MANUAL

SDD-513 Revision 0 Printed December 2018

RAVEN Software Design Description

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The Idaho National Laboratory is a multiprogram laboratory operated by Battelle Energy Alliance for the United States Department of Energy under DOE Idaho Operations Office. Contract DE-AC07-05ID14517.

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1 Introduction

1.1 System Purpose

RAVEN is a flexible and multi-purpose uncertainty quantification (UQ), regression analysis, probabilistic risk assessment (PRA), data analysis and model optimization software. Depending on the tasks to be accomplished and on the probabilistic characterization of the problem, RAVEN perturbs (Monte-Carlo, latin hyper-cube, reliability surface search, etc.) the response of the system under consideration by altering its own parameters. The system is modeled by third party software (RELAP5-3D, MAAP5, BISON, etc.) and accessible to RAVEN either directly (software coupling) or indirectly (via input/output files). The data generated by the sampling process is analyzed using classical statistical and more advanced data mining approaches. RAVEN also manages the parallel dispatching (i.e. both on desktop/workstation and large High-Performance Computing machines) of the software representing the physical model. RAVEN heavily relies on artificial intelligence algorithms to construct surrogate models of complex physical systems in order to perform uncertainty quantification, reliability analysis (limit state surface) and parametric studies.

1.2 System Scope

RAVEN's scope is to provide a set of capabilities to build analysis flows based on UQ, PRA, Optimization and Data Analysis techniques to be applied to any physical model(s). The main objective of the software is to assist the engineer/user to:

- identify the best design (on any physics/model), its safety and confidence;
- estimate the likelihood of undesired outcomes (risk analysis);
- identify main drivers/events to act on for reducing impact/consequences of anomalous dynamic behaviors of the system under analysis;
- to construct analysis flows combining multiple physical models and analysis procedures.

In other words, the RAVEN software is aimed to be employed for:

- Uncertainty Quantification;
- Sensitivity Analysis / Regression Analysis;
- Probabilistic Risk and Reliability Analysis (PRA);

- Data Mining Analysis;
- Model Optimization.

The combination of all the previously mentioned analysis capabilities is a key component to define safety margins in engineering design that are more representative of real prediction deficiencies. This could reduce cost and maintain a more coherent safety level of the system (no excess/no lack of safety margins in any operational condition). The risk analysis, assisted by the data mining algorithms, is used to find engineering solutions to reduce costs, while preserving safety margins, or to increase safety at the minimum cost. These tasks can be automatically achieved by using optimization algorithms available in the RAVEN software. Moreover, the knowledge of the relationship between input and system response uncertainties allows identifying effective experiments, which are the most suitable for increasing the accuracy of the model. This approach reduces time and cost of the deployment of complex engineering systems and new technologies.

The RAVEN software employs several novel and unique techniques, based on extensive usage of artificial intelligence algorithms, such as adaptive (smart) sampling, adaptive branching algorithms (Dynamic Event Tree), time-dependent statistical analysis and data mining. The overall set of algorithms implemented in the RAVEN software are designed to handle highly non-linear systems, characterized by system response discontinuities and discrete variables. These capabilities are crucial for handling complex system models, such as nuclear power plants. For example, reliability surface analysis, as implemented in RAVEN, is unique and capable to handle non-linear, discontinuous systems, allowing for faster and more accurate assessing of failure risk for complex systems.

In addition, the RAVEN software provides the unique capability to combine any model (e.g. physical models, surrogate models, data analysis models, etc.) in a single entity (named Ensemble Model) where each model can feedback into others. This capability allows the user to analyze system that could be simulated only by using complex computational work-flows.

1.3 User Characteristics

The users of the RAVEN software are expected to be part of any of the following categories:

- Core developers (RAVEN core team): These are the developers of the RAVEN software. They will be responsible for following and enforcing the appropriate software development standards. They will be responsible for designing, implementing and maintaining the software.
- External developers: A Scientist or Engineer that utilizes the RAVEN framework and wants to extend its capabilities (new interface to external applications, new data analysis tecniques, new sampling strategies, etc). This user will typically have a background in modeling and

simulation techniques and/or numerical analysis but may only have a limited skill-set when it comes to object-oriented coding, C++/Python languages.

Analysts: These are users that will run the code and perform various analysis on the simulations they perform. These users may interact with developers of the system requesting new features and reporting bugs found and will typically make heavy use of the input file format.

1.4 Other Design Documentation

In addition to this document, an automatic software documentation is generated every time a new CR (see def.) is approved. This documentation is automatically extracted from the source code using doxygen (see def.) and is available to developers at https://hpcsc.inl.gov/ssl/RAVEN/docs/classes.html.

In order to generate(locally) a hard copy in "html" or "latex", any user/developer can launch the following command (in the raven directory):

```
doxygen ./doc/doxygen/Doxyfile
```

Once the documentation is generated, any user/developer can navigate to the folder

```
./doc/doxygen/latex
```

and type the following command:

```
make refman.pdf
```

Once the command is executed, a "pdf" file named "refman.pdf" will be available.

The doxygen software is under configuration management process identified in "RAVEN Configuration Management" PLN-5553.

1.5 Dependencies and Limitations

The software should be designed with the fewest possible constraints. Ideally the software should run on a wide variety of evolving hardware, so it should follow well-adopted standards and guidelines. The software should run on any POSIX compliant system (including Windows POSIX emulators such as MinGW). The software will also make use of artificial intelligence and numerical libraries that run on POSIX systems as well. The main interface for the software will be command line based with no assumptions requiring advanced terminal capabilities such as coloring and line control.

In order to be functional, RAVEN depends on the following software/libraries.

- h5py-2.7.1
- numpy-1.12.1
- scipy-1.1.0
- scikit-learn-0.19.1
- pandas-0.20.3
- xarray-0.10.3
- netcdf4-1.4.0
- matplotlib-2.1.1
- statsmodels-0.8.0
- python-2.7
- hdf5-1.8.18
- swig
- pylint
- coverage
- lxml
- psutil
- pyside
- pillow

2 References

- ASME NQA 1 2008 with the NQA-1a-2009 addenda, "Quality Assurance Requirements for Nuclear Facility Applications," First Edition, August 31, 2009.
- ISO/IEC/IEEE 24765:2010(E), "Systems and software engineering Vocabulary," First Edition, December 15, 2010.
- LWP 13620, "Managing Information Technology Assets"

3 Definitions and Acronyms

3.1 Definitions

- **Baseline.** A specification or product (e.g., project plan, maintenance and operations [M&O] plan, requirements, or design) that has been formally reviewed and agreed upon, that thereafter serves as the basis for use and further development, and that can be changed only by using an approved change control process. [ASME NQA-1-2008 with the NQA-1a-2009 addenda edited]
- **Validation.** Confirmation, through the provision of objective evidence (e.g., acceptance test), that the requirements for a specific intended use or application have been fulfilled. [ISO/IEC/IEEE 24765:2010(E) edited]

· Verification.

- The process of evaluating a system or component to determine whether the products of a given development phase satisfy the conditions imposed at the start of that phase.
- Formal proof of program correctness (e.g., requirements, design, implementation reviews, system tests). [ISO/IEC/IEEE 24765:2010(E) edited]

3.2 Acronyms

API Application Programming Interfaces

ASME American Society of Mechanical Engineers

CDF Comulative Distribution Functions

DET Dynamic Event Tree

DOE Department of Energy

HDF5 Hierarchical Data Format (5)

LWRS Light Water Reactor Sustainability

NEAMS Nuclear Energy Advanced Modeling and Simulation

NHES Nuclear-Renewable Hybrid Energy Systems

INL Idaho National Laboratory

IT Information Technology

M&O Maintenance and Operations

MC Monte Carlo

MOOSE Multiphysics Object Oriented Simulation Environment

NQA Nuclear Quality Assurance

POSIX Portable Operating System Interface

PDF Probability Distribution (Density) Functions

PP Post-Processor

PRA Probabilistic Risk Assessment

QA Quality Assurance

RAVEN Risk Analysis and Virtual ENviroment

ROM Reduced Order Model

SDD System Design Description

XML eXtensible Markup Language

4 Design Stakeholders and Concerns

4.1 Design Stakeholders

- Light Water Reactor Sustainability (LWRS) program
- Nuclear Energy Advanced Modeling and Simulation Program (NEAMS)
- Nuclear-Renewable Hybrid Energy Systems (NHES)
- Open-source community

4.2 Stakeholder Design Concerns

The design of the RAVEN software in terms of functionality and capabilities to be deployed has been performed in accordance with the funding programs reported above. No specific concerns have been raised during the design and deployment of the RAVEN software.

5 Software Design

5.1 Introduction

The Risk Analysis and Virtual ENviroment (RAVEN) mission is to provide a framework/container of capabilities for engineers and scientists to analyze the response of systems, physics and multiphysics, employing advanced numerical techniques and algorithms. RAVEN was conceived with two major objectives:

- to be as easy and straightforward to use by scientists and engineers as possible.
- to allow its expansion in a straightforward manner, providing clear and modular APIs to developers.

The RAVEN software is meant to be approachable by any type of user (computational scientists, engineers and analysts). Every single aspect of RAVEN was driven by this singular principle from the build system to the APIs to the software development cycle and input syntax.

The main idea behind the design of the RAVEN software was/is the creation of a multi-purpose framework characterized by high flexibility with respect to the possible perform-able analysis. The framework must be capable of constructing the analysis/calculation flow at run-time, interpreting the user-defined instructions and assembling the different analysis tasks following a user specified scheme. In order to achieve such flexibility, combined with reasonably fast development, a programming language naturally suitable for this kind of approach was needed: *Python*. Hence, RAVEN is coded in *Python* and is characterized by an object-oriented design.

5.2 System Structure

The core of the analysis perform-able through RAVEN is represented by a set of basic entities (components/objects) the user can combine, in order to create a customized analysis flow.

Figure 1 shows a schematic representation of the RAVEN software, highlighting the communication pipes among the different modules and engines.

A list of these components and a summary of their most important characteristics are reported as follows:

• **Distributions**: Aimed to explore the input/output space of a system/physics. RAVEN requires the capability to perturb the input space (initial conditions and/or model coefficients of a system). The input space is generally characterized by probability distribution (density) functions (PDFs), which might need to be considered when a perturbation is applied. In this respect, a large library of PDFs is available.

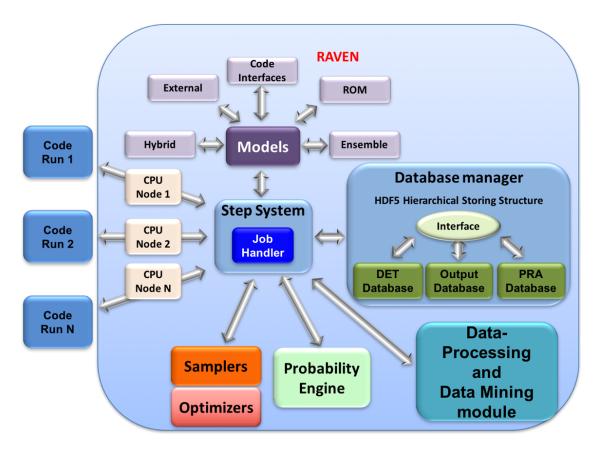


Figure 1: RAVEN framework layout

- Samplers: Aimed to define the strategy for perturbing the input space of a system/physics. A proper approach to sample the input space is fundamental for the optimization of the computational time. In RAVEN, a "sampler" employs a unique perturbation strategy that is applied to the input space of a system. The input space is defined through the connection of uncertain variables (initial conditions and/or model coefficients of a system) and their relative probability distributions. The link of the input space to the relative distributions, will allow the Sampler to perform a probability-weighted exploration.
- **Optimizers**: Aimed to define the strategy for optimizing (constrained or unconstrained) the controllable input space (parameters) in order to minimize/maximize an objective function of the system/physics under examination. In RAVEN, an "optimizer" employs an active learning process (feedback from the underlying model/system/physics) aimed to accelerate the minimization/maximization of an objective function.
- **Models**: A model is the representation of a physical system (e.g. Nuclear Power Plant); it is therefore capable of predicting the evolution of a system given a coordinate set in the input space. In addition it can represent an action on a data in order to extract key features (e.g. Data mining).

- **DataObjects and Databases**: Aimed to provide standardized APIs for storing the results of any RAVEN analysis (Sampling, Optimization, Statistical Analysis, etc.). In addition, these storage structures represent the common "pipe network" among any entity in RAVEN.
- Outstreams: Aimed to export the results of any RAVEN analysis (Sampling, Optimization, Statistical Analysis, etc.). This entity allows to expose the results of an analysis to the user, both in text-based (XML, CSV, etc.) or graphical (pictures, graphs, etc.) output files.
- **Steps**: Aimed to provide a standardized way for the user to combine the entities reported above for the construction of any particular analysis. As shown in Fig. 1, the **Step** is the core of the calculation flow of RAVEN and is the only system that is aware of any component of the simulation.
- **Job Handler**: Aimed to coordinate and regulate the dispatch of jobs in the RAVEN software. It is able to monitor/handle parallelism in the driven Models, to interact with High Performance Computing systems, etc.

In the following sections, a detailed description of the entities (and their underlying algorithm-s/schemes) is reported.

5.2.1 Models

The Model entity, in the RAVEN software, represents a "connection pipeline" between the input and the output space. The RAVEN software does not own any physical model (i.e. it does not posses the equations needed to simulate a generic physical system, such as Navier-Stocks equations, Maxwell equations, etc.), but implements APIs by which any generic model can be integrated and interrogated. The RAVEN framework provides APIs for 6 main model categories:

- Codes
- Externals
- Reduced Order Models (ROMs)
- Hybrid Models
- Ensemble Models
- Post-Processors (PPs)

In the following paragraphs, a brief explanation of each of these Model categories is reported.

5.2.1.1 Code

The *Code* model represents the communication pipe between the RAVEN framework and any system and/or physical code/model. The communication between RAVEN and any driven code is performed through the implementation of interfaces directly operated by the framework.

The procedure of coupling a new code/application with RAVEN is a straightforward process. The coupling is performed through a *Python* interface that interprets the information coming from RAVEN and translates them to the input of the driven code. The coupling procedure does not require modifying RAVEN itself. Instead, the developer creates a new *Python* interface that is going to be embedded in RAVEN at run-time (no need to introduce hard-coded coupling statements). If the coupled code is parallelized and/or multi-threaded, RAVEN is going to manage the system in order to optimize the computational resources in both workstations and High Performance Computing systems.

5.2.1.2 External Model

The External model allows the user to create, in a *Python* file (imported, at run-time, in the RAVEN framework), its own model (e.g. set of equations representing a physical model, connection to another code, control logic, etc.). This model will be interpreted/used by the framework and, at run-time, will become part of RAVEN itself.

5.2.1.3 Reduced Order Model

A ROM (also called Surrogate Model) is a mathematical representation of a system, used to predict a selected output space of a physical system. The "training" is a process that uses sampling of the physical model to improve the prediction capability (capability to predict the status of the system given a realization of the input space) of the ROM. More specifically, in RAVEN the Reduced Order Model is trained to emulate a high fidelity numerical representation (system codes) of the physical system. Two general characteristics of these models can be generally assumed (even if exceptions are possible):

1. The higher the number of realizations in the training sets, the higher is the accuracy of the prediction performed by the reduced order model. This statement is true for most of the cases although some ROMs might be subject to the overfitting issues. The over-fitting phenomenon is not discussed here, since its occurrence is highly dependent on the algorithm type, (and there is large number of ROM options available in RAVEN). Every time the user

chooses a particular reduced order model algorithm to use, he should consult the relevant literature;

2. The smaller the size of the input domain with respect to the variability of the system response, the more likely the surrogate model will be able to represent the system output space.

5.2.1.4 Hybrid Models

The Hybrid Model is able to combine ROM and any other high-fidelity Model (e.g. Code, ExternalModel). The ROMs will be "trained" based on the results from the high-fidelity model. The accuracy of the ROMs will be evaluated based on the cross validation scores, and the validity of the ROMs will be determined via some local validation metrics. After these ROMs are trained, the HybridModel can decide which of the Model (i.e the ROMs or high-fidelity model) to be executed based on the accuracy and validity of the ROMs.

5.2.1.5 Ensemble Models

The Ensemble Model is aimed to create a chain of Models (whose execution order is determined by the Input/Output relationships among them). If the relationships among the models evolve in a non-linear system, a Picard's Iteration scheme is employed.

5.2.1.6 PostProcessors

The Post-Processor model represents the container of all the data analysis capabilities in the RAVEN code. This model is aimed to process the data (for example, derived from the sampling of a physical code) in order to identify representative F Figure of Merits. For example, RAVEN owns Post-Processors for performing statistical and regression/correlation analysis, data mining and clustering, reliability evaluation, topological decomposition, etc.

5.2.2 Distributions

The perturbation of the input space, through the initial conditions (parameters) affected by uncertainties, needs to be performed by the proper distribution functions. RAVEN owns several uni-variate (truncated and not) distributions, among which the following:

- Bernoulli
- Binomial
- Exponential
- Logistic
- Log-Normal
- Normal
- Poisson
- Triangular
- Uniform
- Weibull
- Gamma
- Beta

The usage of uni-variate distributions for sampling initial conditions is based on the assumption that the uncertain parameters are not correlated with each other. Quite often uncertain parameters are subject to correlations and thus the uni-variate approach is not applicable. This happens when a generic outcome is dependent on different phenomena simultaneously (i.e. the outcome dependency description can not be collapsed to a function of a single variable). RAVEN currently supports both N-dimensional (N-D) custom or multivariate Normal distributions. About the custom N-dimensional distributions, the user can provide the PDF or CDF values on either Cartesian or sparse grid, which determines the interpolation algorithm used in the evaluation of the imported CDF/PDF:

- 1. N-Dimensional Spline, for cartesian grids
- 2. Inverse weight, for sparse grids

Internally, RAVEN provides the needed N-D differentiation and integration algorithms to compute the PDF from the CDF and vice-versa.

As already mentioned, the sampling methods use the distributions in order to perform probability-weighted perturbations. For example, in the Monte Carlo approach, a random number $\in [0,1]$ is generated (probability threshold) and the CDF, corresponding to that probability, is inverted in order to retrieve the parameter value used in the simulation. The existence of the inverse for uni-variate distributions is guaranteed by the monotonicity of the CDF. For N-D distributions this

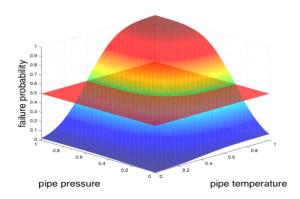


Figure 2: 2-D CDF, function of pressure and temperature

condition is not sufficient since the $CDF(X) \longrightarrow [0,1], X \in \mathbb{R}^N$ and therefore it could not be a bijective function. From an application point of view, this means the inverse of a N-D CDF is not unique.

As an example, Figure 2 shows a multivariate normal distribution for a pipe failure as function of the pressure and temperature. The plane identifies an isoprobability surface (in this case, a line) that represents a probability threshold of 50 % in this example. Hence, the inverse of this CDF is an infinite number of points.

As easily infer-able, the standard sampling approach cannot directly be employed. When multi-variate distributions are used, RAVEN implements a surface search algorithm for identifying the iso-probability surface location. Once the location of the surface has been found, RAVEN randomly chooses one point on it.

5.2.3 Samplers

The sampler performs the driving of the specific sampling strategy and, hence, determines the effectiveness of the analysis, from both an accuracy and computational point of view. The samplers, available in RAVEN, can be categorized in three main classes:

- Forward
- Dynamic Event Tree (DET)
- Adaptive

5.2.3.1 Forward Samplers

The Forward sampler category collects all the strategies that perform the sampling of the input

space without exploiting, through dynamic learning approaches, the information made available from the outcomes of calculation previously performed (adaptive sampling) and the common system evolution (patterns) that different sampled calculations can generate in the phase space (dynamic event tree). In the RAVEN framework, several different and well-known forward samplers are available:

- Monte Carlo (MC)
- Stratified based, whose most known specialization is the Latin Hyper-Cube Sampling (LHS)
- Grid Based
- Response Surface Design of Experiment
- Sparse Grid
- Factorials
- Etc.

5.2.3.2 Dynamic Event Tree Samplers

In order to clarify the idea behind the Dynamic Event Tree Sampler currently available in RAVEN, a small overview is needed.

In technologically complex systems, as nuclear power plants, an accident scenario begins with an initiating event and then evolves over time through the interaction of dynamics and stochastic events. This mutual action leads to the production of infinitely many different scenarios, which define a continuous dynamic event tree with infinite branches. At each time point, the stochastic variability of the accident outcomes is determined by a multivariate probability distribution. The PRA analysis needs an approximation to this distribution for selected consequence variables. A way to achieve this goal is an Event Tree approach. In dynamic PRA analysis, Conventional Event Tree sequences are run simultaneously starting from a single initiating event. The branches occur at user specified times and/or when an action is required by the operator and/or the system, creating a deterministic sequence of events based on the time of their occurrence. One of the disadvantages of this method is that the timing/sequencing of events and system dynamics is not explicitly accounted for in the analysis. In order to overcome these limitations a "dynamic" approach is needed. The Dynamic Event Tree (DET) technique brings several advantages, among which is the fact that it simulates probabilistic system evolution in a way that is consistent with the severe accident model. This leads to a more realistic and mechanistically consistent analysis of the system taken into consideration. The dynamic PRA, in general, and the Dynamic Event Tree methodologies in particular, are designed to take the timing of events explicitly into account, which can become very important especially when uncertainties in complex phenomena are considered. Hence, the main

idea of this methodology is to let a system code determine the pathway of an accident scenario.

From an application point of view, a N-D grid is built on the CDF space. A single simulation is spawned and a set of triggers is added to the system code control logic. Every time a trigger gets activated (one of the CDF thresholds in the grid is violated), a new set of simulations (branches) is spawned. Each branch carries its own probability.

Figure 3 shows a practical example. In this particular case, it is assumed that the probability failure of a pipe depends on the fluid pressure magnitude. Three probability thresholds are defined on the cumulative distribution function. One simulation is spawned (0). As soon as the pressure of the fluid reaches a value corresponding to a 33% probability (CDF), a stop signal is sent and the framework starts two new simulations (branches). The branch in which the system evolved to the newer condition (pipe failed, red line) carries 33% of the probability, while the other the complementary amount. The same procedure is repeated at point 2.

Generally, not all the input space can be explored using a DET approach. For instance, usually the parameters affected by aleatory uncertainty are sampled using a dynamic event tree approach, while the ones characterized by epistemic uncertainty are sampled through "forward" sampling strategies.

As already mentioned, this strategy requires a tight interaction between the system code and the sampling driver (i.e., RAVEN framework). In addition, the system code must have a control logic capability (i.e. trigger system).

In the RAVEN framework, several different DET-based samplers are available:

- Dynamic Event Tree (aleatory sampling);
- Hybrid Dynamic Event Tree (aleatory and epistemic sampling);
- Adaptive Dynamic Event Tree (goal-oriented sampling for aleatory sampling);
- Adaptive Hybrid Dynamic Event Tree (goal-oriented sampling for aleatory and epistemic sampling).

5.2.3.3 Adaptive Samplers

A key feature available within RAVEN is the possibility to perform smart sampling (also known as adaptive sampling) as an alternative to classical "forward" techniques.

The motivation is that nuclear simulations are often computationally expensive, time-consuming, and high dimensional with respect to the number of input parameters. Thus, exploring the space of all possible simulation outcomes is unfeasible using finite computing resources. During simulation-based probabilistic risk analysis, it is important to discover the relationship between a potentially large number of input parameters and the output of a simulation using as few simulation trials as possible.

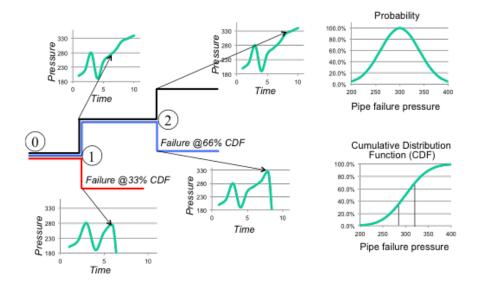


Figure 3: Dynamic Event Tree simulation pattern

This is a typical context for performing adaptive sampling where a few observations are obtained from the simulation, a reduced order model (ROM) is built to represent the simulation space, and new samples are selected based on the model constructed. The ROM is then updated based on the simulation results of the sampled points. In this way, it is attempted to gain the most information possible with a small number of carefully selected sampled points, limiting the number of expensive trials needed to understand features of the system space.

In the RAVEN framework, several different adaptive samplers are available:

- Limit Surface Search;
- Adaptive Dynamic Event Tree;
- Adaptive Hybrid Dynamic Event Tree;
- Adaptive Sparse Grid;
- Adaptive Sobol Decomposition.
- Etc.

5.2.4 Optimizers

The optimizer performs the driving of a specific goal function over the model for value optimization. The difference between an optimizer and a sampler is that the former does not require sampling over a distribution, although certain specific optimizers may utilize stochastic approach to

locate the optimal. The optimizers currently available in RAVEN can be categorized into the following classes:

• Gradient Based Optimizer

5.2.4.1 Gradient Based Optimizers

The Gradient Based Optimizer category collects all the strategies that perform the optimization based on gradient information, either directly provided or estimated by optimization strategy. From a practical point of view, these optimization strategies represent different ways to estimate the gradient based on information from previously performed model evaluation.

5.2.5 DataObject and Database

The *DataObjects*' system is a container of objects of various types that are aimed to collect the results of any RAVEN calculation analysis. Currently, RAVEN supports 3 different data types, each with a particular conceptual meaning:

- *PointSet*, is a collection of individual objects, each describing the state of the system at a certain point (e.g. in time). It can be considered a mapping between multiple sets of parameters in the input space and the resulting sets of outcomes in the output space at a particular point (e.g. in time);
- *HistorySet*, is a collection of individual objects each describing the temporal evolution of the state of the system within a certain input domain. It can be considered a mapping between multiple sets of parameters in the input space and the resulting sets of temporal evolution in the output space.
- *DataSet*, is a generalization of the previously described DataObject, aimed to contain a mixture of data (scalars, arrays, etc.). The variables here stored can be independent (i.e. scalars) or dependent (arrays) on certain dimensions (e.g. time, coordinates, etc.). It can be considered a mapping between multiple sets of parameters in the input space (both dependent and/or independent) and the resulting sets of evolution in the output space (both dependent and/or independent).

The *DataObjects* (storage structures) represent the common "pipe network" among any entity in RAVEN.

The Databases' system provides the capability to store and retrieve data to/from external databases (e.g. HDF5).

5.2.6 OutStreams

RAVEN provides the capabilities to visualize and dump out the data that are generated, imported and post-processed during the analysis. These capabilities are contained in the "OutStream" system. Actually, two different OutStream types are available:

- **Print**, module that lets the user dump the data contained in the internal objects;
- Plot, module aimed to provide advanced plotting capabilities.

Both the types listed above accept as "input" a *DataObjects* object type. This choice is due to the "DataObjects" system having the main advantage of ensuring a standardized approach for exchanging the data/meta-data among the different RAVEN entities. Every module can project its outcomes into a DataObjects object. This provides the user with the capability to visualize/dump all the modules' results.

5.3 Steps

The core of the RAVEN calculation flow is the Step system. The Step is in charge of assembling different entities in RAVEN (e.g. Samplers, Models, Databases, etc.) in order to perform a task defined by the kind of step being used. A sequence of different Steps represents the calculation flow.

In order to understand the information flow represented in a particular **Step**, it is key to introduce the concept of "*Role*" in a generic **Step**. In the following example, a general example of a Step is shown:

```
</Steps>
...
</Simulation>
```

As shown above each **Step** consists of a list of entities organized into "*Roles*". Each role represents a behavior the entity (object) will assume during the evaluation of the **Step**. In RAVEN, several different roles are available:

- **Input** represents the input of the **Step**. The allowable input objects depend on the type of **Model** in the **Step**.
- Output defines where to collect the results of an action performed by the Model. It is generally one of the following types: DataObjects, Databases, or OutStreams.
- **Model** represents a physical or mathematical system or behavior. The object used in this role defines the allowable types of **Inputs** and **Outputs** usable in this step.
- **Sampler or Optimizer** defines the sampling (or optimization) strategy to be used to probe the model.
- **Function** is an extremely important role. It introduces the capability to perform pre or post processing of Model **Inputs** and **Outputs**. Its specific behavior depends on the **Step** is using it.
- **ROM** defines an acceleration Reduced Order Model to use for a **Step**.
- **SolutionExport** represents the container of the eventual output of a Step. For example, a **Step** is employing the search of the Limit Surface (LS), through the class of Adaptive **Samplers**); in this case, it contains the coordinates of the LS in the input space.

Depending on the **Step** type, different combinations of these roles can be used. The available steps are the following

- SingleRun
- MultiRun
- IOStep
- RomTrainer
- PostProcess

In order to show the information flow for a **Step**, the *MultiRun* can be considered (being the most complex one). The *MultiRun* **Step** is aimed to handle calculations that involve multiple runs of a driven **Model** (e.g. Codes, ROMs, etc.), via a sampling or optimization strategy. Firstly, the RAVEN input file associates the variables to a set of PDFs and to a sampling strategy. The *MultiRun* step is used to perform several runs of a model (e.g. in a Monte Carlo sampling). At the

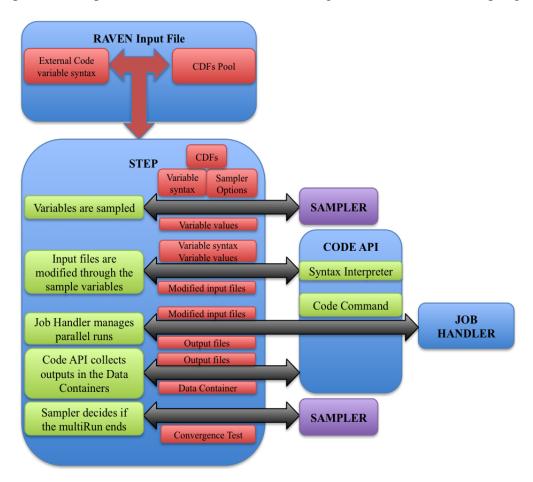


Figure 4: Calculation flow for a multi-run sampling

beginning of each sub-sequential run, the sampler provides the new values of the variables to be perturbed. The **Model** API places those values in the input of the driven **Model** (e.g. Code, ROMs, etc.). At this point, the code API generates the run command and asks to be queued by the job handler (job scheduler). The job handler manages the parallel execution of as many runs as possible within a user prescribed range and communicates with the **Step** controller when a new set of outputs are ready to be processed. The **Model** API receives the new outputs and collects the data in the RAVEN internal format (**DataObjects** or **Databases**). The sampler is queried to assess if the sequence of runs is ended; if not, the **Step** controller asks for a new set of values from the sampler and the sequence is restarted as described in Figure 4.

5.4 Raven Input Structure

The RAVEN software does not have a fixed calculation flow, since all of its basic objects can be combined in order to create a user-defined calculation flow. Thus, its input (XML format) is organized in different XML blocks, each with a different functionality. The main input blocks are as follows:

- **<Simulation>**: The root node containing the entire input, all of the following blocks fit inside the *Simulation* block.
- **<RunInfo>**: Specifies the calculation settings (number of parallel simulations, etc.).
- **<Files>**: Specifies the files to be used in the calculation.
- **<Distributions>**: Defines distributions needed for describing parameters, etc.
- **<Samplers>**: Sets up the strategies used for exploring an uncertain domain.
- <Optimizers>: Sets up the strategies used for minimizing/maximizing an objective function.
- **<DataObjects>**: Specifies internal data objects used by RAVEN.
- **<Databases>**: Lists the HDF5 databases used as input/output to a RAVEN run.
- **<OutStreams>**: Visualization and Printing system block.
- <Models>: Specifies codes, ROMs, post-processing analysis, etc.
- **<Functions>**: Details interfaces to external user-defined functions and modules. the user will be building and/or running.
- **<Steps>**: Combines other blocks to detail a step in the RAVEN workflow including I/O and computations to be performed.

Each of these blocks are explained in dedicated sections in the user manual [1].

5.5 Data Design and Control

The data transfer in the RAVEN software is fully standardized:

- *Input*: API deployed by Code Interfaces and/or Model APIs;
- Output: API deployed by the DataObjects and Databases.

The documentation of these APIs is reported in the RAVEN user manual ([1])

5.6 Human-Machine Interface Design

There are no human system integration requirements associated with this software.

5.7 System Interface Design

RAVEN does not own any physical model. For this reason, it needs to be interfaced with external or user input-defined software representing the engine for simulating physical models (systems). The interface with external systems in the RAVEN software is fully standardized via clear APIs deployed by the **Models** entities. The documentation of these APIs is reported in the RAVEN user manual ([1])

5.8 Security Structure

The software is accessible to the open-source community (Apache License, Version 2.0). No restrictions for downloading or redistributing is applicable.

6 REQUIREMENTS CROSS-REFERENCE

The requirements are detailed in SPC-2366, "RAVEN Software Requirements Specification (SRS) and Traceability Matrix".

References

[1] C. Rabiti, A. Alfonsi, J. Cogliati, D. Mandelli, R. Kinoshita, S. Sen, C. Wang, P. W. Talbot, D. P. Maljovec, and J. Chen, "Raven user manual," tech. rep., Idaho National Laboratory, 2017.

Document Version Information

tag_number_23-331-gf70f16e03 fe74929a53d32a30e2061cf7295754ebd58a4158 Joshua J. Cogliati Wed, 27 Mar 2019 09:17:34 -0600

