OpenQuake for Advanced Users Documentation

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ONE

INTRODUCTION

This manual is for advanced users, i.e. people who already know how to use the engine and have already read the official manual cover-to-cover. If you have just started on your journey of using and working with the OpenQuake engine, this manual is probably NOT for you. Beginners should study the official manual first. This manual is intended for users who are either running *large* calculations or those who are interested in programatically interacting with the datastore.

For the purposes of this manual a calculation is large if it cannot be run, i.e. if it runs out of memory, it fails with strange errors (rabbitmq errors, pickling errors, etc.) or it just takes too long to complete.

There are various reasons why a calculation can be too large. 90% of the times it is because the user is making some mistakes and she is trying to run a calculation larger than she really needs. In the remaining 10% of the times the calculation is genuinely large and the solution is to buy a larger machine, or to ask the OpenQuake developers to optimize the engine for the specific calculation that is giving issues.

The first things to do when you have a large calculation is to run the command `oq info --report job.ini`, that will tell you essential information to estimate the size of the full calculation, in particular the number of hazard sites, the number of ruptures, the number of assets and the most relevant parameters you are using. If generating the report is slow, it means that there is something wrong with your calculation and you will never be able to run it completely unless you reduce it.

The single most important parameter in the report is the *number of effective ruptures*, i.e. the number of ruptures after distance and magnitude filtering. For instance your report could contain numbers like the following:

```
#eff_ruptures 239,556
#tot_ruptures 8,454,592
```

This is an example of a computation which is potentially large - there are over 8 million ruptures generated by the model - but that in practice will be very fast, since 97% of the ruptures will be filtered away. The report gives a conservative estimate, in reality even more ruptures will be discarded.

It is very common to have an unhappy combinations of parameters in the `job.ini` file, like discretization parameters that are too small. Then your source model with contains millions and millions of ruptures and the computation will become impossibly slow or it will run out of memory. By playing with the parameters and producing various reports, one can get an idea of how much a calculation can be reduced even before running it.

Now, it is a good time to read the section about common mistakes.

CHAPTER

TWO

COMMON MISTAKES: BAD CONFIGURATION PARAMETERS

By far, the most common source of problems with the engine is the choice of parameters in the *job.ini* file. It is very easy to make mistakes, because users typically copy the parameters from the OpenQuake demos. However, the demos are meant to show off all of the features of the engine in simple calculations, they are not meant for getting performance in large calculations.

2.1 The quadratic parameters

In large calculations, it is essential to tune a few parameters that are really important. Here is a list of parameters relevant for all calculators:

maximum_distance: The larger the maximum_distance, the more sources and ruptures will be considered; the effect is quadratic, i.e. a calculation with `maximum_distance=500` km could take up to 6.25 times more time than a calculation with `maximum_distance=200` km.

region_grid_spacing: The hazard sites can be specified by giving a region and a grid step. Clearly the size of the computation is quadratic with the inverse grid step: a calculation with `region_grid_spacing=1` will be up to 100 times slower than a computation with `region_grid_spacing=10`.

area_source_discretization: Area sources are converted into point sources, by splitting the area region into a grid of points. The `area_source_discretization` (in km) is the step of the grid. The computation time is inversely proportional to the square of the discretization step, i.e. calculation with `area_source_discretization=5` will take up to four times more time than a calculation with `area_source_discretization=10`.

rupture_mesh_spacing: Fault sources are computed by converting the geometry of the fault into a mesh of points; the `rupture_mesh_spacing` is the parameter determining the size of the mesh. The computation time is quadratic with the inverse mesh spacing. Using a `rupture_mesh_spacing=2` instead of `rupture_mesh_spacing=5` will make

your calculation up to 6.25 times slower. Be warned that the engine may complain if the `rupture_mesh_spacing` is too large.

complex_fault_mesh_spacing: The same as the `rupture_mesh_spacing`, but for complex fault sources. If not specified, the value of `rupture_mesh_spacing` will be used. This is a common cause of problems; if you have performance issue you should consider using a larger `complex_fault_mesh_spacing`. For instance, if you use a `rupture_mesh_spacing=2` for simple fault sources but `complex_fault_mesh_spacing=10` for complex fault sources, your computation can become up to 25 times faster, assuming the complex fault sources are dominating the computation time.

2.2 Maximum distance

The engine gives users a lot of control on the maximum distance parameter. For instance, you can have a different maximum distance depending on the tectonic region, like in the following example:

maximum_distance = {'Active Shallow Crust': 200, 'Subduction': 500}

You can also have a magnitude-dependent maximum distance:

```
maximum_distance = [(5, 0), (6, 100), (7, 200), (8, 300)]
```

In this case, given a site, the engine will completely discard ruptures with magnitude below 5, keep ruptures up to 100 km for magnitudes between 5 and 6, keep ruptures up to 200 km for magnitudes between 6 and 7, keep ruptures up to 300 km for magnitudes over 7.

You can have both trt-dependent and mag-dependent maximum distance:

```
maximum_distance = {
   'Active Shallow Crust': [(5, 0), (6, 100), (7, 200), (8, 300)],
   'Subduction': [(6.5, 300), (9, 500)]}
```

Given a rupture with tectonic region type `trt` and magnitude `mag`, the engine will ignore all sites over the maximum distance `md(trt, mag)`. The precise value is given via linear interpolation of the values listed in the job.ini; you can determine the distance as follows:

```
>>> from openquake.hazardlib.calc.filters import MagDepDistance
>>> md = MagDepDistance.new('[(5, 0), (6, 100), (7, 200), (8, 300)]')
>>> md('TRT', 4.5)
0.0
>>> md('TRT', 5.5)
50.0
>>> md('TRT', 6.5)
150.0
```

```
>>> md('TRT', 7.5)
250.0
>>> md('TRT', 8.5)
300.0
```

2.3 pointsource_distance

PointSources (and MultiPointSources and AreaSources, which are split into PointSources and therefore are effectively the same thing) are not pointwise for the engine: they actually generate ruptures with rectangular surfaces which size is determined by the magnitude scaling relationship. The geometry and position of such rectangles depends on the hypocenter distribution and the nodal plane distribution of the point source, which are used to model the uncertainties on the hypocenter location and on the orientation of the underlying ruptures.

Is the effect of the hypocenter/nodal planes distributions relevant? Not always: in particular, if you are interested in points that are far away from the rupture the effect is minimal. So if you have a nodal plane distribution with 20 planes and a hypocenter distribution with 5 hypocenters, the engine will consider 20 x 5 ruptures and perform 100 times more calculations than needed, since at large distance the hazard will be more or less the same for each rupture.

To avoid this performance problem there is a `pointsource_distance` parameter: you can set it in the `job.ini` as a dictionary (tectonic region type -> distance in km) or as a scalar (in that case it is converted into a dictionary `{"default": distance}` and the same distance is used for all TRTs). For sites that are more distant than the *pointsource_distance* from the point source, the engine (starting from release 3.11) creates an average rupture by taking weighted means of the parameters *strike*, *dip*, *rake* and *depth* from the nodal plane and hypocenter distributions and by rescaling the occurrence rate. For closer points, all the original ruptures are considered. This approximation (we call it *rupture collapsing* because it essentially reduces the number of ruptures) can give a substantial speedup if the model is dominated by PointSources and there are several nodal planes/hypocenters in the distribution. In some situations it also makes sense to set

```
pointsource_distance = 0
```

to completely remove the nodal plane/hypocenter distributions. For instance the Indonesia model has 20 nodal planes for each point sources; however such model uses the so-called equivalent distance approximation which considers the point sources to be really pointwise. In this case the contribution to the hazard is totally independent from the nodal plane and by using `pointsource_distance = 0` one can get *exactly* the same numbers and run the model in 1 hour instead of 20 hours. Actually, starting from engine 3.3 the engine is smart enough to recognize the cases where the equivalent distance approximation is used and automatically set `pointsource_distance = 0`.

Even if you not using the equivalent distance approximation, the effect of the nodal plane/hypocenter distribution can be negligible: I have seen cases when setting setting

`pointsource_distance = 0` changed the result in the hazard maps only by 0.1% and gained an order of magnitude of speedup. You have to check on a case by case basis.

The `pointsource_distance` is also crucial when using the point source gridding approximation: then it can be used to speedup calculations even when the nodal plane and hypocenter distributions are trivial and no speedup would be expected.

NB: the `pointsource_distance` approximation has changed a lot across engine releases and you should not expect it to give always the same results. In particular, in engine 3.8 it has been extended to take into account the fact that small magnitudes will have a smaller collapse distance. For instance, if you set `pointsource_distance=100`, the engine will collapse the ruptures over 100 km for the maximum magnitude, but for lower magnitudes the engine will consider a (much) shorter collapse distance and will collapse a lot more ruptures. This is possible because given a tectonic region type the engine knows all the GMPEs associated to that tectonic region and can compute an upper limit for the maximum intensity generated by a rupture at any distance. Then it can invert the curve and given the magnitude and the maximum intensity can determine the collapse distance for that magnitude.

In engine 3.9 this feature has been removed and it is not used anymore. However, you will not get the same results than in engine 3.7 because the underlying logic has changed: before we were just picking one nodal plane/hypocenter from the distribution, now the approximation neglects completely the finite size effects by replacing planar ruptures with point ruptures of zero lenght. This is the reason why in engine 3.9 one should use larger pointsource_distances than before, since the approximation is cruder. On the other hand, it collapses more than before and it makes the engine much faster for single site analysis.

Starting from engine 3.9 you can set

pointsource_distance = ?

and the engine will automagically define a magnitude-dependent magnitude pointsource_distance, but it is recommended that you use your own distance, because in the next version the algorithm used with *pointsource_distance = ?* may change again.

In engine 3.11, contrarily to all previous releases, finite side effects are not ignored for distance sites, they are simply averaged over. This gives a better precision. In some case (i.e. the Alaska model) versions of the engine before 3.11 could give giving a completely wrong hazard on some sites. This is now fixed.

2.4 The linear parameters: *width_of_mfd_bin* and intensity levels

The number of ruptures generated by the engine is controlled by the parameter *width_of_mfd_bin*; for instance if you raise it from 0.1 to 0.2 you will reduce by half the number of ruptures and double the speed of the calculation. It is a linear parameter, at least approximately. Classical calculations

are also roughly linear in the number of intensity measure types and levels. A common mistake is to use too many levels. For instance a configuration like the following one:

```
intensity_measure_types_and_levels = {
  "PGA":  logscale(0.001,4.0, 100),
  "SA(0.3)":  logscale(0.001,4.0, 100),
  "SA(1.0)":  logscale(0.001,4.0, 100)}
```

requires computing the PoEs on 300 levels. Is that really what the user wants? It could very well be that using only 20 levels per each intensity measure type produces good enough results, while potentially reducing the computation time by a factor of 5.

2.5 concurrent_tasks parameter

There is a last parameter which is worthy of mention, because of its effect on the memory occupation in the risk calculators and in the event based hazard calculator.

concurrent_tasks: This is a parameter that you should not set, since in most cases the engine will figure out the correct value to use. However, in some cases, you may be forced to set it. Typically this happens in event based calculations, when computing the ground motion fields. If you run out of memory, increasing this parameter will help, since the engine will produce smaller tasks. Another case when it may help is when computing hazard statistics with lots of sites and realizations, since by increasing this parameter the tasks will contain less sites.

Notice that if the number of `concurrent_tasks` is too big the performance will get worse and the data transfer will increase: at a certain point the calculation will run out of memory. I have seen this to happen when generating tens of thousands of tasks. Again, it is best not to touch this parameter unless you know what you are doing.

CHAPTER

THREE

TIPS FOR RUNNING LARGE HAZARD CALCULATIONS

Running large hazard calculations, especially ones with large logic trees, is an art, and there are various techniques that can be used to reduce an impossible calculation to a feasible one.

3.1 Reducing a calculation

The first thing to do when you have a large calculation is to reduce it so that it can run in a reasonable amount of time. For instance you could reduce the number of sites, by considering a small geographic portion of the region interested, of by increasing the grid spacing. Once the calculation has been reduced, you can run it and determine what are the factors dominating the run time.

As we discussed in section common mistakes, you may want to tweak the quadratic parameters (`maximum_distance`, `area_source_discretization`, `rupture_mesh_spacing`, `complex_fault_mesh_spacing`). Also, you may want to choose different GMPEs, since some are faster than others. You may want to play with the logic tree, to reduce the number of realizations: this is especially important, in particular for event based calculation were the number of generated ground motion fields is linear with the number of realizations.

Once you have tuned the reduced computation, you can have an idea of the time required for the full calculation. It will be less than linear with the number of sites, so if you reduced your sites by a factor by a number of 100, the full computation will take a lot less than 100 times the time of the reduced calculation (fortunately). Still, the full calculation can be impossible because of the memory/data transfer requirements, especially in the case of event based calculations. Sometimes it is necessary to reduce your expectations. The examples below will discuss a few concrete cases. But first of all, we must stress an important point:

```
Our experience tells us that THE PERFORMANCE BOTTLENECKS OF THE
REDUCED CALCULATION ARE TOTALLY DIFFERENT FROM THE BOTTLENECKS OF
THE FULL CALCULATION. Do not trust your performance intuition.
```

3.2 Classical PSHA for Europe

Suppose you want to run a classical PSHA calculation for the latest model for Europe and that it turns out to be too slow to run on your infrastructure. Let's say it takes 4 days to run. How do you proceed to reduce the computation time?

The first thing that comes to mind is to tune the `area_source_discretization` parameter, since the calculation (as most calculations) is dominated by area sources. For instance, by doubling it (say from 10 km to 20 km) we would expect to reduce the calculation time from 4 days to just 1 day, a definite improvement.

But how do we check if the results are still acceptable? Also, how we check that in less than 4+1=5 days? As we said before we have to reduce the calculation and the engine provides several ways to do that.

If you want to reduce the number of sites, IMTs and realizations you can:

- manually change the `sites.csv` or `site_model.csv` files
- manually change the `region_grid_spacing`
- manually change the `intensity_measure_types_and_levels` variable
- manually change the GMPE logic tree file by commenting out branches
- manually change the source logic tree file by commenting out branches
- use the environment variable `OQ_SAMPLE_SITES`
- use the environment variable `OQ_REDUCE`

Starting from engine 3.11 the simplest approach is to use the `OQ_REDUCE` environment variable than not only reduce reduces the number of sites, but also reduces the number of intensity measure types (it takes the first one only) and the number of realizations to just 1 (it sets `number_of_logic_tree_samples=1`) and if you are in an event based calculation reduces the parameter `ses_per_logic_tree_path` too. For instance the command:

```
$ OQ_REDUCE=.01 oq engine --run job.ini
```

will reduce the number of sites by 100 times by random sampling, as well a reducing to 1 the number of IMTs and realizations. As a result the calculation will be very fast (say 1 hour instead of 4 days) and it will possible to re-run it multiple times with different parameters. For instance, you can test the impact of the area source discretization parameter by running:

```
$ OQ_REDUCE=.01 oq engine --run job.ini --param area_source_
↪discretization=20
```

Then the engine provides a command *oq compare* to compare calculations; for instance:

```
$ oq compare hmaps PGA -2 -1 --atol .01
```

will compare the hazard maps for PGA for the original (ID=-2, area_source_discretization=10 km) and the new calculation (ID=-2, area_source_discretization=20 km) on all sites, printing out the sites where the hazard values are different more than .01 g (`--atol` means absolute tolerence). You can use `oq compare --help` to see what other options are available.

If the call to `oq compare` gives a result:

```
There are no differences within the tolerances atol=0.01, rtol=0%,␣
↪sids=[...]
```

it means that within the specified tolerance the hazard is the same on all the sites, so you can safely use the area discretization of 20 km. Of course, the complete calculation will contain 100 times more sites, so it could be that in the complete calculation some sites will have different hazard. But that's life. If you want absolute certitude you will need to run the full calculation and to wait. Still, the reduced calculation is useful, because if you see that are already big differences there, you can immediately assess that doubling the `area_source_discretization` parameter is a no go and you can try other strategies, like for instance doubling the `width_of_mfd_bin` parameter.

As of version 3.11, the `oq compare hmaps` command will give an output like the following, in case of differences:

```
site_id calc_id 0.5     0.1     0.05    0.02    0.01    0.005
======= ======= ======= ======= ======= ======= ======= =======
767     -2      0.10593 0.28307 0.37808 0.51918 0.63259 0.76299
767     -1      0.10390 0.27636 0.36955 0.50503 0.61676 0.74079
======= ======= ======= ======= ======= ======= ======= =======

===== =========
poe   rms-diff
===== =========
0.5   1.871E-04
0.1   4.253E-04
0.05  5.307E-04
0.02  7.410E-04
0.01  8.856E-04
0.005 0.00106
===== =========
```

This is an example with 6 hazard maps, for poe = .5, .1, .05, .02, .01 and .005 respectively. Here the only site that shows some discrepancy if the site number 767. If that site is in Greenland where nobody lives one can decide that the approximation is good anyway ;-) The engine also report the RMS-differences by considering all the sites, i.e.

rms-diff = sqrt<(hmap1 - hmap2)^2> # mediating on all the sites

As to be expected, the differences are larger for maps with a smaller poe, i.e. a larger return period. But even in the worst case the RMS difference is only of 1E-3 g, which is not much. The complete

calculation will have more sites, so the RMS difference will likely be even smaller. If you can check the few outlier sites and convince yourself that they are not important, you have succeeded in doubling the speed on your computation. And then you can start to work on the other quadratic and linear parameter and to get an ever bigger speedup!

3.3 GMFs for California

We had an user asking for the GMFs of California on 707,920 hazard sites, using the UCERF mean model and an investigation time of 100,000 years. Is this feasible or not? Some back of the envelope calculations suggests that it is unfeasible, but reality can be different.

The relevant parameters are the following:

```
N = 707,920 hazard sites
E = 10^5 estimated events of magnitude greater then 5.5 in the␣
↪investigation
    time of 100,000 years
B = 1 number of branches in the UCERF logic tree
G = 5 number of GSIMS in the GMPE logic tree
I = 6 number of intensity measure types
S1 = 13 number of bytes used by the engine to store a single GMV
```

The maximum size of generated GMFs is

```
N * E * B * G * I * S1 = 25 TB (terabytes)
```

Storing and sharing 25 TB of data is a big issue, so the problem seems without solution. However, most of the ground motion values are zero, because there is a maximum distance of 300 km and a rupture cannot affect all of the sites. So the size of the GMFs should be less than 25 TB. Moreover, if you want to use such GMFs for a damage analysis, you may want to discard very small shaking that will not cause any damage to your buildings. The engine has a parameter to discard all GMFs below a minimum threshold, the `minimum_intensity` parameter. The higher the threshold, the smaller the size of the GMFs. By playing with that parameter you can reduce the size of the output by orders of magnitudes. Terabytes could easily become gigabytes with a well chosen threshold.

In practice, we were able to run the full 707,920 sites by splitting the sites in 70 tiles and by using a minimum intensity of 0.1 g. This was the limit configuration for our cluster which has 5 machines with 128 GB of RAM each.

The full calculation was completed in only 4 hours because our calculators are highly optimized. The total size of the generated HDF5 files was of 400 GB. This is a lot less than 25 TB, but still too large for sharing purposes.

Another way to reduce the output is to reduce the number of intensity measure types. Currently in your calculations there are 6 of them (PGA, SA(0.1), SA(0.2), SA(0.5), SA(1.0), SA(2.0)) but if you restrict yourself to only PGA the computation and the output will become 6 times smaller.

Also, there are 5 GMPEs: if you restrict yourself to 1 GMPE you gain a factor of 5. Similarly, you can reduce the investigation period from 100,000 year to 10,000 years, thus gaining another order of magnitude. Also, raising the minimum magnitude reduces the number of events significantly.

But the best approach is to be smart. For instance, we know from experience that if the final goal is to estimate the total loss for a given exposure, the correct way to do that is to aggregate the exposure on a smaller number of hazard sites. For instance, instead of the original 707,920 hazard sites we could aggregate on only ~7,000 hazard sites and we would a calculation which is 100 times faster, produces 100 times less GMFs and still produces a good estimate for the total loss.

In short, risk calculations for the mean field UCERF model are routines now, in spite of what the naive expectations could be.

CHAPTER

FOUR

TIPS FOR RUNNING LARGE RISK CALCULATIONS

Scenario risk calculations usually do not pose a performance problem, since they involve a single rupture and a limited geography for analysis. Some event-based risk calculations, however, may involve millions of ruptures and exposures spanning entire countries or even larger regions. This section offers some practical tips for running large event based risk calculations, especially ones involving large logic trees, and proposes techniques that might be used to make an intractable calculation tractable.

4.1 Understanding the hazard

Event-based calculations are typically dominated by the hazard component (unless there are lots of assets aggregated on few hazard sites) and therefore the first thing to do is to estimate the size of the hazard, i.e. the number of GMFs that will be produced. Since we are talking about a large calculation, first of all we need reduce it to a size that is guaranteed to run quickly. The simplest way to do that is to reduce the parameters directly affecting the number of ruptures generated, i.e.

- investigation_time
- ses_per_logic_tree_path
- number_of_logic_tree_samples

For instance, if you have `ses_per_logic_tree_path = 10,000` reduce it to 10, run the calculation and you will see in the log something like this:

```
[2018-12-16 09:09:57,689 #35263 INFO] Received
{'gmfdata': '752.18 MB', 'hcurves': '224 B', 'indices': '29.42 MB'}
```

The amount of GMFs generated for the reduced calculation is 752.18 MB; and since the calculation has been reduced by a factor of 1,000, the full computation is likely to generate around 750 GB of GMFs. Even if you have sufficient disk space to store this large quantity of GMFs, most likely you will run out of memory. Even if the hazard part of the calculation manages to run to completion, the risk part of the calculation is very likely to fail — managing 750 GB of GMFs is beyond the current capabilities of the engine. Thus, you will have to find ways to reduce the size of the computation.

A good start would be to carefully set the parameters `minimum_magnitude` and `minimum_intensity`:

- `minimum_magnitude` is a scalar or a dictionary keyed by tectonic region; the engine will discard ruptures with magnitudes below the given threshoulds
- `minimum_intensity` is a scalar or a dictionary keyed by the intensity measure type; the engine will discard GMFs below the given intensity threshoulds

Choosing reasonable cutoff thresholds with these parameters can significantly reduce the size of your computation when there are a large number of small magnitude ruptures or low intensity GMFs being generated, which may have a negligible impact on the damage or losses, and thus could be safely discarded.

4.2 Collapsing of branches

When one is not interested so much in the uncertainty around the loss estimates, but more interested simply in the mean estimates, all of the source model branches can be "collapsed" into one branch. Using the collapsed source model should yield the same mean hazard or loss estimates as using the full source model logic tree and then computing the weighted mean of the individual branch results.

Similarly, the GMPE logic tree for each tectonic region can also be "collapsed" into a single branch. Using a single collapsed GMPE for each TRT should also yield the same mean hazard estimates as using the full GMPE logic tree and then computing the weighted mean of the individual branch results. This has become possible through the introduction of AvgGMPE feature in version 3.9.

4.3 Splitting the calculation into subregions

If one is interested in propagating the full uncertainty in the source models or ground motion models to the hazard or loss estimates, collapsing the logic trees into a single branch to reduce computational expense is not an option. But before going through the effort of trimming the logic trees, there is an interim step that must be explored, at least for large regions like the entire continental United States. This step is to geographically divide the large region into logical smaller subregions, such that the contribution to the hazard or losses in one subregion from the other subregions is negligibly small or even zero. The effective realizations in each of the subregions will then be much fewer than when trying to cover the entire large region in a single calculation.

4.4 Trimming of the logic-trees or sampling of the branches

Trimming or sampling may be necessary if the following two conditions hold:

1. You are interested in propagating the full uncertainty to the hazard and loss estimates; only the mean or quantile results are not sufficient for your analysis requirements, AND
2. The region of interest cannot be logically divided further as described above; the logic-tree for your chosen region of interest still leads to a very large number of effective realizations.

Sampling is the easier of the two options now. You only need to ensure that you sample a sufficient number of branches to capture the underlying distribution of the hazard or loss results you are interested in. The drawback of random sampling is that you may still need to sample hundreds of branches to capture well the underlying distribution of the results.

Trimming can be much more efficient than sampling, because you pick a few branches such that the distribution of the hazard or loss results obtained from a full-enumeration of these branches is nearly the same as the distribution of the hazard or loss results obtained from a full-enumeration of the entire logic-tree.

4.5 Disabling the propagation of vulnerability uncertainty to losses

The vulnerability functions using continuous distributions (such as the lognormal distribution or beta distribution) to characterize the uncertainty in the loss ratio conditional on the shaking intensity level, specify the mean loss ratios and the corresponding coefficients of variation for a set of intensity levels. They are used to build the so called epsilon matrix within the engine, which is how loss ratios are sampled from the distribution for each asset.

There is clearly a performance penalty associated with the propagation of uncertainty in the vulnerability to losses. The epsilon matrix has to be computed and stored, and then the worker processes have to read it, which involves large quantities of data transfer and memory usage.

Setting

```
ignore_covs = true
```

in your *job.ini* file will result in the engine using just the mean loss ratio conditioned on the shaking intensity and ignoring the uncertainty. This tradeoff of not propagating the vulnerabilty uncertainty to the loss estimates can lead to a significant boost in performance and tractability.

4.6 The ebrisk calculator

Even with all the tricks in the book, some problems cannot be solved with the traditional `event_based_risk` calculator, in particular when there are too many hazard sites. Suppose for instance that you have a very detailed exposure for Canada with 462,000 hazard sites, and a corresponding site model covering all of the sites. It would be a pity to lose such detailed information by aggregating the assets onto a coarser grid, but this may be the only viable option for the traditional `event_based_risk` calculator.

The issue is that the `event_based_risk` cannot work well with so many sites, unless you reduce your investigation_time considerably. If the investigation_time is long enough for a reasonable computation, you will most likely run into issues such as:

1. running out of memory when computing the GMFs
2. running out of disk space when saving the GMFs
3. running out of memory when reading the GMFs
4. having an impossibly slow risk calculation

The solution - in theory - would be to split Canada in regions, but this comes with its own problems. For instance,

1. one has to compute the ruptures for all Canada in a single run, to make sure that the random seeds are consistent for all regions
2. then one has to run several calculations starting from the ruptures, one per sub-region
3. finally one has to carefully aggregate the results from the different calculations

Such steps are tedious, time consuming and very much error prone.

In order to solve such issues a new calculator, tentatively called `ebrisk`, has been introduced in engine 3.4. For small calculations the `ebrisk` calculator will not be much better than the `event_based_risk` calculator, but the larger your calculation is, the better it will work, and in situations like the Canada example here it can be orders of magnitude more efficient, both in speed and memory consumption. The reason why the `ebrisk` calculator is so efficient is that it computes the GMFs in memory instead of reading them from the datastore.

The older `event_based_risk` calculator works by storing the GMFs in the hazard phase of the calculation and by reading them in the risk phase. For small to medium sized risk calculations, this approach has the following advantages:

1. if the GMFs calculation is expensive, it is good to avoid repeating it when you change a risk parameter without changing the hazard parameters
2. it is convenient to have the GMFs saved on disk to debug issues with the calculation
3. except for huge calculations, writing and reading the GMFs is fast, since they stored in a very optimized HDF5 format

On the other hand, there are other considerations for large national or continental risk calculations:

1. these larger risk calculations are typically dominated by the reading time of the GMFs, which happens concurrently
2. saving disk space matters, as such large calculations can generate hundreds of gigabytes or even terabytes of GMFs that cannot be stored conveniently

So, in practice, in very large calculations the strategy of computing the GMFs on-the-fly wins over over the strategy of saving them to disk and this is why the `ebrisk` calculator exists.

4.7 Differences with the event_based_risk calculator

The `event_based_risk` calculator parallelizes by hazard sites: it splits the exposure in spatial blocks and then each task reads the GMFs for each site in the block it gets.

The `ebrisk` calculator instead parallelizes by ruptures: it splits the ruptures in blocks and then each task generates the corresponding GMFs on the fly.

Since the amount of data in ruptures form is typically two orders of magnitude smaller than the amount of data in GMFs, and since the GMF-generation is fast, the `ebrisk` calculator is able to beat the `event_based_risk` calculator.

Moreover, since each task in the `ebrisk` calculator gets sent the entire exposure, it is able to aggregate the losses without problems, while the `event_based_risk` calculator has troubles doing that — even if each task has access to all events, it only receives a subset of the exposure, so it cannot aggregate on the assets. Starting from engine 3.11 the `event_based_risk` calculator can compute aggregate losses and aggregate loss curves, but in an inefficient way, by collection partial returns from all tasks and aggregating them. That means that your calculation can easily run out of memory or can be extremely slow, while it would work much better by setting `calculation_mode=ebrisk`.

Aggregation of average annual losses, is computed simply by summing the component values. The algorithm is linear and both the `event_based_risk` calculator and the `ebrisk` calculator are capable of this aggregation, but the first calculator is more efficient.

4.8 The asset loss table and the agg_loss_table

When performing an event based risk (or ebrisk) calculation the engine keeps in memory a table with the losses for each asset and each event, for each loss type. It is usually impossible to fully store such table, because it is extremely large; for instance, for 1 million assets, 1 million events, 2 loss types and 4 bytes per loss ~8 TB of disk space would be required. It is true that many events will produce zero losses because of the *maximum_distance* and *minimum_intensity* parameters, but still the asset loss table is prohibitively large and for many years could not be stored. In engine 3.8 we made a breakthrough: we decided to store a partial asset loss table, obtained by discarding small

losses, by leveraging on the fact that loss curves for long enough return periods are dominated by extreme events, i.e. there is no point in saving all the small losses.

To that aim,the engine honors a parameter called `minimum_asset_loss` which determine how many losses are discarded when storing the asset loss table. The rule is simple: losses below `minimum_asset_loss` are discarded. By choosing the threshold properly in an ideal world

1. the vast majority of the losses would be discarded, thus making the asset loss table storable;
2. the loss curves would still be nearly identical to the ones without discarding any loss, except for small return periods.

It is the job of the user to verify if 1 and 2 are true in the real world. He can assess that by playing with the `minimum_asset_loss` in a small calculation, finding a good value for it, and then extending to the large calculation. Clearly it is a matter of compromise: by sacrificing precision it is possible to reduce enourmously the size of the stored asset loss table and to make an impossible calculation possible.

NB: starting from engine 3.11 the asset loss table is stored if the user specifies

```
aggregate_by = id
```

in the job.ini file. In large calculations it extremely easy to run out of memory or the make the calculation extremely slow, so we recommend not to store the asset loss table. The functionality is there for the sole purpose of debugging small calculations, for instance to see the effect of the `minimum_asset_loss` approximation at the asset level.

For large calculations usually one is interested in the aggregate loss table, which contains the losses per event and per aggregation tag (or multi-tag). For instance, the tag `occupancy` has the three values "Residential", "Industrial" and "Commercial" and by setting

```
aggregate_by = occupancy
```

the engine will store a pandas DataFrame with field `agg_id` with 4 possible value: 0 for "Residential", 1 for "Industrial", 2 for "Commercial" and 3 for the full aggregation.

NB: if the parameter `aggregate_by` is not specified, the engine will still compute the `agg_loss_table` but then the `agg_id` field will have a single value 0 corresponding to the total portfolio losses.

4.9 The Probable Maximum Loss (PML) and the loss curves

Given an effective investigation time, a return period and an `agg_loss_table`, the engine is able to compute a PML for each aggregation tag. It does so by using the function `openquake.risklib.scientific.losses_by_period` which takes in input an array of cumulative losses associated to the aggregation tag, a list of or return periods, and the effective investigation time. If there is a single return period the function returns the PML; if there are multiple return

periods it returns the loss curve. The two concepts are essentially the same thing, since a loss curve is just an array of PMLs, one for each return period. For instance

computes the Probably Maximum Loss at 500 years for the given losses with an effective investigation time of 1000 years. The algorithm works by ordering the losses (suppose there are E > 1 losses) generating E time periods `eff_time/E, eff_time/(E-1), ... eff_time/1` and log-interpolating the loss at the return period. Of course this works only if the condition

```
eff_time/E < return_period < eff_time
```

is respected. In this example there are E=16 losses, so the return period must be in the range 62.5 .. 1000 years. If the return period is too small the PML will be zero

```
>>> losses_by_period(losses, [50], eff_time=1000)
array([0.])
```

while if the return period is outside the investigation range we will refuse the temptation to extrapolate and we will return NaN instead:

```
>>> losses_by_period(losses, [1500], eff_time=1000)
array([nan])
```

The rules above are the reason while you will see zeros or NaNs in the loss curves generated by the engine sometimes, especially when there are too few events: the valid range will be small and some return periods may slip outside the range.

In order to compute aggregate loss curves you must set the `aggregate_by` parameter in the `job.ini` to one or more tags over which you wish to perform the aggregation. Your exposure must contain the specified tags with values for each asset. We have an example for Nepal in our event based risk demo. The exposure for this demo contains various tags and in particular a geographic tag called NAME1 with values "Mid-Western", "Far-Western", "West", "East", "Central", and the `job_eb.ini` file defines

```
aggregate_by = NAME_1
```

When running the calculation you will see something like this:

```
 Calculation 1 finished correctly in 17 seconds
id | name
 9 | Aggregate Event Losses
 1 | Aggregate Loss Curves
 2 | Aggregate Loss Curves Statistics
 3 | Aggregate Losses
 4 | Aggregate Losses Statistics
 5 | Average Asset Losses Statistics
11 | Earthquake Ruptures
 6 | Events
 7 | Full Report
 8 | Input Files
```

```
10 | Realizations
12 | Total Loss Curves
13 | Total Loss Curves Statistics
14 | Total Losses
15 | Total Losses Statistics
```

Exporting the *Aggregate Loss Curves Statistics* output will give you the mean and quantile loss curves in a format like the following one:

```
annual_frequency_of_exceedence,return_period,loss_type,loss_value,loss_
↪ratio
5.00000E-01,2,nonstructural,0.00000E+00,0.00000E+00
5.00000E-01,2,structural,0.00000E+00,0.00000E+00
2.00000E-01,5,nonstructural,0.00000E+00,0.00000E+00
2.00000E-01,5,structural,0.00000E+00,0.00000E+00
1.00000E-01,10,nonstructural,0.00000E+00,0.00000E+00
1.00000E-01,10,structural,0.00000E+00,0.00000E+00
5.00000E-02,20,nonstructural,0.00000E+00,0.00000E+00
5.00000E-02,20,structural,0.00000E+00,0.00000E+00
2.00000E-02,50,nonstructural,0.00000E+00,0.00000E+00
2.00000E-02,50,structural,0.00000E+00,0.00000E+00
1.00000E-02,100,nonstructural,0.00000E+00,0.00000E+00
1.00000E-02,100,structural,0.00000E+00,0.00000E+00
5.00000E-03,200,nonstructural,1.35279E+05,1.26664E-06
5.00000E-03,200,structural,2.36901E+05,9.02027E-03
2.00000E-03,500,nonstructural,1.74918E+06,1.63779E-05
2.00000E-03,500,structural,2.99670E+06,1.14103E-01
1.00000E-03,1000,nonstructural,6.92401E+06,6.48308E-05
1.00000E-03,1000,structural,1.15148E+07,4.38439E-01
```

If you do not set the `aggregate_by` parameter you will still able to compute the total loss curve (for the entire portfolio of assets), and the total average losses.

CHAPTER

FIVE

THE CONCEPT OF EFFECTIVE REALIZATIONS

The management of the logic trees is the most complicated thing in the OpenQuake engine. It is important to manage the logic trees in an efficient way, by avoiding redundant computation and storage, otherwise the engine will not be able to cope with large computations. To that aim, it is essential to understand the concept of *effective realizations*.

The crucial point is that in many calculations it is possible to reduce the full logic tree (the tree of the potential realizations) to a much smaller one (the tree of the effective realizations).

First, it is best to give some terminology.

1. for each source model in the source model logic tree there is potentially a different GMPE logic tree
2. the total number of realizations is the sum of the number of realizations of each GMPE logic tree
3. a GMPE logic tree is *trivial* if it has no tectonic region types with multiple GMPEs
4. a GMPE logic tree is *simple* if it has at most one tectonic region type with multiple GMPEs
5. a GMPE logic tree is *complex* if it has more than one tectonic region type with multiple GMPEs.

Here is an example of trivial GMPE logic tree, in its XML input representation:

```
<?xml version="1.0" encoding="UTF-8"?>
<nrml xmlns:gml="http://www.opengis.net/gml"
      xmlns="http://openquake.org/xmlns/nrml/0.4">
   <logicTree logicTreeID='lt1'>
            <logicTreeBranchSet uncertaintyType="gmpeModel" branchSetID=
↪"bs1"
                        applyToTectonicRegionType="active shallow crust">

                <logicTreeBranch branchID="b1">
                    <uncertaintyModel>SadighEtAl1997</uncertaintyModel>
                    <uncertaintyWeight>1.0</uncertaintyWeight>
                </logicTreeBranch>
```

```
            </logicTreeBranchSet>
    </logicTree>
</nrml>
```

The logic tree is trivial since there is a single branch ("b1") and GMPE ("SadighEtAl1997") for each tectonic region type ("active shallow crust"). A logic tree with multiple branches can be simple, or even trivial if the tectonic region type with multiple branches is not present in the underlying source model. This is the key to the logic tree reduction concept.

5.1 Reduction of the logic tree

The simplest case of logic tree reduction is when the actual sources do not span the full range of tectonic region types in the GMPE logic tree file. This happens very often. FOr instance, in the SHARE calculation for Europe the GMPE logic tree potentially contains 1280 realizations coming from 7 different tectonic region types:

Active_Shallow: 4 GMPEs (b1, b2, b3, b4)

Stable_Shallow: 5 GMPEs (b21, b22, b23, b24, b25)

Shield: 2 GMPEs (b31, b32)

Subduction_Interface: 4 GMPEs (b41, b42, b43, b44)

Subduction_InSlab: 4 GMPEs (b51, b52, b53, b54)

Volcanic: 1 GMPE (b61)

Deep: 2 GMPEs (b71, b72)

The number of paths in the logic tree is 4 * 5 * 2 * 4 * 4 * 1 * 2 = 1280, pretty large. We say that there are 1280 *potential realizations* per source model. However, in most computations, the user will be interested only in a subset of them. For instance, if the sources contributing to your region of interest are only of kind *Active_Shallow* and *Stable_Shallow*, you would consider only 4 * 5 = 20 effective realizations instead of 1280. Doing so may improve the computation time and the needed storage by a factor of 1280 / 20 = 64, which is very significant.

Having motivated the need for the concept of effective realizations, let explain how it works in practice. For sake of simplicity let us consider the simplest possible situation, when there are two tectonic region types in the logic tree file, but the engine contains only sources of one tectonic region type. Let us assume that for the first tectonic region type (T1) the GMPE logic tree file contains 3 GMPEs (A, B, C) and that for the second tectonic region type (T2) the GMPE logic tree file contains 2 GMPEs (D, E). The total number of realizations (assuming full enumeration) is

$$total\_num\_rlzs = 3 * 2 = 6$$

The realizations are identified by an ordered pair of GMPEs, one for each tectonic region type. Let's number the realizations, starting from zero, and let's identify the logic tree path with the notation <*GMPE of first region type*>_<*GMPE of second region type*>:

#	lt_path
0	*A_D*
1	*B_D*
2	*C_D*
3	*A_E*
4	*B_E*
5	*C_E*

Now assume that the source model does not contain sources of tectonic region type T1, or that such sources are filtered away since they are too distant to have an effect: in such a situation we would expect to have only 2 effective realizations corresponding to the GMPEs in the second tectonic region type. The weight of each effective realizations will be three times the weight of a regular representation, since three different paths in the first tectonic region type will produce exactly the same result. It is not important which GMPE was chosen for the first tectonic region type because there are no sources of kind T1. In such a situation there will be 2 effective realizations coming from a total of 6 total realizations. It means that there will be three copies of the outputs, i.e. three identical outputs for each effective realization.

Starting from engine 3.9 *the logic tree reduction must be performed manually*, by discarding the irrelevant tectonic region types; in this example the user must add in the *job.ini* a line

```
discard_trts = Shield, Subduction_Interface, Subduction_InSlab,
Volcanic, Deep
```

If not, multiple copies of the same outputs will appear.

5.2 How to analyze the logic tree of a calculation without running the calculation

The engine provides some facilities to explore the logic tree of a computation without running it. The command you need is the `oq info` command.

Let's assume that you have a zip archive called *SHARE.zip* containing the SHARE source model, the SHARE source model logic tree file and the SHARE GMPE logic tree file as provided by the SHARE collaboration, as well as a *job.ini* file. If you run

```
$ oq info SHARE.zip
```

all the files will be parsed and the full logic tree of the computation will be generated. This is very fast, it runs in exactly 1 minute on my laptop, which is impressive, since the XML of the SHARE source models is larger than 250 MB. Such speed come with a price: all the sources are parsed, but

they are not filtered, so you will get the complete logic tree, not the one used by your computation, which will likely be reduced because filtering will likely remove some tectonic region types.

The output of the *info* command will start with a *CompositionInfo* object, which contains information about the composition of the source model. You will get something like this:

```
<CompositionInfo
b1, area_source_model.xml, trt=[0, 1, 2, 3, 4, 5, 6], weight=0.500:␣
↪1280 realization(s)
b2, faults_backg_source_model.xml, trt=[7, 8, 9, 10, 11, 12, 13],␣
↪weight=0.200: 1280 realization(s)
b3, seifa_model.xml, trt=[14, 15, 16, 17, 18, 19], weight=0.300: 640␣
↪realization(s)>
```

You can read the lines above as follows. The SHARE model is composed by three submodels:

- *area_source_model.xml* contains 7 Tectonic Region Types numbered from 0 to 7 and produces 1280 potential realizations;
- *faults_backg_source_model.xml* contains 7 Tectonic Region Types numbered from 7 to 13 and produces 1280 potential realizations;
- *seifa_model.xml* contains 6 Tectonic Region Types numbered from 14 to 19 and produces 640 potential realizations;

In practice, you want to know if your complete logic tree will be reduced by the filtering, i.e. you want to know the effective realizations, not the potential ones. You can perform that check by using the *–report* flag. This will generate a report with a name like *report_<calc_id>.rst*:

```
$ oq info --report SHARE.zip
...
[2020-04-14 11:11:50 #2493 WARNING] No sources for some TRTs: you␣
↪should set
discard_trts = Subduction_InSlab, Deep
...
Generated /home/michele/report_2493.rst
```

If you open that file you will find a lot of useful information about the source model, its composition, the number of sources and ruptures and the effective realizations.

Depending on the location of the points and the maximum distance, one or more submodels could be completely filtered out and could produce zero effective realizations, so the reduction effect could be even stronger.

In any case *the warning tells the user what she should do* in order to remove the duplication and reduce the calculation only to the effective realizations, i.e. which are the TRTs to discard in the *job.ini* file.

CHAPTER

SIX

LOGIC TREE SAMPLING STRATEGIES

Stating from version 3.10, the OpenQuake engine suppports 4 different strategies for sampling the logic tree. They are called, respectively, `early_weights`, `late_weights`, `early_latin`, `late_latin`. Here we will discuss how they work.

First of all, we must point out that logic tree sampling is controlled by three parameters in the job.ini:

- number_of_logic_tree_samples (default 0, no sampling)
- sampling_method (default `early_weights`)
- random_seed (default 42)

When sampling is enabled `number_of_logic_tree_samples` is a positive number, equal to the number of branches to be randomly extracted from full logic tree of the calculation. The precise why the random extraction works depends on the sampling method.

early_weights We this sampling method, the engine randomly choose branches depending on the weights in the logic tree; having done that, the hazard curve statistics (mean and quantiles) are computed with equal weights.

late_weights We this sampling method, the engine randomly choose branches ignoring the weights in the logic tree; however, the hazard curve statistics are computed by taking into account the weights.

early_latin We this sampling method, the engine randomly choose branches depending on the weights in the logic tree by using an hypercube latin sampling; having done that, the hazard curve statistics are computed with equal weights.

late_latin We this sampling method, the engine randomly choose branches ignoring the weights in the logic tree, but still using an hypercube sampling; then, the hazard curve statistics are computed by taking into account the weights.

More precisely, the engine calls something like the function

‘‘**openquake.hazardlib.lt.random_sample(** branchsets, num_samples, seed, sampling_method)‘‘

You are invited to play with it; in general the latin sampling produces samples much closer to the expected weights even with few samples. Here in an example with two branchsets with weights [.4, .6] and [.2, .3, .5] respectively.

```
>>> bsets = [[('X', .4), ('Y', .6)], [('A', .2), ('B', .3), ('C', .5)]]
```

With 100 samples one would expect to get the path XA 8 times, XB 12 times, XC 20 times, YA 12 times, YB 18 times, YC 30 times. Instead we get:

```
>>> paths = random_sample(bsets, 100, 42, 'early_weights')
>>> collections.Counter(paths)
Counter({'YC': 26, 'XC': 24, 'YB': 17, 'XA': 13, 'YA': 10, 'XB': 10})
```

```
>>> paths = random_sample(bsets, 100, 42, 'late_weights')
>>> collections.Counter(paths)
Counter({'XA': 20, 'YA': 18, 'XB': 17, 'XC': 15, 'YB': 15, 'YC': 15})
```

```
>>> paths = random_sample(bsets, 100, 42, 'early_latin')
>>> collections.Counter(paths)
Counter({'YC': 31, 'XC': 19, 'YB': 17, 'XB': 13, 'YA': 12, 'XA': 8})
```

```
>>> paths = random_sample(bsets, 100, 45, 'late_latin')
>>> collections.Counter(paths)
Counter({'YC': 18, 'XA': 18, 'XC': 16, 'YA': 16, 'XB': 16, 'YB': 16})
```

CHAPTER

SEVEN

RUPTURE SAMPLING: HOW DOES IT WORK?

In this section we will explain how the sampling of ruptures in event based calculations works, at least for the case of poissonian sources. As an example, we will consider the following point source:

```
>>> from openquake.hazardlib import nrml
>>> src = nrml.get('''\
... <pointSource id="1" name="Point Source"
...              tectonicRegion="Active Shallow Crust">
...     <pointGeometry>
...         <gml:Point><gml:pos>179.5 0</gml:pos></gml:Point>
...         <upperSeismoDepth>0</upperSeismoDepth>
...         <lowerSeismoDepth>10</lowerSeismoDepth>
...     </pointGeometry>
...     <magScaleRel>WC1994</magScaleRel>
...     <ruptAspectRatio>1.5</ruptAspectRatio>
...     <truncGutenbergRichterMFD aValue="3" bValue="1" minMag="5"␣
↪maxMag="7"/>
...     <nodalPlaneDist>
...         <nodalPlane dip="30" probability="1" strike="45" rake="90"␣
↪/>
...     </nodalPlaneDist>
...     <hypoDepthDist>
...         <hypoDepth depth="4" probability="1"/>
...     </hypoDepthDist>
... </pointSource>''', investigation_time=1, width_of_mfd_bin=1.0)
```

The source here is particularly simple, with only one seismogenic depth and one nodal plane. It generates two ruptures, because with a `width_of_mfd_bin` of 1 there are only two magnitudes in the range from 5 to 7:

```
>>> [(mag1, rate1), (mag2, rate2)] = src.get_annual_occurrence_rates()
>>> mag1
5.5
>>> mag2
```

```
6.5
```

The occurrence rates are respectively 0.009 and 0.0009. So, if we set the number of stochastic event sets to 1,000,000

```
>>> num_ses = 1_000_000
```

we would expect the first rupture (the one with magnitude 5.5) to occur around 9000 times and the second rupture (the one with magnitude 6.5) to occur around 900 times. Clearly the exact numbers will depend on the stochastic seed; if we set

```
>>> import numpy.random
>>> numpy.random.seed(42)
```

then we will have (for investigation_time=1)

```
>>> numpy.random.poisson(rate1 * num_ses * 1)
8966
>>> numpy.random.poisson(rate2 * num_ses * 1)
921
```

These are the number of occurrences of each rupture in the effective investigation time, i.e. the investigation time multiplied by the number of stochastic event sets and the number of realizations (here we assumed 1 realization).

The total number of events generated by the source will be

```
number_of_events = sum(n_occ for each rupture)
```

i.e. 8966 + 921 = 9887, with ~91% of the events associated to the first rupture and ~9% of the events associated to the second rupture.

Since the details of the seed algorithm changes at each release of the engine, if you run an event based calculation with the same parameters you will not get exactly the same number of events, but something close. After running the calculation inside the datastore, in the `ruptures` dataset you will find the two ruptures, their occurrence rates and their integer number of occurrences (`n_occ`). If the effective investigation time is large enough the relation

```
n_occ ~ occurrence_rate * eff_investigation_time
```

will hold. If the effective investigation time is not large enough, or the occurrence rate is extremely small, then there will be big differences between the expected number of occurrences and `n_occ`, as well as a strong seed dependency.

It is important to notice than in order to determine the effective investigation time the engine takes into account also the logic tree and the correct formula to use is

```
eff_investigation_time = investigation_time * num_ses * num_rlzs
```

where `num_rlzs` is the number of realizations in the logic tree.

Just to be concrete, if you run a calculation with the same parameters as described before, but with two GMPEs instead of one (and `number_of_logic_tree_samples=0`), then the total number of paths admitted by the logic tree will be 2 and you should expect to get about twice the number of occurrences for each rupture.

Users wanting to know the nitty-gritty details should look at the code, inside hazardlib/source/base.py, in the method `src.sample_ruptures(eff_num_ses, ses_seed)`.

CHAPTER

EIGHT

EXTRA TIPS SPECIFIC TO EVENT BASED CALCULATIONS

Event based calculations differ from classical calculations because they produce visible ruptures, which can be exported and made accessible to the user. In classical calculations, instead, the underlying ruptures only live in memory and are normally not saved in the datastore, nor are exportable. The limitation is fundamentally a technical one: in the case of an event based calculation only a small fraction of the ruptures contained in a source are actually generated, so it is possible to store them. In a classical calculation *all* ruptures are generated and there are so many millions of them that it is impractical to save them, unless there are very few sites. For this reason they live in memory, they are used to produce the hazard curves and immediately discarded right after. The exception if for the case of few sites, i.e. if the number of sites is less than the parameter `max_sites_disagg` which by default is 10.

8.1 Sampling of the logic tree

There are real life examples of very complex logic trees, like the model for South Africa which features 3,194,799,993,706,229,268,480 branches. In such situations it is impossible to perform a full computation. However, the engine allows to sample the branches of the complete logic tree. More precisely, for each branch sampled from the source model logic tree a branch of the GMPE logic tree is chosen randomly, by taking into account the weights in the GMPE logic tree file.

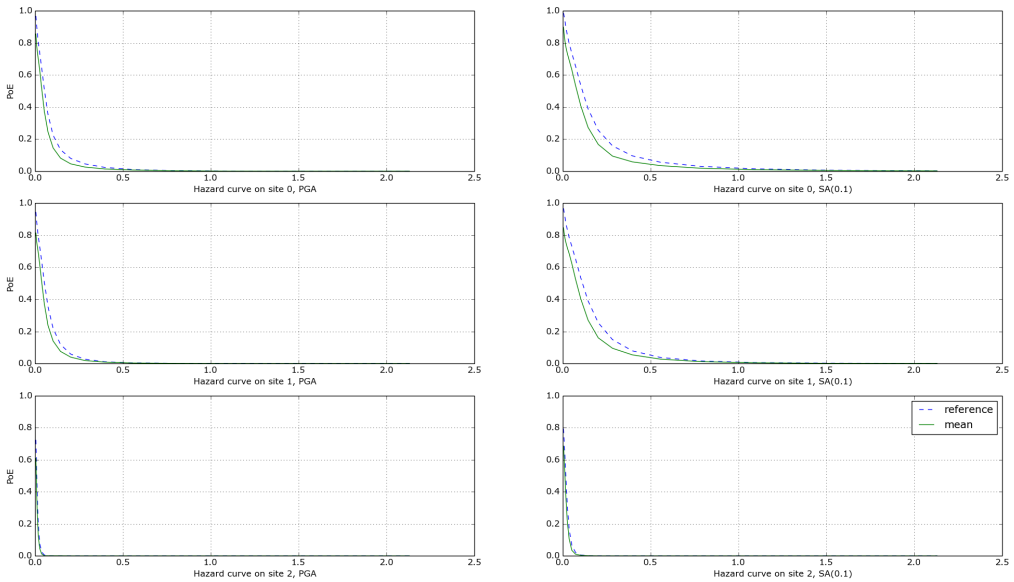
The details of how the sampling works are documented here:

It should be noticed that even if source model path is sampled several times, the model is parsed and sent to the workers *only once*. In particular if there is a single source model (like for South America) and `number_of_logic_tree_samples =100`, we generate effectively 1 source model realization and not 100 equivalent source model realizations, as we did in past (actually in the engine version 1.3). The engine keeps track of how many times a model has been sampled (say *Ns*) and in the event based case it produce ruptures (*with different seeds*) by calling the appropriate hazardlib function *Ns* times. This is done inside the worker nodes. In the classical case, all the ruptures are identical and there are no seeds, so the computation is done only once, in an efficient way.

8.2 Convergency of the GMFs for non-trivial logic trees

In theory, the hazard curves produced by an event based calculation should converge to the curves produced by an equivalent classical calculation. In practice, if the parameters `number_of_logic_tree_samples` and `ses_per_logic_tree_path` (the product of them is the relevant one) are not large enough they may be different. The engine is able to compare the mean hazard curves and to see how well they converge. This is done automatically if the option `mean_hazard_curves = true` is set. Here is an example of how to generate and plot the curves for one of our QA tests (a case with bad convergence was chosen on purpose):

```
$ oq engine --run event_based/case_7/job.ini
<snip>
WARNING:root:Relative difference with the classical mean curves for␣
 ↪IMT=SA(0.1): 51%
WARNING:root:Relative difference with the classical mean curves for␣
 ↪IMT=PGA: 49%
<snip>
$ oq plot /tmp/cl/hazard.pik /tmp/hazard.pik --sites=0,1,2
```



The relative difference between the classical and event based curves is computed by computing the relative difference between each point of the curves for each curve, and by taking the maximum, at least for probabilities of exceedence larger than 1% (for low values of the probability the convergency may be bad). For the details I suggest you to look at the code.

CHAPTER

NINE

SITE-SPECIFIC CLASSICAL CALCULATIONS

Starting from version 3.9, the engine offers some optimizations for site specific classical calculations.

9.1 Rupture collapsing

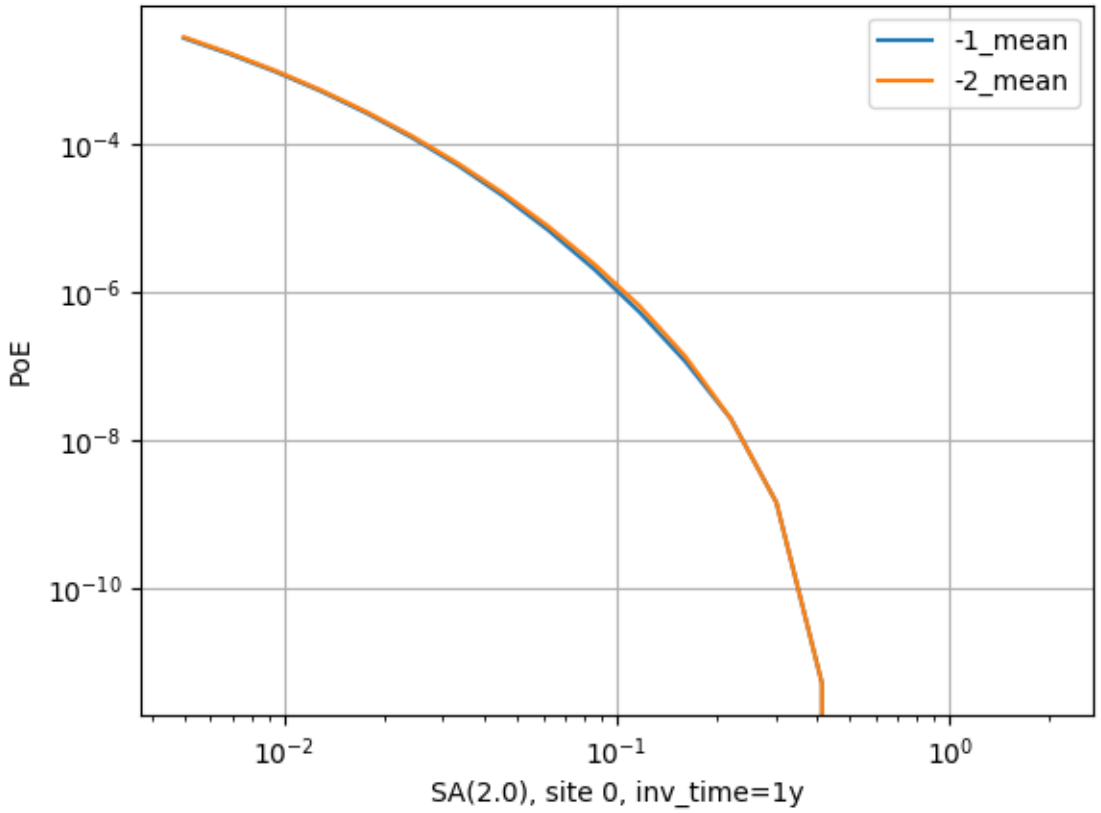
If you have multiple sites and you have set the *pointsource_distance* parameter in the job.ini, then the nodal plane distributions and hypocenter distributions will be collapsed for far away ruptures, as we discussed in the section about common mistakes. If you have a single site, and if you have set in the `job.ini` the parameter

```
collapse_level = 1
```

an additional collapsing will be applied, that will further reduce the effective number of ruptures, even in the case of trivial nodal plane distributions and hypocenter distributions. This additional collapsing takes the ruptures that are more distant than the *pointsource_distance* from the site of interest, groups them by magnitude and distance, and take only one representative per bin. The number of distance bins is determined by the parameter *point_rupture_bins*, which has a default of 20, and which can be tuned in the *job.ini* file. This reduces greatly the number of ruptures at the cost of a minor loss in precision.

By setting `collapse_level = 2` one can get even a greater collapsing, which for the moment is left undocumented.

There is a discussion of the mechanism in the MultiPointClassicalPSHA demo. Here we will just show a plot displaying the hazard curve without *pointsource_distance* (with ID=-2) and with *pointsource_distance=200* km (with ID=-1). As you see they are nearly identical but the second calculation is ten times faster.


-1_mean
-2_mean
10^{-4}
10^{-6}
10^{-8}
10^{-10}
PoE
10^{-2}
10^{-1}
10^{0}
SA(2.0), site 0, inv_time=1y

CHAPTER

TEN

EXTRACTING DATA FROM CALCULATIONS

The engine has a relatively large set of predefined outputs, that you can get in various formats, like CSV, XML or HDF5. They are all documented in the manual and they are the recommended way of interacting with the engine, if you are not tech-savvy.

However, sometimes you *must* be tech-savvy: for instance if you want to post-process hundreds of GB of ground motion fields produced by an event based calculation, you should *not* use the CSV output, at least if you care about efficiency. To manage this case (huge amounts of data) there a specific solution, which is also able to manage the case of data lacking a predefined exporter: the `Extractor` API.

There are actually two different kind of extractors: the simple `Extractor`, which is meant to manage large data sets (say > 100 MB) and the `WebExtractor`, which is able to interact with the WebAPI and to extract data from a remote machine. The WebExtractor is nice, but cannot be used for large amount of data for various reasons; in particular, unless your Internet connection is ultra-fast, downloading GBs of data will probably send the web request in timeout, causing it to fail. Even if there is no timeout, the WebAPI will block, everything will be slow, the memory occupation and disk space will go up, and at certain moment something will fail.

The `WebExtractor` is meant for small to medium outputs, things like the mean hazard maps - an hazard map containing 100,000 points and 3 PoEs requires only 1.1 MB of data at 4 bytes per point. Mean hazard curves or mean average losses in risk calculation are still small enough for the `WebExtractor`. But if you want to extract all of the realizations you must go with the simple `Extractor`: in that case your postprocessing script must run in the remote machine, since it requires direct access to the datastore.

Here is an example of usage of the `Extractor` to retrieve mean hazard curves:

```
>>> from openquake.calculators.extract import Extractor
>>> calc_id = 42  # for example
>>> extractor = Extractor(calc_id)
>>> obj = extractor.get('hcurves?kind=mean&imt=PGA')  # returns an␣
↪ArrayWrapper
>>> obj.array.shape  # an example with 10,000 sites and 20 levels per␣
↪PGA
(10000, 20)
```

```
>>> extractor.close()
```

Here is an example of using the *WebExtractor* to retrieve hazard maps. Here we assumes that there is available in a remote machine where there is a WebAPI server running, a.k.a. the Engine Server. The first thing to is to set up the credentials to access the WebAPI. There are two cases:

1. you have a production installation of the engine in `/opt`
2. you have a development installation of the engine in a virtualenv

In both case you need to create a file called `openquake.cfg` with the following format:

```
[webapi]
server = http(s)://the-url-of-the-server(:port)
username = my-username
password = my-password
```

`username` and `password` can be left empty if the authentication is not enabled in the server, which is the recommended way, if the server is in your own secure LAN. Otherwise you must set the right credentials. The difference between case 1 and case 2 is in where to put the `openquake.cfg` file: if you have a production installation, put it in your $HOME, if you have a development installation, put it in your virtualenv directory.

The usage then is the same as the regular extractor:

```
>>> from openquake.calculators.extract import WebExtractor
>>> extractor = WebExtractor(calc_id)
>>> obj = extractor.get('hmaps?kind=mean&imt=PGA')  # returns an␣
↪ArrayWrapper
>>> obj.array.shape  # an example with 10,000 sites and 4 PoEs
(10000, 4)
>>> extractor.close()
```

If you do not want to put your credentials in the `openquake.cfg` file, you can do so, but then you need to pass them explicitly to the WebExtractor:

```
>>> extractor = WebExtractor(calc_id, server, username, password)
```

10.1 Plotting

The (Web)Extractor is used in the *oq plot* command: by configuring `openquake.cfg` it is possible to plot things like hazard curves, hazard maps and uniform hazard spectra for remote (or local) calculations. Here are three examples of use:

```
$ oq plot 'hcurves?kind=mean&imt=PGA&site_id=0' <calc_id>
$ oq plot 'hmaps?kind=mean&imt=PGA' <calc_id>
$ oq plot 'uhs?kind=mean&site_id=0' <calc_id>
```

The `site_id` is optional; if missing only the first site (`site_id=0`) will be plotted. If you want to plot all the realizations you can do:

```
$ oq plot 'hcurves?kind=rlzs&imt=PGA' <calc_id>
```

If you want to plot all statistics you can do:

```
$ oq plot 'hcurves?kind=stats&imt=PGA' <calc_id>
```

It is also possible to combine plots. For instance if you want to plot all realizations and also the mean the command to give is:

```
$ oq plot 'hcurves?kind=rlzs&kind=mean&imt=PGA' <calc_id>
```

If you want to plot the mean and the median the command is:

```
$ oq plot 'hcurves?kind=quantile-0.5&kind=mean&imt=PGA' <calc_id>
```

assuming the median (i.e. *quantile-0.5*) is available in the calculation. If you want to compare say rlz-0 with rlz-2 and rlz-5 you can just just say so:

```
$ oq plot 'hcurves?kind=rlz-0&kind=rlz-2&kind=rlz-5&imt=PGA' <calc_id>
```

You can combine as many kinds of curves as you want. Clearly if your are specifying a kind that is not available you will get an error.

10.2 Extracting ruptures

Here is an example for the event based demo:

```
$ cd oq-engine/demos/hazard/EventBasedPSHA/
$ oq engine --run job.ini
$ oq shell
IPython shell with a global object "o"
In [1]: from openquake.calculators.extract import Extractor
In [2]: extractor = Extractor(calc_id=-1)
In [3]: aw = extractor.get('rupture_info?min_mag=5')
In [4]: aw
Out[4]: <ArrayWrapper(1511,)>
In [5]: aw.array
Out[5]:
```

```
array([(   0, 1, 5.05, 0.08456118,  0.15503392, 5., b'Active Shallow␣
↪Crust', 0.0000000e+00, 90.      , 0.),
       (   1, 1, 5.05, 0.08456119,  0.15503392, 5., b'Active Shallow␣
↪Crust', 4.4999969e+01, 90.      , 0.),
       (   2, 1, 5.05, 0.08456118,  0.15503392, 5., b'Active Shallow␣
↪Crust', 3.5999997e+02, 49.999985, 0.),
       ...,
       (1508, 2, 6.15, 0.26448786, -0.7442877 , 5., b'Active Shallow␣
↪Crust', 0.0000000e+00, 90.      , 0.),
       (1509, 1, 6.15, 0.26448786, -0.74428767, 5., b'Active Shallow␣
↪Crust', 2.2499924e+02, 50.000004, 0.),
       (1510, 1, 6.85, 0.26448786, -0.74428767, 5., b'Active Shallow␣
↪Crust', 4.9094699e-04, 50.000046, 0.)],
      dtype=[('rup_id', '<u4'), ('multiplicity', '<u2'), ('mag', '<f4
↪'), ('centroid_lon', '<f4'),
             ('centroid_lat', '<f4'), ('centroid_depth', '<f4'), ('trt
↪', 'S50'), ('strike', '<f4'),
             ('dip', '<f4'), ('rake', '<f4')])
In [6]: extractor.close()
```

CHAPTER

ELEVEN

READING OUTPUTS WITH PANDAS

If you are a scientist familiar with Pandas, you will be happy to know that it is possible to process the engine outputs with it. Here we will give an example involving hazard curves.

Suppose you ran the AreaSourceClassicalPSHA demo, with calculation ID=42; then you can process the hazard curves as follows:

```
>>> from openquake.baselib.datastore import read
>>> dstore = read(42)
>>> df = dstore.read_df('hcurves-stats', index='lvl',
...                     sel=dict(imt='PGA', stat='mean', site_id=0))
     site_id stat     imt     value
lvl
0          0  b'mean'  b'PGA'  0.999982
1          0  b'mean'  b'PGA'  0.999949
2          0  b'mean'  b'PGA'  0.999850
3          0  b'mean'  b'PGA'  0.999545
4          0  b'mean'  b'PGA'  0.998634
..       ...      ...     ...       ...
44         0  b'mean'  b'PGA'  0.000000
```

The dictionary `dict(imt='PGA', stat='mean', site_id=0)` is used to select subsets of the entire dataset: in this case hazard curves for mean PGA for the first site.

If you do not like pandas, or for some reason you prefer plain numpy arrays, you can get a slice of hazard curves by using the `.sel` method:

```
>>> arr = dstore.sel('hcurves-stats', imt='PGA', stat='mean', site_
↪id=0)
>>> arr.shape  # (num_sites, num_stats, num_imts, num_levels)
(1, 1, 1, 45)
```

Notice that the *.sel* method does not reduce the number of dimensions of the original array (4 in this case), it just reduces the number of elements. It was inspired by a similar functionality in xarray.

11.1 Example: how many events per magnitude?

When analyzing an event based calculation, users are often interested in checking the magnitude-frequency distribution, i.e. to count how many events of a given magnitude present in the stochastic event set for a fixed investigation time and a fixed `ses_per_logic_tree_path`. You can do that with code like the following:

```
def print_events_by_mag(calc_id):
    # open the DataStore for the current calculation
    dstore = datastore.read(calc_id)
    # read the events table as a Pandas dataset indexed by the event ID
    events = dstore.read_df('events', 'id')
    # find the magnitude of each event by looking at the 'ruptures'␣
↪table
    events['mag'] = dstore['ruptures']['mag'][events['rup_id']]
    # group the events by magnitude
    for mag, grp in events.groupby(['mag']):
        print(mag, len(grp))    # number of events per group
```

If you want to now the number of events per realization and per stochastic event set you can just refine the *groupby* clause, using the list `['mag', 'rlz_id', 'ses_id']` instead of simply `['mag']`.

Given an event, it is trivial to extract the ground motion field generated by that event, if it has been stored (warning: events producing zero ground motion are not stored). It is enough to read the `gmf_data` table indexed by event ID, i.e. the `eid` field:

```
>>> eid = 20  # consider event with ID 20
>>> gmf_data = dstore.read_df('gmf_data', index='eid') # engine>3.11
>>> gmf_data.loc[eid]
      sid     gmv_0
eid
20     93   0.113241
20    102   0.114756
20    121   0.242828
20    142   0.111506
```

The `gmv_0` refers to the first IMT; here I have shown an example with a single IMT, in presence of multiple IMTs you would see multiple columns `gmv_0, gmv_1, gmv_2, ...`. The `sid` column refers to the site ID.

As a following step, you can compute the mean hazard curves at each site from the ground motion values by using the function *gmvs_to_poes*, available since engine 3.10:

```
>>> from openquake.commonlib.calc import gmvs_to_poes
>>> gmf_data = dstore.read_df('gmf_data', index='sid')
>>> df = gmf_data.loc[0]  # first site
```

```
>>> gmvs = [df[col].to_numpy() for col in df.columns
...         if col.startswith('gmv_')]  # list of M arrays
>>> oq = dstore['oqparam']  # calculation parameters
>>> poes = gmvs_to_poes(gmvs, oq.imtls, oq.ses_per_logic_tree_path)
```

This will return an array of shape (M, L) where M is the number of intensity measure types and L the number of levels per IMT.

CHAPTER

TWELVE

PARAMETRIC GMPES

Most of the Ground Motion Prediction Equations (GMPEs) in hazardlib are classes that can be instantiated without arguments. However, there is now a growing number of exceptions. Here I will describe some of the parametric GMPEs we have, as well as give some guidance for authors wanting to implement a parametric GMPE.

12.1 Signature of a GMPE class

The more robust way to define parametric GMPEs is to use a `**kwargs` signature (robust against subclassing):

```
from openquake.hazardlib.gsim.base import GMPE

class MyGMPE(GMPE):
    def __init__(self, **kwargs):
        super().__init__(**kwargs)
        # doing some initialization here
```

The call to `super().__init__` will set a `self.kwargs` attribute and perform a few checks, like raising a warning if the GMPE is experimental. In absence of parameters `self.kwargs` is the empty dictionary, but in general it is non-empty and it can be arbitrarily nested, with only one limitation: it must be a *dictionary of literal Python objects* so that it admits a TOML representation.

TOML is a simple format similar to the `.ini` format but hierarchical (see https://github.com/toml-lang/toml#user-content-example). It is used by lots of people in the IT world, not only in Python. The advantage of TOML is that it is a lot more readable than JSON and XML and simpler than YAML: moreover, it is perfect for serializing into text literal Python objects like dictionaries and lists. The serialization feature is essential for the engine since the GMPEs are read from the GMPE logic tree file which is a text file, and because the GMPEs are saved into the datastore as text, in the dataset `full_lt/gsim_lt`.

The examples below will clarify how it works.

12.2 GMPETable

Historically, the first parametric GMPE was the GMPETable, introduced many years ago to support the Canada model. The GMPETable class has a single parameter, called `gmpe_table`, which is a (relative) pathname to an .hdf5 file with a fixed format, containing a tabular representation of the GMPE, numeric rather than analytic.

You can find an example of use of GMPETables in the test openquake/qa_tests_data/case_18, which contains three tables in its logic tree:

```
<logicTreeBranch branchID="b11">
  <uncertaintyModel>
    [GMPETable]
    gmpe_table = "Wcrust_low_rhypo.hdf5"
  </uncertaintyModel>
  <uncertaintyWeight>0.16</uncertaintyWeight>
</logicTreeBranch>
<logicTreeBranch branchID="b12">
  <uncertaintyModel>
    [GMPETable]
    gmpe_table = "Wcrust_med_rhypo.hdf5"
  </uncertaintyModel>
  <uncertaintyWeight>0.68</uncertaintyWeight>
</logicTreeBranch>
<logicTreeBranch branchID="b13">
  <uncertaintyModel>
    [GMPETable]
    gmpe_table = "Wcrust_high_rhypo.hdf5"
  </uncertaintyModel>
  <uncertaintyWeight>0.16</uncertaintyWeight>
</logicTreeBranch>
```

As you see, the TOML format is used inside the `uncertaintyModel` tag; the text:

```
[GMPETable]
gmpe_table = "Wcrust_low_rhypo.hdf5"
```

is automatically translated into a dictionary `{'GMPETable': {'gmpe_table': "Wcrust_low_rhypo.hdf5"}}` and the `.kwargs` dictionary passed to the GMPE class is simply

```
{'gmpe_table': "Wcrust_low_rhypo.hdf5"}
```

NB: you may see around old GMPE logic files using a different syntax, without TOML:

```
<logicTreeBranch branchID="b11">
   <uncertaintyModel gmpe_table="Wcrust_low_rhypo.hdf5">
```

```
      GMPETable
   </uncertaintyModel>
   <uncertaintyWeight>0.16</uncertaintyWeight>
</logicTreeBranch>
   <logicTreeBranch branchID="b12">
   <uncertaintyModel gmpe_table="Wcrust_med_rhypo.hdf5">
      GMPETable
   </uncertaintyModel>
   <uncertaintyWeight>0.68</uncertaintyWeight>
</logicTreeBranch>
   <logicTreeBranch branchID="b13">
   <uncertaintyModel gmpe_table="Wcrust_high_rhypo.hdf5">
      GMPETable
   </uncertaintyModel>
   <uncertaintyWeight>0.16</uncertaintyWeight>
</logicTreeBranch>
```

This is a legacy syntax, which is still supported and will likely be supported forever, but we recommend to use the new TOML-based syntax, which is more general. The old syntax has the limitation of being non-hierarchic, making it impossible to define MultiGMPEs involving parametric GMPEs: this is why we switched to TOML.

12.3 File-dependent GMPEs

It is possible to define other GMPEs taking one or more filenames as parameters. Everything will work provided you respect the following rules:

1. there is a naming convention on the file parameters, that must end with the suffix `_file` or `_table`
2. the files must be read at GMPE initialization time (i.e. in the `__init__` method)
3. they must be read with the `GMPE.open` method, NOT with the `open` builtin;
4. in the gsim logic tree file you must use **relative** path names

The constraint on the argument names makes it possible for the engine to collect all the files required by the GMPEs; moreover, since the path names are relative, the *oq zip* command can work making it easy to ship runnable calculations. The engine also stores in the datastore a copy of all of the required input files. Without the copy, it would not be possible from the datastore to reconstruct the inputs, thus making it impossible to dump and restore calculations from a server to a different machine.

The constraint about reading at initialization time makes it possible for the engine to work on a cluster. The issue is that GMPEs are instantiated in the controller and used in the worker nodes,

which *do not have access to the same filesystem*. If the files are read after instantiation, you will get a file not found error when running on a cluster.

The reason why you cannot use the standard `open` builtin to read the files is that the engine must be able to read the GMPE inputs from the datastore copies (think of the case when the `calc_XXX.hdf5` has been copied to a different machine). In order to do that, there is some magic based on the naming convention. For instance, if your GMPE must read a text file with argument name *text_file* you should write the following code:

```
class GMPEWithTextFile(GMPE):
    def __init__(self, **kwargs):
        super().__init__(**kwargs)
        with self.open(kwargs['text_file']) as myfile:  # good
            self.text = myfile.read().decode('utf-8')
```

You should NOT write the following, because it will break the engine, for instance by making it impossible to export the results of a calculation:

```
class GMPEWithTextFile(GMPE):
    def __init__(self, **kwargs):
        super().__init__(**kwargs)
        with open(kwargs['text_file']) as myfile:  # bad
            self.text = myfile.read()
```

NB: writing

```
class GMPEWithTextFile(GMPE):
    def __init__(self, text_file):
        super().__init__(text_file=text_file)
        with self.open(text_file) as myfile:  # good
            self.text = myfile.read().decode('utf-8')
```

would work but it is discouraged. It is best to keep the `**kwargs` signature so that the call to `super().__init__(**kwargs)` will work out-of-the-box even if in the future subclasses of *GMPEWithTextFile* with different parameters will appear: this is defensive programming.

12.4 MultiGMPE

Another example of parametric GMPE is the MultiGMPE class. A MultiGMPE is a dictionary of GMPEs, keyed by Intensity Measure Type. It is useful in geotechnical applications and in general in any situation where you have GMPEs depending on the IMTs. You can find an example in our test openquake/qa_tests_data/classical/case_1:

```
<logicTreeBranch branchID="b1">
   <uncertaintyModel>
```

```
    [MultiGMPE."PGA".AkkarBommer2010]
    [MultiGMPE."SA(0.1)".SadighEtAl1997]
  </uncertaintyModel>
  <uncertaintyWeight>1.0</uncertaintyWeight>
 </logicTreeBranch>
```

Here the engine will use the GMPE `AkkarBommer2010` for `PGA` and `SadighEtAl1997` for `SA(0.1)`. The `.kwargs` passed to the `MultiGMPE` class will have the form:

```
{'PGA': {'AkkarBommer2010': {}},
 'SA(0.1)': {'SadighEtAl1997': {}}}
```

The beauty of the TOML format is that it is hierarchic, so if we wanted to use parametric GMPEs in a MultiGMPE we could. Here is an example using the GMPETable *Wcrust_low_rhypo.hdf5* for `PGA` and *Wcrust_med_rhypo.hdf5* for `SA(0.1)` (the example has no physical meaning, it is just an example):

```
<logicTreeBranch branchID="b1">
  <uncertaintyModel>
    [MultiGMPE."PGA".GMPETable]
      gmpe_table = "Wcrust_low_rhypo.hdf5"
    [MultiGMPE."SA(0.1)".GMPETable]
      gmpe_table = "Wcrust_med_rhypo.hdf5"
  </uncertaintyModel>
  <uncertaintyWeight>1.0</uncertaintyWeight>
 </logicTreeBranch>
```

12.5 GenericGmpeAvgSA

In engine 3.4 we introduced a GMPE that manages a range of spectral accelerations and acts in terms of an average spectral acceleration. You can find an example of use in openquake/qa_tests/data/classical/case_34:

```
<logicTreeBranch branchID="b1">
    <uncertaintyModel>
       [GenericGmpeAvgSA]
       gmpe_name = "BooreAtkinson2008"
       avg_periods = [0.5, 1.0, 2.0]
       corr_func = "baker_jayaram"
    </uncertaintyModel>
    <uncertaintyWeight>1.0</uncertaintyWeight>
</logicTreeBranch>
```

As you see, the format is quite convenient when there are several arguments of different types:

here we have two strings (`gmpe_name` and `corr_func`) and a list of floats (`avg_periods`). The dictionary passed to the underlying class will be

```
{'gmpe_name': "BooreAtkinson2008",
 'avg_periods': [0.5, 1.0, 2.0],
 'corr_func': "baker_jayaram"}
```

12.6 ModifiableGMPE

In engine 3.10 we introduced a `ModifiableGMPE` class which is able to modify the behavior of an underlying GMPE. Here is an example of use in the logic tree file:

```
<uncertaintyModel>
    [ModifiableGMPE]
    gmpe.AkkarEtAlRjb2014 = {}
    set_between_epsilon.epsilon_tau = 0.5
</uncertaintyModel>
```

Here *set_between_epsilon* is simply shifting the mean with the formula *mean -> mean + epsilon_tau * inter_event*. In the future `ModifiableGMPE` will likely grow more methods. If you want to understand how it works you should look at the source code:

https://github.com/gem/oq-engine/blob/master/openquake/hazardlib/gsim/mgmpe/modifiable_gmpe.py

CHAPTER

THIRTEEN

MULTIPOINTSOURCES

Starting from version 2.5, the OpenQuake Engine is able to manage MultiPointSources, i.e. collections of point sources with specific properties. A MultiPointSource is determined by a mesh of points, a MultiMFD magnitude-frequency-distribution and 9 other parameters:

1. tectonic region type
2. rupture mesh spacing
3. magnitude-scaling relationship
4. rupture aspect ratio
5. temporal occurrence model
6. upper seismogenic depth
7. lower seismogenic depth
8. NodalPlaneDistribution
9. HypoDepthDistribution

The MultiMFD magnitude-frequency-distribution is a collection of regular MFD instances (one per point); in order to instantiate a MultiMFD object you need to pass a string describing the kind of underlying MFD ('arbitraryMFD', 'incrementalMFD', 'truncGutenbergRichterMFD' or 'YoungsCoppersmithMFD'), a float determining the magnitude bin width and few arrays describing the parameters of the underlying MFDs. For instance, in the case of an 'incrementalMFD', the parameters are *min_mag* and *occurRates* and a *MultiMFD* object can be instantiated as follows:

```
mmfd = MultiMFD('incrementalMFD',
                size=2,
                bin_width=[2.0, 2.0],
                min_mag=[4.5, 4.5],
                occurRates=[[.3, .1], [.4, .2, .1]])
```

In this example there are two points and two underlying MFDs; the occurrence rates can be different for different MFDs: here the first one has 2 occurrence rates while the second one has 3 occurrence rates.

Having instantiated the *MultiMFD*, a *MultiPointSource* can be instantiated as in this example:

```
npd = PMF([(0.5, NodalPlane(1, 20, 3)),
           (0.5, NodalPlane(2, 2, 4))])
hd = PMF([(1, 4)])
mesh = Mesh(numpy.array([0, 1]), numpy.array([0.5, 1]))
tom = PoissonTOM(50.)
rms = 2.0
rar = 1.0
usd = 10
lsd = 20
mps = MultiPointSource('mp1', 'multi point source',
                       'Active Shallow Crust',
                        mmfd, rms, PeerMSR(), rar,
                        tom, usd, lsd, npd, hd, mesh)
```

There are two major advantages when using *MultiPointSources*:

1. the space used is a lot less than the space needed for an equivalent set of PointSources (less memory, less data transfer)
2. the XML serialization of a MultiPointSource is a lot more efficient (say 10 times less disk space, and faster read/write times)

At computation time MultiPointSources are split into PointSources and are indistinguishable from those. The serialization is the same as for other source typologies (call *write_source_model(fname, [mps])* or *nrml.to_python(fname, sourceconverter)*) and in XML a *multiPointSource* looks like this:

```
<multiPointSource
id="mp1"
name="multi point source"
tectonicRegion="Stable Continental Crust"
>
    <multiPointGeometry>
        <gml:posList>
            0.0 1.0 0.5 1.0
        </gml:posList>
        <upperSeismoDepth>
            10.0
        </upperSeismoDepth>
        <lowerSeismoDepth>
            20.0
        </lowerSeismoDepth>
    </multiPointGeometry>
    <magScaleRel>
        PeerMSR
    </magScaleRel>
    <ruptAspectRatio>
        1.0
```

```
    </ruptAspectRatio>
    <multiMFD
    kind="incrementalMFD"
    size=2
    >
        <bin_width>
            2.0 2.0
        </bin_width>
        <min_mag>
            4.5 4.5
        </min_mag>
        <occurRates>
            0.10 0.05 0.40 0.20 0.10
        </occurRates>
        <lengths>
            2 3
        </lengths>
    </multiMFD>
    <nodalPlaneDist>
        <nodalPlane dip="20.0" probability="0.5" rake="3.0" strike="1.0
↪"/>
        <nodalPlane dip="2.0" probability="0.5" rake="4.0" strike="2.0
↪"/>
    </nodalPlaneDist>
    <hypoDepthDist>
        <hypoDepth depth="14.0" probability="1.0"/>
    </hypoDepthDist>
</multiPointSource>
```

The node <*lengths*> contains the lengths of the occurrence rates, 2 and 3 respectively in this example. This is needed since the serializer writes the occurrence rates sequentially (in this example they are the 5 floats *0.10 0.05 0.40 0.20 0.10*) and the information about their grouping would be lost otherwise.

There is an optimization for the case of homogeneous parameters; for instance in this example the *bin_width* and *min_mag* are the same in all points; then it is possible to store these as one-element lists:

```
mmfd = MultiMFD('incrementalMFD',
                size=2,
                bin_width=[2.0],
                min_mag=[4.5],
                occurRates=[[.3, .1], [.4, .2, .1]])
```

This saves memory and data transfer, compared to the version of the code above.

Notice that writing *bin_width=2.0* or *min_mag=4.5* would be an error: the parameters must be

vector objects; if their length is 1 they are treated as homogeneous vectors of size *size*. If their length is different from 1 it must be equal to *size*, otherwise you will get an error at instantiation time.

CHAPTER

FOURTEEN

HOW THE PARALLELIZATION WORKS IN THE ENGINE

The engine builds on top of existing parallelization libraries. Specifically, on a single machine it is based on multiprocessing, which is part of the Python standard library, while on a cluster it is based on the combination celery/rabbitmq, which are well-known and maintained tools.

While the parallelization used by the engine may look trivial in theory (it only addresses embarrassingly parallel problems, not true concurrency) in practice it is far from being so. For instance a crucial feature that the GEM staff requires is the ability to kill (revoke) a running calculation without affecting other calculations that may be running concurrently.

Because of this requirement, we abandoned *concurrent.futures*, which is also in the standard library, but is lacking the ability to kill the pool of processes, which is instead available in multiprocessing with the *Pool.shutdown* method. For the same reason, we discarded *dask*, which is a lot more powerful than *celery* but lacks the revoke functionality.

Using a real cluster scheduling mechanism (like SLURM) would be of course better, but we do not want to impose on our users a specific cluster architecture. celery/rabbitmq have the advantage of being simple to install and manage. Still, the architecture of the engine parallelization library is such that it is very simple to replace celery/rabbitmq with other parallelization mechanisms: people interested in doing so should just contact us.

Another tricky aspects of parallelizing large scientific calculations is that the amount of data returned can exceed the 4 GB limit of Python pickles: in this case one gets ugly runtime errors. The solution we found is to make it possible to yield partial results from a task: in this way instead of returning say 40 GB from one task, one can yield 40 times partial results of 1 GB each, thus bypassing the 4 GB limit. It is up to the implementor to code the task carefully. In order to do so, it is essential to have in place some monitoring mechanism measuring how much data is returned back from a task, as well as other essential informations like how much memory is allocated and how long it takes to run a task.

To this aim the OpenQuake engine offers a `Monitor` class (located in `openquake.baselib.performance`) which is perfectly well integrated with the parallelization framework, so much that every task gets a `Monitor` object, a context manager that can be used to measure time and memory of specific parts of a task. Moreover, the monitor automatically measures time and memory for the whole task, as well as the size of the returned output (or outputs). Such information

is stored in an HDF5 file that you must pass to the monitor when instantiating it. The engine automatically does that for you by passing the pathname of the datastore.

In OpenQuake a task is just a Python function (or generator) with positional arguments, where the last argument is a `Monitor` instance. For instance the rupture generator task in an event based calculation is coded more or less like this:

```
def sample_ruptures(sources, num_samples, monitor):  # simplified code
    ebruptures = []
    for src in sources:
        for rup, n_occ in src.sample_ruptures(num_samples):
            ebr = EBRupture(rup, src.id, grp_id, n_occ)
            eb_ruptures.append(ebr)
        if len(eb_ruptures) > MAX_RUPTURES:
            # yield partial result to avoid running out of memory
            yield eb_ruptures
            eb_ruptures.clear()
    if ebruptures:
        yield eb_ruptures
```

If you know that there is no risk of running out of memory and/or passing the pickle limit you can just use a regular function and return a single result instead of yielding partial results. This is the case when computing the hazard curves, because the algorithm is considering one rupture at the time and it is not accumulating ruptures in memory, differently from what happens when sampling the ruptures in event based.

If you have ever coded in celery, you will see that the OpenQuake engine concept of task is different: there is no `@task` decorator and while at the end engine tasks will become celery tasks this is hidden to the developer. The reason is that we needed a celery-independent abstraction layer to make it possible to use different kinds of parallelization frameworks/

From the point of view of the coder, in the engine there is no difference between a task running on a cluster using celery and a task running locally using `multiprocessing.Pool`: they are coded the same, but depending on a configuration parameter in openquake.cfg (`distribute=celery` or `distribute=processpool`) the engine will treat them differently. You can also set an environment variable `OQ_DISTRIBUTE`, which takes the precedence over openquake.cfg, to specify which kind of distribution you want to use (`celery` or `processpool`): this is mostly used when debugging, when you typically insert a breakpoint in the task and then run the calculation with

```
$ OQ_DISTRIBUTE=no oq run job.ini
```

`no` is a perfectly valid distribution mechanism in which there is actually no distribution and all the tasks run sequentially in the same core. Having this functionality is invaluable for debugging.

Another tricky bit of real life parallelism in Python is that forking does not play well with the HDF5 library: so in the engine we are using multiprocessing in the `spawn` mode, not in `fork` mode: fortunately this feature has become available to us in Python 3 and it made our life a lot happier. Before it was extremely easy to incur unspecified behavior, meaning that reading an HDF5 file

from a forked process could

1. work perfectly well
2. read bogus numbers
3. cause a segmentation fault

and all of the three things could happen unpredictably at any moment, depending on the machine where the calculation was running, the load on the machine, and any kind of environmental circumstances.

Also, while in theory with the newest HDF5 libraries it should be possible to use a SWMR architecture (Single Writer Multiple Reader) we were not able to get this working in the engine. Instead, we are using a two files approach which is simple and works very well: we read from one file (with multiple readers) and we write on the other file (with a single writer), instead of reading/writing on the same file. This bypasses all the limitations of the SWMR mode in HDF5 and did not require a large refactoring of our existing code.

Another tricky point in cluster situations is that rabbitmq is not good at transferring gigabytes of data: it was meant to manage lots of small messages, but here we are perverting it to manage huge messages, i.e. the large arrays coming from a scientific calculations.

Hence, since recent versions of the engine we are no longer returning data from the tasks via celery/rabbitmq: instead, we use zeromq. This is hidden from the user, but internally the engine keeps track of all tasks that were submitted and waits until they send the message that they finished. If one tasks runs out of memory badly and never sends the message that it finished, the engine may hang, waiting for the results of a task that does not exist anymore. You have to be careful. What we did in our cluster is to set some memory limit on the celery user with the cgroups technology, so that an out of memory task normally fails in a clean way with a Python MemoryError, sends the message that it finished and nothing particularly bad happens. Still, in situations of very heavy load the OOM killer may enter in action aggressively and the main calculation may hang: in such cases you need a good sysadmin having put in place some monitor mechanism, so that you can see if the OOM killer entered in action and then you can kill the main process of the calculation by hand. There is not much more that can be done for really huge calculations that stress the hardware as much as possible. You must be prepared for failures.

14.1 How to use openquake.baselib.parallel

Suppose you want to code a character-counting algorithm, which is a textbook exercise in parallel computing and suppose that you want to store information about the performance of the algorithm. Then you should use the OpenQuake `Monitor` class, as well as the utility `openquake.baselib.datastore.hdf5new` that build an empty datastore for you. Having done that, the `openquake.baselib.parallel.Starmap` class can take care of the parallelization for you as in the following example:

```
import os
import sys
import pathlib
import collections
from openquake.baselib.performance import Monitor
from openquake.baselib.parallel import Starmap
from openquake.baselib.datastore import hdf5new


def count(text):
    c = collections.Counter()
    for word in text.split():
        c += collections.Counter(word)
    return c


def main(dirname):
    dname = pathlib.Path(dirname)
    with hdf5new() as hdf5:  # create a new datastore
        monitor = Monitor('count', hdf5)  # create a new monitor
        iterargs = ((open(dname/fname, encoding='utf-8').read(),)
                    for fname in os.listdir(dname)
                    if fname.endswith('.rst'))  # read the docs
        c = collections.Counter()  # intially empty counter
        for counter in Starmap(count, iterargs, monitor):
            c += counter
        print(c)  # total counts
        print('Performance info stored in', hdf5)


if __name__ == '__main__':
    main(sys.argv[1])  # pass the directory where the .rst files are
```

The name `Starmap` was chosen it looks very similar to `multiprocessing.Pool.starmap` works, the only apparent difference being in the additional monitor argument:

```
pool.starmap(func, iterargs) ->  Starmap(func, iterargs, monitor)
```

In reality the `Starmap` has a few other differences:

1. it does not use the multiprocessing mechanism to returns back the results, it uses zmq instead;
2. thanks to that, it can be extended to generator functions and can yield partial results, thus overcoming the limitations of multiprocessing
3. the `Starmap` has a `.submit` method and it is actually more similar to `concurrent.futures` than to multiprocessing.

Here is how you would write the same example by using `.submit`:

```
def main(dirname):
    dname = pathlib.Path(dirname)
    with hdf5new() as hdf5:
        smap = Starmap(count, monitor=Monitor('count', hdf5))
        for fname in os.listdir(dname):
            if fname.endswith('.rst'):
                smap.submit(open(dname/fname, encoding='utf-8').read())
        c = collections.Counter()
        for counter in smap:
            c += counter
```

The difference with `concurrent.futures` is that the `Starmap` takes care for of all submitted tasks, so you do not need to use something like `concurrent.futures.completed`, you can just loop on the `Starmap` object to get the results from the various tasks.

The `.submit` approach is more general: for instance you could define more than one `Starmap` object at the same time and submit some tasks with a starmap and some others with another starmap: this may help parallelizing complex situations where it is expensive to use a single starmap. However, there is limit on the number of starmaps that can be alive at the same moment.

Moreover the `Starmap` has a `.shutdown` methods that allows to shutdown the underlying pool.

The idea is to submit the text of each file - here I am considering .rst files, like the ones composing this manual - and then loop over the results of the `Starmap`. This is very similar to how `concurrent.futures` works.

CHAPTER

FIFTEEN

SPECIAL FEATURES OF THE ENGINE

There are few rarely used feature of the engine that are not documented in the manual, since their usage is quite specific. They are documented here.

15.1 GMPE logic trees with *minimum_distance*

GMPEs have a range of validity. In particular they may give wrong results for points too close to the rupture. To avoid this problem some GSIMs in hazardlib have a minimum distance cutoff: for distances below the `minimum_distance` they give always the same result, which is the value at the minimum distance. The `minimum_distance` is normally provided by the author of the GSIMs, but it is somewhat heuristic. It may be useful to experiment with different values of the `minimum_distance`, to see how the hazard and risk change. It would be too inconvenient to have to change the source code of the GSIM every time. Instead, the user can specify a `minimum_distance` attribute in the GSIM logic tree branch that will take precedence over the one in hazardlib. Here is an example:

```
<logicTreeBranchSet uncertaintyType="gmpeModel" branchSetID="bs1"
                    applyToTectonicRegionType="Subduction Deep">

   <logicTreeBranch branchID="b1">
     <uncertaintyModel minimum_distance="10">
       LinLee2008SSlab
     </uncertaintyModel>
     <uncertaintyWeight>0.60</uncertaintyWeight>
   </logicTreeBranch>

   <logicTreeBranch branchID="b2">
     <uncertaintyModel minimum_distance="5">
       YoungsEtAl1997SSlab
     </uncertaintyModel>
     <uncertaintyWeight>0.40</uncertaintyWeight>
   </logicTreeBranch>
 </logicTreeBranchSet>
```

Most GSIMs do not have a `minimum_distance` parameter in hazardlib, which is equivalent to say that the minimum distance is zero. Even for them, however, it is possible to set a minimum distance in the logic tree in order to perform sensitivity experiments at small distances.

15.2 GMPE logic trees with weighted IMTs

Our Canadian users asked us to implement GMPE logic trees with a different weight per each IMT. For instance you could have a GMPE applicable to PGA with a certain level of uncertainty, to SA(0.1) with another and to SA(1.0) with still another one. The user may want to give an higher weight to the IMTs were the GMPE has a small uncertainty and a lower weight to the IMTs with a large uncertainty. Moreover the GMPE could not be applicable for some period, and in that case the user can assign to it a zero weight, to ignore it. This is useful when you have a logic tree with multiple GMPEs per branchset, some of which are applicable for some IMTs and not for others. Here is an example:

```
<logicTreeBranchSet uncertaintyType="gmpeModel" branchSetID="bs1"
        applyToTectonicRegionType="Volcanic">
    <logicTreeBranch branchID="BooreEtAl1997GeometricMean">
        <uncertaintyModel>BooreEtAl1997GeometricMean</uncertaintyModel>
        <uncertaintyWeight>0.33</uncertaintyWeight>
        <uncertaintyWeight imt="PGA">0.25</uncertaintyWeight>
        <uncertaintyWeight imt="SA(0.5)">0.5</uncertaintyWeight>
        <uncertaintyWeight imt="SA(1.0)">0.5</uncertaintyWeight>
        <uncertaintyWeight imt="SA(2.0)">0.5</uncertaintyWeight>
    </logicTreeBranch>
    <logicTreeBranch branchID="SadighEtAl1997">
        <uncertaintyModel>SadighEtAl1997</uncertaintyModel>
        <uncertaintyWeight>0.33</uncertaintyWeight>
        <uncertaintyWeight imt="PGA">0.25</uncertaintyWeight>
        <uncertaintyWeight imt="SA(0.5)">0.5</uncertaintyWeight>
        <uncertaintyWeight imt="SA(1.0)">0.5</uncertaintyWeight>
        <uncertaintyWeight imt="SA(2.0)">0.5</uncertaintyWeight>
    </logicTreeBranch>
    <logicTreeBranch branchID="MunsonThurber1997Hawaii">
        <uncertaintyModel>MunsonThurber1997Hawaii</uncertaintyModel>
        <uncertaintyWeight>0.34</uncertaintyWeight>
        <uncertaintyWeight imt="PGA">0.25</uncertaintyWeight>
        <uncertaintyWeight imt="SA(0.5)">0.0</uncertaintyWeight>
        <uncertaintyWeight imt="SA(1.0)">0.0</uncertaintyWeight>
        <uncertaintyWeight imt="SA(2.0)">0.0</uncertaintyWeight>
    </logicTreeBranch>
    <logicTreeBranch branchID="Campbell1997">
        <uncertaintyModel>Campbell1997</uncertaintyModel>
        <uncertaintyWeight>0.0</uncertaintyWeight>
        <uncertaintyWeight imt="PGA">0.25</uncertaintyWeight>
```

```
        <uncertaintyWeight imt="SA(0.5)">0.0</uncertaintyWeight>
        <uncertaintyWeight imt="SA(1.0)">0.0</uncertaintyWeight>
        <uncertaintyWeight imt="SA(2.0)">0.0</uncertaintyWeight>
    </logicTreeBranch>
</logicTreeBranchSet>
```

Clearly the weights for each IMT must sum up to 1, otherwise the engine will complain. Note that this feature only works for the classical and disaggregation calculators: in the event based case only the default `uncertaintyWeight` (i.e. the first in the list of weights, the one without `imt` attribute) would be taken for all IMTs.

15.3 Equivalent Epicenter Distance Approximation

The equivalent epicenter distance approximation (`reqv` for short) was introduced in engine 3.2 to enable the comparison of the OpenQuake engine with time-honored Fortran codes using the same approximation.

You can enable it in the engine by adding a `[reqv]` section to the job.ini, like in our example in openquake/qa_tests_data/classical/case_2/job.ini:

reqv_hdf5 = {'active shallow crust': 'lookup_asc.hdf5', 'stable shallow crust': 'lookup_sta.hdf5'}

For each tectonic region type to which the approximation should be applied, the user must provide a lookup table in .hdf5 format containing arrays `mags` of shape M, `repi` of shape N and `reqv` of shape (M, N).

The examples in openquake/qa_tests_data/classical/case_2 will give you the exact format required. M is the number of magnitudes (in the examples there are 26 magnitudes ranging from 6.05 to 8.55) and N is the number of epicenter distances (in the examples ranging from 1 km to 1000 km).

Depending on the tectonic region type and rupture magnitude, the engine converts the epicentral distance `repi` into an equivalent distance by looking at the lookup table and use it to determine the ``rjb and `rrup` distances, instead of the regular routines. This means that within this approximation ruptures are treated as pointwise and not rectangular as the engine usually does.

Notice that the equivalent epicenter distance approximation only applies to ruptures coming from PointSources/AreaSources/MultiPointSources, fault sources are untouched.

15.4 Ruptures in CSV format

Since engine v3.10 there is a way to serialize ruptures in CSV format. The command to give is:

```
$ oq extract "ruptures?min_mag=<mag>" <calc_id>`
```

For instance, assuming there is an event based calculation with ID 42, we can extract the ruptures in the datastore with magnitude larger than 6 with `oq extract "ruptures?min_mag=6" 42`: this will generate a CSV file. Then it is possible to run scenario calculations starting from that rupture by simply setting

```
rupture_model_file = ruptures-min_mag=6_42.csv
```

in the `job.ini` file. The format is provisional and may change in the future, but it will stay a CSV with JSON fields. Here is an example for a planar rupture, i.e. a rupture generated by a point source:

```
#,,,,,,,,,,"trts=['Active Shallow Crust']"
seed,mag,rake,lon,lat,dep,multiplicity,trt,kind,mesh,extra
24,5.050000E+00,0.000000E+00,0.08456,0.15503,5.000000E+00,1,Active␣
↪Shallow Crust,ParametricProbabilisticRupture PlanarSurface,"[[[0.
↪08456, 0.08456, 0.08456, 0.08456]], [[0.13861, 0.17145, 0.13861, 0.
↪17145]], [[3.17413, 3.17413, 6.82587, 6.82587]]]","{""occurrence_rate
↪"": 4e-05}"
```

The format is meant to support all kind of ruptures, including ruptures generated by simple and complex fault sources, characteristic sources, nonparametric sources and new kind of sources that could be introduced in the engine in the future. The header will be the same for all kind of ruptures that will be stored in the same CSV. Here is description of the fields as they are named now (engine 3.11):

seed the random seed used to compute the GMFs generated by the rupture

mag the magnitude of the rupture

rake the rake angle of the rupture surface in degrees

lon the longitude of the hypocenter in degrees

lat the latitude of the hypocenter in degrees

dep the depth of the hypocenter in km

multiplicity the number of occurrences of the rupture (i.e. number of events)

trt the tectonic region type of the rupture; must be consistent with the trts listed in the pre-header of the file

kind a space-separated string listing the rupture class and the surface class used in the engine

mesh nested list with lon, lat, dep of the points of the discretized rupture geometry

extra extra parameters of the rupture as a JSON dictionary, for instance the rupture occurrence rate

Notice that using a CSV file generated with an old version of the engine is inherently risky: for instance if we changed the `ParametricProbabilisticRupture` class or the `PlanarSurface classes` in an incompatible way with the past, then a scenario calculation starting with the CSV would give different results in the new version of the engine. We never changed the rupture classes or the surface classes, but we changed the seed algorithm often, and that too would cause different numbers to be generated (hopefully, statistically consistent). A bug fix or change of logic in the calculator can also change the numbers across engine versions.

15.5 max_sites_disagg

There is a parameter in the *job.ini* called `max_sites_disagg`, with a default value of 10. This parameter controls the maximum number of sites on which it is possible to run a disaggregation. If you need to run a disaggregation on a large number of sites you will have to increase that parameter. Notice that there are technical limits: trying to disaggregate 100 sites will likely succeed, trying to disaggregate 100,000 sites will most likely cause your system to go out of memory or out of disk space, and the calculation will be terribly slow. If you have a really large number of sites to disaggregate, you will have to split the calculation and it will be challenging to complete all the subcalculations.

The parameter `max_sites_disagg` is extremely important not only for disaggregation, but also for classical calculations. Depending on its value and then number of sites (`N`) your calculation can be in the *few sites* regime or the *many sites regime*.

In the *few sites regime* (`N <= max_sites_disagg`) the engine stores information for each rupture in the model (in particular the distances for each site) and therefore uses more disk space. The problem is mitigated since the engine uses a relatively aggressive strategy to collapse ruptures, but that requires more RAM available.

In the *many sites regime* (`N > max_sites_disagg`) the engine does not store rupture information (otherwise it would immediately run out of disk space, since typical hazard models have tens of millions of ruptures) and uses a much less aggressive strategy to collapse ruptures, which has the advantage of requiring less RAM.

15.6 extendModel

Starting from engine 3.9 there is a new feature in the source model logic tree: the ability to define new branches by adding sources to a base model. An example will explain it all:

```
<?xml version="1.0" encoding="UTF-8"?>
<nrml xmlns:gml="http://www.opengis.net/gml"
      xmlns="http://openquake.org/xmlns/nrml/0.4">
  <logicTree logicTreeID="lt1">
    <logicTreeBranchSet uncertaintyType="sourceModel"
```

```
                        branchSetID="bs0">
      <logicTreeBranch branchID="b01">
        <uncertaintyModel>common1.xml</uncertaintyModel>
        <uncertaintyWeight>0.6</uncertaintyWeight>
      </logicTreeBranch>
      <logicTreeBranch branchID="b02">
        <uncertaintyModel>common2.xml</uncertaintyModel>
        <uncertaintyWeight>0.4</uncertaintyWeight>
      </logicTreeBranch>
    </logicTreeBranchSet>
    <logicTreeBranchSet uncertaintyType="extendModel" applyToBranches=
↪"b01"
                        branchSetID="bs1">
      <logicTreeBranch branchID="b11">
        <uncertaintyModel>extra1.xml</uncertaintyModel>
        <uncertaintyWeight>0.6</uncertaintyWeight>
      </logicTreeBranch>
      <logicTreeBranch branchID="b12">
        <uncertaintyModel>extra2.xml</uncertaintyModel>
        <uncertaintyWeight>0.4</uncertaintyWeight>
      </logicTreeBranch>
    </logicTreeBranchSet>
  </logicTree>
</nrml>
```

In this example there are two base source models, named `commom1.xml` and `common2.xml`; the branchset with `uncertaintyType = "extendModel"` is telling the engine to generate two effective source models by extending `common1.xml` first with `extra1.xml` and then with `extra2.xml`. If we removed the constraint `applyToBranches="b01"` then two additional effective source models would be generated by applying `extra1.xml` and `extra2.xml` to `common2.xml`.

CHAPTER

SIXTEEN

HOW THE HAZARD SITES ARE DETERMINED

There are several ways to specify the hazard sites in an engine calculation.

1. The user can specify the sites directly in the job.ini using the `sites` parameter (e.g. `sites = -122.4194 37.7749, -118.2437 34.0522, -117.1611 32.7157`). This method is perhaps most useful when the analysis is limited to a handful of sites.
2. Otherwise the user can specify the list of sites in a CSV file (i.e. `sites_csv = sites.csv`).
3. Otherwise the user can specify a grid via the `region` and `region_grid_spacing` parameters.
4. Otherwise the sites can be inferred from the exposure, if any, in two different ways:
   (a) if `region_grid_spacing` is specified, a grid is implicitly generated from the convex hull of the exposure and used
   (b) otherwise the locations of the assets are used as hazard sites
5. Otherwise the sites can be inferred from the site model file, if any.

It must be noted that the engine rounds longitudes and latitudes to 5 decimal places (or approximately 1 meter spatial resolution), so sites that differ only at the 6th decimal place or beyond will end up being considered as duplicated sites by the engine, and this will be flagged as an error.

Having determined the sites, a `SiteCollection` object is generated by associating the closest parameters from the site model (if any) or using the global site parameters, if any. If the site model is specified, but the closest site parameters are too distant from the sites, a warning is logged for each site.

There are a number of error situations:

1. If both site model and global site parameters are missing, the engine raises an error.
2. If both site model and global site parameters are specified, the engine raises an error.
3. Specifying both the sites.csv and a grid is an error.

4. Specifying both the sites.csv and a site_model.csv is an error. If you are in such situation you should consider using the command `oq prepare_site_model` to manually prepare a site model on the location of the sites.
5. Having duplicates (i.e. rows with identical lon, lat up to 5 digits) in the site model is an error.

If you want to compute the hazard on the locations specified by the site model and not on the exposure locations, you can split the calculation in two files: `job_haz.ini` containing the site model and `job_risk.ini` containing the exposure. Then the risk calculator will find the closest hazard to each asset and use it. However, if the closest hazard is more distant than the `asset_hazard_distance` parameter (default 15 km) an error is raised.

CHAPTER

SEVENTEEN

NEW RISK FEATURES

Here we document some new risk features which have not yet made it into the engine manual. These are new features and cannot be considered fully-tested and stable yet.

17.1 Taxonomy mapping

In an ideal world, for every building type represented in the exposure model, there would be a unique matching function in the vulnerability or fragility models. However, often it may not be possible to have a one-to-one mapping of the taxonomy strings in the exposure and those in the vulnerability or fragility models. For cases where the exposure model has richer detail, many taxonomy strings in the exposure would need to be mapped onto a single vulnerability or fragility function. In other cases where building classes in the exposure are more generic and the fragility or vulnerability functions are available for more specific building types, a modeller may wish to assign more than one vulnerability or fragility function to the same building type in the exposure with different weights.

We may encode such information into a *taxonomy_mapping.csv* file like the following:

taxonomy	conversion
Wood Type A	Wood
Wood Type B	Wood
Wood Type C	Wood

Using an external file is convenient, because we can avoid changing the original exposure. If in the future we will be able to get specific risk functions, then we will just remove the taxonomy mapping. This usage of the taxonomy mapping (use proxies for missing risk functions) is pretty useful, but there is also another usage which is even more interesting.

Consider a situation where there are doubts about the precise composition of the exposure. For instance we may know than in a given geographic region 20% of the building of type "Wood" are of "Wood Type A", 30% of "Wood Type B" and 50% of "Wood Type C", corresponding to different risk functions, but do not know building per building what it its precise taxonomy, so we

just use a generic "Wood" taxonomy in the exposure. We may encode the weight information into a *taxonomy_mapping.csv* file like the following:

taxonomy	conversion	weight
Wood	Wood Type A	0.2
Wood	Wood Type B	0.3
Wood	Wood Type C	0.5

The engine will read this mapping file and when performing the risk calculation will use all three kinds of risk functions to compute a single result with a weighted mean algorithm. The sums of the weights must be 1 for each exposure taxonomy, otherwise the engine will raise an error. In this case the taxonomy mapping file works like a risk logic tree.

Internally both the first usage and the second usage are treated in the same way, since the first usage is a special case of the second when all the weights are equal to 1.

Currently, this taxonomy mapping feature has been tested only for the scenario and event based risk calculators.

17.2 Extended consequences

Scenario damage calculations produce the so called *asset damage table*, i.e. a set of damage distributions (the probability of being in each damage state listed in the fragility functions) per each asset, event and loss type. From the asset damage table it is possible to compute generic consequences by multiplying for known coefficients specified in what are called *consequence model*. For instance, from the probability of being in the collapsed damage state, one might estimate the number of fatalities, given the right multiplicative coefficient.

By default the engine allows to compute economic losses; in that case the coefficients depends on the taxonomy and the consequence model can be represented as a CSV file like the following:

taxonomy	cname	loss_type	slight	moderate	extensive	complete
CR_LFINF-DUH_H2	losses	structural	0.05	0.25	0.6	1
CR_LFINF-DUH_H4	losses	structural	0.05	0.25	0.6	1
MCF_LWAL-DNO_H3	losses	structural	0.05	0.25	0.6	1
MR_LWAL-DNO_H1	losses	structural	0.05	0.25	0.6	1
MR_LWAL-DNO_H2	losses	structural	0.05	0.25	0.6	1
MUR_LWAL-DNO_H1	losses	structural	0.05	0.25	0.6	1
W-WS_LPB-DNO_H1	losses	structural	0.05	0.25	0.6	1
W-WWD_LWAL-DNO_H1	losses	structural	0.05	0.25	0.6	1
MR_LWAL-DNO_H3	losses	structural	0.05	0.25	0.6	1

The first field in the header is the name of a tag in the exposure; in this case it is the taxonomy but

it could be any other tag — for instance, for volcanic ash-fall consequences, the roof-type might be more relevant, and for recovery time estimates, the occupancy class might be more relevant. The framework is meant to be used for generic consequences, not necessarily limited to earthquakes, because since version 3.6 the engine provides a multi-hazard risk calculator.

The second field of the header, the `cname`, is a string identifying the kind of consequence we are considering. It is important because it is associated to the name of the plugin function to use to compute the consequence; right now (engine 3.8) we only support `cname="losses"`, but this will change in the future. The *cname* is also used when saving the consequence outputs in the datastore; right now we are storing only `losses_by_event` and `losses_by_asset` but additional outputs `<cname>_by_event` and `<cname>_by_asset` will be stored in the future, should the CSV file contain references to additional plugin functions. For instance we could have outputs `fatalities_by_event` and `fatalities_by_asset`.

The other fields in the header are the loss_type and the damage states. For instance the coefficient 0.25 for "moderate" means that the cost to bring a structure in "moderate damage" back to its undamaged state is 25% of the total replacement value of the asset.

17.3 Scenarios from ShakeMaps

Beginning with version 3.1, the engine is able to perform *scenario_risk* and *scenario_damage* calculations starting from the GeoJSON feed for ShakeMaps provided by the United States Geological Survey (USGS).

In order to enable this functionality one has to prepare a parent calculation containing the exposure and risk functions for the region of interest, say Peru. To that aim the user will need to write a *prepare_job.ini* file like this one:

```
[general]
description = Peru - Preloading exposure and vulnerability
calculation_mode = scenario
exposure_file = exposure_model.xml
structural_vulnerability_file = structural_vulnerability_model.xml
```

By running the calculation

```
$ oq engine --run prepare_job.ini
```

The exposure and the risk functions will be imported in the datastore.

This example only includes vulnerability functions for the loss type `structural`, but one could also have in this preparatory job file the functions for nonstructural components and contents, and occupants, or fragility functions if damage calculations are of interest.

It is essential that each fragility/vulnerability function in the risk model should be conditioned on one of the intensity measure types that are supported by the ShakeMap service – PGV, PGA,

SA(0.3), SA(1.0), and SA(3.0). If your fragility/vulnerability functions involves an intensity measure type which is not supported by the ShakeMap system (for instance SA(0.6)) the calculation will terminate with an error.

Let's suppose that the calculation ID of this 'pre' calculation is 1000. We can now run the risk calculation starting from a ShakeMap. For that, one need a *job.ini* file like the following:

```
[general]
description = Peru - 2007 M8.0 Pisco earthquake losses
calculation_mode = scenario_risk
number_of_ground_motion_fields = 10
truncation_level = 3
shakemap_id = usp000fjta
hazard_calculation_id = 1000  # ID of the pre-calculation
spatial_correlation = yes
cross_correlation = yes
```

This example refers to the 2007 Mw8.0 Pisco earthquake in Peru (see https://earthquake.usgs.gov/earthquakes/eventpage/usp000fjta#shakemap). The risk can be computed by running the risk job file against the prepared calculation:

```
$ oq engine --run job.ini
```

The engine will perform the following operations:

1. download the ShakeMap from the USGS web service and convert it into a format suitable for further processing, i.e. a ShakeMaps array with lon, lat fields
2. the ShakeMap array will be associated to the hazard sites in the region covered by the ShakeMap
3. by using the parameters `truncation_level` and `number_of_ground_motion_fields` a set of ground motion fields (GMFs) following the truncated Gaussian distribution will be generated and stored in the datastore
4. a regular risk calculation will be performed by using such GMFs and the assets within the region covered by the shakemap.

The performance of the calculation will be crucially determined by the number of hazard sites. For instance, in the case of the Pisco earthquake the ShakeMap has 506,142 sites, which is a significantly large number of sites. However, the extent of the ShakeMap in longitude and latitude is about 6 degrees, with a step of 10 km the grid contains around 65 x 65 sites; most of the sites are without assets because most of the grid is on the sea or on high mountains, so actually there are around ~500 effective sites. Computing a correlation matrix of size 500 x 500 is feasible, so the risk computation can be performed. Clearly in situations in which the number of hazard sites is too large, approximations will have to be made, such as neglecting the spatial or cross correlation effects, or using a larger *region_grid_spacing*.

By default the engine tries to compute both the spatial correlation and the cross correlation between

different intensity measure types. For each kind of correlation you have three choices, that you can set in the *job.ini*, for a total of nine combinations:

```
- spatial_correlation = yes, cross_correlation = yes  # the default
- spatial_correlation = no, cross_correlation = no   # disable␣
↪everything
- spatial_correlation = yes, cross_correlation = no
- spatial_correlation = no, cross_correlation = yes
- spatial_correlation = full, cross_correlation = full
- spatial_correlation = yes, cross_correlation = full
- spatial_correlation = no, cross_correlation = full
- spatial_correlation = full, cross_correlation = no
- spatial_correlation = full, cross_correlation = yes
```

yes means using the correlation matrix of the Silva-Horspool paper; *no* mean using a unity correlation matrix; *full* means using an all-ones correlation matrix.

Disabling either the spatial correlation or the cross correlation (or both) might be useful to see how significant the effect of the correlation is on the damage/loss estimates; sometimes it is also made necessary because the calculation simply cannot be performed otherwise due to the large size of the resulting correlation matrices.

In particular, due to numeric errors, the spatial correlation matrix - that by construction contains only positive numbers - can still produce small negative eigenvalues (of the order of -1E-15) and the calculation fails with an error message saying that the correlation matrix is not positive defined. Welcome to the world of floating point approximation! Rather than magically discarding negative eigenvalues the engine raises an error and the user has two choices: either disable the spatial correlation or reduce the number of sites because that can make the numerical instability go away. The easiest way to reduce the number of sites is setting a *region_grid_spacing* parameter in the *prepare_job.ini* file, then the engine will automatically put the assets on a grid. The larger the grid spacing, the fewer the number of points, and the closer the calculation will be to tractability.

If the ground motion values or the standard deviations are particularly large, the user will get a warning about suspicious GMFs.

Moreover, especially for old ShakeMaps, the USGS can provide them in a format that the engine cannot read.

Thus, this feature is not expected to work in 100% of the cases.

Note: on macOS make sure to run the script located under `/Applications/Python 3.6/Install Certificates.command`, after Python has been installed, to update the SSL certificates and to avoid SSL errors when downloading the ShakeMaps from the USGS website (see the FAQ)

CHAPTER

EIGHTEEN

DEVELOPING WITH THE ENGINE

Some advanced users are interested in developing with the engine, usually to contribute new GMPEs and sometimes to submit a bug fix. There are also users interested in implementing their own customizations of the engine. This part of the manual is for them.

18.1 Prerequisites

It is assumed here that you are a competent scientific Python programmer, i.e. that you have a good familiarity with the Python ecosystem (including pip and virtualenv) and its scientific stack (numpy, scipy, h5py, ...). It should be noticed that since engine v2.0 there is no need to know anything about databases and web development (unless you want to develop on the WebUI part) so the barrier for contribution to the engine is much lower than it used to be. However, contributing is still nontrivial, and it absolutely necessary to know git and the tools of Open Source development in general, in particular about testing. If this is not the case, you should do some study on your own and come back later. There is a huge amount of resources in the net about these topics. This manual will focus solely on the OpenQuake engine and it assume that you already know how to use it, i.e. you have read the User Manual first.

Before starting, it may be useful to have an idea of the architecture of the engine and its internal components, like the DbServer and the WebUI. For that you should read the *Architecture of the OpenQuake engine* document.

There are also external tools which are able to interact with the engine, like the QGIS plugin to run calculations and visualize the outputs and the IPT tool to prepare the required input files (except the hazard models). Unless you are developing for such tools you can safely ignore them.

18.2 The first thing to do

The first thing to do if you want to develop with the engine is to remove any non-development installation of the engine that you may have. While it is perfectly possible to install on the same machine both a development and a production instance of the engine (it is enough to configure

the ports of the DbServer and WebUI) it is easier to work with a single instance. In that way you will have a single code base and no risks of editing the wrong code. A development installation the engine works as any other development installation in Python: you should clone the engine repository, create and activate a virtualenv and then perform a *pip install -e .* from the engine main directory, as normal. You can find the details here:

https://github.com/gem/oq-engine/blob/master/doc/installing/development.md

It is also possible to develop on Windows (https://github.com/gem/oq-engine/blob/master/doc/installing/development.md) but very few people in GEM are doing that, so you are on your own, should you encounter difficulties. We recommend Linux, but Mac also works.

Since you are going to develop with the engine, you should also install the development dependencies that by default are not installed. They are listed in the setup.py file, and currently (January 2020) they are pytest, flake8, pdbpp, silx and ipython. They are not required but very handy and recommended. It is the stack we use daily for development.

18.3 Understanding the engine

Once you have the engine installed you can run calculations. We recommend starting from the demos directory which contains example of hazard and risk calculations. For instance you could run the area source demo with the following command:

```
$ oq run demos/hazard/AreaSourceClassicalPSHA/job.ini
```

You should notice that we used here the command *oq run* while the engine manual recommend the usage of *oq engine –run*. There is no contradiction. The command *oq engine –run* is meant for production usage, it will work with the WebUI and store the logs of the calculation in the engine database. But here we are doing development, so the recommended command is *oq run* which will not interact with the database, will be easier to debug and accept the essential flag `--pdb`, which will start the python debugger should the calculation fail. Since during development is normal to have errors and problems in the calculation, so this ability is invaluable.

Then, if you want to understand what happened during the calculation you should generate the associated .rst report, which can be seen with the command

```
$ oq show fullreport
```

There you will find a lot of interesting information that it is worth studying and we will discuss in detail in the rest of this manual. The most important section of the report is probably the last one, titled “Slowest operations”. For that one can understand the bottlenecks of the calculation and, with experience, he can understand which part of the engine he needs to optimize. Also, it is very useful to play with the parameters of the calculation (like the maximum distance, the area discretization, the magnitude binning, etc etc) and see how the performance change. There is also a command to plot hazard curves and a command to compare hazard curves between different

calculations: it is common to be able to get big speedups simply by changing the input parameters in the *job.ini* of the model, without changing much the results.

There a lot of *oq* commands: if you are doing development you should study all of them. They are documented here.

18.4 Running calculations programmatically

Starting from engine 3.9 the recommended way to run a calculation programmaticaly is the following:

```
>> from openquake.commonlib import logs
>> from openquake.calculators.base import get_calc
>> calc_id = logs.init()  # initialize logs
>> calc = get_calc('job.ini', calc_id)  # instantiate calculator
>> calc.run()  # run the calculation
```

Then the results can be read from the datastore by using the extract API:

```
>> from openquake.calculators.extract import extract
>> extract(calc.datastore, 'something')
```

18.5 Case study: computing the impact of a source on a site

As an exercise showing off how to use the engine as a library, we will solve the problem of computing the hazard on a given site generated by a given source, with a given GMPE logic tree and a few parameters, i.e. the intensity measure levels and the maximum distance.

The first step is to specify the site and the parameters; let's suppose that we want to compute the probability of exceeding a Peak Ground Accelation (PGA) of 0.1g by using the ToroEtAl2002SHARE GMPE:

```
>>> from openquake.commonlib import readinput
>>> oq = readinput.get_oqparam(dict(
... calculation_mode='scenario',
... sites='15.0 45.2',
... reference_vs30_type='measured',
... reference_vs30_value='600.0',
... intensity_measure_types_and_levels="{'PGA': [0.1]}",
... gsim='ToroEtAl2002SHARE',
... maximum_distance='200.0'))
```

Then we need to specify the source:

```
>>> from openquake.hazardlib import nrml
>>> src = nrml.get('''
...         <areaSource
...         id="126"
...         name="HRAS195"
...         >
...             <areaGeometry discretization="10">
...                 <gml:Polygon>
...                     <gml:exterior>
...                         <gml:LinearRing>
...                             <gml:posList>
...                                 1.5026169E+01 4.5773603E+01
...                                 1.5650548E+01 4.6176279E+01
...                                 1.6273108E+01 4.6083465E+01
...                                 1.6398742E+01 4.6024744E+01
...                                 1.5947759E+01 4.5648318E+01
...                                 1.5677179E+01 4.5422577E+01
...                             </gml:posList>
...                         </gml:LinearRing>
...                     </gml:exterior>
...                 </gml:Polygon>
...                 <upperSeismoDepth>0</upperSeismoDepth>
...                 <lowerSeismoDepth>30</lowerSeismoDepth>
...             </areaGeometry>
...             <magScaleRel>WC1994</magScaleRel>
...             <ruptAspectRatio>1</ruptAspectRatio>
...             <incrementalMFD binWidth=".2" minMag="4.7">
...                 <occurRates>
...                     1.4731083E-02 9.2946848E-03 5.8645496E-03
...                     3.7002807E-03 2.3347193E-03 1.4731083E-03
...                     9.2946848E-04 5.8645496E-04 3.7002807E-04
...                     2.3347193E-04 1.4731083E-04 9.2946848E-05
...                     1.7588460E-05 1.1097568E-05 2.3340307E-06
...                 </occurRates>
...             </incrementalMFD>
...             <nodalPlaneDist>
...                 <nodalPlane dip="5.7596810E+01" probability="1"
...                             rake="0" strike="6.9033586E+01"/>
...             </nodalPlaneDist>
...             <hypoDepthDist>
...                 <hypoDepth depth="1.0200000E+01" probability="1"/>
...             </hypoDepthDist>
...         </areaSource>
... ''')
```

Then the hazard curve can be computed as follows:

```
>>> from openquake.hazardlib.calc.hazard_curve import calc_hazard_curve
>>> from openquake.hazardlib import valid
>>> sitecol = readinput.get_site_collection(oq)
>>> gsims = readinput.get_gsim_lt(oq).values['*']
>>> calc_hazard_curve(sitecol, src, gsims, oq)
<ProbabilityCurve
[[0.00507997]]>
```

CHAPTER

NINETEEN

ARCHITECTURE OF THE OPENQUAKE ENGINE

The engine is structured as a regular scientific application: we try to perform calculations as much as possible in memory and when it is not possible intermediate results are stored in HDF5 format. We try work as much as possible in terms of arrays which are efficiently manipulated at C/Fortran speed with a stack of well established scientific libraries (numpy/scipy).

CPU-intensity calculations are parallelized with a custom framework (the engine is ten years old and predates frameworks like dask or ray) which however is quite easy to use and mostly compatible with Python multiprocessing or concurrent.futures. The concurrency architecture is the standard Single Writer Multiple Reader (SWMR), used at the HDF5 level: only one process can write data while multiple processes can read it. The engine runs seamlessly on a single machine or a cluster, using as many cores as possible.

In the past the engine had a database-centric architecture and was more class-oriented than numpy-oriented: some remnants of such dark past are still there, but they are slowly disappearing. Currently the database is only used for storing accessory data and it is a simple SQLite file. It is mainly used by the WebUI to display the logs.

19.1 Components of the OpenQuake Engine

The OpenQuake Engine suite is composed of several components:

- a set of *support libraries* addressing different concerns like reading the inputs and writing the outputs, implementing basic geometric manipulations, managing distributed computing and generic programming utilities
- the *hazardlib* and *risklib* scientific libraries, providing the building blocks for hazard and risk calculations, notably the GMPEs for hazard and the vulnerability/fragility functions for risk
- the hazard and risk *calculators*, implementing the core logic of the engine
- the *datastore*, which is an HDF5 file working as a short term storage/cache for a calculation; it is possible to run a calculation starting from an existing datastore, to avoid recomputing everything every time; there is a separate datastore for each calculation

- the *database*, which is a SQLite file working as a long term storage for the calculation metadata; the database contains the start/stop times of the computations, the owner of a calculation, the calculation descriptions, the performances, the logs, etc; the bulk scientific data (essentially big arrays) are kept in the datastore
- the *DbServer*, which is a service mediating the interaction between the calculators and the database
- the *WebUI* is a web application that allows to run and monitor computations via a browser; multiple calculations can be run in parallel
- the *oq* command-line tool; it allows to run computations and provides an interface to the underlying database and datastores so that it is possible to list and export the results
- the engine can run on a cluster of machines: in that case a minimal amount of configuration is needed, whereas in single machine installations the engine works out of the box
- since v3.8 the engine does not depend anymore from celery and rabbitmq, but can still use such tools until they will be deprecated

This is the full stack of internal libraries used by the engine. Each of these is a Python package containing several modules or event subpackages. The stack is a dependency tower where the higher levels depend on the lower levels but not vice versa:

- level 9: commands (commands for oq script)
- level 8: server (database and Web UI)
- level 7: engine (command-line tool, export, logs)
- level 6: calculators (hazard and risk calculators)
- level 5: commonlib (configuration, logic trees, I/O)
- level 4: risklib (risk validation, risk models, risk inputs)
- level 3: hmtk (catalogues, plotting, . . .)
- level 2: hazardlib (validation, read/write XML, source and site objects, geospatial utilities, GSIM library)
- level 1: baselib (programming utilities, parallelization, monitoring, hdf5. . .)

baselib and *hazardlib* are very stable and can be used outside of the engine; the other libraries are directly related to the engine and are likely to be affected by backward-incompatible changes in the future, as the code base evolves.

The GMPE library in *hazardlib* and the calculators are designed to be extensible, so that it is easy to add a new GMPE class or a new calculator. We routinely add several new GMPEs per release; adding new calculators is less common and it requires more expertise, but it is possible and it has been done several times in the past. In particular it is often easier to add a specific calculator optimized for a given use case rather than complicating the current calculators.

The results of a computation are automatically saved in the datastore and can be exported in a portable format, such as CSV (or XML, for legacy reasons). You can assume that the datastore of version X of the engine *will not work* with version X + 1. On the contrary, the exported files will likely be same across different versions. It is important to export all of the outputs you are interested in before doing an upgrade, otherwise you would be forced to downgrade in order to be able to export the previous results.

The WebUI provides a REST API that can be used in third party applications: for instance a QGIS plugin could download the maps generated by the engine via the WebUI and display them. There is lot of functionality in the API which is documented here: https://github.com/gem/oq-engine/blob/master/doc/web-api.md. It is possible to build your own user interface for the engine on top of it, since the API is stable and kept backward compatible.

19.2 Design principles

The main design principle has been *simplicity*: everything has to be as simple as possible (but not simplest). The goal has been to keep the engine simple enough that a single person can understand it, debug it, and extend it without tremendous effort. All the rest comes from simplicity: transparency, ability to inspect and debug, modularity, adaptability of the code, etc. Even efficiency: in the last three years most of the performance improvements came from free, just from removing complications. When a thing is simple it is easy to make it fast. The battle for simplicity is never ending, so there are still several things in the engine that are more complex than they should: we are working on that.

After simplicity the second design goal has been *performance*: the engine is a number crunching application after all, and we need to run massively parallel calculations taking days or weeks of runtime. Efficiency in terms of computation time and memory requirements is of paramount importance, since it makes the difference between being able to run a computation and being unable to do it. Being too slow to be usable should be considered as a bug.

The third requirement is *reproducibility*, which is the same as testability: it is essential to have a suite of tests checking that the calculators are providing the expected outputs against a set of predefined inputs. Currently we have thousands of tests which are run multiple times per day in our Continuous Integration environments r(avis, GitLab, Jenkins), split into unit tests, end-to-end tests and long running tests.

CHAPTER

TWENTY

SOME USEFUL *OQ* COMMANDS

The *oq* command-line script is the entry point for several commands, the most important one being *oq engine*, which is documented in the manual.

The commands documented here are not in the manual because they have not reached the same level of maturity and stability. Still, some of them are quite stable and quite useful for the final users, so feel free to use them.

You can see the full list of commands by running *oq –help*:

```
$ oq --help
usage: oq [--version]
          {workerpool,webui,dbserver,info,ltcsv,dump,export,celery,
 ↪plot_losses,restore,plot_assets,reduce_sm,check_input,plot_ac,
 ↪upgrade_nrml,shell,plot_pyro,nrml_to,postzip,show,workers,abort,
 ↪engine,reaggregate,db,compare,renumber_sm,download_shakemap,
 ↪importcalc,purge,tidy,from_shapefile,zip,checksum,to_shapefile,to_
 ↪hdf5,extract,reset,run,show_attrs,prepare_site_model,sample,plot}
          ...

positional arguments:
  {workerpool,webui,dbserver,info,ltcsv,dump,export,celery,plot_losses,
 ↪restore,plot_assets,reduce_sm,check_input,plot_ac,upgrade_nrml,shell,
 ↪plot_pyro,nrml_to,postzip,show,workers,abort,engine,reaggregate,db,
 ↪compare,renumber_sm,download_shakemap,importcalc,purge,tidy,from_
 ↪shapefile,zip,checksum,to_shapefile,to_hdf5,extract,reset,run,show_
 ↪attrs,prepare_site_model,sample,plot}
                        available subcommands; use oq <subcmd> --help

optional arguments:
  -h, --help            show this help message and exit
  -v, --version         show program's version number and exit
```

This is the output that you get at the present time (engine 3.11); depending on your version of the engine you may get a different output. As you see, there are several commands, like *purge*,

show_attrs, *export*, *restore*, ... You can get information about each command with *oq <command> –help*; for instance, here is the help for *purge*:

```
$ oq purge --help
usage: oq purge [-h] [-f] calc_id

Remove the given calculation. If you want to remove all calculations,␣
↪use oq
reset.

positional arguments:
  calc_id      calculation ID

optional arguments:
  -h, --help   show this help message and exit
  -f, --force  ignore dependent calculations
```

Some of these commands are highly experimental and may disappear; others are meant for debugging and are not meant to be used by end-users. Here I will document only the commands that are useful for the general public and have reached some level of stability.

Probably the most important command is *oq info*. It has several features.

1. It can be invoked with a *job.ini* file to extract information about the logic tree of the calculation.

2. When invoked with the *–report* option, it produces a *.rst* report with several important informations about the computation. It is ESSENTIAL in the case of large calculations, since it will give you an idea of the feasibility of the computation without running it. Here is an example of usage:

```
$ oq info --report job.ini
Generated /tmp/report_1644.rst
<Monitor info, duration=10.910529613494873s, memory=60.16 MB>
```

You can open */tmp/report_1644.rst* and read the informations listed there (*1644* is the calculation ID, the number will be different each time).

3. It can be invoked without a *job.ini* file, and it that case it provides global information about the engine and its libraries. Try, for instance:

```
$ oq info calculators # list available calculators
$ oq info gsims       # list available GSIMs
$ oq info views       # list available views
$ oq info exports     # list available exports
$ oq info parameters  # list all job.ini parameters
```

The second most important command is *oq export*. It allows customization of the exports from the datastore with additional flexibility compared to the *oq engine* export commands. In the future the *oq engine* exports commands might be deprecated and *oq export* might become the official export command, but we are not there yet.

Here is the usage message:

```
$ oq export --help
usage: oq export [-h] [-e csv] [-d .] datastore_key [calc_id]

Export an output from the datastore.

positional arguments:
  datastore_key         datastore key
  calc_id               number of the calculation [default: -1]

optional arguments:
  -h, --help            show this help message and exit
  -e csv, --exports csv
                        export formats (comma separated)
  -d ., --export-dir .  export directory
```

The list of available exports (i.e. the datastore keys and the available export formats) can be extracted with the *oq info exports* command; at the moment there are 52 exporters defined, but this number changes at each version:

```
$ oq info exports
agg_curves-rlzs ['csv']
agg_curves-stats ['csv']
agg_losses-rlzs ['csv']
agg_losses-stats ['csv']
agg_risk ['csv']
agglosses ['csv']
aggregate_by ['csv']
asset_risk ['csv']
avg_losses-rlzs ['csv']
avg_losses-stats ['csv']
bcr-rlzs ['csv']
bcr-stats ['csv']
damages-rlzs ['npz', 'csv']
damages-stats ['csv']
disagg ['csv', 'xml']
dmg_by_event ['csv']
events ['csv']
fullreport ['rst']
gmf_data ['csv']
hcurves ['csv', 'xml', 'npz']
hmaps ['csv', 'xml', 'npz']
input ['zip']
loss_curves ['csv']
loss_curves-rlzs ['csv']
loss_curves-stats ['csv']
```

```
loss_maps-rlzs ['csv', 'npz']
loss_maps-stats ['csv', 'npz']
losses_by_asset ['npz']
losses_by_event ['csv']
realizations ['csv']
ruptures ['xml', 'csv']
src_loss_table ['csv']
uhs ['csv', 'xml', 'npz']
There are 44 exporters defined.
```

At the present the supported export types are *xml*, *csv*, *rst*, *npz* and *hdf5*. *xml* has been deprecated for some outputs and is not the recommended format for large exports. For large exports, the recommended formats are *npz* (which is a binary format for numpy arrays) and *hdf5*. If you want the data for a specific realization (say the first one), you can use:

```
$ oq export hcurves/rlz-0 --exports csv
$ oq export hmaps/rlz-0 --exports csv
$ oq export uhs/rlz-0 --exports csv
```

but currently this only works for *csv* and *xml*. The exporters are one of the most time-consuming parts on the engine, mostly because of the sheer number of them; the are more than fifty exporters and they are always increasing. If you need new exports, please [add an issue on GitHub](https://github.com/gem/oq-engine/issues).

20.1 oq zip

An extremely useful command if you need to copy the files associated to a computation from a machine to another is *oq zip*:

```
$ oq zip --help
usage: oq zip [-h] [-r] what [archive_zip]

positional arguments:
  what                  path to a job.ini, a ssmLT.xml file, or an␣
↪exposure.xml
  archive_zip           path to a non-existing .zip file [default: '']

optional arguments:
  -h, --help            show this help message and exit
  -r , --risk-file      optional file for risk
```

For instance, if you have two configuration files *job_hazard.ini* and *job_risk.ini*, you can zip all the files they refer to with the command:

```
$ oq zip job_hazard.ini -r job_risk.ini
```

oq zip is actually more powerful than that; other than job.ini files, it can also zip source models:

```
$ oq zip ssmLT.xml
```

and exposures:

```
$ oq zip my_exposure.xml
```

20.2 Importing a remote calculation

Here is the command:

```
$ oq importcalc --help
usage: oq importcalc [-h] calc_id

Import a remote calculation into the local database. server, username␣
↪and
password must be specified in an openquake.cfg file.
NB: calc_id can be a local pathname to a datastore not already present␣
↪in
the database: in that case it is imported in the db.

positional arguments:
  calc_id     calculation ID or pathname

optional arguments:
  -h, --help  show this help message and exit
```

20.3 plotting commands

The engine provides several plotting commands. They are all experimental and subject to change. They will always be. The official way to plot the engine results is by using the QGIS plugin. Still, the *oq* plotting commands are useful for debugging purposes. Here I will describe the *plot_assets* command, which allows to plot the exposure used in a calculation together with the hazard sites:

```
$ oq plot_assets --help
usage: oq plot_assets [-h] [calc_id]

Plot the sites and the assets
```

```
positional arguments:
  calc_id     a computation id [default: -1]

optional arguments:
  -h, --help  show this help message and exit
```

This is particularly interesting when the hazard sites do not coincide with the asset locations, which is normal when gridding the exposure.

Very often, it is interesting to plot the sources. While there is a primitive functionality for that in *oq plot*, we recommend to convert the sources into .gpkg format and use QGIS to plot them:

```
$ oq nrml_to --help
usage: oq nrml_to [-h] [-o .] [-c] {csv,gpkg} fnames [fnames ...]

Convert source models into CSV files or a geopackage.

positional arguments:
  {csv,gpkg}        csv or gpkg
  fnames            source model files in XML

optional arguments:
  -h, --help        show this help message and exit
  -o ., --outdir .  output directory
  -c, --chatty      display sources in progress
```

For instance

```
$ oq nrml_to gpkg source_model.xml -o source_model.gpkg
```

will convert the sources in .gpkg format while

```
$ oq nrml_to csv source_model.xml -o source_model.csv
```

will convert the sources in .csv format. Both are fully supported by QGIS. The CSV format has the advantage of being transparent and easily editable; it also can be imported in a geospatial database like Postgres, if needed.

20.4 prepare_site_model

The command *oq prepare_site_model*, introduced in engine 3.3, is quite useful if you have a vs30 file with fields lon, lat, vs30 and you want to generate a site model from it. Normally this feature is used for risk calculations: given an exposure, one wants to generate a collection of hazard sites covering the exposure and with vs30 values extracted from the vs30 file with a nearest neighbour algorithm:

```
$ oq prepare_site_model -h
usage: oq prepare_site_model [-h] [-1] [-2] [-3]
                             [-e [EXPOSURE_XML [EXPOSURE_XML ...]]]
                             [-s SITES_CSV] [-g 0] [-a 5] [-o site_
 ↪model.csv]
                             vs30_csv [vs30_csv ...]

Prepare a site_model.csv file from exposure xml files/site csv files,␣
 ↪vs30 csv
files and a grid spacing which can be 0 (meaning no grid). For each␣
 ↪site the
closest vs30 parameter is used. The command can also generate (on␣
 ↪demand) the
additional fields z1pt0, z2pt5 and vs30measured which may be needed by␣
 ↪your
hazard model, depending on the required GSIMs.

positional arguments:
  vs30_csv              files with lon,lat,vs30 and no header

optional arguments:
  -h, --help            show this help message and exit
  -1, --z1pt0
  -2, --z2pt5           build the z2pt5
  -3, --vs30measured    build the vs30measured
  -e [EXPOSURE_XML [EXPOSURE_XML ...]], --exposure-xml [EXPOSURE_XML␣
 ↪[EXPOSURE_XML ...]]
                        exposure(s) in XML format
  -s SITES_CSV, --sites-csv SITES_CSV
  -g 0, --grid-spacing 0
                        grid spacing in km (the default 0 means no␣
 ↪grid)
  -a 5, --assoc-distance 5
                        sites over this distance are discarded
  -o site_model.csv, --output site_model.csv
                        output file
```

The command works in two modes: with non-gridded exposures (the default) and with gridded exposures. In the first case the assets are aggregated in unique locations and for each location the vs30 coming from the closest vs30 record is taken. In the second case, when a *grid_spacing* parameter is passed, a grid containing all of the exposure is built and the points with assets are associated to the vs30 records. In both cases if the closest vs30 record is over the *site_param_distance* - which by default is 5 km - a warning is printed.

In large risk calculations, it is quite preferable *to use the gridded mode* because with a well spaced grid,

1. the results are the nearly the same than without the grid and
2. the calculation is a lot faster and uses a lot less memory.

Gridding of the exposure makes large calculations more manageable. The command is able to manage multiple Vs30 files at once. Here is an example of usage:

```
$ oq prepare_site_model Vs30/Ecuador.csv Vs30/Bolivia.csv -e Exposure/
↪Exposure_Res_Ecuador.csv Exposure/Exposure_Res_Bolivia.csv --grid-
↪spacing=10
```

20.5 Reducing the source model

Source models are usually large, at the continental scale. If you are interested in a city or in a small region, it makes sense to reduce the model to only the sources that would affect the region, within the integration distance. To fulfil this purpose there is the *oq reduce_sm* command. The suggestion is run a preclassical calculation (i.e. set *calculation_mode=preclassical* in the job.ini) with the full model in the region of interest, keep track of the calculation ID and then run:

```
$ oq reduce_sm <calc_id>
```

The command will reduce the source model files and add an extension *.bak* to the original ones.

```
$ oq reduce_sm -h
usage: oq reduce_sm [-h] calc_id

Reduce the source model of the given (pre)calculation by discarding all
sources that do not contribute to the hazard.

positional arguments:
  calc_id     calculation ID

optional arguments:
  -h, --help  show this help message and exit
```

20.6 Comparing hazard results

If you are interested in sensitivity analysis, i.e. in how much the results of the engine change by tuning a parameter, the *oq compare* command is useful. For the moment it is able to compare hazard curves and hazard maps. Here is the help message:

```
$ oq compare --help
usage: oq compare [-h] [-f] [-s 100] [-r 0] [-a 0.001] [-t 0.01]
```

```
                  {hcurves,hmaps} imt calc_ids [calc_ids ...]

Compare the hazard curves or maps of two or more calculations

positional arguments:
  {hcurves,hmaps}       hmaps or hcurves
  imt                   intensity measure type to compare
  calc_ids              calculation IDs

optional arguments:
  -h, --help            show this help message and exit
  -f, --files           write the results in multiple files
  -s 100, --samplesites 100
                        sites to sample (or fname with site IDs)
  -r 0, --rtol 0        relative tolerance
  -a 0.001, --atol 0.001
                        absolute tolerance
  -t 0.01, --threshold 0.01
                        ignore the hazard curves below it
```

CHAPTER

TWENTYONE

LIMITATIONS OF FLOATING-POINT ARITHMETIC

Most practitioners of numeric calculations are aware that addition of floating-point numbers is non-associative; for instance

```
>>>  (.1 + .2) + .3
0.6000000000000001
```

is not identical to

```
>>> .1 + (.2 + .3)
0.6
```

Other floating-point operations, such as multiplication, are also non-associative. The order in which operations are performed plays a role in the results of a calculation.

Single-precision floating-point variables are able to represent integers between [-16777216, 16777216] exactly, but start losing precision beyond that range; for instance:

```
>>> numpy.float32(16777216)
16777216.0
```

```
>>> numpy.float32(16777217)
16777216.0
```

This loss of precision is even more apparent for larger values:

```
>>> numpy.float32(123456786432)
123456780000.0
```

```
>>> numpy.float32(123456786433)
123456790000.0
```

These properties of floating-point numbers have critical implications for numerical reproducibility of scientific computations, particularly in a parallel or distributed computing environment.

For the purposes of this discussion, let us define numerical reproducibility as obtaining bit-wise identical results for different runs of the same computation on either the same machine or different machines.

Given that the OpenQuake engine works by parallelizing calculations, numerical reproducibility cannot be fully guaranteed, even for different runs on the same machine (unless the computation is run using the –no-distribute or –nd flag).

Consider the following strategies for distributing the calculation of the asset losses for a set of events, followed by aggregation of the results for the portfolio due to all of the events. The assets could be split into blocks with each task computing the losses for a particular block of assets and for all events, and the partial losses coming in from each task is aggregated at the end. Alternatively, the assets could be kept as a single block, splitting the set of events/ruptures into blocks instead; once again the engine has to aggregate partial losses coming in from each of the tasks. The order of the tasks is arbitrary, because it is impossible to know how long each task will take before the computation actually begins.

For instance, suppose there are 3 tasks, the first one producing a partial loss of 0.1 billion, the second one of 0.2 billion, and the third one of 0.3 billion. If we run the calculation and the order in which the results are received is 1-2-3, we will compute a total loss of (.1 + .2) + .3 = 0.6000000000000001 billion. On the other hand, if for some reason the order in which the results arrive is 2-3-1, say for instance, if the first core is particularly hot and the operating system decides to enable some throttling on it, then the aggregation will be (.2 + .3) + .1 = 0.6 billion, which is different from the previous value by 1.11E-7 units. This example assumes the use of Python's IEEE-754 "double precision" 64-bit floats.

However, the engine uses single-precision 32-bit floats rather than double-precision 64-bit floats in a tradeoff necessary for reducing the memory demand (both RAM and disk space) for large computations, so the precision of results is less than in the above example. 64-bit floats have 53 bits of precision, and this why the relative error in the example above was around 1.11E-16 (i.e. 2^-53). 32-bit floats have only 24 bits of precision, so we should expect a relative error of around 6E-8 (i.e. 2^-24), which for the example above would be around 60 units. Loss of precision in representing and storing large numbers is a factor that *must* be considered when running large computations.

By itself, such differences may be negligible for most computations. However, small differences may accumulate when there are hundreds or even thousands of tasks handling different parts of the overall computation and sending back results for aggregation.

Anticipating these issues, some adjustments can be made to the input models in order to circumvent or at least minimize surprises arising from floating-point arithmetic. Representing asset values in the exposure using thousands of dollars as the unit instead of dollars could be one such defensive measure.

This is why, as an aid to the interested user, starting from version 3.9, the engine logs a warning if it finds inconsistencies beyond a tolerance level in the aggregated loss results.

Recommended readings:

- Goldberg, D. (1991). What every computer scientist should know about floating-point arithmetic. *ACM Computing Surveys (CSUR)*, 23(1), 5-48. Reprinted at https://docs.oracle.com/cd/E19957-01/806-3568/ncg_goldberg.html
- https://docs.python.org/3/tutorial/floatingpoint.html
- https://en.wikipedia.org/wiki/Single-precision_floating-point_format
- https://en.wikipedia.org/wiki/Double-precision_floating-point_format