Rethinking How We Manage Failures

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Large-scale Computational Science Applications



Latency-sensitive applications plus batch jobs





High Performance Computing Data Centers

Enterprise Computing Data Centers

Large-scale Computational Science Applications





Long running "tightly-coupled" applications, explicit focus on resilience mechanisms (e.g., checkpoint-restart), improvements in system throughput and utilization desired. Latency-sensitive applications plus batch jobs





Short running jobs (in the order of milliseconds to seconds), restart-onfailure, focus on achieving tighter SLAs and reducing tail latency



Large-scale scientific applications will face severe resilience challenge at exascale!



Top Ten Exascale

Research Challenges

DOE ASCAC Subcommittee Report February 10, 2014

Rethinking How We Manage Failures

You can't avoid them, you can't predict them, but you can choose who gets hit by them!

Key is to exploit statistical properties of failures and diversity in characteristics of jobs

Who gets hit by failures: Part I

Who gets hit by failures in time!

Garg et al., "Shiraz: Exploiting System Reliability and Application Resilience Characteristics to Improve Large Scale System Throughput", DSN 2018.

What new territory does this work explore?



Prior efforts increase effective system MTBF Building more reliable system components Failure prediction, Quarantine job scheduling



Prior efforts reduce checkpointing overhead Incremental checkpointing of system state Checkpoint compression, Lazy checkpointing

Shiraz improves both system throughput and individual application performance by exploiting (a) differences in application resilience characteristics, and (b) dynamic system reliability behavior

Observation 1: Large variations exist in checkpointing overheads



Checkpointing overhead varies with application type, simulation parameters, memory-resident data size, input size, etc.

Observation 1: Large variations exist in checkpointing overheads

| Machine | Application Domain | Checkpointing |
|------------------|--------------------------------|------------------------|
| | | Duration (sec.) |
| Titan (OLCF) | Climate Change Simulation | 1.5 |
| | with the Community Earth | |
| | System Model | |
| Hopper (NERSC) | 20th Century Reanalysis | 2 |
| Franklin (NERSC) | | |
| Jaguar (ORNL) | Molecular Simulation | 6 |
| Hopper (NERSC) | in Energy Biosciences | |
| Carver and | Computational Predictions | 50 |
| Euclid (NERSC) | of Trans. Factor Binding Sites | |
| Cori (NERSC) | Chombo-crunch | 70 |
| Hopper (NERSC) | Climate Science for a | 150 |
| | Sustainable Energy Future | |
| Hopper (NERSC) | Laser Plasma Interactions | 1800 |
| Hopper (NERSC) | Plasma Based Accelerators | 2000 |
| Hopper (NERSC) | Plasma Science Studies | 2700 |



Application

Light Applications (LW): low checkpointing overhead lower optimal checkpointing interval: $OCI_{LW} = \sqrt{2M\delta_{LW}}$ Heavy Applications (HW): high checkpointing overhead; higher optimal checkpointing interval: $OCI_{HW} = \sqrt{2M\delta_{HW}}$

Observation 2: System failure rate is not constant over time



The hazard rate monotonically decreases between two failures, although that does not imply that the system becomes more or less reliable over a long period of time

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Observation III: Conventional scheduling is inefficient

Switch between applications at every failure



Light applications (LW) have lower average lost work per failure compared to heavy applications (HW)





Schedule a light-weight application after a failure, and switch to a heavy-weight application, at an *optimal point* between two failures

Optimal Switching Point

Optimal switching point is the number of checkpoints that LW application takes before yielding to the HW application such that the system throughput (i.e., total useful work per failure) is maximized, without hurting any application's performance



Shiraz Model

• Inputs MTBF (M), Checkpointing overheads (δ_{LW} and δ_{HW})

 δ -factor = δ_{HW} / δ_{LW} (ratio of checkpointing overheads)

 Output Optimal switching point (k) -- the number of checkpoints by LW application before scheduling HW application

$$T_{\text{useful-shiraz}}^{\text{LW}} - T_{\text{useful-base}}^{\text{LW}} = T_{\text{useful-shiraz}}^{\text{HW}} - T_{\text{useful-base}}^{\text{HW}}$$

s.t. $(T_{\text{useful-shiraz}}^{\text{LW}} - T_{\text{useful-base}}^{\text{LW}}) \ge 0$
and $(T_{\text{useful-shiraz}}^{\text{HW}} - T_{\text{useful-base}}^{\text{HW}}) \ge 0$

$$\operatorname{Fail}_{(t_{\operatorname{start}}, t_{\operatorname{end}})}^{\operatorname{num}} = \frac{T_{\operatorname{total}}}{M} \times \left(e^{-\left(\frac{t_{\operatorname{start}}}{\lambda}\right)^{\beta}} - e^{-\left(\frac{t_{\operatorname{end}}}{\lambda}\right)^{\beta}}\right)$$
$$T_{\operatorname{lost-base}}^{\operatorname{LW}} = \epsilon \times \left(\operatorname{OCI}_{\operatorname{LW}} + \delta_{\operatorname{LW}}\right) \times \operatorname{Fail}_{\operatorname{total}}^{\operatorname{num}}$$
$$T_{\operatorname{lost-base}}^{\operatorname{HW}} = \epsilon \times \left(\operatorname{OCI}_{\operatorname{HW}} + \delta_{\operatorname{HW}}\right) \times \operatorname{Fail}_{\operatorname{total}}^{\operatorname{num}}$$

More modeling details and tricks in the paper

$$T_{\text{useful-base}}^{\text{LW}} = \sum_{i=1}^{\infty} i \times \text{OCI}_{\text{LW}} \times \text{Fail}_{i,i+1}^{\text{num}}(\text{OCI}_{\text{LW}} + \delta_{\text{LW}}) \qquad T_{\text{useful-shiraz}}^{\text{LW}} = \sum_{i=1}^{k} i \times \text{OCI}_{\text{LW}} \times \text{Fail}_{i,i+1}^{\text{num}}(\text{OCI}_{\text{LW}} + \delta_{\text{LW}}) \qquad T_{\text{useful-shiraz}}^{\text{HW}} = \sum_{i=1}^{\infty} i \times \text{OCI}_{\text{HW}} \times \text{Fail}_{i,i+1}^{\text{num}}(\text{OCI}_{\text{HW}} + \delta_{\text{HW}}) \qquad T_{\text{useful-shiraz}}^{\text{HW}} = \sum_{i=k}^{\infty} i \times \text{OCI}_{\text{HW}} \times \text{Fail}_{i,i+1}^{\text{num}}(\text{OCI}_{\text{HW}} + \delta_{\text{HW}})$$

Shiraz Model Validation

Shiraz's per-application predictions validated against simulation

- Useful work, checkpointing overhead, and lost work
- Different system scale and storage system I/O bandwidth
- Optimal switching point **Extensive validation in the paper**

No assumptions about order and type of scheduled applications







Shiraz Optimal Switching Points

| System Type | Checkpointing Overhead Ratio | Model Optimal Switching Point | Simulation Optimal Switch Point |
|-------------|---------------------------------|----------------------------------|------------------------------------|
| Exascale | 5x | 6 | 6 |
| Exascale | 25x | 13 | 13 |
| Exascale | 100x | 26 | 26 |
| Exascale | 1000x | 81 | 79 |
| Petascale | 5x | 12 | 11 |
| Petascale | 25x | 26 | 24 |
| Petascale | 100x | 51 | 51 |
| Petascale | 1000x | 161 | 161 |

Shiraz model accurately predicts the optimal switch point across different scales and different checkpointing overhead ratios

Shiraz Evaluation



Exploration of real-world system parameters through simulations

Peta/Exa- scale, varying checkpointing overheads, multiple applications Real-world prototype on a cluster with system-level checkpointing

Optimal Switching Point: Insights



Optimal switching point shifts to the Optimal switching point shifts to right and benefits increase as the difference in the time-to-checkpoint but the benefits increase (i.e., between applications increases Shiraz is more useful at exascale)

Optimal Switching Point: Insights

Intuitively, one may think the optimal switching point to be half of the MTBF (in terms of time), but Shiraz discovers that it can be larger than even the MTBF in many cases!

Shiraz is Effective in Multi-Job Mix



Shiraz extended to a multi-job mix by intelligent application pairing No application is hurt in the job mix for a representative workload mix Throughput improvement increases at exascale (total 157 hours)

Shiraz: Energy Saving Analysis

Representative workload mix 40 jobs (only 5 heavy-weight and rest 35 light-weight applications) run for a year

Shiraz results in savings* of \$57K per annum for a 10 MW Petascale system (MTBF: 20 hours); savings of \$285K over a lifetime of 5 years

Shiraz results in savings* of \$178K per annum for a 20 MW future Exascale system (MTBF: 5 hours); savings for \$890K over a lifetime of 5 years

* Electricity @ \$0.1 per KW-hour

Shiraz improves system throughput, but does not mitigate the I/O overhead!

Shiraz+: Key Idea



Use the throughput gains obtained by Shiraz to reduce the checkpointing overhead of HW application Intuition: HW application is already running in a high-reliability zone

Shiraz+ Reduces I/O Overhead



60% reduction in checkpointing overhead when checkpointing frequency is reduced by 4x; throughput degrades only by 4.8%

No throughput degradation with 2x reduction in checkpointing frequency and 40% reduction in checkpointing overhead

Shiraz+ is Effective in Multi-Job Mix

Shiraz+ can reduce the overall checkpointing overhead by 52%, without degrading the system throughput (with 3x OCI)

With 4x OCI, the overall checkpointing overhead reduces by up to 60%, with a throughput degradation of 1%



Who gets hit by failures: Part II

Who gets hit by failures in space!

"Failures in Large Scale Systems: Long-term Measurement, Analysis, and Implications", SC 2017.

"Understanding and Exploiting Spatial Properties of System Failures on Extreme- Scale HPC Systems", DSN 2015.

Uneven Spatial Failure Distribution

Titan XK7

% Failures Distribution by Rows and Columns of Cabinets



Cabinet level distribution



Titan XK7





Holds True for Other Systems too!

Jaguar XT5

Jaguar XK6



Cabinet level distribution



% Failures Distribution by Rows and Columns of Cabinets



Cabinet level distribution



Neighborhood Recurrence Property of System Failures



Evidences Supporting Neighborhood Recurrence Property by Other Researchers for Other Systems!

Di et al., Exploring Properties and Correlations of Fatal Events in a Large-Scale HPC System, TPDS 2019



Patwari et al., Exploring Properties and Correlations of Fatal Events in a Large-Scale HPC System, FTXS 2017



Evidences Supporting Neighborhood Recurrence Property by <u>Other Researchers</u> for Other Systems!

Bautista-Gomez et al., Unprotected Computing : A Large-Scale Study of DRAM Raw Error Rate on a Supercomputer, SC 2016



Wang et al., What Can We Learn from Four Years of Data Center Hardware Failures?, DSN 2017



Exploiting Spatial Locality for Improving the Effective Reliability



On job restart or a new job allocation a fraction of compute capacity is not utilized or is allocated to lower-priority / smaller jobs

Quarantine: Design Challenges



Quarantine Granularity

Fraction of avoided system failures versus compute resource waste



Quarantine Time Duration

Diminishing returns on the number of avoided failures



System Utilization vs. Reliability

Trading-off lower system utilization for improved reliability





A significant fraction of failures can be avoided from interrupting production or critical applications and scheduling debug jobs in the quarantine region

Interesting Use Cases

Hussian et al., Partial Redundancy in HPC Systems with Non-Uniform Node Reliabilities, SC 2018 Zimmer et al., GPU age-aware scheduling to improve the reliability of leadership jobs on Titan, SC 2018



GPU-Aware Ordering

Large-scale Computational Science Applications



Latency-sensitive applications plus batch jobs





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Vibration Effects of Storage Devices

"What does Vibration do to Your SSD?" Janki Bhimani, Tirthak Patel, Ningfang Mi, Devesh Tiwari, In the Proceedings of the 56th Annual Design Automation Conference (DAC), 2019.

We know vibration hurts hard disks!

PYouTube



Shouting in the Datacenter

1,671,897 views

● 9.6K 🗣 111 🏕 SHARE =+ SAVE ••••

December 2008

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Yes, there are fixes.



Since 1987 - Covering the Fastest Computers in the World and the People Who Run Them Startup Takes Aim at Performance-Killing Vibration in Datacenter By Michael Feldman January 19, 2010

But, they are expensive!

The price premium for a Green Platform rack compared to a traditional metal rack is significant. According to Gordon, an AVP will cost four to five times that of a steel rack (which runs around \$2,000). But to Gordon, that's not the way to look at this solution. Since the AVP-1000 improves performance and lowers energy costs, the rack can pay for itself in less than 12 months — sometimes

https://www.hpcwire.com/2010/01/19/startup_takes_aim_at_per formance-killing_vibration_in_datacenter/

December 2008

Because....



SSDs are higher performant and do not have moving mechanical parts.

Now, SSDs are operating in increasingly vibration-prone environments!



Battlefield

Space Explorations

-Drivinc

Self-Driving

Cars

Time to repeat what Brendan **Gregg did to hard** disks in 2008, but this time to SSDs?





Shouting in the Datacenter 1.671.897 views

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Perhaps, a bit more scientific and controlled!



Vibration intensity lower than the vendor-specified limits!

As the conventional wisdom would suggest, vibration does not seem to have any visible effect on SSD performance!



Effect on mean I/O bandwidth Effect on mean I/O latency



But, when we dig deeper...

Vibration can affect the I/O tail latency significantly!



Tail latency degraded by up to 10% across vendors and I/O type (read and write).

Axis of Vibration

Parallel Orientation to the Vibration (=) Vibration VIBRATION GENERATOR VIBRATION GENERATOR 1000701 Fuse: F1A 1000701 of Fuse: F1A Axis (37) Perpendicular Orientation to the Vibration (\bot)

Axis of Vibration Matters a Lot!



Effect of \perp vibration on tail latency is much worse than = vibration, up to 30% in some cases!

I/O tail latency gets worse under active vibration across vendors and I/O types, and the magnitude may depend on the <u>axis of vibration</u>! I/O tail latency gets worse under active vibration across vendors and I/O types, and the magnitude may depend on the <u>axis of vibration</u>!

Then, all I need to do is not operate under active vibrations, just like hard disk days!

Unfortunately, no!

Vibration effects on SSDs tend to persist.

Nature and magnitude of post-effects depends on the length of the vibration!

Short-term Vibrations Can Leave Permanent Post-effects on Tail Latency!



Long-term vibrations are even more harmful!

Time

No Vibration

= Vibration

⊥ Vibration

T2

 \leftrightarrow

T1

 \leftrightarrow



Long-term exposure to vibration can degrade the tail latency by as much as 45%!

Surprisingly, long-term vibrations can also lead to SSD failures !

Some SSDs operating under vibration observed silent and transient failures soon after the end of the long-term window, but <u>before reaching their write-endurance limit</u>. These SSDs functioned correctly after a restart, until the next failure.

Failures prone to be classified as NDFs (No Defect Found)

These failures result in permanent performance degradation!



SSD vibration effects tend to persist even if the length of exposure to vibration is short!

Long-term vibrations can degrade both the tail I/O latency and bandwidth.

Long-term vibrations can also lead to silent failures and permanent bandwidth degradation.

Conclusion

Vibrations considered harmful even for SSDs!

Next time, you borrow or buy an SSD, inquire if the device <u>was exposed to vibration</u>, <u>in</u> <u>what axis</u>, and <u>for how long</u>?

Back Up Slides

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