

As there are many ways to combine each configuration, we select a few configurations by examining them through simulations.

To avoid confusion, we refer to each unique phase combination as a model-configuration. For instance, one model-configuration would consist of [a **DatabBasedInitiator**, an **ElitismSelector**, a **OnePointCrosser**, **SamplinBasedMutator** and a **FittestSurvivorRecombiner**]. We refer to a specific model-configuration in terms of its abbreviated operators. For instance, the earlier example is denoted as **[DBI-ES-OPC-SBM-FSR]**.

The model-configuration set contains [144] elements. We choose to run each model-configuration for [50] evolution cycles. For all model-configurations, we use the same set of [4] factual process instances, which are randomly sampled from the test set. We ensure, that the outcomes of these factuals are evenly divided. We decide to return a maximum of [1000] counterfactuals for each factual case. Within each evolutionary cycle, we generate [100] new offsprings. We keep the mutation rate at [0.1] for each mutation type. Hence, across all cases that are mutated, the algorithm deletes, inserts, and changes [1%] of events. We collect the means viability and its components across the iterative cycles of the model.

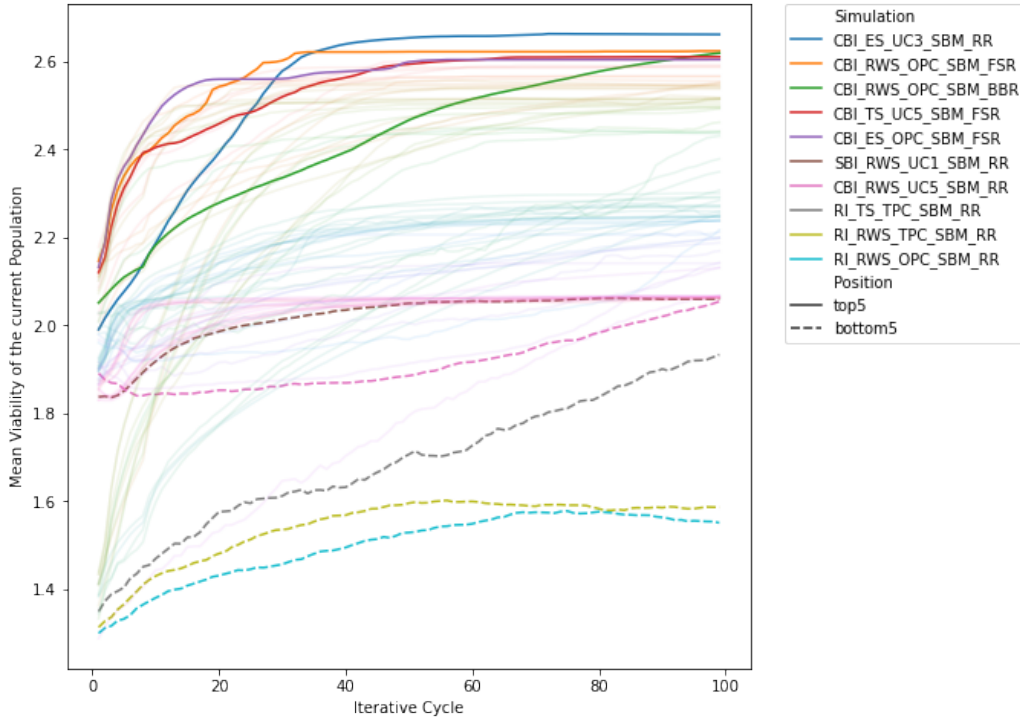


Figure 1: This figure shows the average viability of the [10] best and worst model-configurations. The x-axis shows how the viability evolves for each evolutionary cycle.

Figure 1 shows the bottom and top-[k] model-configurations based on the viability after the final iterative cycle. We also show how the viability evolves for each iteration. **[change evolutionary cycle to iterative cycle]** The results reveal a couple of patterns. First, all of the top-[k] algorithms use **[either CaseBasedInitiator or SampleBasedInitiator]** as initiation operation. In contrast, the bottom-[k] all use **[RandomInitiator]** as initialisation. Second, we see that most of the top-[k] algorithms use the **[ElitismSelector]**. The complete table of results are in ??.

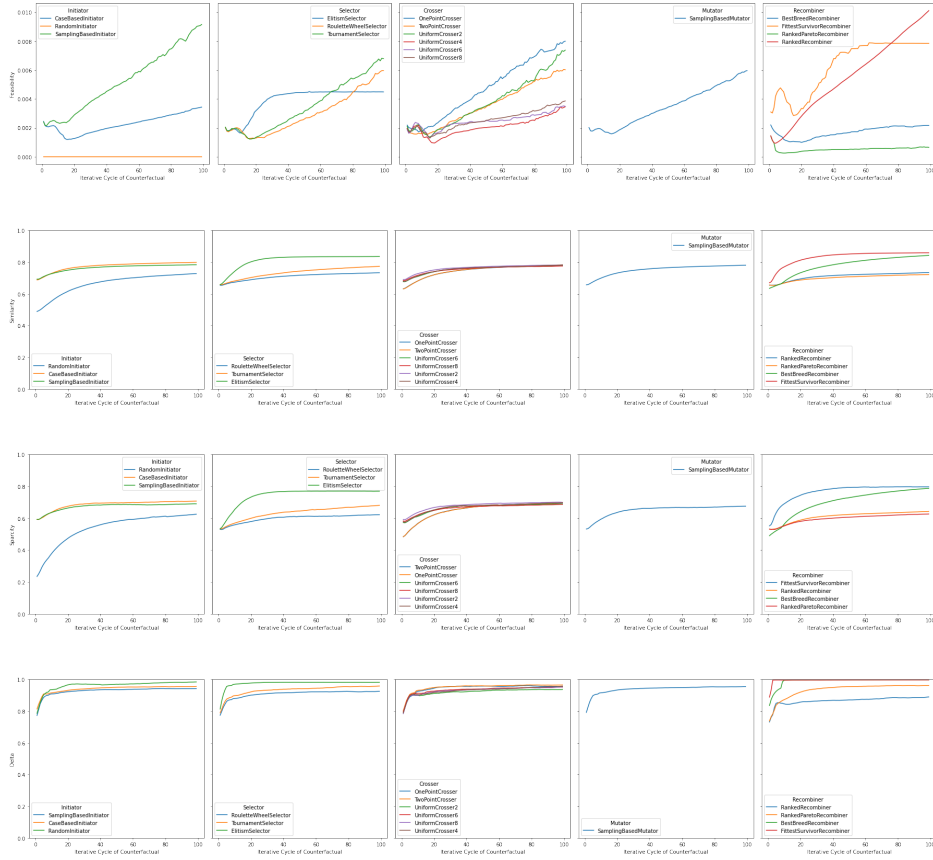


Figure 2: Shows the evolution of each viability measure over the entire span of iterative cycles. Each figure adjust the respective operator type by taking the average over all other operator types. **[Make sure, that the legends are aligned in color.]**

[FOR XIXI: Shall I discuss the big figure or just viability in this section?] In Figure 2, we see the effects of each operator type, except the mutation operation.

Starting with some commonalities across operator-type and measure, the figure shows that the initiator heavily determines the starting point for

each measure. For instance, the **[RandomInitiator]** starts well below the other initiator operations when it comes to sparsity and similarity. Another noteworthy general observation is the delta measure **[Change some of the names to align with Dice4EL]**. Here, for each operator type we see a movement towards the highest possible delta value. Hence, most configurations are capable of changing the source class to the desired class.

In terms of viability Figure ??, shows an increase only for cases, in which the **[SampleBasedInitiator]** is used. Similar holds for recombination with **[FittestSurvivorRecombiner]**.

The results for the selection operator type are undeniably in favor of **[ElitismSelector]** for all viability measures. The same holds for the recombination operation. Here, the **[FittestSurvivorRecombiner]** yields better results.

When it comes to the crossing operation, the results indicate, the differences between **[OnePointCrosser]** and **[TwoPointCrosser]** are inconclusive for all viability measures except feasibility. One can explain that by noting, that both operations are very similar in nature. However, cutting the sequence only once retains produces less impossible sequences for the child sequences.

Moving forward, we have to choose a set of operators. We consider the following operators: We choose the **[SampleBasedInitiator]** as it might increase our chances to generate feasible variables.

For selection, we use the **[ElitismSelector]**, as it generally appears to return better results.

Furthermore, we choose to move forward with the **[OnePointCrosser]**. This crossing operation is slightly better in yielding feasible results.

For selection and recombination, we use the **[ElitismSelector]** and the **[FittestSurvivorRecombiner]**, respectively. They all outcompete their alternatives for all similarity, sparsity and feasibility.

In the next experiment we vary mutation rates, using SBI-ES-OPC-SBM-FSR Generator .

Hyperparameter Selection

[FOR XIXI: Shall I include other analysis for selecting the model?]

We also ran additional simulations to determine the optimal hyper parameter settings nad iteration count. These simulations were conducted in a similar fashion. These preliminary experiments revealed that, a delete-rate of **[0.14]**, an insert rate of **[0.21]** and a change rate of **[0.23]** are most beneficial. Also, we should run the evolutionary algorithm around **[35]** iterations long. Otherwise the algorithm tends to get stuck in a local optimum.