*G4* *– Develop Scenario Co-Optimizer Input Framework:*

*Incorporate capability for sensitivity analyses of individual uncertain components, implement possibility for different distributions. We will test the method on synthetic data.*

The overarching goal of developing the co-optimizer tool is to support scientists in making informed decisions about future (fuel/engine) experiments or simulation test runs by offering a variety of optimization options (single-objective, multi-objective, deterministic, uncertain). One important part of the co-optimizer that is currently being developed is the treatment of uncertainty that may arise, for example, from cost estimates for fuel components that go into the fuel blend or from coefficients in the Miles merit function (Miles, 2018). Previously, the only probability distribution that could be used within the co-optimizer to investigate the sensitivity of the solution was a normal distribution, which may be a justified assumption for the coefficients in the Miles function, but possibly inaccurate for the cost of the fuel components, which must be larger than zero.

During FY18-Q2, we therefore extended the capabilities of the co-optimizer tool by adding more options for probability distributions. These options now include

1. A normal distribution for a given mean and variance (old, fixed bug);
2. A truncated normal distribution for a given mean and variance (new addition);
3. A log-normal distribution for a given mean and variance (new addition);
4. A uniform distribution for given lower and upper limits (new addition);

For uncertainty in fuel component costs, we currently use synthetic data for which we make assumptions about the expected values and the corresponding variance . Ideally at a future point, we will have marketplace data available that truly reflect the cost of the fuel components. For 1. above, we draw a random number from the normal distribution for the cost of each fuel component, and we regenerate the random number should the realization of the random variable be negative (negative costs are unrealistic). To improve this “resampling when negative” strategy, we introduce a truncated normal distribution in 2. Here, we limit the support of the cost (the random variable) to the interval while using the same mean and variance information as in 1. As prices often follow a log-normal distribution, we also added this option in 3. For the log-normal, we also use the same mean and variance as for option 1. Lastly, we added the option of a uniform distribution whose support is the interval in 4., again restricting the fuel component costs to be larger than zero. The current implementation allows the user to investigate how the uncertainty attached with the cost of each individual fuel component affects the optimization results (expected cost versus efficiency) and how uncertainty in all fuel components changes the results. Identifying fuel components that lead to a high price volatility can potentially influence the decision about fuel blends that should or should not be further investigated in experiments.

In order to investigate how sensitive the Miles function is to changes in the coefficients of the individual terms, options 1., 2., and 4. above can be used for defining the uncertainty. Since the miles function is a weighted linear combination of fuel properties, we also have to enforce that the (uncertain) weights (the coefficients) have to be larger than zero. Thus, we use the same approach as for 1.,2., and 4. above to enforce this constraint. We use as mean values for the coefficients the values that are defined in the merit function report. For the variance, we either use the information provided in the merit function report (if given), or otherwise we assume ~10% of the mean value. Similar to the treatment of the fuel component costs, as we continue to learn more about the merit function and its ability to represent engine efficiency, these values can easily be updated and the analysis repeated. For the uncertainty in the coefficients of the merit function, the co-optimizer allows to investigate the influence of the variability of individual parts of the merit function on the optimization results. This allows us to examine which parts introduce the larges variability in the results which might then be worthwhile to further investigate.