NavP: Enabling Navigational Programming for Science Data Processing via Application-Initiated Checkpointing

Lei Pan
Jet Propulsion Laboratory
California Institute of Technology
Pasadena, USA
lei.pan@jpl.nasa.gov

Twinkle Jain*
Northeastern University
Boston, USA
jain.t@northeastern.edu

Abstract

Science Data Systems (SDS) handle science data from acquisition through processing to distribution. They are deployed in the Cloud today, and the efficiency of Cloud instance utilization is critical to success. Conventional SDS are unable to take advantage of a cost-effective Amazon EC2 spot market, especially for long-running tasks. Some of the difficulties found in current practice at NASA/JPL are: a lack of mechanism for app programmers to save valuable partial results for future processing continuation, the heavy weight from using container-based (Singularity) sandboxes with more than 200,000 OS-level files; and the gap between scientists developing algorithms/programs on a laptop and the SDS experts deploying software in Cloud computing or supercomputing.

All of the above difficulties can be ameliorated if the process carrying out computations on the scientist’s laptop can be directly migrated among multiple nodes in the Cloud or on the supercomputer. The key idea is to allow the scientist programmers to directly navigate the computations to the data, or help them move the remaining computations to a new Cloud instance when the old one is taken away. We present a first proof-of-principle of this using NavP (Navigational Programming) and fault-tolerant computing (FTC) in SDS, by employing program state migration facilitated by Checkpoint-Restart (C/R). NavP provides a new navigational view of computations in a distributed world for the application programmers. The tool of DHP (DMTCP Hop and Publish) we developed enables the application programmers to navigate the computation among instances or nodes by inserting hop(destination) statements in their app code, and choose when to publish partial results at stages of their algorithms that they think worthwhile for future continuation. The result of using DHP is that a parallel distributed SDS becomes easier to program and deploy, and this enables more efficient leveraging of the Amazon EC2 Spot market. This technical report describes a high-level design and an initial implementation.

NASA/Jet Propulsion Laboratory acquires massive amounts of observatory instrument data in their missions from planetary (e.g., Mars Exploration, Cassini, Rosetta, Psyche) to earth science (e.g., Jason, OCO, NISAR, SMAP, MAIA). This instrument data is then processed into science data on massively parallel distributed computing facilities such as the Cloud and supercomputers. Innovations in SDS programming are the key to the success of JPL missions.

*This work was partially supported by National Science Foundation Grant OAC-1740218 and a grant from Intel Corporation.
1 Introduction

Large-scale Science Data Systems (SDS) like Hybrid Cloud Science Data System (HySDS) \[\text{1}\] are widely used in various critical NASA missions \[\text{1}\]. Cloud computing is elastic and scalable, making it an ideal choice for SDS. Another platform for SDS is cluster computers, an example of which is NASA’s petascale supercomputer, Pleiades, which has seen heavy investment over the last decade.

Our first goal is to help the scientist programmers to go directly from algorithms on paper to final production runs in SDS, without much help from an outside specialist in SDS. By allowing the scientist-programmers to directly program and immediately test and deploy (without much help of the SDS expert), the edit-test-debug-production cycle of software development will be greatly accelerated. Another goal is to facilitate high performance and effective resource leveraging.

However, in the currently available SDS, there are three major problems that prevent us from achieving this goal.

1. Long-running tasks are not readily broken down into smaller ones to leverage the Amazon EC2 spot market. This makes it hard or impossible to exploit the steep discounts of the EC2 spot market. It is the temporal aspect of atomic jobs.

2. The prevailing container-based approach to deploying programs and moving computation to data is heavyweight, in that it moves much more loaded data than the strictly necessary program state. In the case of a Singularity sandbox, which is the virtualization technique adopted on Pleiades, the run-time environment being moved includes 200,000+ OS-level files. Furthermore, container images, in which app programs are installed, take a long time to build, and require knowledge and skills in SDS deployment, such as Terraform scripting, AWS instance management, Docker/Singularity build scripting, and Jenkins pipeline scripting, which scientist programmers in general are not familiar with. One would always have to work with an SDS expert in virtualizing and deploying the application-level programs, and that is even true for doing version updates. Part of the problem is mixing different levels of abstraction for different concerns, such as app algorithms vs. details of data distribution. Therefore, unnecessary burdens are placed on the scientist programmer’s shoulders. This is the spatial aspect of atomic jobs.

3. Only embarrassingly parallel algorithms (e.g., MapReduce) are easily programmable. In general, parallel programming is a non-trivial task, especially in a distributed environment. This is due to the fact that prevailing programming methodologies provide a stationary view of the distributed systems where stationary processes work with each other using messages. Using an analogy in traveling as an example, there are two views, namely arrivals-and-departures in the train stations/airports and an itinerary in a traveler’s hand. These two views both capture the exact same information, spatial and temporal, about a traveler. Our proposal is that, just as a traveler should be using an itinerary to travel with, distributed parallel programming should be using the navigational view. The reality though is that all prevailing programming paradigms today are as awkward as traveling using the arrivals-and-departures view. Our proposal comes with a grand challenge: how to make NavP almost as efficient as message passing, for all major programming languages. This would mean optimizations at the underlying DMTCP level: (1) To travel to a remote node carrying only the data needed for future computation; and (2) To avoid moving code, including both app level code and
run-time environment level code, e.g., OS code, python modules, shared libraries, to visit a
node more than once.

We leverage checkpoint-restart (C/R) to enable Navigational Programming (NavP) \(^2\) in order
to facilitate high performance, effective resource leveraging, and ease of use for scientist programmers.

Navigational Programming (NavP) was originally developed in 2004 \(^2\). The advantage of
NavP for distributed parallel programming is that it brings the computation to the data using an
intuitive navigational view of the distributed programming environment, as opposed to the conven-
tional view of message passing, which in general would force massive restructuring of the original
sequential algorithms. NavP has not yet been widely adopted because process migration for mul-
tiple programming languages across the board is difficult. Furthermore, making process migration
as efficient as message passing is a grand challenge at the underlying system level. However, we
argue that the time has now come for this novel paradigm. This work presents an architecture that
leverages a principled implementation relying on checkpointing in order to enable NavP.

The next five items each present background on the practical requirements of Scientific Data
Systems (SDS), followed by a question that motivates the goals of the NavP project. This paper
answers those questions in the positive, by showing a first proof-of-principle for NavP.

1. Large-scale software development typically uses Continuous Integration (CI) and Continuous
Deployment (CD) to check in, build, test, and deploy incremental changes in code develop-
ment. In practice, new versions of the code are built in and deployed using Docker/Singularity
images. The overhead of this approach is the virtual run-time environment, i.e., some 200,000
files from the operating system, and cannot be ignored since CI/CD happens continuously
and frequently as scientists update their algorithms. This overhead can become overwhelm-
ing in some cases. For example, NASA’s supercomputer Pleiades uses Singularity instead of
Docker for security considerations. A Singularity sandbox with more than 200,000 small files
will take an enormous amount of time to handle (untarring or deleting) on Pleiades’ Lustre
file system \(^3\).

Can programs be made to migrate themselves? If so, the virtual containers are then deployed
only once, and the subsequent CI/CD operations deploy only the software applications.

2. Scientific application developers are usually scientists who write code on their laptops or
desktops, where data is a small sample, and where processing power is limited. Going to
the Cloud or supercomputer involves CI/CD administered by SDS experts. So if a scientist
develops a new algorithm that works on laptops with small input data, it will require days or
even weeks for the scientist to try it out on a larger scale. This is not acceptable.

Can we convert the Cloud or supercomputer into a virtual environment that acts as an
extension of the scientist’s laptop? If so, the scientist can test their new algorithms at any
time, even at midnight when a new idea suddenly comes to them. The program’s self-
migration envisioned here enables the scientists to do just this.

3. Webification tools such as JPL’s Pomegranate \(^4\) use the http protocol and web browsers
to open HDF/netCDF files remotely and transfer only what is needed by the clients. This
avoids downloading entire files in cases where only a fraction is useful. Over the years, people
have developed HDF/netCDF readers that work on local files efficiently.
Can we can migrate the readers to where the HDF/netCDF files are? If so, file access can be made just as efficient as using HDF/netCDF readers. And at the same time, all of the existing code can be reused. If this can be done, there would be no need to develop or learn to use new tools such as Pomegranate.

4. Over the past decades, people spent tremendous effort developing techniques for web services. Corba, JWS, Flask are among the tools provided. These use data in some format, such as xml or json to facilitate communication between the client and the server.

Can programs migrate across the server and client run-time environments? If so, then the right way to facilitate remote communication will be through the familiar program variables, and programmers will not need to learn anything new.

5. In physics there are two different views of observing moving phenomena: the Eulerian and the Lagrangian views. These correspond to the arrivals-and-departures (Eulerian) information shown on the screens of airports or train stations, versus the itinerary (Lagrangian) held in the travellers’ hand. Computers were originally invented without networking. Hence processes typically are not migrated through the network. So programming using the Eulerian view has been the natural view in programming: all program lines describe local, stationary computation activities, and when a remote computer service is needed, message passing or its variant is used. In earlier work, process self-navigation is proposed as the solution to describe distributed computation — following its locus of computation in the Lagrangian view. The result is the Distributed Sequential Computing (DSC) program model from 2001. And multiple DSC’s are then synchronized to carry out parallel computation using the idea of a Mobile Pipeline (2005). Scalable performance and easy of programming has been demonstrated in this way, for notoriously hard-to-parallelize numerical algorithms.

In the modern networked world, can NavP now be made a first-class object at the operating system level? Or can NavP use a development toolkit, such as DMTCP, which in theory can be done as efficiently as message passing, by switching between the two different views? This would be used to describe exactly the same physical phenomenon, using the same amount of message passing, along with some small implementation overhead.

2 Background

2.1 SDS

Science Data Systems (SDS) handle science data from acquisition through processing to distribution. This makes a generic SDS a multi-stage workflow, as depicted in Figure 1. Science values are being put into the data as higher level processing are being advanced to. Typically, high level processing requires capabilities involving petascale data storage and processing power.

![Figure 1: Data processing phases in SDS](image-url)
2.2 Fault-Tolerant Computing in the Cloud

Amazon provides EC2 spot instances, which offer spare compute capacity in the AWS Cloud, available at steep discounts (90% savings), but they can be taken away at any time. In the meantime, each atomic task can take hours to finish. Our strategy is to break the original task into smaller pieces using checkpointing and introduce Fault-Tolerant Computing. So, the “remaining” computation can be brought to and restarted on a new instance after the old instance disappears.

2.3 NavP: Navigational Programming

A distributed parallel system is not directly programmable by scientist-programmers. One would always have to work with an SDS expert in virtualizing and deploying the application-level programs, and even when doing version updates. The levels of abstraction for different concerns, application algorithms vs. details of distribution, are coupled. Scientists develop original algorithms that carry out numerical calculations toward data in the form of abstract data structures and variables. The reality of petascale distributed data over the networked systems forces the scientists to work closely with SDS experts to restructure their original algorithms into actual code (e.g., client and server code), install the code in virtual boxes (e.g., Docker images), and deploy the programs in virtual containers onto computer nodes or Cloud instances. Therefore unnecessary burdens are placed on the application developers’ shoulders. For applications that are not by nature embarrassingly parallel, this task is difficult, if not impossible. NavP was introduced to address these difficulties [2]. A new view of distributed programming, namely the NavP view, is introduced. In this view, the description of a computation follows its locus to where the large data is found [5]. This is done by inserting `hop()` statements in the original sequential code. A `hop(dest)` statement pauses the computation, collects all the program/thread state, migrates to the `dest` node, and resumes computation.

2.4 Application-initiated transparent C/R

We use the DMTCP (Distributed MultiThreaded CheckPointing) [8] package for C/R. It transparently checkpoints computations in user-space. It saves a copy of the program state (called a Checkpoint Memory Image (CMI)) to disk and resumes the process later. It requires no modifications to the user application code nor to the operating system.

The DMTCP plugins [9] and hooks for application-initiated checkpointing provide a flexible way to introduce add-on behaviors around DMTCP events [8].

We develop DHP (DMTCP Hop and Publish), a new Python tool, around DMTCP. This provides two utilities around the checkpoint and restart: a) `hop(dest)` — i.e., responsible for generating CMI on the source node, migrating to, and resuming CMI on the destination node; and b) `publish(dest, status)` — i.e., responsible of publishing job’s status and result on the destination node.

The next section describes how to enable `hop()` and FTC using DHP and web services for program state migration.
3 The NavP Bridging Services (NBS)

3.1 The NavP Bridging Services (NBS) with DHP

The NavP Bridging Services (NBS) run on each compute node and serve the client requests from the application processes. The NBS service for communication and data migration (i.e., svc/hop), running on both source and destination nodes, enables DHP to migrate CMI(s) between two nodes. We provide an overview of the workflow of a NBS in Figure 2. In the figure, there is a source node i.e., Host A and a destination node i.e., Host B with NBS services running on each node. Now, an application process running on Host A can call the DHP.hop(B) utility, which in turn initiates checkpoint that generates CMI(s) as well as a restart script, and then calls the svc/hop NBS service running on Host B before it terminates itself. The svc/hop NBS service on Host B copies the CMI and restart script from Host A to B, and runs the restart script to resume the computation. This way DHP is able to utilize existing data migration utility.

3.2 NBS to enable NavP

We use DHP.hop(dest) and svc/hop to enable NavP. Pseudocode for the DHP.hop(dest) is in Figure 3, in which S3 means some shared disk volume, either in an S3 bucket or bound to the containers. Pseudocode for svc/hop is in Figure 4.

![Figure 2: Overview of NavP Bridging Service workflow](image)

```
(1) checkpoint()
(2) if isResume() : # after checkpointing
(3) copy CMI and restart script to S3
(4) request svc/hop on dest
(5) exit
```

Figure 3: Pseudocode for the DHP.hop(dest) utility

3.3 NBS to enable FTC in SDS

When jobs in SDS are treated as atomic operations, they can be either “new” before the run, or “finished” after the run. Any interrupted jobs return to the “new” status. A new job has input
datasets, and a finished job has products. For the sake of brevity, we ignore more sophisticated situations, such as a “running” status, in which a job can have both input datasets and partial products. These additional combinations can be handled in real life applications using the same principle.

The key idea is to introduce a new job status, called “ckpt”, in which the CMI is treated as a “special product”. We implement three services to handle the following jobs: (1) svc/list_jobs: this returns all jobs with their job_id’s along with their statuses, such as those shown in Figure 5.

(2) svc/get_job: this returns the status of a job given its job_id, or the next job that is not finished when no job_id is provided. (3) svc/publish_job: this publishes jobs with two possible statuses: “ckpt”, in which case the CMI and restart script are uploaded, and “finished”, in which case the final product is uploaded.

A DHP utility, DHP.publish(dest, status), is listed in Figure 6. This is similar to DHP.hop(dest). An application uses DHP.publish() to publish with two possible statuses: “ckpt” (checkpoints and calls svc/publish_job service with a “ckpt” status) or “finished” (calls svc/publish_job with a “finished” status). The “dest” is the job scheduler service.

Figure 4: Pseudocode for the svc/hop service

Figure 5: Sample list of jobs with job-ID and status

Figure 6: Pseudocode for DHP.publish(dest, status) utility
4 Experiments: Proof of Concept

Our experiments are designed to answer the following questions:

1. How to enable NavP in SDS?

   The test case application chosen is called “the co-location of satellite observation data”. Specifically, the data from the instrument VIIRS (Visible Infrared Imaging Radiometer Suite) is mapped to the geometry of CrIS (Cross-track Infrared Sounder) [10] [12]. The first experiment has the pseudocode listed in Figure 7, in which the calls to `svc/publish('ckpt')` are where we checkpoint and where the CMIs are published as “partial products”. So when the execution fails for any reason at any time, restart will happen from the most-recent-checkpoint. The application programmer is thus in control of where and how frequently checkpoints happen. The last call to `svc/publish('finished')` publishes the real product.

   ![Pseudocode for JPL application of VIIRS/CrIS co-location.](image)

   Figure 7: Pseudocode for JPL application of VIIRS/CrIS co-location.

   The second experiment assumes that the input data granules are available on a remote server. So the application needs to first hop to read the input data. Assuming further that this remote server is only for hosting data (input data and output product), the application hops back to the client server to carry out co-location matching, before hopping to the remote server again to publish the final product. The pseudocode listed in Figure 8 therefore has three `hop()` statements inserted in the original code.

2. What is the performance overhead of DMTCP checkpointing and restart? How does this overhead, which is primarily incurred by disk I/O, from writing out and loading up the CMIs, as compared to the cost of migrating the CMIs over the network?

   There are two experimental environments, chosen for two different purposes. The first is a single desktop computer running the Linux operating system, with an Intel Xeon 4GHz CPU with 8 cores and 32GB of physical memory. Two virtual NBS containers are run on the
same computer, making process migration to happen virtually remotely, but physically only locally. This removes networking cost from the equation, making it ideal for assessing the cost and impact of CMI from checkpointing done by DMTCP. The second system is the Amazon Cloud with m4.4xlarge instances and AWS S3 buckets for storage. This is the real world for JPL SDS, in which the network and S3 performance are all taken into consideration.

We have implementations of all the pseudocode listed in this report working. From this, we quickly realized that our general purpose DMTCP needs to be optimized before further experiments can be meaningfully carried out. This is because as a general purpose C/R tool, DMTCP currently puts everything our app needs from the run-time environment, e.g., python modules and shared libraries, into the CMIs. As a result, the cost of disk I/O and network transfer of CMIs overshadows the cost of numerical computation in the app. The Docker/Singularity containers to which the app does hop() or publish(), are assumed to have identical run-time environments, with the same python/modules/shared libraries etc. So DMTCP can conveniently skip checkpointing anything related to the run-time environment. Upon arriving at a remote container, the DMTCP restart shell script will load the modules and shared libraries from the local installation. This will make the CMIs much more lightweight than they currently are.

Hence, our immediate future work includes a special-purpose, NavP-oriented DMTCP that will be optimized for navigational programming.

5 Discussion

In this section, we answer following questions related to the current work.

Question 1. How to predict when to checkpoint considering spot instance can take their resources back anytime?

Amazon EC2 spot instances are cost-effective resources but can be reclaimed with just two minutes of instance termination notice. This is not sufficient time to initiate, complete, and migrate CMIs for a large-scale job. Jangjaimon et. al \cite{13} takes account of past resource reclaim events to predict a checkpoint interval for their adaptive checkpoint scheme. However, the result of an incomplete job is equivalent to no result for an SDS job. Therefore, prediction of the next resource reclaim event would not benefit the user significantly.
Question 2. What are some advantages of application-initiated checkpoint over conventional periodic checkpoint?

Fixed-interval periodic checkpoints work well where jobs are not considered atomic, and where intermediate results can also be useful. However, application-initiated checkpoint is an application-aware technique and enables two important features: 1) applications that interact with large data often have a small memory footprint before and after the job, which makes the checkpointing task faster, and makes the CMI’s size feasible for migration over the network; and 2) more control and awareness by the application where it’s safe to checkpoint with a minimal side effect.

Question 3. How to keep a CMI’s size small?

We either migrate CMIs over the network or write on a shared disk for NavP. Amazon S3 buckets are often not the fastest I/O option because of their physical location. Therefore, it is important to keep CMIs small in size. The size directly depends on the memory footprint (and associated files if one wants to checkpoint open files as well). One solution is to make the memory footprint small by zeroing out or unmapping unused memory within process address space at the time of checkpoint. However, this would require changes in the application, and the solution would no longer remain transparent.

Another solution is to save the CMIs incrementally by saving only deltas of each consecutive checkpoint. This would optimize I/O interaction, but this would require an extra step to replay deltas at restart with the current DMTCP open-source code. We checkpoint after a job finishes and before the application loads another data set into memory, in order to ensure a small size for the CMI. DHP currently replaces the last CMI with the latest CMI. In addition, incremental checkpointing is an option for future work.

Question 4. What if the checkpoint task is interrupted?

DHP guarantees an atomic checkpointing phase. Thus, DHP makes sure to not replace previous CMIs if the resources were reclaimed in the middle of an ongoing checkpointing phase.

Question 5. What are some future optimization to this work?

Currently, DHP writes a CMI first on the shared disk, and then it migrates the saved CMI over network. With a small modification to DMTCP, it is possible to directly stream CMIs over the network, in a manner similar to live migration. Also, currently, checkpoint and migration is a two-step process. However, consider a scenario in which the checkpointing task is finished, but the migration has yet to finish. This can lead to an inconsistent state. Therefore, we currently consider DHP.hop to be complete only once the migration is complete.

Question 6. What is the difference between existing adaptive checkpoint and the current work?

The current implementation doesn’t take account of previous events, duration, and patterns of EC2 spot instance termination. However, this information can help in choosing a candidate node where DHP should migrate CMIs to within cloud. One can choose a node that is unlikely to be terminated before a job finishes.

6 Related Work

Fault tolerance for long running application in high performance computing (HPC) has been a major area for checkpoint-restart. In recent years, checkpointing is found useful for cost-effective
resource utilization within and beyond HPC. Jangjaimon et al. \[13\] discuss effective cost reduction for elastic clouds through adaptive checkpointing. However, the current work does not rely on previous events to checkpoint but focuses on keeping the CMI size small to allow checkpointing at any time.

Yi et al. \[14\] compares several checkpointing schemes including adaptive checkpointing based on hourly, rising edge, basic adaptive and current-price events. However, they assume that the checkpointing cost is known, which is unlikely when the memory footprint varies throughout the workflow. In addition, atomic jobs are not flexible enough to be checkpointed at an arbitrary time. This adds an extra restriction to the existing checkpointing schemes for applications in the cloud.

In order to make checkpoint invocation cost-effective, Jung et al. \[15\] predicts termination (out-of-bid) and a price hike for spot instances, based on the history. They use Virtual Machine-based (VM-based) checkpoint and migration to avoid any waiting time at restart. However, migrating a VM instead of an application requires more data transfer over the network, and the migration cost varies based on the network. The current work focuses on reducing the memory footprint to minimize data transfer, while migrating CMIs as data.

To the best of our knowledge, this is the first work to enable the navigational programming model for SDS applications via checkpoint-restart over commercial cloud systems, such as Amazon EC2 spot market.

7 Conclusion and Future Work

This is an initial attempt in applying Navigational Programming, enabled with process checkpointing by DMTCP, to NASA/JPL science data processing. We have successfully built the NavP Bridging Services (NBS) and demonstrated its application for JPL Satellite Data Co-location processing. With our current implementation, we are able to successfully checkpoint, migrate, and resume our app. We also mimicked successfully the continuation of a job on a new instance with intermediate partial results published during the most recent checkpointing. Initial performance studies showed large overhead in our current implementation. We plan to customize and optimize DMTCP, and publish case studies and performance analysis, in a future version of this report.

This report introduced and described several concepts in the NavP paradigm, and provided a rationale behind why this is superior to the currently prevailing methods. It has also raised many questions. More case studies are necessary to provide experimental evidence. With an optimized NBS/DMTCP system in the future, we plan to attack more JPL science data processing problems, and answer the questions that were raised in this report.

Acknowledgment

The authors wish to acknowledge useful discussions on this topic with Gene Cooperman.

References

[1] H. Hua, G. Manipon, and the JPL HySDS Team, “The hybrid cloud science data system,” https://hysds-core.atlassian.net/wiki/spaces/HYS/overview Sep. 2021.
[2] L. Pan, M. K. Lai, K. Noguchi, J. J. Huseynov, L. F. Bic, and M. B. Dillencourt, “Distributed parallel computing using navigational programming,” in *International Journal of Parallel Programming*, vol. 32, no. 1. Springer, Feb 2004.

[3] X. Li, B. Dong, L. Xiao, L. Ruan, and Y. Ding, “Small files problem in parallel file system,” in *2011 International Conference on Network Computing and Information Security*, vol. 2, 2011, pp. 227–232.

[4] Z. Xing, “Webification for earth science,” Jet Propulsion Laboratory, California Institute of Technology, Pasadena, CA, Tech. Rep., Mar 2018, white paper.

[5] L. Pan, L. F. Bic, M. B. Dillencourt, and M. K. Lai, “NavP versus SPMD: Two views of distributed computation,” in *Proceedings of the Fifteenth IASTED International Conference on Parallel and Distributed Computing and Systems*, T. Gonzalez, Ed., vol. 2, Algorithms. Anaheim, Calif.: ACTA Press, Nov. 2003, pp. 666–673.

[6] L. Pan, L. Bic, and M. Dillencourt, “Distributed sequential computing using mobile code: Moving computation to data,” in *International Conference on Parallel Processing, 2001*, 2001, pp. 77–84.

[7] L. Pan, M. K. Lai, M. B. Dillencourt, and L. F. Bic, “Mobile Pipelines: Parallelizing left-looking algorithms using Navigational Programming,” in *High Performance Computing – HiPC 2005*, D. A. Bader, M. Parashar, V. Sridhar, and V. K. Prasanna, Eds. Berlin, Heidelberg: Springer Berlin Heidelberg, 2005, pp. 201–212.

[8] J. Ansel, K. Arya, and G. Cooperman, “DMTCP: Transparent checkpointing for cluster computations and the desktop,” in *2009 IEEE International Symposium on Parallel & Distributed Processing*. IEEE, 2009, pp. 1–12.

[9] G. C. Kapil Arya, “Dmtcp: Bringing checkpoint-restart to python,” in *Test Proceedings for OpenProceedings*, A. Zonca, Ed., 2013. [Online]. Available: [http://dx.doi.org/10.6084/m9.figshare.935502](http://dx.doi.org/10.6084/m9.figshare.935502)

[10] L. Wang, D. Tremblay, B. Zhang, and Y. Han, “Fast and accurate collocation of the visible infrared imaging radiometer suite measurements with cross-track infrared sounder,” *Remote Sensing*, vol. 8, no. 1, 2016. [Online]. Available: [https://www.mdpi.com/2072-4292/8/1/76](https://www.mdpi.com/2072-4292/8/1/76)

[11] Q. Yue, E. J. Fetzer, L. Wang, B. H. Kahn, I. Tkatcheva, M. Schreier, B. Lambrigsten, N. Smith, J. Blaisdell, and K. G. Meyer, “Evaluating the consistency and continuity of cloud property data records from Aqua and SNPP on the pixel scale,” submitted to Journal of Geophysical Research: Atmospheres.

[12] E. J. Fetzer, Q. Yue, S. Wong, A. Guillaume, R. A. Stachnik, T. Wang, G. Manipon, B. H. Kahn, B. D. Wilson, and H. Hua, “A multi-sensor water vapor, temperature and cloud climate data record from the A-train,” in *American Geophysical Union, Fall Meeting 2016*, Dec 2016.

[13] I. Jangjaimon and N.-F. Tzeng, “Effective cost reduction for elastic clouds under spot instance pricing through adaptive checkpointing,” *IEEE Transactions on Computers*, vol. 64, no. 2, pp. 396–409, 2013.
[14] S. Yi, A. Andrzejak, and D. Kondo, “Monetary cost-aware checkpointing and migration on Amazon cloud spot instances,” *IEEE Transactions on Services Computing*, vol. 5, no. 4, pp. 512–524, 2011.

[15] D. Jung, S. Chin, K. S. Chung, and H. Yu, “VM migration for fault tolerance in spot instance based cloud computing,” in *International Conference on Grid and Pervasive Computing*. Springer, 2013, pp. 142–151.