RADICAL-Cybertools: Middleware Building Blocks for Scalable Science

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Abstract

RADICAL-Cybertools (RCT) are a set of software systems that serve as middleware to develop efficient and effective tools for scientific computing. Specifically, RCT enable executing many-task applications at extreme scale and on a variety of computing infrastructures. RCT are building blocks, designed to work as stand-alone systems, integrated among themselves or integrated with third-party systems. RCT enables innovative science in multiple domains, including but not limited to biophysics, climate science and particle physics, consuming hundreds of millions of core hours. This paper provides an overview of RCT components, their impact, and the architectural principle and software engineering underlying RCT.

Keywords:
Middleware, Pilot System, Building Blocks

1. Motivation and significance

The design of distributed systems to support scientific computing has never been more challenging. Unprecedented diversity in application requirements, and disruptive changes in the resources and technology landscapes, intermix with new discovery modalities and need for scalable computing.

Set against this dynamic landscape, two critical question must be addressed: How can middleware be designed and implemented to meet the collective challenges of scale, new and diverse functionality, and usability? How can critical middleware components be designed to be sustainable software implementations while being forward looking and enable innovative capabilities?

RADICAL-Cybertools (RCT) are a set of systems developed to address these challenges. RCT are building blocks, which can be used as a stand-alone system, or integrated with other RCT, or third-party tools to enable...
diverse functionalities. RCT offer several innovative features to support the
design and implementation of middleware.

This paper takes a software perspective to present the overarching ar-
chitectural paradigm of RCT, discussing the design and implementation of
two cybertools: RADICAL-Pilot and Ensemble-Toolkit (EnTK). We outline
the direct impact that RCT are having on domain sciences, focusing the dis-
cussion on architectural and design paradigms of middleware for scientific
computing. In this way, we show how RCT further the “state-of-theory” and
practice of scientific computing.

2. Software description

The RADICAL Cyberinfrastructure tools (RCT) [1] have three main
components: RADICAL-SAGA (RS) [2], RADICAL-Pilot (RP) [3] and
RADICAL-Ensemble Toolkit (EnTK) [4].

RS is a Python implementation of the Open Grid Forum SAGA standard
GFD.90 [5], a high-level interface to distributed infrastructure components
like job schedulers, file transfer and resource provisioning services. RS enables
interoperability across heterogeneous distributed infrastructures, improving
on their usability and enhancing the sustainability of services and tools.

RP is a Python implementation of the pilot paradigm and architectural
pattern [6]. Pilot systems enable users to submit pilot jobs to computing
infrastructures and then use the resources acquired by the pilot to execute
one or more tasks. These tasks are directly scheduled via the pilot, without
having to queue in the infrastructure’s batch system. RP focuses on
High Performance Computing (HPC) resources, enabling the concurrent and
consecutive execution of heterogeneous workloads comprised of one or more
scalar, MPI, OpenMP, multi-process, and multi-threaded tasks. These tasks
can be executed on CPUs, GPUs and other accelerators, on the same pilot
or across multiple pilots.

EnTK supports the concurrent or sequential execution of tasks that can
be in an arbitrary priority relation (i.e., ensemble or pipelines of tasks).
EnTK promotes ensembles of tasks to a high-level abstraction, providing a
programming interface and execution model specific to ensemble-based ap-
lications. EnTK is engineered for scale and a diversity of computing plat-
forms and runtime systems, agnostic of the size, type and coupling of the
tasks comprising the ensemble.

RCT are designed to work both individually and as an integrated system,
with or without third party systems. This requires a “Building Block” ap-
proach to their design and development, based on applying the traditional
notions of modularity at system level. The Building Block approach derives
from the work on Service-oriented Architecture and its Microservice variants, and the component-based software development approaches where computational and compositional elements are explicitly separated [7, 8, 9, 10, 11]. AirFlow, Oozie, Azkaban, Spark Streaming, Storm, or Kafka are examples of tools that have a design consistent with the building blocks approach and that have been integrated with RCT [12].

2.1. Software Architecture

All RCT are stand-alone, distributed systems. Architecturally, each tool consists of one or more subsystems, each with several components. Components are isolated into individual processes and some components are used only in specific deployment scenarios, depending on both application requirements and resource capabilities. Components are stateless and some of them can be instantiated concurrently to simultaneously manage multiple entities, like workflows, workloads, tasks or pilots. This enables scaling of throughput and tolerance to component failure.

Concurrent components are coordinated via a dedicated communication mesh, which introduces runtime and infrastructure-specific overheads, but improves overall scalability of the system and lowers component complexity. Components can have different implementations; configuration files can tailor each RCT to specific resources types, workloads, or scaling requirements. Components exchange data about the entities specific to each RCT and data about the state of the components and subsystems. Each type of data has dedicated modules and communication channel, separating communication from coordination with explicit states and events for each entity.

Ref. [2] details RADICAL-SAGA architecture and capabilities. In the rest of the paper, we focus on RP and EnTK, first introducing each system individually, then showing how RCT as a whole can be composed to serve diverse use cases.

2.1.1. RADICAL-Pilot

RP implements two main abstractions: Pilot and Compute Unit (CU). Pilots and CUs abstract away specificities of resources and workloads, making it possible to schedule workloads either concurrently or sequentially on resource placeholders. Pilots are such placeholders for computing resources, where resources are represented independent from architecture and topological details. CUs are units of work (i.e., tasks), specified as an application executable alongside its resource and execution environment requirements. Note that a task is not a function, method, thread or process but a program that runs as a self-contained executable.
Fig. 1 depicts RP’s architecture with two subsystems (white boxes) and several components (purple and yellow boxes). In each subsystem, purple components manage pilots and CUs while yellow components manage the communication among components. Subsystems can execute locally or remotely, communicating and coordinating over TCP/IP, and enabling multiple deployment scenarios. For example, users can run Client locally, and distribute MongoDB and one or more instances of Agent on remote computing infrastructures. Alternatively, users can run all components on a local or remote resource.

The first subsystem, called Client, has two main components: PilotManager and UnitManager. PilotManager manages pilots and has a main component called ‘Launcher’. Launcher uses resource configuration files to define the number, placement, and properties of the Agent’s components of each pilot. Currently, configuration files are made available for all the HPC machines of the Extreme Science and Engineering Discovery Environment (XSEDE), Blue Waters at the National Center For supercomputing Applications (NCSA), Cheyenne at NCAR-Wyoming Supercomputing Center (NWSC), and Rhea, Titan and Summit at the Oak Ridge National Laboratory (ORNL). Users can provide new files or alter existing configuration parameters at runtime, both for a single pilot or a whole RP session.

UnitManager manages CUs and has two main components: Scheduler
Scheduler schedules CUs onto one or more pilots, available on one or more machines. This enables late binding of CUs to resources, depending on their availability. CUs are bound to resources that satisfy their execution requirements only when these resources are actually available. StagerInput distributes the input files that CU may need for their execution to the machines on which each CU has been scheduled.

The second subsystem of RP is called ‘Agent’ and has four main components: StagerInput and StagerOutput for staging CUs’ input and output data, Scheduler and Executer to schedule CUs on a pilot resources and execute those CUs on them. Multiple instances of the Stager and Executer components can coexist in a single Agent. Depending on the architecture of the target machine, Agent’s components can individually be placed on cluster head nodes, MOM/batch nodes, compute nodes, virtual machines, or any combination thereof. ZeroMQ communication bridges connect the Agent components, creating a network to support the transitions of CUs through components.

Data management in RP focuses on providing input files to CUs before their execution, and on moving output files to later CUs, or back into the user environment. On HPC resources which provide both local and network storage, RP can select the most appropriate storage, depending on CUs I/O requirements. Data can be exclusive to CUs, or can be shared between CUs.

Each component of each subsystem of RP has a dedicated queue to feed entities into that component. Orange Queues in Fig. [1a] are dedicated to pilots and CUs, blue Queues to the messages exchanged by communication components. All Queues support bulk communication to obtain performance at scale in a distributed systems. Further, queues enable load balancing among concurrent components. Note that concurrent components are used for performance optimization at scale.

A special queue instance is rendered as collection in a MongoDB database. That collection is used to communicate between Client and Agent, while preserving the semantics used for all other queues in Fig. [1a]. Since the MongoDB entries are persistent, that database is also used to store data for post mortem profiling and analysis.

2.1.2. RADICAL Ensemble Toolkit

EnTK implements three main abstractions: task, stage and pipeline. Tasks contain information regarding an executable, its software environment and its data dependences. Stages are a set of tasks where the tasks have no mutual dependences and can therefore execute concurrently, depending on resource availability. Pipelines are lists of stages where a stage $i$ can be executed only after stage $i-1$ has completed.
As for RP, a task is an executable, i.e., a program. This is important: EnTK enables concurrent and sequential execution at program-level, not at function or method level. Parallelism is still possible within each program run by an EnTK task, enabling concurrent execution of multi-threaded, multi-process and MPI programs. Note that, at the moment, EnTK requires a runtime system (RTS) that support the same task abstraction for task execution.

Fig. 1b shows the architecture of EnTK (white) with three components (purple), each with subcomponents dedicated to the management of EnTK’s entities (green) or coordination of the entities’ execution (yellow). The three components are AppManager, WFProcessor and TaskManager that enable workflow specification, workflow execution management, and workload management.

AppManager exposes an API for the development of ensemble-based applications in terms of tasks, stages and pipelines, and for specifying resource requirements for the application execution. AppManager initializes EnTK and holds the global state of the application at runtime. AppManager is the sole stateful component of EnTK, allowing to restart other components upon failure, without interrupting the execution of the ensemble-based application.

WFProcessor uses the Enqueue and Dequeue subcomponents to queue and dequeue tasks pulled from AppManager. TaskManager uses ExecManager to schedule tasks on the RTS and keep track of the state of each task during execution. TaskManager uses ResManager as an interface to the chosen RTS. RTS have to provide capabilities to acquire resources and schedule tasks on those resources for execution. ResManager isolates RTS from EnTK, enabling restarting of the RTS without losing information about tasks that have been already executed. Currently, EnTK supports only RP as RTS but it is designed to use other task-based RTS as, for example, Coasters or HTCondor.

2.2. Software Functionalities

As a pilot system, the defining capability of a RP is to decouple resource acquisition from task execution, enabling execution of tasks on a pilot without using the resource’s queuing system. RP offers an API to describe both pilots and CUs, alongside classes and methods to manage acquisition of resources, scheduling and execution of CUs on those resources, and the staging of input and output files. Reporting capabilities and notifications update the user about ongoing executions, and profiling capabilities enable detailed postmortem analysis of workload executions and runtime behavior.

RP offers four unique features when compared to other pilot systems or tools that enable the execution of many-task applications on HPC systems:
(1) concurrent execution of heterogeneous tasks on the same pilot; (2) support of all the major HPC batch systems; (3) support of more than twelve methods to launch tasks; and (4) a general purpose architecture. RP can execute single or multi core tasks within a single compute node, or across multiple nodes, isolating the execution of each tasks into a dedicated process and enabling concurrent execution of heterogeneous tasks by design.

As a workflow engine, EnTK is designed to execute ensemble applications, respecting the relations of priority among tasks. Compared to similar systems, EnTK allows to codify relations in terms of pipelines, stages and tasks, where relations may be determined by input/output data or control flow requirements. For example, two tasks may have to be executed sequentially when the output of the first task is the input of the second task; and two tasks (or ensembles) may have to be executed sequentially when the output of the first tasks determines whether executing the second task.

Consistently, EnTK provides adaptive capabilities and dedicated constructs to pause, resume and stop pipelines at runtime. Adaptive applications change the ensemble specifications, creating new pipelines, stages and tasks, or changing the properties of those already defined. Further, pipelines and stages can be paused while waiting to perform ad hoc computations. This enables the implementation of high-level application patterns as, for example, simulation-analysis or replica exchange.

3. Illustrative Examples

Multiple scientific domains can benefit from executing many-task applications at scale, especially at the scale enabled by leadership-class HPC machines [13, 14]. Independent of the domain for which these applications are developed, their execution requires to run a single task, a bag of tasks, or a workflow. In this context, tasks refers to programs like, for example, GROMACS, NAMD, AMBER, AthenaMP, SPECFEM and many others. Many-task applications requires to concurrently run multiple instances of programs, using scale to reduce the total time to completion of the whole execution.

As seen in Sec. 2, RCT support the execution of a single task, a bag of tasks, and workflows expressed as a set or a sequence of pipelines with stages and tasks. Because of the separation between manging the concurrent and consecutive execution of tasks, and the computation performance by each task, RCT support many-task application independent from the scientific domain in which they are used. From RCT point of view, every execution reduces exclusively to manging the execution of single or multiple sets of programs in the form of black boxes.
RP executes set of tasks. The degree of concurrency of the execution depends on the amount of available resources. Consider for example a many-task application for the simulation of molecular dynamics with an ensemble of 128 GROMACS simulations, each requiring 24 CPU cores as those used in Ref. [15]. The user can use RP API to describe a pilot job with 3072 cores (Lis. 1), 128 CUs (Lis. 2) and two managers to coordinate the acquisition of the pilot resources via RADICAL-SAGA on an HPC machine and the execution of the 128 tasks on those resources (Lis. 3).

```
pdesc = rp.ComputePilotDescription()
pdesc.resource = target
pdesc.cores = 3072
pdesc.runtime = 120
pdesc.project = config[resource]['project']
pdesc.queue = config[resource]['queue']
pdesc.access_schema = config[resource]['schema']
```

Listing 1: RADICAL-Pilot API: define a 3072-core pilot that runs for 120 minutes on resource ‘target’

```
n = 128  # number of units to run
cuds = list()
for i in range(0, n):
    cud = rp.ComputeUnitDescription()
    cud.executable = "/bin/bash"
    cud.pre_exec = ["module load gromacs/5.1.2"]
    cud.arguments = ["-l", "-c", "/opt/gromacs/bin/gmx_mpi
mrun -s min.tpr -v -deffnm npt"]
    cud.input_staging = ["FRF.itp", "dynamic.mdp", "FF.itp",
"martini_v2.2.itp", "85-20.top", "init85-20.gro"]
    cud.cores = 24
    cud.mpi = True
    cuds.append(cud)
```

Listing 2: RADICAL-Pilot API: define 128 24-cores MPI CU descriptions.

```
pmgr = rp.PilotManager(session=session)
pilot = pmgr.submit_pilots(pdesc)
umgr = rp.UnitManager(session=session)
umgr.add_pilots(pilot)
umgr.submit_units(cuds)
umgr.wait_units()
```

Listing 3: RADICAL-Pilot API: create pilot and unit managers, submit units, and wait for their completion.

Fig. 1a’s numbers illustrate the resource acquisition and task execution process. PilotManager queues the pilot description on one of the available
Launcher in RP client (Fig. 1a.1). That Launcher uses RADICAL-SAGA to schedule the pilot as a job on the target resource via the resource’s batch system (Fig. 1a.2). The pilot job waits in the resource management system queue and, once scheduled, bootstraps the pilot’s AgentManager and Updater. AgentManager forks the StagerInput, Scheduler, Executor and StagerOutput components and the Updater notifies RP Client’s Notifier that RP Agent is ready to execute tasks (Fig. 1a.3).

Upon notification, UnitManager queues all the available tasks onto Client’s Scheduler that, in turns, queues those tasks into the StagerInput, depending on the chosen scheduling algorithm (Fig. 1a.4). If required, StagerInput stages the tasks’ input files to the target resource and then tasks are queued to the Updater and passed to the chosen RP Agent’s AgentManager (Fig. 1a.5). At that point, tasks are passed to a StagerInput where input files are linked and made available to each task, and then queued to the RP Agent’s Scheduler (Fig. 1a.6). Scheduler places tasks on suitable partitions of the pilot’s resources and then queues tasks to the Executor so that, when those partitions of resource becomes available, tasks are executed (Fig. 1a.7). Executor sets up the environment required by each task and then forks each task for execution (Fig. 1a.8). This is why tasks are black boxes to RP; also note that Scheduler and Executor can place and fork heterogeneous tasks, i.e., task requiring different type and amount core/GPUs and different execution time.

RP API cannot express dependences among tasks. For RP, every task that is passed to UnitManager is assumed to be ready for execution. For example, assume a typical simulation-analysis workflow for molecular dynamics with a simulation stage and an analysis stage that depends upon the completion of the simulation stage. Users can explicitly code priorities among stages in the applications they write with the RP API but they have no dedicated abstractions in that API for expressing those priorities. EnTK offers these abstractions at API level: each stage of each pipeline is submitted to RP for execution, respecting their priority relation.

Fig. 1b’s numbers illustrate the execution of workflows in EnTK. Users instantiate an AppManager (Lis. 4), define a set of resources on which to run their workflow (Lis. 5), describe that workflow in terms of pipelines, stages and tasks (Code 6) and execute it (Code 7). AppManager passes a copy of the workflow description to WFProcessor that, based on the priorities between stages and tasks, uses Enquerer to queue tasks that are ready for execution to the task manager (Fig. 1b.1). Meanwhile, ResManager users the chosen runtime system to acquire the requested resources (Fig. 1b.2) and, once available, TaskManagers uses those resources to execute the queued tasks (Fig. 1b.3) and dequeuing them once they have been executed. Ex-
ecManager uses queues to communicate the state of each task execution to AppManager (Fig. 1b.4). Note that AppManager is the only stateful component of EnTK: both WFProcessor and ExecManager can fail without loss of information about the execution.

```python
appman = AppManager(hostname=hostname, port=port)
```

Listing 4: RADICAL-EnsembleToolkit (EnTK) API: Create AppManager.

```python
res_dict = {
    'resource': 'target',
    'walltime': 120,
    'cpus': 3072
}
```

Listing 5: RADICAL-EnsembleToolkit (EnTK) API: Describe a resource request.

```python
p = Pipeline()
s = Stage()
n = 128
for i in range(0, n):
    t = Task()
    t.executable = "/bin/bash"
    t.pre_exec = ['module load gromacs/5.1.2']
    t.arguments = ['-l', '-c', '/opt/gromacs/bin/gmx_mpi mdrun
    -s min.tpr -v -deffnm npt']
    t.copy_input_data = ['FRF.itp', 'dynamic.mdp', 'FF.itp',
    'martini_v2.2.itp', '85-20.top', 'init85-20.gro']
    t.cpu_reqs = {
        'processes': 24,
        'process_type': MPI
    }
    s.add_tasks(t)
p.add_stages(s)
```

Listing 6: RADICAL-EnsembleToolkit (EnTK) API: Describe a pipeline with 1 stage with 128 24-cores MPI tasks.

```python
appman.resource_desc = res_dict
appman.workflow = set([p])
appman.run()
```

Listing 7: RADICAL-EnsembleToolkit (EnTK) API: Describe a pipeline with

4. Impact

The impact of RCT spans domain science, high-performance computing and the design of software systems. RCT have enabled domain-scientists...
to achieve scientific results that would not have been possible otherwise; they have facilitated research advances in high-performance and distributed computing systems, while serving as an leading and important prototype implementation for exploring a paradigmatic shift in the design of middleware for high-performance scientific workflows.

RCT has enabled the development of scientific applications in multiple and diverse domains, including software engineering, chemical physics, materials science, health science, climate science, drug discovery and particle physics. These users form a worldwide community of domain scientists and system engineers that actively contribute to the open source development of RCT. A comprehensive assessment across multiple dimensions is needed to evaluate the true impact of a software system such as RCT. Whereas the absolute number of users is a useful metric, an equally important metric is what those users were able to achieve scientifically and how RCT enabled them.

Currently, RCT supports a dozen active science projects across the USA and Europe. The size of projects varies from single PIs with large allocations, to very large international collaborations. Thus, there is intrinsic uncertainty in the number of users at any given instant of time but good faith, best estimates suggest upwards of 30 direct users.

RADICAL-SAGA and RADICAL-Pilot support use cases, spanning functional and scientific domains. RADICAL-SAGA is mostly integrated into end-to-end middleware solutions while RADICAL-Pilot is used both as standalone system and integrated with other systems. As seen in Sec. 2.1, RADICAL-PILOT uses RADICAL-SAGA to submit pilots to a large array of resources, including HPC and distributed systems.

RADICAL-SAGA enables the Production ANd Distributed Analysis (PanDA) system to submit batch jobs to Titan and Summit, the two leadership class machines managed by the Oak Ridge Leadership Computing Facility (OLCF) at the Oak Ridge National Laboratory (ORNL) [16]. PanDA is the workload management system used by the ATLAS experiment to execute hundred of millions of jobs a year on both grid and High Performance Computing (HPC) infrastructures [17]. The usage of ORNL resources constitutes 10-12% of all of ATLAS computing. There are several thousand researchers that directly or indirectly use PanDA, and thereby RADICAL-SAGA. In the near future, RADICAL-Pilot will also become a staple of the PanDA workload management system on HPC platforms.

Reflecting the state of distributed computing systems – the lack of simplified and uniform interface to heterogeneous systems, RADICAL-SAGA was used to develop Science Gateways as part of the Distributed Application Runtime Environment (DARE) framework. These gateways supported
several projects, including DECIDE and neuGRID, to study the early diagnosis of Alzheimer and other neurodegenerative diseases. In that capacity RADICAL-SAGA enabled submission of jobs to distributed computing infrastructures managed by the European Grid Initiative (EGI), interconnected via GEANT, the pan-European research and education network that interconnects Europe’s National Research and Education Networks. Recently, the emergence of toolkits such as Agave which integrate identity management have provided higher-level solutions for Gateway developers, but they retain the RADICAL-SAGA based approach to job submission to distributed computing systems.

Since its first release in 2013, RP has supported a total of two dozen projects and around 100 active and direct users. Of these, approximately a dozen projects used RP as a standalone system to support the execution of many-task applications on single and/or multiple computing infrastructures. Motivated by the practical lessons from supporting many independent applications usage of RP as a standalone system, and the realization that an increasing number of HPC applications were adopting the ensemble computational model to overcome limitations of single task applications to achieve significant performance gains on large-scale parallel machines, in 2015 we designed and implemented the Ensemble Toolkit (EnTK) \cite{15} as the latest addition to RCT.

EnTK has enabled the development of domain specific workflow (DSW) frameworks which provide a specific higher-level functionality. Although, driven by specific application needs, each DSW is characterized by a unique execution and coordination pattern and can serve multiple applications. The four ensemble-based DSW developed using EnTK and other RCT are: ExTASY \cite{15}, RepEx \cite{18}, HTBAC \cite{19}, and ICEBERG. Details can be found in Ref. \cite{12}.

ExTASY and RepEx implement advanced sampling algorithms using biomolecular simulations. Both use the EnTK API to implement diverse coordination patterns amongst ensembles of biomolecular simulations and analysis. HTBAC supports multiple algorithms that compute free-energy calculations that are critical to drug design and resistance studies. HTBAC allows the runtime adaptation at multiple levels: algorithms, pipelines and tasks within a pipeline. This capability has been demonstrated to reduce the time-to-solution by a factor 2.5 in controlled experiments on real drug candidates \cite{20}. ICEBERG supports scalable image analysis applications using multiple concurrent pipelines.

ExTASY, RepEx, HTBAC and ICEBERG benefit from integrating RCT by not having to re-implement workflow processing, efficient task management and interoperable task execution capabilities on distinct and heteroge-
neous platforms. This, in turn, enables both a focus on and ease of “last mile customization” for the DSW.

RCT are a testbed for engineering research, mostly focused on foundational abstractions [21], architectural paradigms [6], application patterns [15, 4], and performance analysis of distributed middleware on diverse computing infrastructures [21, 19]. Among the most representative projects supported by RP as a standalone system, the Abstractions and Integrated Middleware for Extreme-Scale Science (AIMES) project enabled extreme-scale distributed computing via dynamic federation of heterogeneous computing infrastructures. We used RP to execute millions of tasks on both HPC and HTC resources, studying the federated behavior of multiple infrastructures, establishing for the first time ever the importance of integrating task and resource information in scheduling and placement decision making for federated supercomputers [22].

The Building Blocks approach helps to create systems that can support use cases both individually and as integrated, end-to-end solution [12]. This is important when supporting projects with multiple, distinct use cases. For example, ICEBERG has to support five use cases, each investigating a specific problem in the domain of polar science. Four of these use cases require the concurrent execution of pipelines but one requires only the execution of bag of tasks. The first four cases can use EnTK while the latter only RADICAL-Pilot. Importantly, all use cases can be served by the ICEBERG framework with a minor change in the private API to call EnTK or RP, depending on the use cases and therefore without any engineering overheads.

5. Conclusions

RCT is a small operation with at most two developers working on the systems at the same time. In order to implement the aforementioned capabilities while supporting more than ten concurrent projects at every point in time, we adopted a specific methodology for the design, development and maintenance of RCT. This methodology is based on the Building Blocks approach, the use of git for distributed version control of the code base [11], and a tailored project management process.

Overall, these processes and insight have an impact on how to approach the development of middleware for supporting scientific research. Based on more than ten years of experience, our approach show a sustainable and effective way to organize software development, promote community adoption and leverage the specific characteristics of the academic financial model. This signs the transition from a development model based on end-to-end, monolithic solutions with stringent requirements on infrastructures’ software
stack, to a model based on small, independent and composable systems, each with a well-defined capability. Note that these systems must be composable with third-party systems, i.e., systems developed independently by different development teams. This approach enables a model of sustainability based on smaller and shorter funding sources but requires a certain convergence in the vision of diverse groups competing in the same research field.

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Required Metadata

Current code version

Current executable software version
| Nr. | Code metadata description | Please fill in this column |
|-----|--------------------------|---------------------------|
| C1  | Current code version     | 0.60                      |
| C2  | Permanent link to code/repository used for this code version | [https://github.com/radical-cybertools](https://github.com/radical-cybertools) |
| C3  | Legal Code License       | MIT License (MIT)         |
| C4  | Code versioning system used | git                       |
| C5  | Software code languages, tools, and services used | python, shell, C          |
| C6  | Compilation requirements, operating environments & dependencies | virtualenv, pip or conda |
| C7  | Developer documentation/manual | [https://radicalpilot.readthedocs.io/](https://radicalpilot.readthedocs.io/) |
| C8  | Support email for questions | radical-cybertools@googlegroups.com |

Table 1: Code metadata

| Nr. | Exec. metadata description | Please fill in this column |
|-----|-----------------------------|---------------------------|
| S1  | Current software version    | 0.60                      |
| S2  | Permanent link to executables of this version | [https://pypi.org/project/radical.pilot/](https://pypi.org/project/radical.pilot/) |
| S3  | Legal Software License      | MIT License (MIT)         |
| S4  | Computing platforms/Operating Systems | GNU/Linux operating systems |
| S5  | Installation requirements & dependencies | virtualenv, pip or conda |
| S6  | User manual and publications | User manual: [https://radicalpilot.readthedocs.io/](https://radicalpilot.readthedocs.io/); Publications: Refs [2, 4, 3] |
| S7  | Support email for questions | radical-cybertools@googlegroups.com |

Table 2: Software metadata