Embedding a Scheduler in Execution for a Planetary Rover: Additional Materials

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Abstract

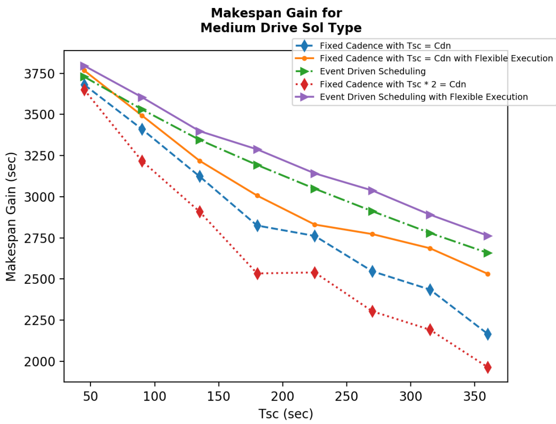
This document contains additional information and empirical data for the paper Embedding a Scheduler in Execution for a Planetary Rover (Chi et al. 2018).

Additional Materials

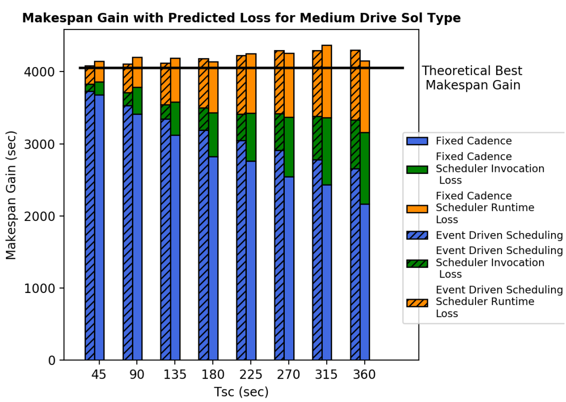
Detailed Sol Type Data

Below we provide the execution and scheduler data for several individual sol types for completeness.

Figure 7 shows results for the Medium drive sol type. Figure 8 shows the Short Drive sol type. Figure 9 shows the Long Drive sol type. Figure 10 shows the Workspace sol type. Figure 11 shows the Survey Remote Sensing sol type.

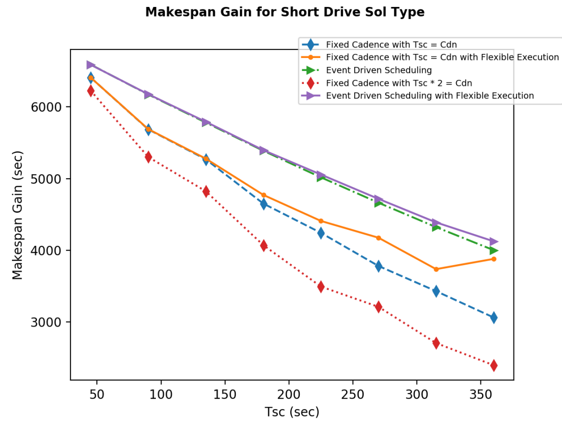


(a) Makespan gain for varying scheduler run times (T_{sc}) and methods averaged across a Medium Drive Sol Type.

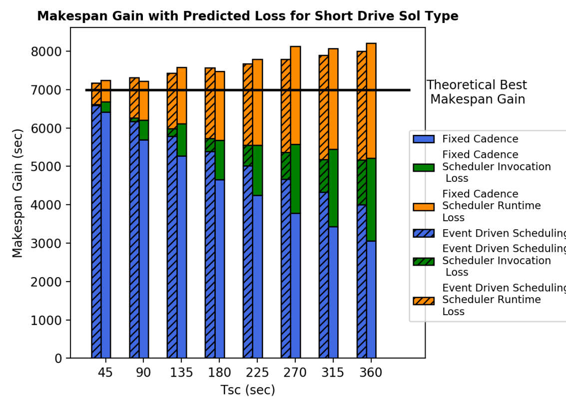


(b) The predicted total loss + makespan gained is equal to the theoretical best makespan gain (if we had an instantaneous scheduler) for the Medium Drive Sol Type.

Figure 7



(a) Makespan gain for varying scheduler run times (T_{sc}) and methods averaged across a Short Drive Sol Type.



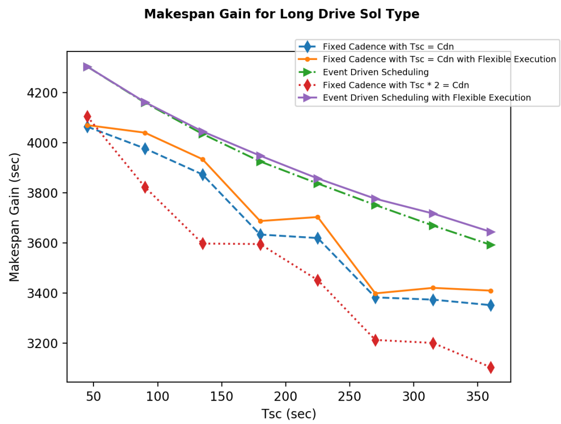
(b) The predicted total loss + makespan gained is equal to the theoretical best makespan gain (if we had an instantaneous scheduler) for the Short Drive Sol Type.

Figure 8

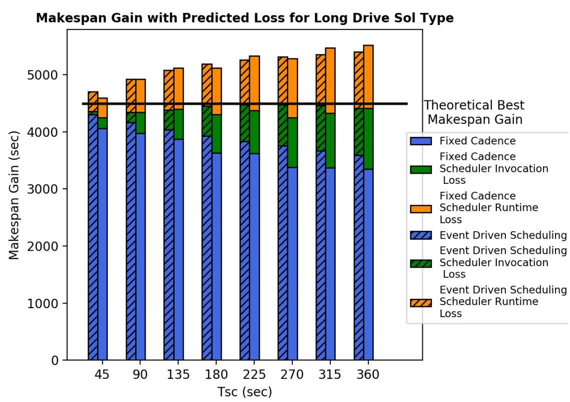
In the above Figures 7b, 10b, and 11b the predicted loss does not well correlate with the actual loss.

For all of them, the model overestimates the predicted loss. There are several reasons for this overestimation. Figure 12 shows specific instances from the sol types that violate the loss model assumptions.

1. *Setup Activities*. In sol types, activities may require earlier activities including preheats. When an earlier activity A completes early, this may allow a later activity B to move earlier, but if B has a preheat or setup activity it may prevent B from moving earlier. However, the computational loss model will still calculate the loss although even the optimal scheduler is unable to recoup the loss. Figure 12b shows an example in the Workspace sol type where an activity setup prevents the scheduler (including the optimal scheduler) from benefiting from an activity ending early.
2. *Parallelism*. In a non serial schedule, there may be activities not in the critical path. When activities are not in the critical path, no matter how early they finish they do not affect the makespan. As a result, any loss predicted from those activities is an overestimation as even the optimal scheduler cannot convert the early completion into makespan reduction. Figure 12a shows parallel activities in the Long Drive Sol Type.
3. *Execution Time Constraints*. Execution time constraints can limit activities from being rescheduled earlier. As a result, any time before that activity cannot be gained back anyways and may result in a loss overestimation. Figure 12c shows an execution time window constraint in the Medium Drive Sol Type that prevents the scheduler from

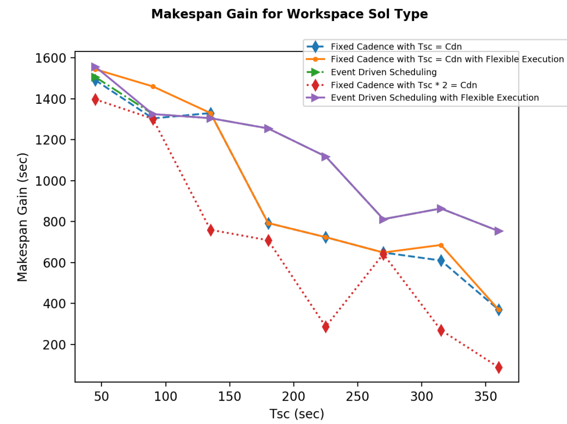


(a) Makespan gain for varying scheduler run times (T_{sc}) and methods averaged across a Long Drive Sol Type.

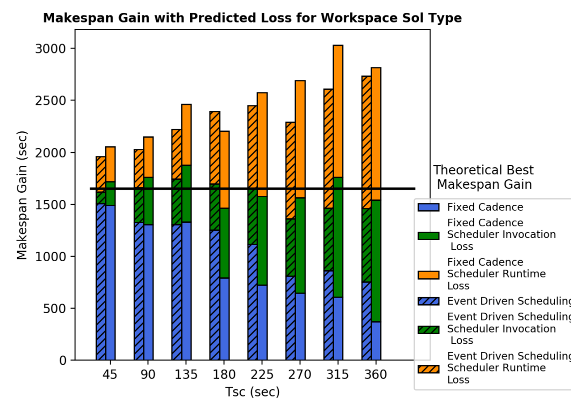


(b) The predicted total loss + makespan gained is equal to the theoretical best makespan gain (if we had an instantaneous scheduler) for the Long Drive Sol Type.

Figure 9



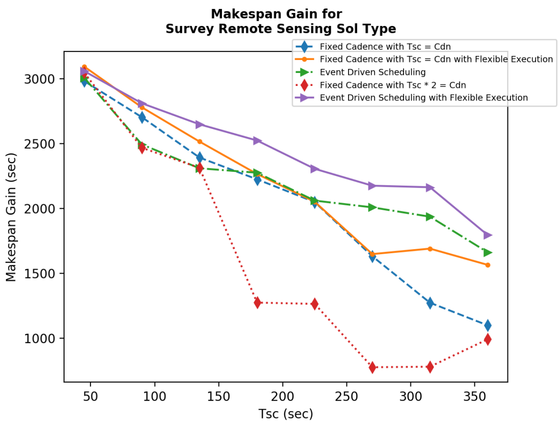
(a) Makespan gain for varying scheduler run times (T_{sc}) and methods averaged across a Workspace Sol Type.



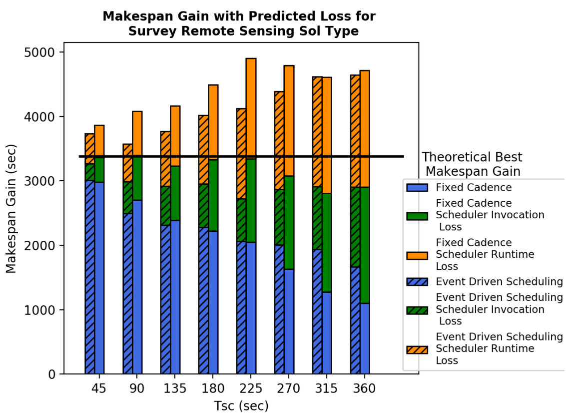
(b) The predicted total loss + makespan gained is equal to the theoretical best makespan gain (if we had an instantaneous scheduler) for the Workspace Sol Type.

Figure 10

taking advantage of an early completing activity.

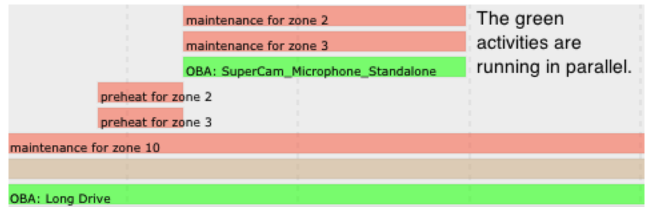


(a) Makespan gain for varying scheduler run times (T_{sc}) and methods averaged across a Survey Remote Sensing Sol Type.

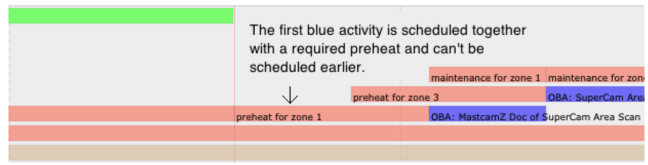


(b) The predicted total loss + makespan gained is equal to the theoretical best makespan gain (if we had an instantaneous scheduler) for the Survey Remote Sensing Sol Type.

Figure 11



(a) Many sol types are not fully serial. In the Long Drive Sol Type, activities run parallel.



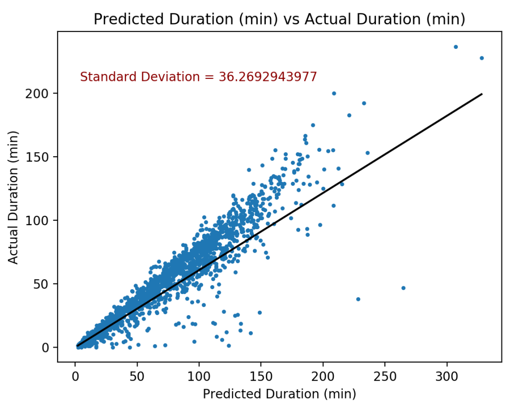
(b) In the Workspace Sol Type, a preheat prevents even the optimal scheduler ($T_{sc} = 0$) from scheduling the next activity earlier.

(c) In the Medium Drive Sol Type, the Medium Drive has an execution time constraint that prevents it from being scheduled earlier.

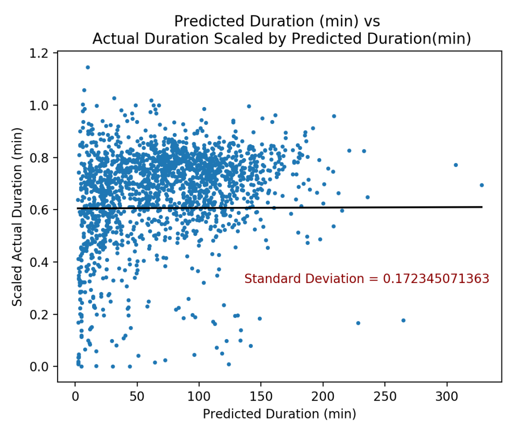
Figure 12: Three issues with predicting loss

Model for Activity Execution Durations

To simulate execution we derive a model for actual execution duration of an activity given a conservative scheduling model activity duration. We use predicted and actual durations from the MSL Submaster data (Gaines et al. 2016) to generate such a model. First, each of the actual execution durations provided are scaled by dividing by the corresponding predicted execution durations. We use a linear regression on the scaled data values to derive a mean and standard deviation presuming the ratio of predicted to actual execution times is normally distributed. The value on the regression line for the given conservative duration is used as the mean. A scaled prediction of the actual duration is generated from a normal distribution using this mean and the standard deviation of the scaled durations. This value is then scaled back by multiplying by the given conservative duration. Empirically this model indicates that on average activities will complete 32 percent early.



(a) The trend represents the actual duration compared to its predicted durations. We use the actual durations derived as the mean for a normal distribution. We then randomly choose an actual duration from that distribution.



(b) The trend is based on the means derived from the regression of the scaled actual durations.

Figure 13: Mars Science Laboratory Curiosity Rover execution data used to develop a model activity execution shortfall compared to their predicted durations (Gaines et al. 2016). We use that data for the shortfalls in our schedules.

Acknowledgments

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References

Chi, W.; Chien, S.; Agrawal, J.; Rabideau, G.; Benowitz, E.; Gaines, D.; Fosse, E.; Kuhn, S.; and Biehl, J. 2018. Embedding a scheduler in execution for a planetary rover. In *International Conference on Automated Planning and Scheduling (ICAPS 2018)*.

Gaines, D.; Doran, G.; Justice, H.; Rabideau, G.; Schaffer, S.; Verma, V.; Wagstaff, K.; Vasavada, A.; Huffman, W.; Anderson, R.; et al. 2016. Productivity challenges for mars rover operations: A case study of mars science laboratory operations. Technical report, Technical Report D-97908, Jet Propulsion Laboratory.