

MPCDF HPC Performance Monitoring System: Enabling Insight via Job-Specific Analysis

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Abstract. This paper reports on the design and implementation of the HPC performance monitoring system deployed to continuously monitor performance metrics of all jobs on the HPC systems at the Max Planck Computing and Data Facility (MPCDF). Thereby it reveals important information to various stakeholders, in particular to users, application support, system administrators, and management. On each compute node, hardware and software performance monitoring data is collected by our newly developed lightweight open-source *hpcmd* middleware which builds upon standard Linux tools. The data is transported via rsyslog, and aggregated and processed by a Splunk system, enabling detailed percluster and per-job interactive analysis in a web browser. Additionally, performance reports are provided to the users as PDF files. Finally, we report on practical experience and benefits from large-scale deployments on MPCDF HPC systems, demonstrating how our solution can be useful to any HPC center.

Keywords: HPC · Cluster monitoring · Performance analysis

1 Introduction

HPC systems are highly expensive facilities that are rapidly evolving with respect to computational power, complexity, and size. More and more scientific disciplines use HPC resources in their research process to gain insight from numerical simulations or from data analytics. Hence, it is essential to strive to maximize the performance of the applications running on these precious resources. However, an efficient usage requires expert knowledge in parallel algorithms and programming, and a lot of effort spent on optimization and parameter tuning. This point became more important in recent years with the advent of processors with many cores and accelerators, which made parallel programming even more complex. Having performance numbers available for each job is therefore essential for the stakeholders of the HPC system, first, to make them aware of potentially suboptimal usage of resources, and second, to enable them to take action to improve the way these resources are used.

-c Springer Nature Switzerland AG 2020

U. Schwardmann et al. (Eds.): Euro-Par 2019 Workshops, LNCS 11997, pp. 613–625, 2020. [https://doi.org/10.1007/978-3-030-48340-1](https://doi.org/10.1007/978-3-030-48340-1_47)_47

Jobs on a HPC cluster are commonly orchestrated by a batch scheduler, which can easily provide usage statistics based on *allocated* resources. These are often quantified in terms of CPU or GPU hours, and have proven useful for accounting purposes. However, these numbers do not carry information about the actual resource *utilization*. Performance metrics measured for each job are therefore crucial to learn, e.g., about under-utilization of allocated resources (idle vector units, or idle cores and accelerators), or other problematic usage patterns.

Modern hardware provides a plethora of counters that can be used for performance monitoring. In addition to the arithmetic units, CPUs have performance monitoring units (PMUs) that can be programmed to count certain instructions (e.g., scalar and vectorized floating point operations) with very little performance overhead. Hardware such as GPUs and network adapters provides similar counters. These hardware-related metrics can be complemented by softwarerelated metrics, obtainable from the Linux kernel or from system tools. Such metrics include information on the running processes, their memory footprint, filesystem-related counters, etc.

Selecting and efficiently collecting these metrics is a challenge which we address in the present work. We developed a new lightweight software daemon, $hpcmd¹$ $hpcmd¹$ $hpcmd¹$, that runs on each node, performs measurements periodically in the background, and finally writes the data to the syslog. The syslog lines from all nodes are then propagated to the Splunk framework, for which we have developed special dashboards to perform advanced interactive data analysis. As a service to the users, we also provide PDF reports downloadable for each job. These two main components, *hpcmd* and Splunk dashboards together with few additional scripts compose a comprehensive suite designed to continuously monitor the performance of all jobs on the HPC systems at the MPCDF. We believe that other centers could also benefit from our system.

In the following, we first elaborate on the insight and benefits the various stakeholders of an HPC system may draw from a performance monitoring system. Second, we discuss related work before we describe in detail our solution in the main part of the paper. Finally, we illustrate several cases in which our system has already proven very useful, before closing with a summary.

2 Benefits from an HPC Performance Monitoring System

The following four groups of key stakeholders of an HPC system benefit from the insight enabled by HPC performance monitoring data.

Computational scientists and other users who run jobs on an HPC system typically have to apply for CPU hours. They have a strong intrinsic motivation to use the resources as efficiently as possible, in order to maximize the scientific knowledge they can obtain from the results. Based on HPC monitoring data, experienced users are often capable of identifying and fixing issues themselves, e.g., by applying appropriate compiler optimization for a specific architecture.

¹ hpcmd stands for HPC monitoring daemon.

Less skilled users might be motivated to approach application support when facing poor performance indicated by monitoring data.

Application support at a computing center provides technical support and is in charge of porting and optimizing applications for the HPC systems. HPC performance monitoring data enables application support to detect problematic jobs, and consequently, to proactively approach users who are potentially in need of assistance.

System administrators may benefit from performance monitoring data, e.g., to better judge the impact of software updates, security patches, and hardware settings. Potential changes in application performance after some maintenance work can be traced in an objective way based on current and historical performance data.

Management is interested in learning performance numbers that represent the actual resource utilization in addition to knowing the allocation of plain CPU hours, a metric that has been widely used up to now to quantify the resource share. Moreover, performance data gathered on present systems can be used to steer decisions for the procurement of future HPC clusters. For example, looking at a roofline plot with measurement data from most used applications enables decision makers to judge quickly if these applications are limited by the memory bandwidth or by the peak floating-point performance, and thereby if investing in new architectures with higher memory bandwidths would pay off. Similarly, analysis of network traffic may hint at applications that would benefit, e.g., from higher network bandwidth or lower latency. Finally, performance data documents to which degree GPUs are actually used, especially on multi-GPU nodes. In these respects, HPC performance monitoring data helps to close important information gaps.

3 Related Work

There are at least two big challenges regarding the implementation of a HPC performance monitoring system that have been addressed by various solutions in recent years.

The first, data-related, challenge is to choose which metrics should be tracked, how to interpret the collected data, how to identify performance bottlenecks, and how to ultimately detect if there is a significant problem in an application code. There are several software tools that can be used to analyze the performance of a running job. For example, for CPU codes, there are Linux perf [\[15](#page-11-0)], PAPI [\[3](#page-11-1)], LIKWID [\[14](#page-11-2)], and VTune [\[7](#page-11-3)], among others. These tools provide access to hardware counters which are then often analyzed using a "top-down" method [\[17](#page-12-0)]. One compares the counter values to the theoretical peak values of the machine and deduces how well the compute resources are utilized. However, there are cases when utilization values appear rather low even for well-optimized applications, e.g., due to the nature of the problem the code is solving or the required data structures. Hence, looking only at the utilization numbers can be misleading, and one needs to be careful before declaring that a job has a performance issue. To alleviate this effect, some researchers prefer to rely on cross-comparisons between different runs and applications [\[5\]](#page-11-4), recently proposing machine learning techniques for such analysis [\[2](#page-11-5)[,9](#page-11-6)].

The second, technical, challenge is to design and deploy a system that works reliably on (multiple) large HPC clusters while introducing minimal overhead, efficiently collects the data from many nodes into a centralized database, and provides a powerful framework for analysis and visualization. For example, the *TACC stat* framework has been developed to achieve these goals [\[4](#page-11-7),[5\]](#page-11-4). It combines information collected by various standard Linux tools and some custom tools, e.g., *REMORA* [\[10](#page-11-8)], to monitor resource utilization at the Texas Advanced Computing Center. Next, the *PerSyst* monitoring system developed at the Leibnitz Supercomputing Center comprises a hierarchical system of collectors and aggregators, a central database and a web interface to monitor large-scale HPC systems [\[6](#page-11-9)]. Thanks to the data aggregation using quantiles, this tool is well suited for jobs that run on a large number of nodes. The *LIKWID Monitoring Stack* targets small to medium scale systems [\[11](#page-11-10)]. It is partly based on the LIKWID performance tool suite developed by the same group of authors [\[14\]](#page-11-2). Finally, the *Lightweight Distributed Metric Service (LDMS)* was developed for performance monitoring at Sandia National Labs [\[1](#page-11-11)]. This framework provided very useful information for the system administrators and users, while having minimal impact on the application performance.

All the aforementioned solutions gave us valuable ideas and helped us to better define the goals for our approach. However, there are several reasons why we decided to develop our own system. Most importantly, all of these systems either rely on data-measurement software or on infrastructure setups (e.g., batch system configuration) that are specific to the center where they have been developed, and hence, would be difficult to adapt and maintain. Moreover, many of the existing approaches appear to rely on complex hierarchical communication layers and custom web-based visualization platforms, while we found ourselves in the convenient position to use rsyslog and Splunk systems that had already been deployed at the MPCDF for other monitoring purposes, e.g., the monitoring of the system "health" status.

4 Solution Architecture

In this section, we detail on how our system can obtain, collect, analyze, and present performance data from HPC clusters, addressing the needs of all stakeholder groups mentioned in Sect. [2.](#page-1-1)

Figure [1](#page-4-0) presents a schematic overview on the architecture of the MPCDF HPC monitoring system. The design was motivated by the principle of simplicity and the focus on key questions which implied the reuse of existing infrastructure. To this end, our programming efforts focused on two major components (shown with red background in Fig. [1\)](#page-4-0).

Fig. 1. Schematic showing the architecture of the MPCDF HPC monitoring system. The *hpcmd* middleware and various Splunk analysis dashboards were written by the authors, while the other infrastructure had already been existing. Automatic analysis using machine learning techniques is under development. (Color figure online)

The first component, labeled *hpcmd*, is a lightweight middleware that runs as a daemon in the background on each compute node, performs measurements at regular intervals, and computes derived metrics if necessary. A thorough evaluation of the overhead of *hpcmd* showed that the impact on the application performance is negligible, e.g., being much smaller than the influence of unavoidable machine and OS jitter on the application runtime. *hpcmd* is written in plain Python (both versions 2.7 and 3 are supported) and configurable via a flexible, hierarchical YAML configuration file. Measured values are simply written by *hpcmd* to syslog messages, forwarded via rsyslog, and finally fed into a Splunk repository.

The second major component are dashboards for Splunk written in XML, that we have developed for performance data analysis and visualization. The Splunk [\[12\]](#page-11-12) platform excels in the analysis of large volumes of temporally ordered log-line data via a powerful query language. Hence, Splunk is suitable for crunching performance data collected from many nodes over long periods of time. After having collected performance data for nearly one year now, we do not notice any performance degradation and do not see any reason to limit the storage lifetime of the data. There are several viable alternatives to Splunk which could be used similarly, such as the open-source ELK (Elasticsearch, Logstash, Kibana) stack, the InfluxDB-Grafana stack, or even custom frameworks. However, the Splunk infrastructure was already installed and used at MPCDF systems for system monitoring, and thus it was the natural choice to employ it for performance

monitoring as well. We are considering the aforementioned alternative solutions for evaluation in the future.

In the rest of this section, we detail on the different aspects of the data flow as depicted on the top of Fig. [1.](#page-4-0)

4.1 Data Sources

From a technical point of view, today's HPC hardware and software offer a plethora of metrics to look at. Given these possibilities, it is necessary to carefully choose a set of observables essential to yield valuable insight, and at the same time, keep the impact on the application performance negligible and the data volume of the measured values tractable. *hpcmd* uses the following data sources.

CPU Core Events: State-of-the-art CPUs provide performance monitoring units (PMUs) for each core. These can be programmed to count events, e.g., scalar and vector instructions, cache misses, and many more. Since the PMUs are additional programmable hardware units, the event counting induces only minimal overhead, typically not noticeable for the running scientific application.

CPU Uncore Events: In addition to the core PMUs, modern CPUs provide uncore PMUs that enable to monitor, e.g., the memory controller traffic and the traffic between different sockets. To access the core and uncore counters, the Linux *perf* subsystem is used.

GPU: At present, monitoring GPUs is much more difficult than CPUs due to the dependencies on proprietary tools and APIs from hardware vendors, as well as due to the lack of publicly available counter specifications. Nevertheless, it is possible to track some values, such as the memory occupation and the overall utilization, which we do using the *nvidia-smi* tool.

I/O: Large parallel file systems are crucial components of any HPC system. They are a shared resource, and wrong usage may affect not only a single problematic job but potentially even the whole system. Monitoring the I/O traffic and characteristics per node can give valuable hints at harmful use patterns. Since Spectrum Scale (GPFS) is the preferred file system at MPCDF, its CLI tools are used for monitoring.

Network: High-speed networks represent the backbone of an HPC system. Communication characteristics at per-node resolution complement many other metrics with valuable insight. Relevant counters can be queried using the CLI tools that come with InfiniBand or OmniPath network adapters.

Software: The Linux kernel complemented by various system tools gives access to a rich set of application-related metrics, e.g., the number of tasks (processes and threads) actually launched by the job, the pinning of these tasks, the memory usage, the job's environment variables, and many more. The *hpcmd* software accesses this kind of information using the *ps* and *numastat* tools, and the */proc* virtual filesystem in some cases.

Any of these observables can be sampled at regular intervals by *hpcmd* and used directly or after some arithmetic manipulation (e.g., computing the GFLOP/s) as performance metrics.

4.2 Data Collection

On each compute node, an instance of the *hpcmd* middleware is running in the background as a systemd service, measuring at regular intervals and sequentially collecting data from the aforementioned sources. The measurements are synchronized across the nodes via the system clock, avoiding any communication between nodes. In addition to a continuous operation mode, the *hpcmd* daemon supports the widely used SLURM batch system [\[8\]](#page-11-13), and determines the state of a node (allocated, idle, shared) and job information automatically. We are typically monitoring only nodes which have a single job running on them, i.e., data is not collected for nodes that are currently idle or shared, as such cases are considered less relevant in our context and would be much harder to interpret. *hpcmd* allows for a highly flexible configuration, e.g., to perform more frequent sampling or per-core monitoring of performance counters. Moreover, users may suspend the *hpcmd* systemd service during the runtime of a job to get exclusive access to hardware counters, e.g., for running performance profilers such as VTUNE or using libraries such as PAPI. Measured values and derived metrics are written as log lines containing key-value pairs to the local syslog file. For further details, we kindly refer the reader to the documentation of *hpcmd* [\[13\]](#page-11-14).

4.3 Data Aggregation

From each monitored node, the *hpcmd* log lines are transported via rsyslog, collected, and finally fed into a central Splunk system. At MPCDF, HPC systems are configured such that the rsyslog traffic goes via the Ethernet link, not putting any load on the high performance network reserved for the applications. For large HPC systems, there may be intermediate (per-"island") rsyslog servers. Operating at sampling intervals on the order of minutes we do not see any scalability issues for our present and future HPC cluster sizes. See Sect. [5](#page-9-0) for some practical experience.

4.4 Data Visualization and Interactive Analysis

Data visualization and analysis takes place in the Splunk system, for which we have developed several dashboards providing views at different levels of detail.

Roofline View: The roofline model is a simple yet intuitive performance model widely used in performance engineering [\[16](#page-12-1)]. This type of overview is suitable in particular when the performance of a job needs to be condensed into only

Search Datasets Reports Alerts	Dashboards			Search & Reporting							
hpcmd_roofline Cluster Time range Last 24 hours ۰ cobra GroupID UserID \star $ \times$ any any	Partition \star $\,$ $\,\times$ ۰ any Last executable $- x$ $- x$ any	Status Min duration \cdot \times correctly finished 1 hour Hide Filters Submit	Min number of nodes $- x$ $\overline{4}$	Edit Export * \sim							
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Fig. 2. Overview on a selection of jobs from the previous 24 h in a roofline plot on a specific HPC system. Each circle represents a job with its average performance, where the circle sizes are scaled by the actual CPU core hours of the jobs.

two numbers and related to the theoretical peak values of the machine. In a 2d system of coordinates, the horizontal axis denotes the arithmetic intensity in FLOP/Byte, while the vertical axis denotes the performance in GFLOP/s. We pragmatically chose to solely rely on CPU-RAM memory bandwidth for the roofline plot, computed from CPU uncore events. For the application support staff, the entry point for the inspection of performance data in Splunk is a roofline-type of overview plot, as shown in Fig. [2.](#page-7-0) All finished jobs that fall into a certain time frame and satisfy certain constraints, which are specified by the user using drop-downs on the top of the web-page, are displayed as colored circles, scaled in size by their consumption of CPU hours. This dashboard represents an intuitive performance map showing the current or historic utilization status of the system. Clicking on a circle in the plot or on a line in the data table below forwards to the detailed job view.

Detailed Job Views: This dashboard provides a detailed view on the job's performance characteristics through temporal plots of the performance metrics described in Subsect. [4.1.](#page-5-0) An excerpt from the dashboard is shown in Fig. [3.](#page-8-0) To make the data from large jobs more comprehensible, a second dashboard is provided that displays the data using statistical variables such as maximum, median, and minimum curves, taken from all nodes or sockets. These two dashboards are intended to be used by the application support staff through the interactive Splunk web interface. For the users, static PDF reports are provided for download containing the same information. Based on these detailed job views it is typically possible to draw well-grounded conclusions about performance issues of application codes.

Performance of every socket											
	res \Leftrightarrow	max(GFLOPS) ÷	avg(GFLOPS) #	max(MEM_BW) =	avg(MEM_BW) #	max(ALGO_INT) #	avg(ALGO_INT) #	sparkline(ALGO_INT) ÷			
	dra0872_S0	155.73	111.93	54.74	29.70	5.08	3.87	Λ Λ Λ			
$\overline{2}$	dra0872_S1	134.69	65.15	43.22	14.75	6.33	4.46				
3	dra0878_S0	154.57	110.94	55.47	29.12	5.22	3.92				
	dra0878 S1	134.01	67.32	42.85	16.41	5.68	4.07				
5	dra0880_S0	158.80	114.40	54.84	33.43	4.92	3.49				
6	dra0880_S1	133.89	66.63	42.61	16.04	5.63	4.13				
$\overline{}$	dra0884_S0	158.44	114.14	56.20	32.33	5.01	3.60				
8	dra0884_S1	132.70	66.99	42.88	16.27	5.65	4.05				
$\overline{9}$	dra0885_S0	157.91	114.06	54.92	32.66	4.91	3.56				
10	dra0885_S1	133.87	66.61	42.54	15.80	5.89	4.18	$\begin{array}{ccccccccccccccccc}\n\Lambda & \Lambda & \Lambda & \Lambda & \Lambda & \Lambda & \Lambda\n\end{array}$			
		2,334.47	1,440.49	784.88	382.91	85.84	62.38				
$\overline{1}$ $\overline{2}$ next > « prev											
Performance [GFLOP/s]				Memory Bandwidth [GB/s]			Algorithmic Intensity [FLOP/Byte]				
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					Time			Time			

Fig. 3. Excerpt from a detailed view on a specific job, showing the achieved performance in GFLOP/s, the memory bandwidth, and the algorithmic intensity for each socket. In addition to the averaged and maximum values shown in the table, plots over time are available per socket. Moreover, the Splunk dashboard contains about 30 more plots for other CPU, GPU, network, filesystem, and software metrics (not shown here).

Specialized Views: System administrators and the management of a computing center are often interested in specific analysis of many jobs. To obtain such information, they can submit custom queries to the Splunk database. As some of their questions are recurrent, we have developed several dashboards to ease their access to the data. Currently we are providing plots that show the most executed applications by core hours, jobs that reserved GPU nodes without using GPUs, jobs that reserved large memory nodes without using much memory, and jobs that use less than half of the available CPU cores.

4.5 Per-job Reports for Users

To make the performance data accessible to the users, a performance report can be generated for each job and provided as a PDF file for download via a web server after login. We decided not to grant the users access to Splunk directly for security, data protection, and administrative reasons.

4.6 Data Analytics and Automation

On the MPCDF HPC systems, several thousands of jobs are typically run per day. To be able to cope with these numbers and the massive amount of generated data, an automatic data analytics system is indispensable in order to identify problematic jobs on the systems, and notify both support staff and users in critical cases. The data analytics module of the HPC monitoring system is currently under development, but goes beyond the scope of this paper.

5 Scenario- and Case-Studies

The HPC monitoring system is used to continuously monitor the HPC systems DRACO (\approx 940 nodes, \approx 32K cores) and COBRA (\approx 3250 nodes, \approx 130K cores) at the MPCDF. These HPC systems are heterogeneous, containing nodes with different CPU micro-architectures, with different RAM sizes, and with or without GPU accelerators of different models. The system is configured to write performance data every 10 min which generates up to 3 KiB of raw log line data per node. Hence, the total data volume per sample for both machines is about 12.5 MiB, which amounts to about 1.8 GiB per day in total. Note that the rsyslog system is able to easily cope with that data volume, making complex custom hierarchical transport agents unnecessary in our case. In the following, we illustrate with 4 examples how the HPC monitoring system already proved to be helpful in practice at the MPCDF.

Suboptimal Job Scripts: We provide users with a detailed job-specific report (see Subsect. [4.5](#page-8-1) for more details), based on which they can quickly spot potential errors related to their job scripts. We are aware of several cases where HPC monitoring was already helpful in this respect.

Hanging Jobs: Even though HPC clusters are supposed to be used to run stable programs, there are still jobs that encounter problems at runtime without shutting down in a controlled manner. For example, in cases of livelocks or deadlocks, the processes of a job continue to run without actually executing any useful instructions, thereby occupying the reserved resources. This can potentially waste a large number of CPU hours. Such "hanging" jobs are typically manifested by very low values in certain performance metrics, especially in GFLOP/s and IPC. To report on a specific example, it was observed from the HPC monitoring data that jobs from a particular user often demonstrated the aforementioned behavior. We contacted the user and showed the plots that illustrated the performance problem. The user then investigated the code and fixed the issue. Catching this particular case was achieved unintentionally, by manual inspection of the data, however an automatic detection system for such types of jobs is under development.

Verification of the Utilization of Extra Resources: To satisfy the compute needs for a broad spectrum of users, computing centers often equip parts of their HPC systems with nodes that contain very large amounts of RAM memory or with nodes that contain GPU accelerators. Sometimes, users with applications that require only moderate amounts of memory or lack GPU support, by mistake or by convenience, allocate such nodes with extra resources instead of regular ones.

This is not a problem if these nodes would otherwise be idle, but if not, such allocations mean a waste of resources and increased queueing times for legitimate users. HPC monitoring can easily detect this type of wrong usage and warn staff or the users directly.

Coarse-Grain Overview for Experts: The HPC monitoring system has not been designed for in-depth code profiling. Nevertheless, it can still provide coarsegrain performance information that can be useful to code developers and application support. Indeed, several members of the application support group at the MPCDF routinely use HPC monitoring to inspect the performance of applications they personally contributed to during development. In most cases, HPC monitoring confirmed their expectations. Interestingly, there were some occasions when even these experts were surprised. In fact, the Splunk analysis of the data showed that the performance in some stages of the application was much worse than expected, which had notable influence on the overall runtimes of the programs. The reason was the lack of code vectorization for some code blocks that were initially considered less relevant. As a next step, the developers profiled the code with more specialized tools which confirmed the observation from the Splunk dashboards and were able to point to the exact lines of code that caused the performance issue.

6 Summary and Outlook

This paper reports on the requirement analysis, the design, and the implementation of the MPCDF HPC performance monitoring system. Our solution is simple, modular, lightweight, mostly based on standard Linux tools, and thus it can easily be adopted by other HPC centers. The system is in operation to comprehensively monitor the performance of all jobs running on two large HPC systems at the MPCDF with about 4200 nodes and more than 160.000 CPU cores in total. After several months of production we have collected a large amount of job-related performance data, and doing data analytics on it will be the main topic of our future work. Additionally, we plan to extend the deployment of our performance monitoring system to more (medium-sized) clusters at the MPCDF, and will continue to develop and maintain the *hpcmd* middleware.

Software: The *hpcmd* software is free of charge and publicly available for download at [https://gitlab.mpcdf.mpg.de/mpcdf/hpcmd.](https://gitlab.mpcdf.mpg.de/mpcdf/hpcmd) Online documentation is available at [http://mpcdf.pages.mpcdf.de/hpcmd.](http://mpcdf.pages.mpcdf.de/hpcmd) The software is licensed under the permissive MIT license. We kindly request to cite this paper in case the software is used and reported on in publications.

Acknowledgements. We are grateful to Christof Hanke for the continuous support with Splunk and the implementation of major parts of the PDF generation web service. We are indebted to Alexis Huxley and Christian Guggenberger for the regular (re)installation of the HPC monitoring software on the HPC systems at short notice. Finally, we thank Lorenz Hüdepohl, Andreas Marek, Pavel Kus, Sebastian Ohlmann, and Markus Rampp from the application support group for many valuable suggestions and fruitful discussions.

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