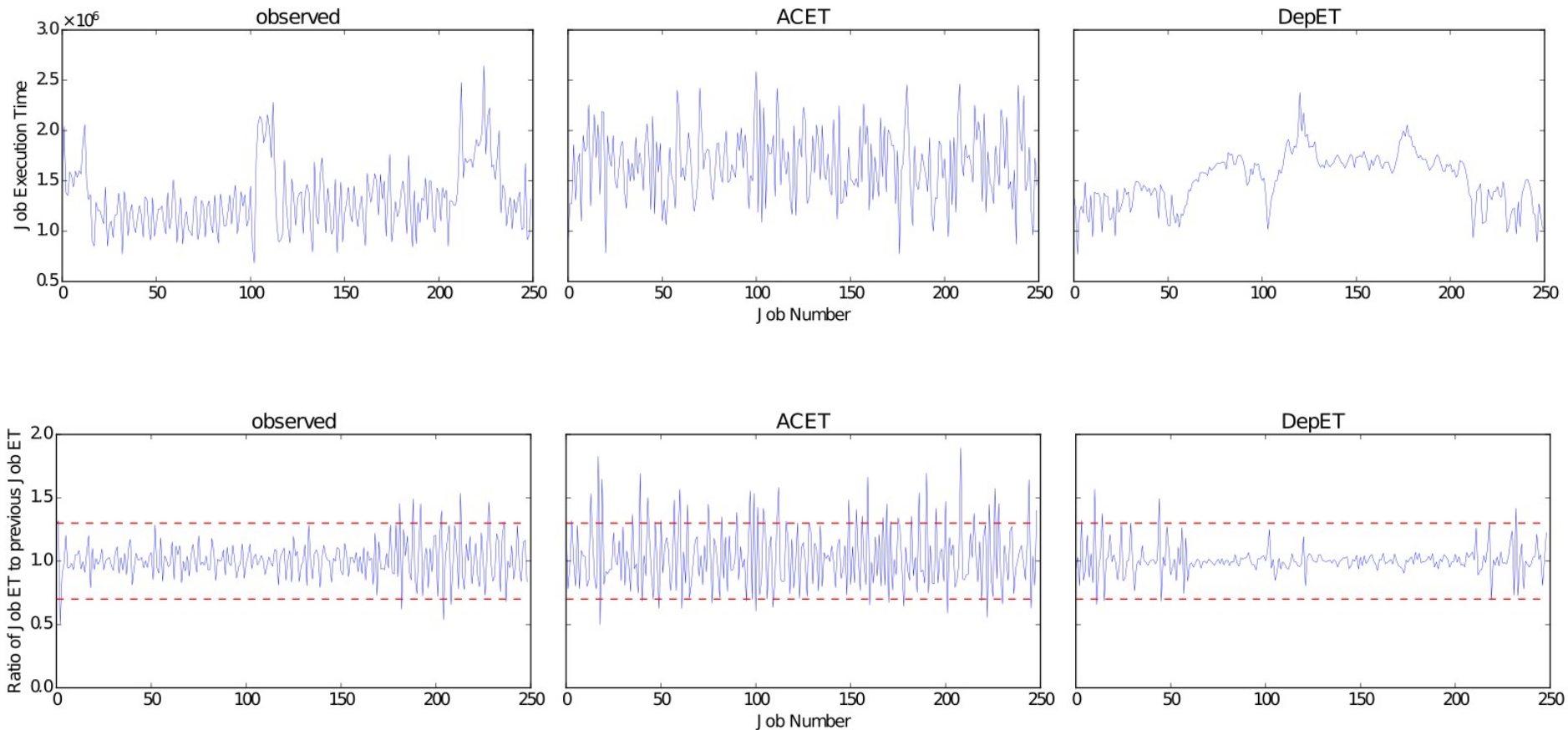
Evaluation - Overall Distribution



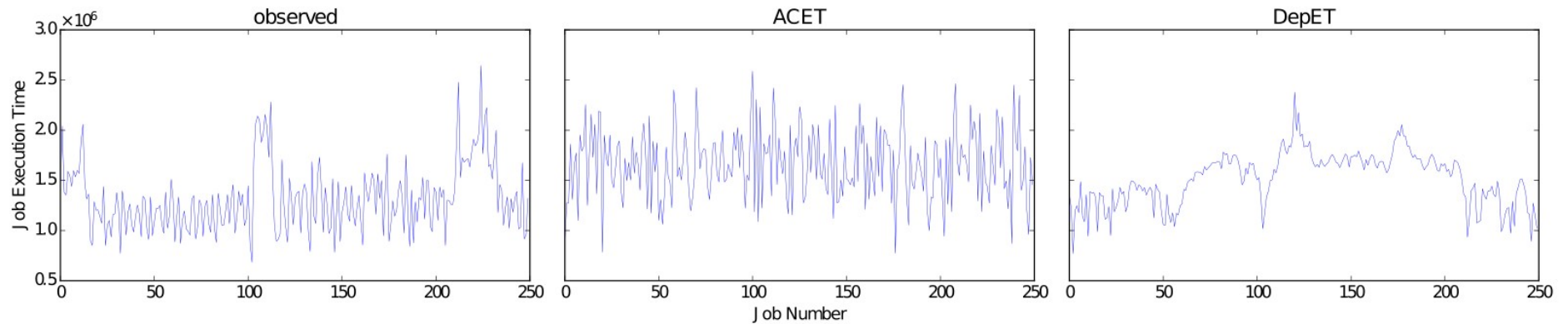
Both methods give a good overall fit

Although DepET has some inaccuracies due to compression

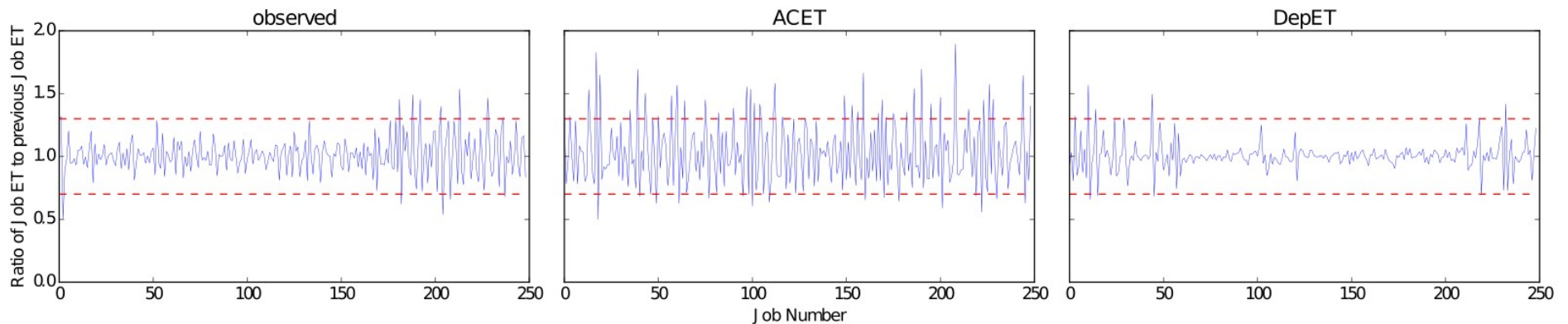
Evaluation - Dependencies



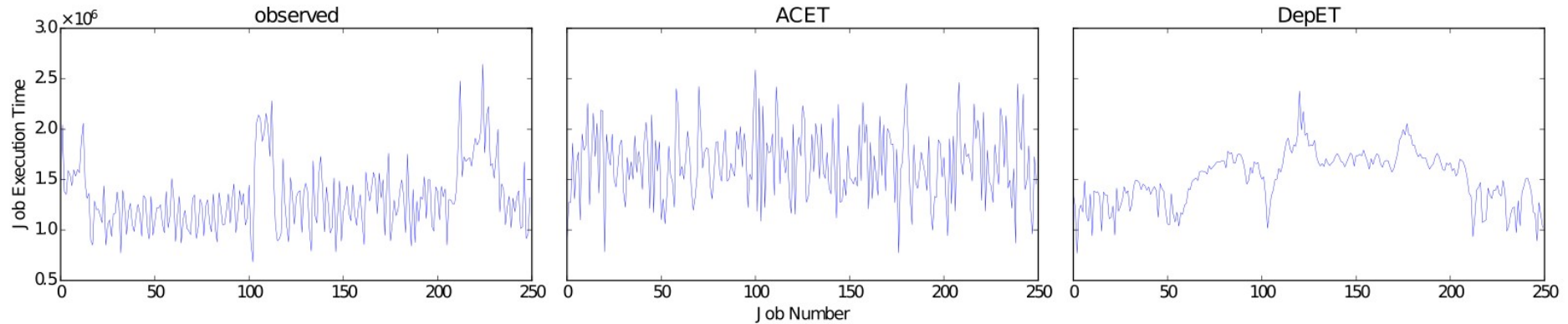
Evaluation - Dependencies



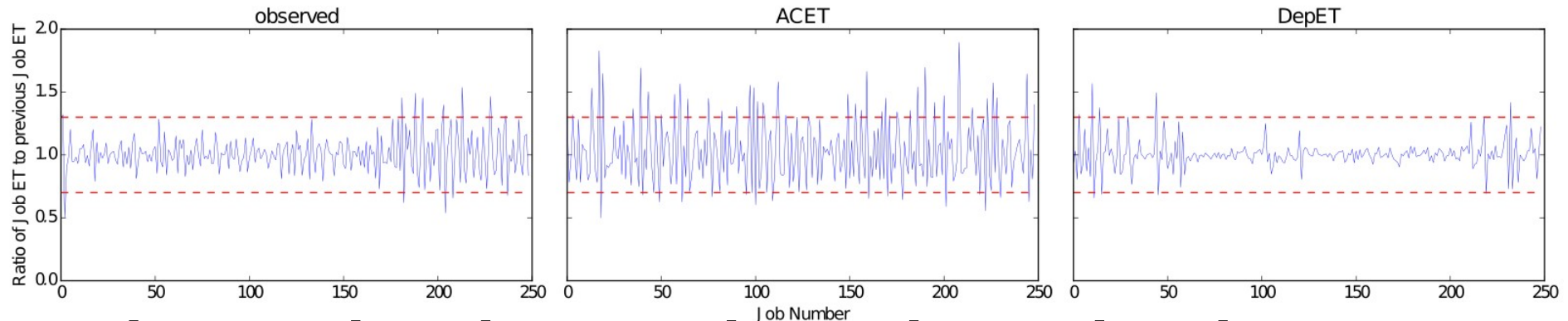
ACET has no dependencies



Evaluation - Dependencies



ACET has no dependencies



Observed and DepET have dependencies
In both, a good indicator of job execution time
Is previous job execution time

Conclusions

- Need to do better on dependencies between job execution times
 - Independence is not a realistic assumption
- Forecasting can be used to determine the expected duration of faults with reasonable accuracy
- Possible to use forecast models to generate dependent execution times using the new DepET algorithm

Any Questions?

