Mean Performance with Varying Injection Rate

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March 12, 2020

The experiment consists of changing injection rates inj_1 and inj_2, for 2 applications in Supersim, and optimize the execution times $\mathcal{P}(inj_1)$ and $\mathcal{P}(inj_2)$. The experimental settings are:

Parameter	Value
Injection Rate 1 (inj_1)	$[0.0, 1.0]$
Injection Rate 2 (inj_2)	$[0.0, 1.0]$
Performance Metric	$\frac{1}{(inj_1+inj_2)} + \frac{\mathcal{P}_1(inj_1)+\mathcal{P}_2(inj_2)}{2}$

The interval for injection rates was limited because the simulator crashed for larger rates. The problem must be better understood to determine the proper injection rate ranges.

Low-discrepancy samples of size 20 were taken for both injection rates on the specified intervals, and 10 repetitions were performed. In total, 200 samples were measured, and the best value according to the performance metric was logged separately for each repetition.

1 Weighted Sum of Averages of Injection Rates and Execution Times

The figure below shows the injection rates, for both applications, in the 200 samples tested.

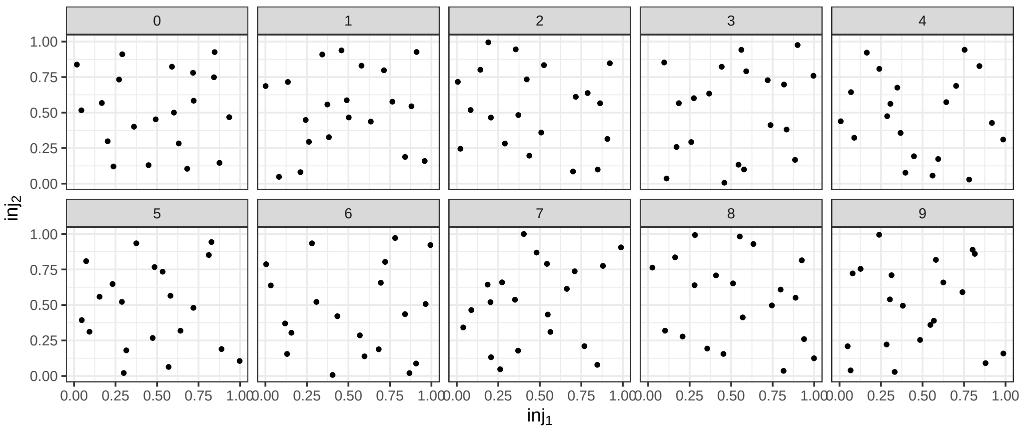

Figure 1: Values of inj_1 and inj_2 in each of the 10 repetitions

1.1 Histograms

Looking at the histograms of the performance metric and the execution times of both applications, in the figure below, we see that almost 150 of the configurations tested had performance below 10^9.

1.2 Mean Performance and Injection Rate

We now look at the performance metric measured for each injection rate configuration. The figure below splits the values of injection rate for each application, and shows the performance metric computed using the execution times of both applications.

The solid lines represent the fit of the collected data to the linear models

$$\frac{\mathcal{P}(inj_1)+\mathcal{P}(inj_2)}{2} = Y_1 = \beta_1 inj_1 + \beta_2 \left(\frac{1}{inj_1}\right),$$

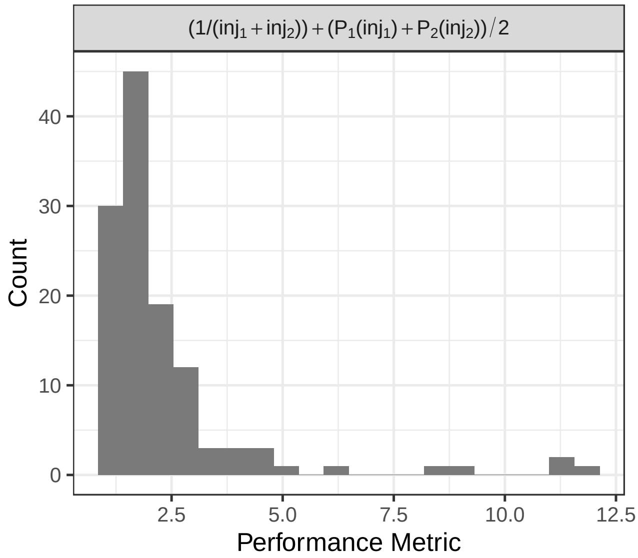

Figure 2: Performance metric distribution, for all tested injection rates

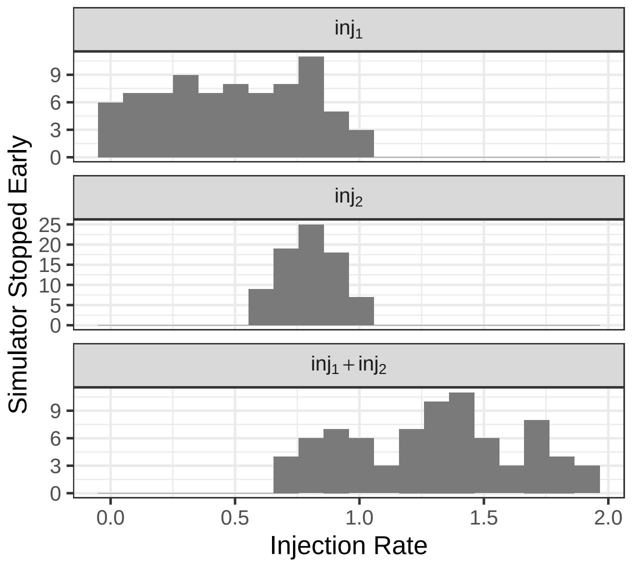

Figure 3: Injection rates for experiments where the simulator stopped early

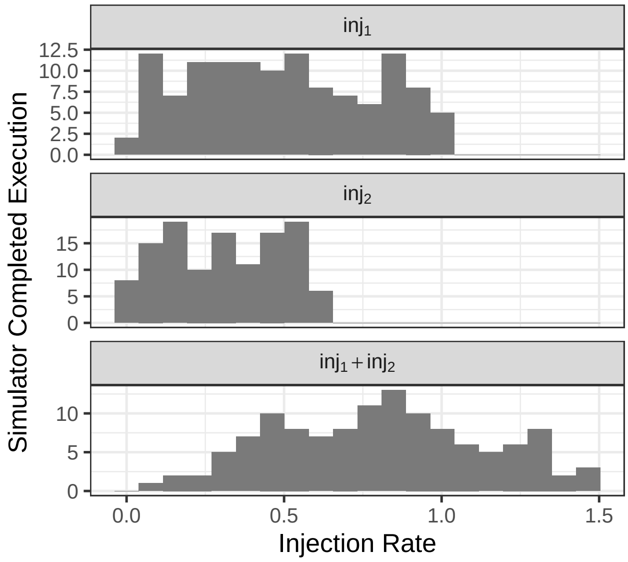

Figure 4: Injection rates for experiments where the simulator finished the complete experiment

for the top box, and

$$\frac{\mathcal{P}(inj_1) + \mathcal{P}(inj_2)}{2} = Y_2 = \beta_3 inj_2 + \beta_4 \left(\frac{1}{inj_2}\right),$$

for the bottom box. The shaded regions represent the 95% confidence interval of the mean.

Visual inspection of these fits indicates that inj_1 does not affect the mean performance metric as much as inj_2, which also have a strong effect in the performance of application 1. The mean performance metric seems to fit well to the model using inj_2.

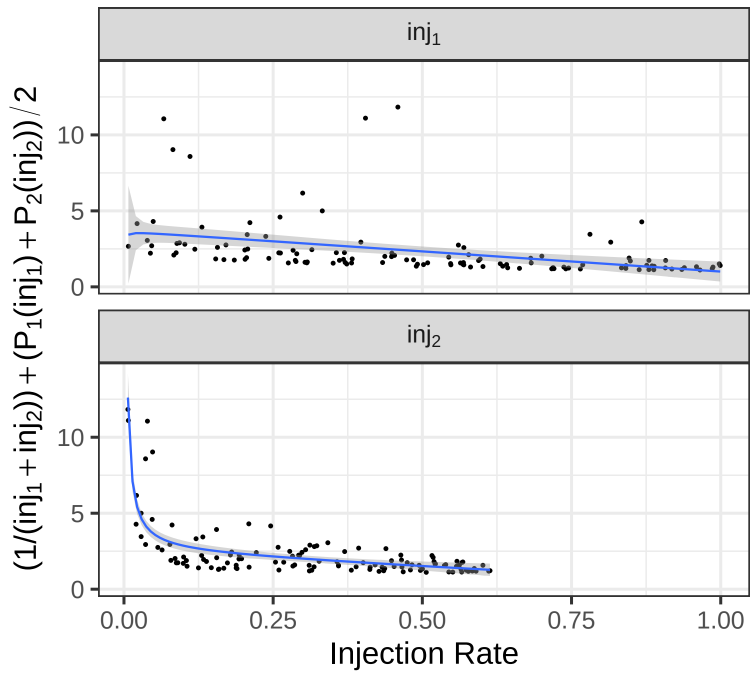

Figure 5: Linear model fit for the performance metric, with respect to inj_1 and inj_2, for the ensemble of data

1.2.1 Scatters for other metrics

1.3 ANOVA and Linear Model Fit

We now perform statistical tests to confirm the visual analyses from the previous section. We perform a linear model fit using the 20 samples from a single experiment, picked at random between the 10 repetitions performed.

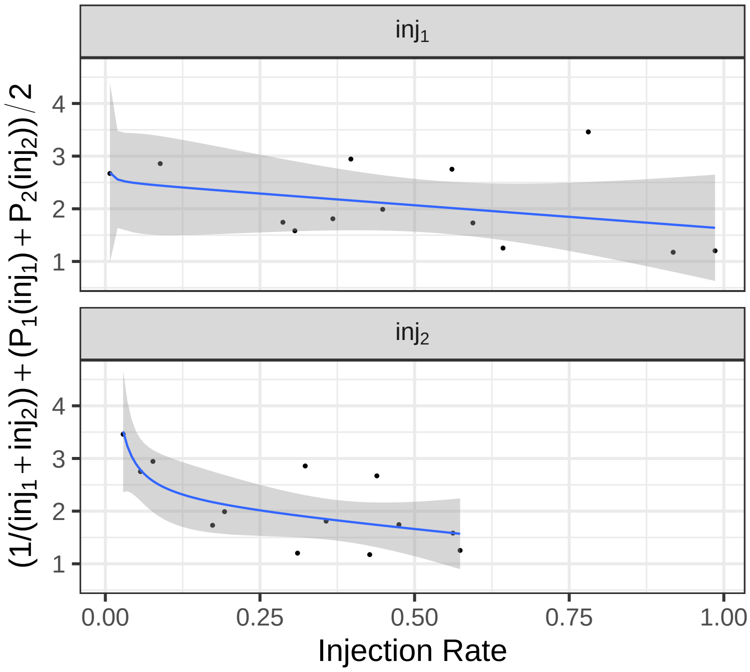

Figure 6: Linear model fit for the performance metric, with respect to inj_1 and inj_2, for a single experiment

The linear model we have used was

$$\frac{\mathcal{P}(inj_1) + \mathcal{P}(inj_2)}{2} = Y = \beta_1 inj_1 + \beta_2 inj_2 + \beta_3 \left(\frac{1}{inj_1}\right) + \beta_4 \left(\frac{1}{inj_2}\right) + \beta_5 \left(inj_1 inj_2\right) + \beta_6 \left(\frac{1}{inj_1 inj_2}\right).$$

Table 1: Regression coefficients for a linear model fit using 20 experiments

Model Term	Coefficient	Significance p-value
Intercept	2.5×10^{0}	1.2×10^{-4}
injection_rate_1	-1.1×10^{0}	4.9×10^{-2}
injection_rate_2	-8.5×10^{-1}	2.2×10^{-1}
1/injection_rate_1	-1.0×10^{-1}	5.1×10^{-3}
1/injection_rate_2	-5.2×10^{-2}	1.6×10^{-1}
injection_rate_1 × injection_rate_2	2.6×10^{-1}	8.0×10^{-1}
1/injection_rate_1 × 1/injection_rate_2	6.0×10^{-2}	1.7×10^{-3}

The model coefficient magnitude and significance values confirm that inj_2 impacts the mean performance more than inj_1, and the interaction between these factors seem to not be significant in this experiment. We also perform analysis of variance, using the same performance mode, for a single 20-run experiment picked at random, shown in the table below.

Table 2: Analisys of variance for a linear model fit using 20 experiments

Model Term	Significance p-value
injection_rate_1	1.5×10^{-3}
injection_rate_2	3.0×10^{-5}
1/injection_rate_1	6.9×10^{-2}
1/injection_rate_2	7.6×10^{-4}
injection_rate_1 × injection_rate_2	1.1×10^{-1}
1/injection_rate_1 × 1/injection_rate_2	1.5×10^{-1}

We see again that the terms using inj_2 explain more of the observed variance on the performance metric. For further experiments using these two applications, performance mean can be modeled and minimized using only a linear and an inverse term for inj_2. Further steps should be attempting to generalize the statistical analysis for more applications running at the same time, or with more controllable parameters.

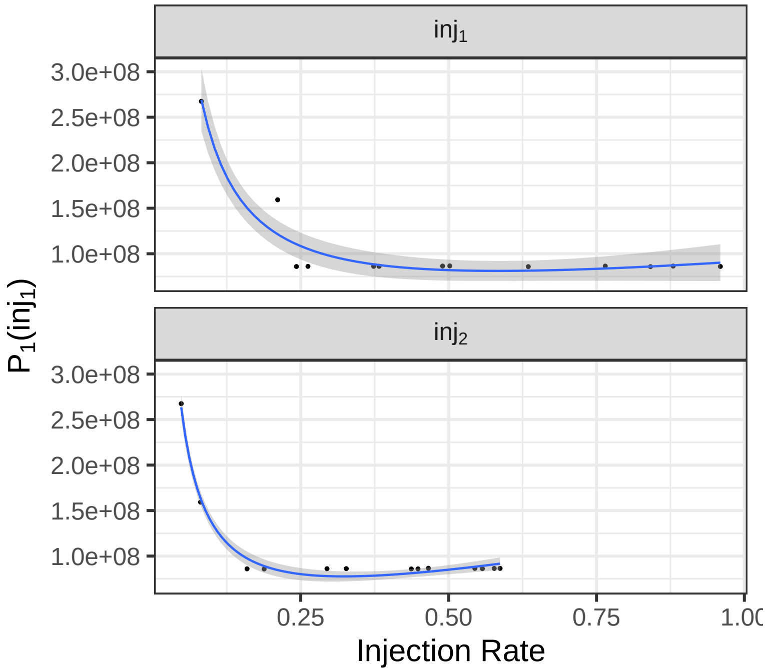

Figure 7: Linear model fit for the performance of application 1, with respect to inj_1 and inj_2, for a single experiment

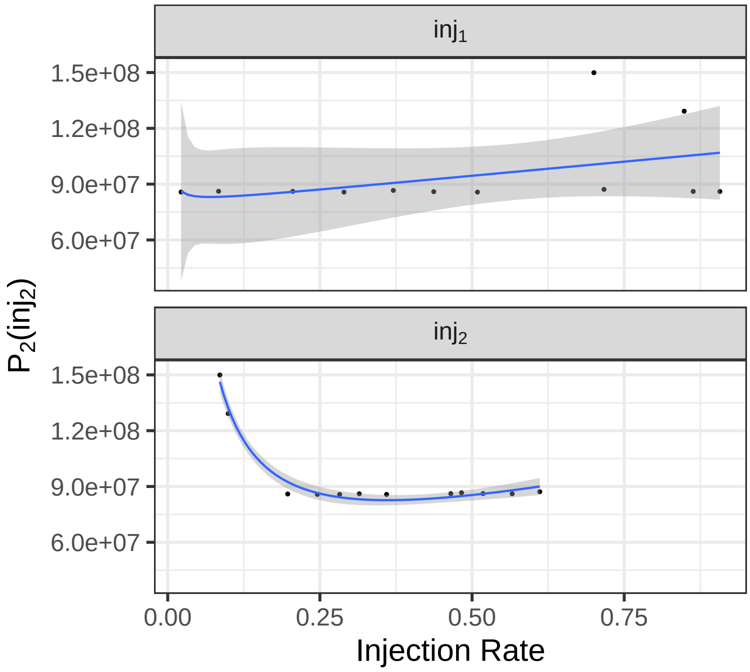

Figure 8: Linear model fit for the performance of application 2, with respect to inj_1 and inj_2, for a single experiment