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Implementing Software Resiliency in HPX for Extreme Scale Computing

Extended Abstract

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***Index Terms*—software resilience, parallel and distributed computing, asynchronous many-task systems, HPX**

I. Introduction

The DOE Office of Science Exascale Computing Project (ECP) [1] outlines the next milestones in the supercomputing domain. The target computing systems under the project will deliver 10x performance while keeping the power budget under 30 megawatts. With such large machines, the need to make applications resilient has become paramount. The benefits of adding resiliency to mission critical and scientific applications, includes the reduced cost of restarting the failed simulation both in terms of time and power.

Most of the current implementation of resiliency at the software level makes use of a Coordinated Checkpoint and Restart (C/R) [2]–[7]. This technique of resiliency generates a consistent global snapshot, also called a checkpoint. Generating snapshots involves global communication and coordination and is achieved by synchronizing all running processes. The generated checkpoint is then stored in some form of persistent storage. On failure detection, the runtime initiates a global rollback to the most recent previously saved checkpoint. This involves aborting all running processes, rolling them back to the previous state and restarting them.

In its current form, the Coordinated C/R is excessively expensive on extreme-scale systems. This is due to the high overhead costs of global rollback followed by global restart. Adding to these overheads are the significant overheads of global I/O access. In many cases, millions of processes have to respond to a local process failure which leads to heavy loss of useful CPU computation cycles and leads to a significant performance penalty. This was observed when node level resiliency was implemented in a production application running on Titan system at Oak Ridge National Laboratory [8]. The overheads of resiliency had a significant impact on performance as the overheads of C/R were 20-30% of the total execution time.

Emerging resilience techniques, such as Uncoordinated C/R [10] and Local Failure Local Recovery (LFLR) [9] attempts to mitigate some of the overheads of coordinated C/R by eliminating the requirement of aborting all running processes and restarting. However, these techniques are based on assumptions exclusive to Single Program Multiple Data (SPMD) model i.e. the same program execution across all running processes. Asynchronous Many-Task (AMT) execution models provide similar resilience techniques without any of these assumptions.

In this paper, we explore the implementation of resiliency techniques in Asynchronous Many-Task (AMT) Runtime Systems. We have chosen to use HPX as a model AMT as it exposes a standards conforming API which is easy to understand and adopt. AMTs replace the bulk-synchronous MPI model with fine-grained tasks and explicit task dependencies. They rely on a runtime system to schedule the tasks and manage their synchronization. In an AMT model, a program can be seen as a flow of data which is processed by tasks, each task executing a distinct kernel. Failures within a program are nothing but a manifestation of a failed task, which can be identified as a local point of failure. This significantly simplifies the implementations of a resilient interface. The two intuitive choices of resiliency in AMT are task replay and task replicate. Task replay reschedules a failed task until it runs to completion or exhausts the number of replay trials. Task replicate schedules a single task multiple times (decided by the application developer) and, from the successfully completed tasks, determines the appropriate result.

The section II talks about Related Work in AMT resilience. Section III discusses about HPX and Resilience with HPX. Section IV discusses about the implementation details of implementing resilience. Section V describes the benchmarks and Section VI discusses the results.

II. Related Work

Software based resilience for SPMD programs have been well studied and explored including but not limited to coordinated checkpoint and restart (C/R). Enabling resilience in AMT execution model has not been well studied despite the fact that the AMT paradigm facilitates an easier implementation. Subasi *et al* [11]–[13] have discussed a combination of task replay and replicate with C/R for task-parallel runtime, OmpSs. For task repication, they suggested to defer launch of the third replica until duplicated tasks report a failure.

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This differs from our implementation, as we replicate the tasks and do not defer the launch of any task for future. For task replay, they depend on the errors triggered by the operating system. This approach, thus, assumes a reliable failure detection support by the operating system, which is not always available. We also found that automatic global checkpointing has been explored within the Kokkos ecosystem as well [14].

Similar work has recently been explored in AMT with Habanero C [15]. The work, however, is based on on node resiliency. We plan to extend our work to provide distributed resiliency features. Furthermore, Our work implements the AMT resliency APIs with different characteristics. We also provide more control over the APIs by introducing multiple variants of a single resilience API. Finally, HPX is standards C++ conforming, giving application developers the least effort for the addition of resilience over their current non resilient code.

III. Background

A. HPX

HPX [16]–[20] is a C++ standard library for distributed and parallel programming built on top of an asynchronous many-task (AMT) runtime system. Such AMT runtimes may provide a means for helping programming models to fully exploit available parallelism on complex emerging HPC architectures. The HPX programming model includes the following essential components: *(1)* an ISO C++ standard conforming API that enables wait-free asynchronous parallel programming, including futures, channels, and other asynchronization primitives; *(2)* an active global address space (AGAS) that supports load balancing via object migration; *(3)* an active-message networking layer that ships functions to the objects they operate on; *(4)* work-stealing lightweight task scheduler that enables finer-grained parallelization and synchronization.

B. Resilience in HPX

In this work we assume that a "failure" is a manifestation of a failing task. A task is considered "failing" if it either throws an exception or if additional facilities (e.g. a user provided "validation function") identifies the computed result as being incorrect. This notion simplifies the implementation of resilience and makes HPX a suitable platform to perform experiments with resiliency APIs. We present two different ways to expose resiliency capabilities to the user:

Task Replay is analogous to the Checkpoint/Restart mechanism found in conventional execution models. The key difference being localized fault detection. When the runtime detects an error it replays the failing task as opposed to completely rolling back of the entire program to the previous checkpoint.

Task Replicate is designed to provide reliability enhancements by replicating a set of tasks and evaluating their results to determine a consensus among them. This technique is most effective in situations where there are few tasks in the critical path of the DAG which leaves the system underutilized or where hardware or software failures may result in an incorrect result instead of an error. However, the drawback of this method is the additional computational cost incurred by repeating a task multiple times.

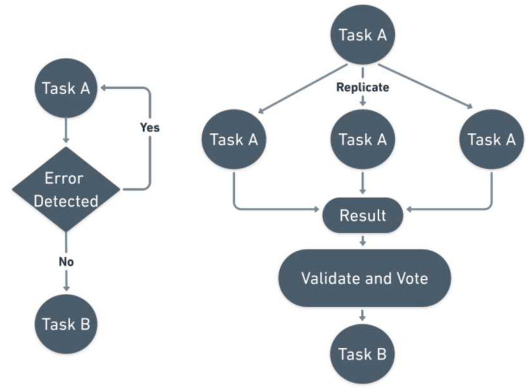


Fig. 1: Task Replay and Task Replicate

IV. Implementation Details

The two main resiliency APIs explored are described below. All new functionalities are implemented as extensions of the existing HPX *async* and *dataflow* API functions. This enables a seamless migration of existing HPX codes to support the described resiliency features.

A. Task Replay

In this technique, a task is automatically replayed (re-run) up-to N times if an error is detected (see Listing 1).

(i) **Async and Dataflow Replay:** This version of task replay will catch user defined exceptions and automatically reschedule the task N times before re-throwing theexception.

(ii) **Async and Dataflow Replay Validate:** This version of replay adds a validation function to the API that is used to validate the individual results. It returns the first positively validated result. If the validation fails or an exception is thrown, the task is replayed until no errors are encountered or the number of specified retries has been exceeded.

```
using namespace hpxr = hpx::resiliency;

hpxr::async_replay(N, F, Args...);
hpxr::dataflow_replay(N, F, Args...);

hpxr::async_replay_validate(N, ValF, F, Args...);
hpxr::dataflow_replay_validate(N, ValF, F, Args...);
```

Listing 1: Task Replay API calls with variations. N represents the number of times the runtime system should attempt to reschedule the task, F is the function (task) to execute, *Args...* are the arguments to pass to F, *ValF* is the function to validate the results.

B. Task Replicate

This feature launches N instances of a task concurrently. The function will take one of four code paths depending on the variation of the API (see Listing 2):

(i) **Async and Dataflow Replicate:** This API returns the first result that runs without errors.

(ii) **Async and Dataflow Replicate Validate:** This API additionally takes a function that validates the idnividual results. It returns the first result that is positively validated.

(iii) **Async and Dataflow Replicate Vote:** This API adds a voting function to the basic replicate function. Many hardware or software failures are silent errors that do not interrupt the program flow. The API determines the “correct” result by using the voting function allowing to build a consensus.

(iv) **Async and Dataflow Replicate Vote Validate:** This combines the features of the previously discussed replicate APIs. Replicate vote validate allows a user to provide a validation function and a voting function to filter results. Any exceptions thrown during execution of the task are handled and are treated as if the task failed. If all of the replicated tasks encounter an error, the last exception encountered while computing the task is re-thrown. If finite results are computed but fail the validation check, an exception is re-thrown.

```
using namespace hpxr = hpx::resiliency;

hpxr::async_replicate(N, F, Args...);
hpxr::dataflow_replicate(N, F, Args...);

hpxr::async_replicate_validate(N, ValF, F, Args...);
hpxr::dataflow_replicate_validate(N, ValF, F, Args
    ...);

hpxr::async_replicate_vote(N, VoteF, F, Args...);
hpxr::dataflow_replicate_vote(N, VoteF, F, Args...);

hpxr::async_replicate_vote_validate(N, VoteF, ValF,
    F, Args...);
hpxr::dataflow_replicate_vote_validate(N, VoteF,
    ValF, F, Args...);
```

Listing 2: Task Replicate API calls with variations. *N* is the number of replicate tasks to be launched concurrently, *F* is the function (task) to execute, *Args...* are the arguments to pass to *F*, *ValF* is the function to validate the results, and *VoteF* is the function to use to select the correct result.

V. Benchmarks

This section discusses the benchmark examples, the machine architecture and the HPX configuration.

Machine: All our benchmarks were run on a single node of NERSC’s Supercomputer Cori. Each node has two sockets, each with Haswell Xeon E5-2698 v3 CPUs at 2.30GHz. While hyperthreading is enabled on the node, we have always run not more than one kernel thread per core (32 CPU threads). Each physical core has a dedicated L1 cache of 32KB and L2 cache of 256KB. Each socket has an L3 cache of 40MB shared between thirty two physical cores.

HPX configuration: We use Boost version 1.70.0, binutils version 2.32 and jemalloc version 5.2.0 for the HPX builds. Boost and HPX were built with gcc 8.3 and all the benchmarks use gcc 8.3 as well [21].

Benchmarks: We ran our experiments with two benchmarks. The first benchmark was written to allow us to easily vary an artificial workload. The second benchmark application is a 1D stencil application that was adapted from a preexisting HPX example.

To ensure statistically relevant results, we ran all of the benchmarks 10 times and report the average timing as the benchmark’s execution time. We did not include the initialization and shutdown costs in the measured execution time.

A. Artificial work loads

This benchmark was written in order for the user to precisely control the task grain size and therefore correctly compute the overheads of the resiliency implementation. The benchmark calls a function 1,000,000 times and measures the execution time. The function takes several arguments including the task grain size and the error rate. The task grain size argument enables the user to change the amount of “work” contained in each task. In order to model random failures in the computation, the function uses an error rate to adjust the percentage of tasks which will “fail”.

Within the function (see Listing 3), we added a timer to accurately measure the user specified task grain size and an atomic counter to count the total number of failed tasks. Furthermore, the task may throw an exception to simulate “failure” based on a probabilistic criterion. In the case of the validate API, we compare the final computed result with our expected result. The benchmark measures the resilience capabilities of the system and the robustness of the APIs themselves.

```
int universal_ans(uint64_t delay_ns, double error)
{
    std::exponential_distribution<> dist(error);
    double num = dist(gen);
    bool error_flag = false;
    if (num > 1.0)
    {
        error_flag = true;
        ++counter;
    }
    uint64_t start = high_resolution_clock::now();
    while (true)
    {
        uint64_t now = high_resolution_clock::now();
        if (now - start >= delay_ns)
        {
            if (error_flag) throw std::exception();
            break;
        }
    }
    return 42;
}
```

Listing 3: Function body of a task run in the artificial benchmark

B. 1D Stencil

For this benchmark, we ported the 1D stencil code from HPX to enable resilience while adding multiple time advancing steps per iteration on a stencil. This benchmark accurately measures the overheads that one can observe while using dataflow resilient variants. The overheads encountered with dataflow arise from two factors. First, the overheads introduced from the creation of the dataflow object, and second the sequence in which the futures passed to the dataflow become ready. A dataflow waits for all provided futures to become ready, and then executes the specified function.

This benchmark solves a linear advection equation. The task decomposition, Lax-Wendroff stencil, and checksum operations are as described in previous work [15]. Each task has three dependencies, the subdomain the current task works on and the left and right neighboring subdomains. The stencil is advanced through multiple time steps in each task by reading an extended "ghost region" of data values from each neighbor, which helps reducing overheads and latency effects.

We run the benchmark with two cases that we call 1D stencil case A and 1D stencil case B. The case A uses 128 subdomains each with 16,000 data points, it runs for 8,192 iterations with 128 time steps per iteration. The case B uses 256 subdomains each with 8,000 data points, it runs for 8,192 iterations with 128 time steps per iteration. The performance depends upon the task grain size, i.e. the subdomain size, the number of time steps advanced per iteration, and the number of dataflow operations involved, i.e. number of subdomains and iterations. The performance overhead of resilience depends upon the number of tasks. Case A invokes a total of 1,048,576 tasks while Case B involves 2,097,152 tasks.

C. Injecting errors

Errors injected within the applications are artificial and not a reflection of any computational or memory errors. We use an exponential distribution function to generate an exponential curve signature such that the probability of errors is equal to e^{-x}, where x is the error rate factor. For example, an error rate of 1 will have the probability of introducing an error within a task equal to e^{-1} or 0.36.

VI. Results

This section discusses the empirical results for the benchmarks described in Section V.

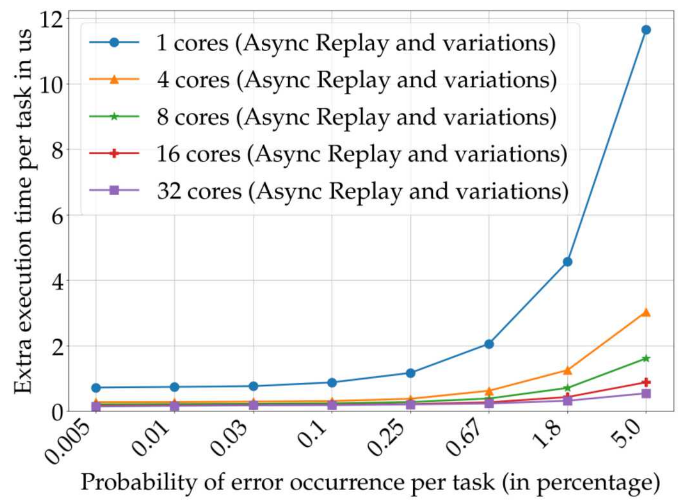
A. Async Replay and Replicate

Resilient variants of *async* were measured with the artificial benchmarks to compute the overheads. The overheads introduced by our implementation are listed in Table I. The observed implementation overheads are very small and are often comparable to the measurement accuracy.

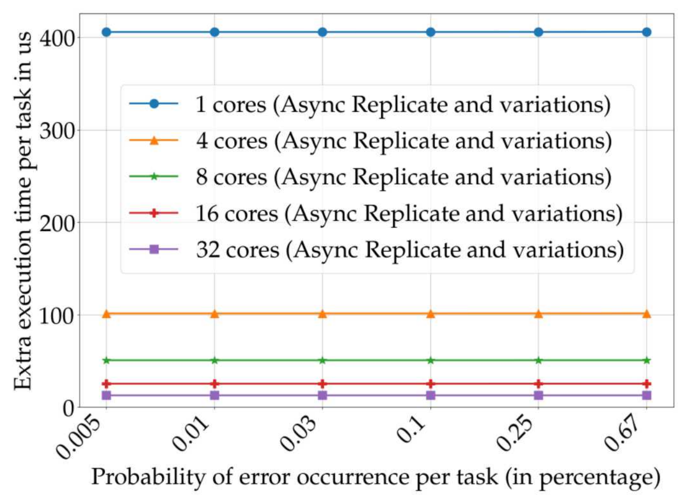
No. of Cores	Async Replay and Replay Validate (in μs)		Async Replicate, Replicate Validate, Replicate Vote and Replicate Vote Validate (in μs)			
1	0.792	0.774	0.985	0.986	0.987	1.023
4	0.251	0.263	0.161	0.165	0.161	0.163
8	0.145	0.150	0.078	0.078	0.078	0.082
16	0.080	0.085	0.034	0.034	0.034	0.036
32	0.057	0.058	0.017	0.017	0.017	0.016

TABLE I: Amortized overheads per task of resilient *async* variants with a task grain size of 200μs

Replicate variants of async behave similarly. The overheads for replicate depends upon the number of replications. Other minor overheads such as vector memory allocation and the number of push back function calls are also dependent on the number of replicates requested. With sufficient compute resources available, one can expect these overheads to be within the margin of error. For a task of 200μs making three replicates, there is thrice the number of tasks involved compared to its replay counterpart (see also Figure 2b). Because these extra tasks are independent of each other, the overheads are quickly amortized when there are available resources than its replay counterpart, which will not be able to take advantage of the added parallelism as efficiently. The minor differences in overheads between resilient variants arises from the underlying implementation, some requiring more boilerplate code to be executed than others.



(a) Async Replay: Extra execution time per task vs. Probability of error occurrence.



(b) Async Replicate: Extra execution time per task vs. Probability of error occurrence

Fig. 2: Extra execution time per task for task grain size of 200μs.

The trend is similar when the applications are injected with artificial errors. When errors are encountered, the resilient logic is activated and behaves as specified. For cases with low probability of failures, we see that amortized overheads of async replay and variants are still small enough to be hidden by system noise (see also Figure 2a). For instance, the overheads, in the worst case scenario for an error rate of 5%, is about 0.54μs or 0.27% of the total overhead per task. Given that the probability of failure within a machine will not be more than a percent in most cases, it is safe to assume that async replay introduces no measurable overheads for applications utilizing the feature. Taken together, the presented results indicate that these resilient features will not incur any meaningful execution time costs.

For cases that use async replicate and variants, we observe that the amortized overhead per task stand at 6.4% for task size of 200μs, which is significantly larger. This is expected as the overheads include running more duplicate tasks. A minor implementation overhead is also present, though dwarfed by the time it takes to repeatedly run a task itself. The graph is a straight line, as expected, since every task is replicated three times irrespective of any encountered errors (see Figure 2b). With these costly overheads, this resiliency feature is only recommended in portions of code which are starved for work (i.e. there are sufficient computational resources available) or for critical portions of code, where computed results have to be guaranteed to be correct.

B. 1D stencil

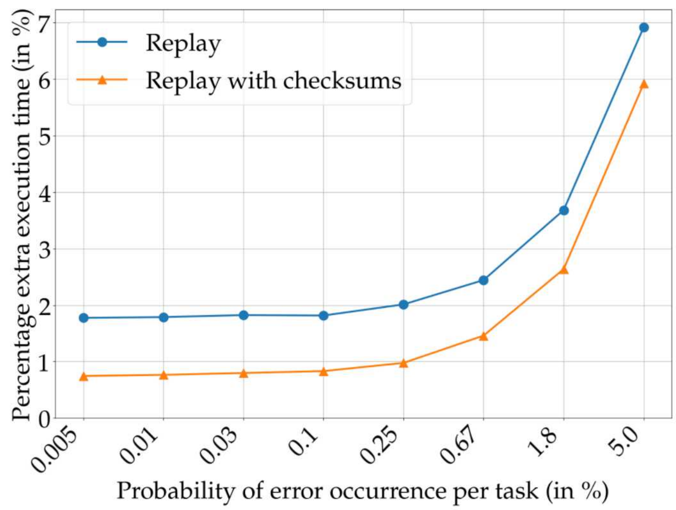
1D stencil example was designed to check the *dataflow* resiliency capabilities. The aim of this benchmark was to observe the extra execution time for different stencil parameters. Table II summarizes the measured results for the case of no failures, comparing the new API variations with a base-line version that is based on basic HPX *dataflow* facilities.

1D stencil	Pure Dataflow (in s)	Replay without checksums (in s)	Replay with checksums (in s)	Replicate without checksums (in s)
Case A	46.564	47.315	46.869	135.871
Case B	47.267	49.756	49.268	139.242

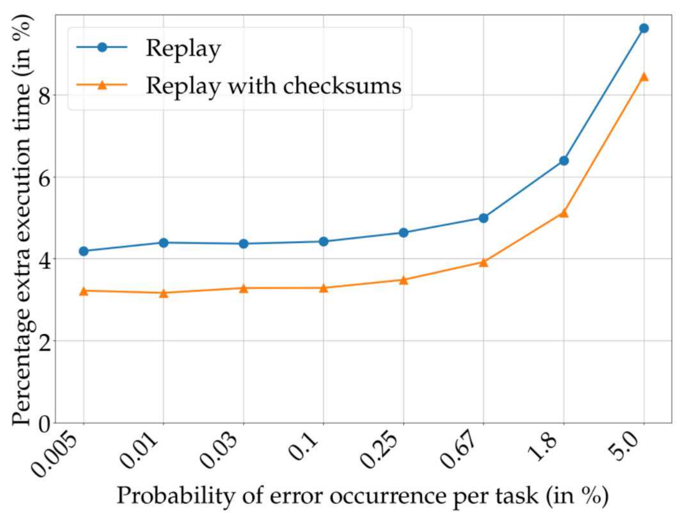
TABLE II: 1D stencil: Execution time in case of no failures for case A and case B, where case A utilizes 128 subdomains each with 16000 data points and case B utilizes 256 subdomains each with 8000 data points, each case iterating 8192 times with 128 times steps per iteration.

Implementing resiliency using the *dataflow* variations with 1D stencil case A introduces 1.5% and 0.4% overheads for replay without and with checksums respectively. Similarly, with case B we observe 5% and 4.1% overheads for replay without and with checksums respectively. These numbers are certainly higher than its *async* variants. This is expected given that dataflow waits for all futures to become ready before executing the function. We currently cannot explain why the benchmarks with checksums runs (slightly) faster. The time difference in execution might arise due to lower overheads of synchronization within dataflow. Resiliency with replication are low as expected as well, which can be attributed owing to efficient parallelism and cache effects.

When we inject errors within the code, we see similar trends as those we observed in the case of its async counterpart. For low failure rates, we observe that the overheads are about the same as the implementation overheads. As expected we see a spike in overheads as the probability of failure increases with 5.9% and 6.9% overheads for Case A and 8.5% and 9.6% for Case B.



(a) 1D stencil case A: Percentage extra execution time vs. Probability of error occurrence.



(b) 1D stencil case B: Percentage extra execution time vs. Probability of error occurrence.

Fig. 3: 1D stencil case A and case B: case A utilizes 128 subdomains each with 16000 doubles and case B utilizes 256 subdomains each with 8000 doubles, and each case iterates 8192 times with 128 times steps periteration.

CONCLUSION

In this paper, we implemented two resiliency APIs in HPX: task replay and task replication. Task replay reschedules a task up to n-times until a valid output is returned. Task replication runs a task n-times concurrently. We demonstrate that only minimal overheads are incurred when utilizing these resiliency features for work loads where the task size is greater than 200 μs. We also show that most of the added execution time arises from the replay or replication of the tasks themselves and not from the implementation of the APIs.

Furthermore, as the new APIs are designed as extensions to the existing HPX *async* facilities that are fully conforming to the C++ standard, these features will be easy enough to embrace and enable a seamless migration of existing code. Porting a non resilient application to its resilient counterpart will require minimal changes, along with the implementation of validation/vote functions, wherever necessary. This removes the necessity of costly code re-writes as well as time spent learning new APIs.

Finally, we developed multiple resilient APIs that are designed to cater to the specific needs of an application. This allows developers the option to choose the optimal resilient function with the least disruption to efficiency.

FUTURE WORK

The current implementation of resiliency is limited to intra node parallelism. We plan to extend the presented resiliency facitities to the distributed case while maintaining the straightforward API. We expect that both – task replay and task replicate – can be seamlessly extended to the distributed use case by introducing special executors that will manage the aspects of resiliency and task distribution across nodes.

The current implementation enables to have both task replay and task replicate within the code independently. Task replicate can be made more robust by adding task replay within its implementation allowing any failed replicated task to replay until its computed without error detection. This will allow for finer consensus in case of soft failures within the system.

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REFERENCES

[1] P. Kogge et al., ExaScale Computing Study: Technology Challenges in Achieving Exascale Systems, tech. report TR-2008-13, Dept. of Computer Science and Eng., Univ. of Notre Dame, 2008

[2] J. T. Daly, "A higher order estimate of the optimum checkpoint interval for restart dumps," Future Gener. Comput. Syst., vol. 22, no. 3, pp. 303–312, Feb. 2006.

[3] J. Duell, P. Hargrove, and E. Roman, "The design and implementation of berkeley lab's linux checkpoint/restart," Lawrence Berkeley National Laboratory, Tech. Rep. LBNL-54941, 2002.

[4] K. Li, J. Naughton, and J. Plank, "Low-latency, concurrent checkpointing for parallel programs," Parallel and Distributed Systems, IEEE Transactions on, vol. 5, no. 8, pp. 874–879, Aug 1994.

[5] A. Moody, G. Bronevetsky, K. Mohror, and B. de Supinski, "Design, modeling, and evaluation of a scalable multi-level checkpointing system," in High Performance Computing, Networking, Storage and Analysis (SC), 2010 International Conference for, 2010, pp. 1–11.

[6] J. S. Plank, K. Li, and M. A. Puening, "Diskless checkpointing," IEEE Transactions on Parallel and Distributed Systems, vol. 9, no. 10, pp. 972–986, October 1998.

[7] E. Roman, "Survey of checkpoint/restart implementations," Lawrence Berkeley National Laboratory, Tech. Rep. LBNL-54942, 2002.

[8] M. Gamell, D. S. Katz, H. Kolla, J. Chen, S. Klasky, and M. Parashar, "Exploring automatic, online failure recovery for scientific applications at extreme scales," in Proceedings of the International Conference on High Performance Computing, Networking, Storage and Analysis, ser. SC '14, 2014.

[9] K. Teranishi and M. A. Heroux, "Toward local failure local recovery resilience model using MPI-ULFM," in Proceedings of EuroMPI/Asia'14, the 21st European MPI User Group Meeting, 2014.

[10] A. Guermouche, T. Ropars, E. Brunet, M. Snir, and F. Cappello, "Uncoordinated checkpointing without domino effect for send-deterministic mpi applications," in Parallel Distributed Processing Symposium (IPDPS), 2011 IEEE International, 2011, pp. 989–1000.

[11] O. Subasi et al., "Nanocheckpoints: A task-based asynchronous datafow framework for efficient and scalable checkpoint/restart," in 2015 23rd Euromicro International Conference on Parallel, Distributed, and Network-Based Processing, pp. 99–102, March 2015.

[12] O. Subasi et al., "A runtime heuristic to selectively replicate tasks for application-specific reliability targets," in 2016 IEEE International Conference on Cluster Computing (CLUSTER), pp. 498–505, Sept 2016.

[13] O. Subasi et al., "Designing and modelling selective replication for fault-tolerant hpc applications," in 2017 17th IEEE/ACM International Symposium on Cluster, Cloud and Grid Computing (CCGRID), pp. 452–457, May 2017.

[14] H. Carter Edwards et.al., "Kokkos: Enabling Manycore Performance Portability through Polymorphic Memory Access Patterns", Journal of Parallel and Distributed Computing, 2014, vol. 74, num. 12, pp. 3202-3216.

[15] K. Teranishi et al., "ASC CSSE level 2 milestone #6362: Resilient asynchronous many-task programming model," Sandia National Laboratories, Tech. Rep. SAND2018-9672, 2018.

[16] Thomas Heller et.al., "Application of the ParalleX Execution Model to Stencil-Based Problems", in Computer Science - Research and Development, 2012, vol. 28, num. 2-3, pp. 253-261.

[17] Thomas Heller et.al., "Using HPX and LibGeoDecomp for Scaling HPC Applications on Heterogeneous Supercomputers", ScalA 2013, SC Workshop.

[18] Hartmut Kaiser et.al., "Higher-level Parallelization for Local and Distributed Asynchronous Task-based Programming", ESPM 2015, SC Workshop.

[19] Thomas Heller et.al., "Closing the Performance Gap with Modern C++", E-MuCoCoS 2016, ISC Workshop.

[20] H.Kaiser et.al., "HPX: A Task Based Programming Model in a Global Address Space", International Conference on Partitioned Global Address Space Programming Models (PGAS), 2014, art. id 6.

[21] HPX GitHub repository, STE||AR Group, https://github.com/STEllAR-GROUP/hpx, 2019, Available under the Boost Software License 1.0.

VII. Artifact Description: Implementing Software Resiliency in HPX forExtreme Scale Computing

A. Abstract

In this section we describe the configuration and environment needed to run our experiments. The experiments are run on a single node of NERSC Cori supercomputer. We present the steps to build the software on Cori and repeat our experiments and how to gather the performance results.

B. Description

1) Check-list (artifact meta information):

- **Program: HPX**
- **Compilation: GCC 8..3**
- **Hardware: Cori**
- **Run-time state:**
- **Output: Benchmark results in text**
- **Publicly available?: Yes**

2) How software can be obtained (if available): HPX can be obtained from https://github.com/STEllAR-GROUP/hpx. Resiliency features are available as an HPX module within HPX itself.

3) Hardware dependencies: Access to Cori can be requested through NERSC.

4) Software dependencies: The following modules need to be loaded to build HPX:

- gcc/8.3.0
- boost/1.70.0
- cmake/3.10.2

The following software need to be built from their source since they are not available on Cori:

- jemalloc. The latest version of CMake can be downloaded from https://github.com/jemalloc/jemalloc.

C. Installation

- HPX

```
cmake
  -H<PATH_TO_HPX_CODE>
  -B<PATH_TO_HPX_BUILD>
  -DCMAKE_BUILD_TYPE=Release
  -DCMAKE_C_COMPILER=gcc
  -DCMAKE_CXX_COMPILER=g++
  -DBOOST_ROOT=<PATH_TO_BOOST>
  -DBoost_NO_SYSTEM_PATHS=True
  -DHPX_WITH_EXAMPLES=False
cmake --build <PATH_TO_HPX_BUILD>
```

D. Running Benchmarks

- Get a job from Cori for a single node haswell and ensure all required modules listed in section VII-B4 are loaded.
- Copy the script files provided at https://github.com/STEllAR-GROUP/hpxr_data/tree/master/benchmark_scripts to the binary directory. Execute the scripts to generate the results.
- Repeat the same for all the shell scripts

E. Evaluation and expected result

Scripts to generate graphs on the returned results are provided at https://github.com/STEllAR-GROUP/hpxr_data/tree/master/benchmark_results/graphs. Copy them to the binary directory and run the python files. To successfully generate the graphs make sure that the following are available:

- python 2.7
- matplotlib
- Tkinter

The emperical results that we achieved running the scripts described above are provided at https://github.com/STEllAR-GROUP/hpxr_data/tree/master/benchmark_results/benchmarks. Running the python scripts on them will result in the graphs used in the paper.