Department of Chemical and Metallurgical Engineering

Project: Synergistic and Intelligent Process Optimization (SINGPRO)

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Incorporation of parameter prediction models of different fidelity into job shop scheduling

Introduction

Industrial job shop processes are inherently stochastic. The optimal scheduling of these processes is dependent on the realization of scheduling parameters (e.g. processing times, customer demand and raw material consumptions). As the information of future realizations is not available, scheduling decisions are typically made based on static tables of estimated scheduling parameters, which contain both inaccuracies and uncertainty.

In this work, we incorporate three data-driven processing time prediction models of different fidelity into a unit-specific continuous time scheduling model.

Duration prediction

Data: We use the New York City (NYC) taxi duration dataset [1] (Fig. 1), containing information of over 1.4 million taxi trips in NYC, including

- the duration of the trip,
- passenger count,
- pick-up and drop-off date, time and coordinates.

Average prediction model: The simplest approach (the low fidelity model) to estimate the duration of a taxi trip is to calculate the average duration in the dataset and assume that all future taxi trips have the same duration.

Rate prediction model: The medium fidelity model involves determining the average speed of the taxi trips in the training set, and using the street distance of the planned trip to predict its duration.

GP prediction model: As the high fidelity model, we use Gaussian process (GP) regression. The features for the model are the pick-up/drop-off coordinates. The contours in Fig. 2 show duration estimates from the red circle in Fig. 1.

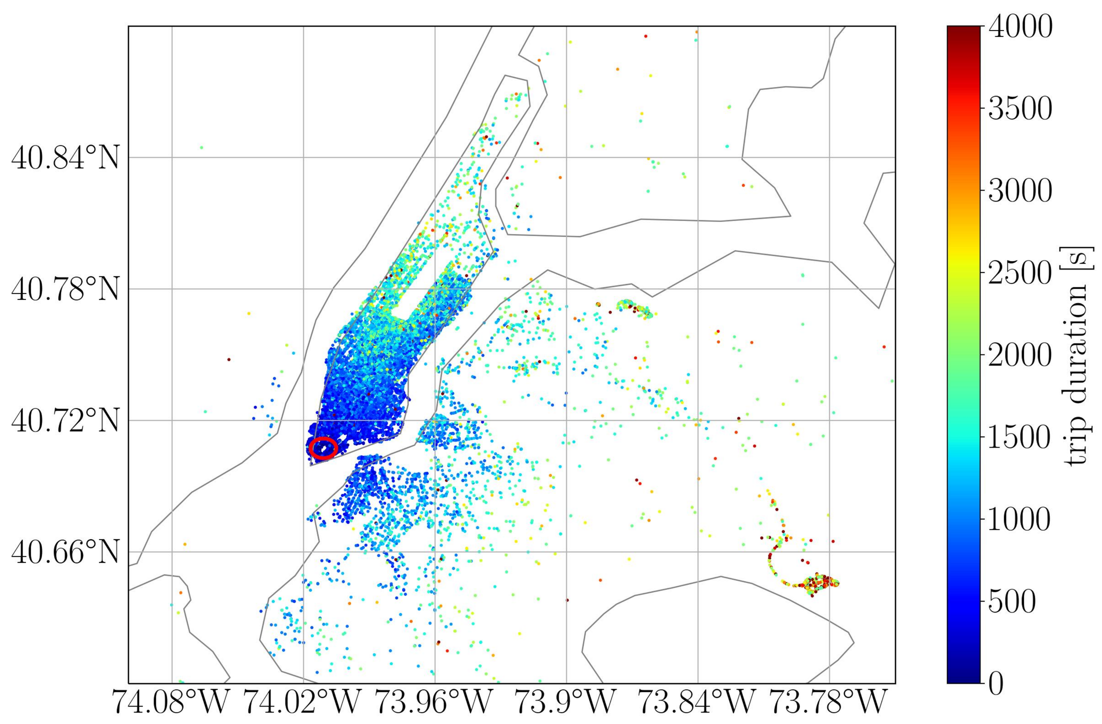

Figure 1

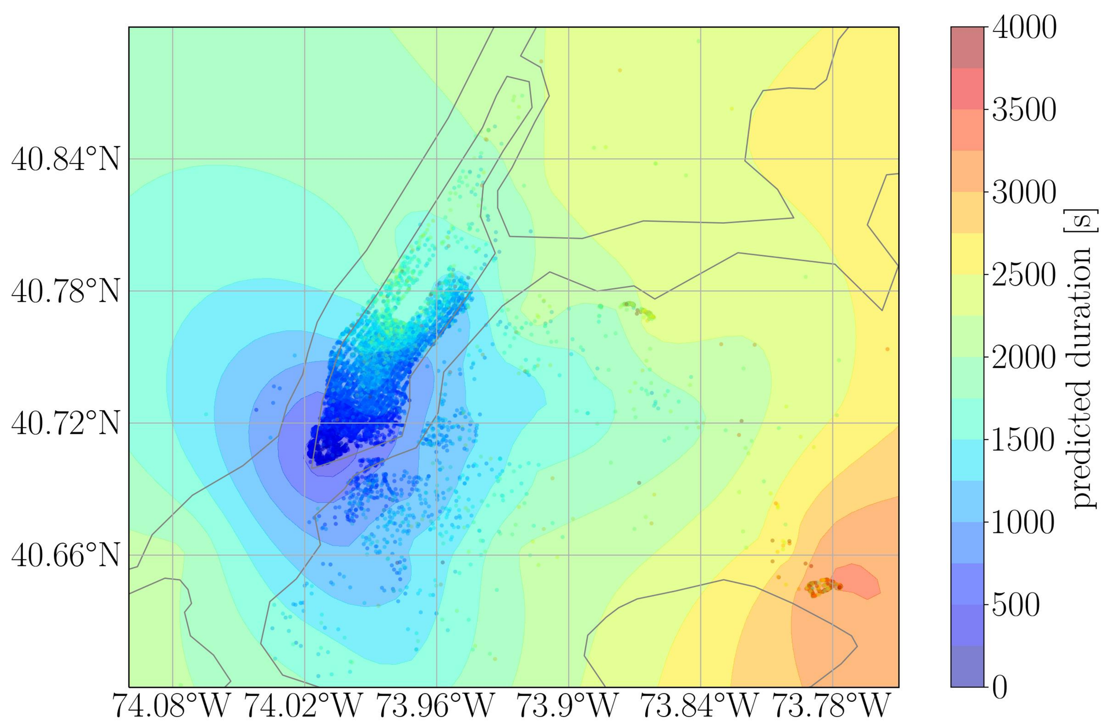

Figure 2

Optimization problem

We consider the following scheduling problem that uses the NYC taxi duration data set:

- A company, which headquarter (HQ) is at Wall Street (the red circle in Fig. 1), performs surveys at remote sites located around NYC
- A survey involves an employee 1) travelling to the site by taxi, 2) performing the survey and 3) returning back to the HQ by taxi (Fig. 3)
- Two taxis are available
- At most, two surveys can be performed concurrently
- The objective is to maximize the make span of performing surveys at six different sites (Fig. 4)

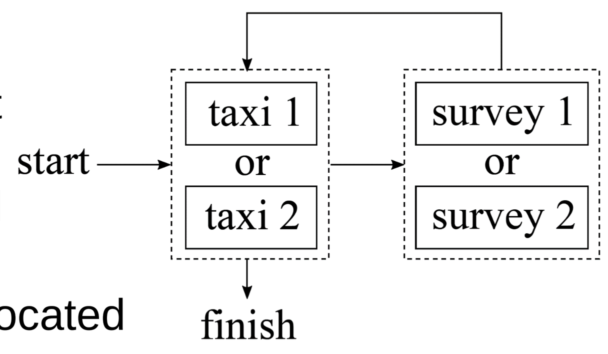

Figure 3

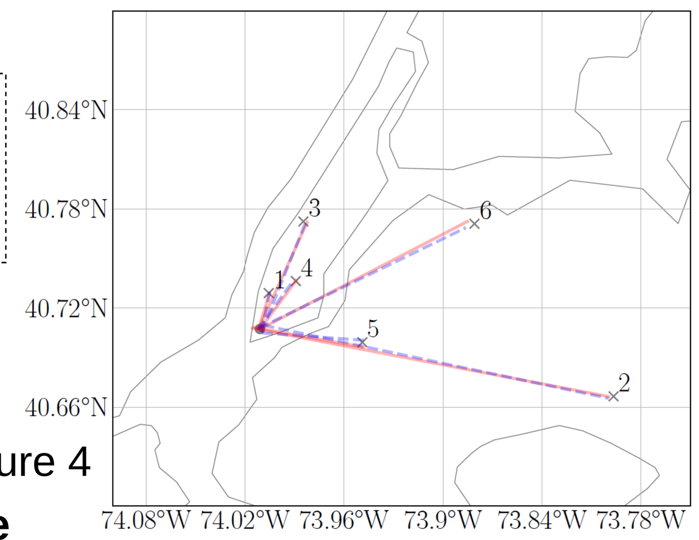

Figure 4

Industrial relevance

Feature	Industrial correspondent
Outbound taxi trip	Preparation, heating
Survey	A chemical reaction
Inbound taxi trip	Purification, cooling
Average prediction model	Static duration table
Rate prediction model	A model considering a task to have a constant, volume-specific processing rate

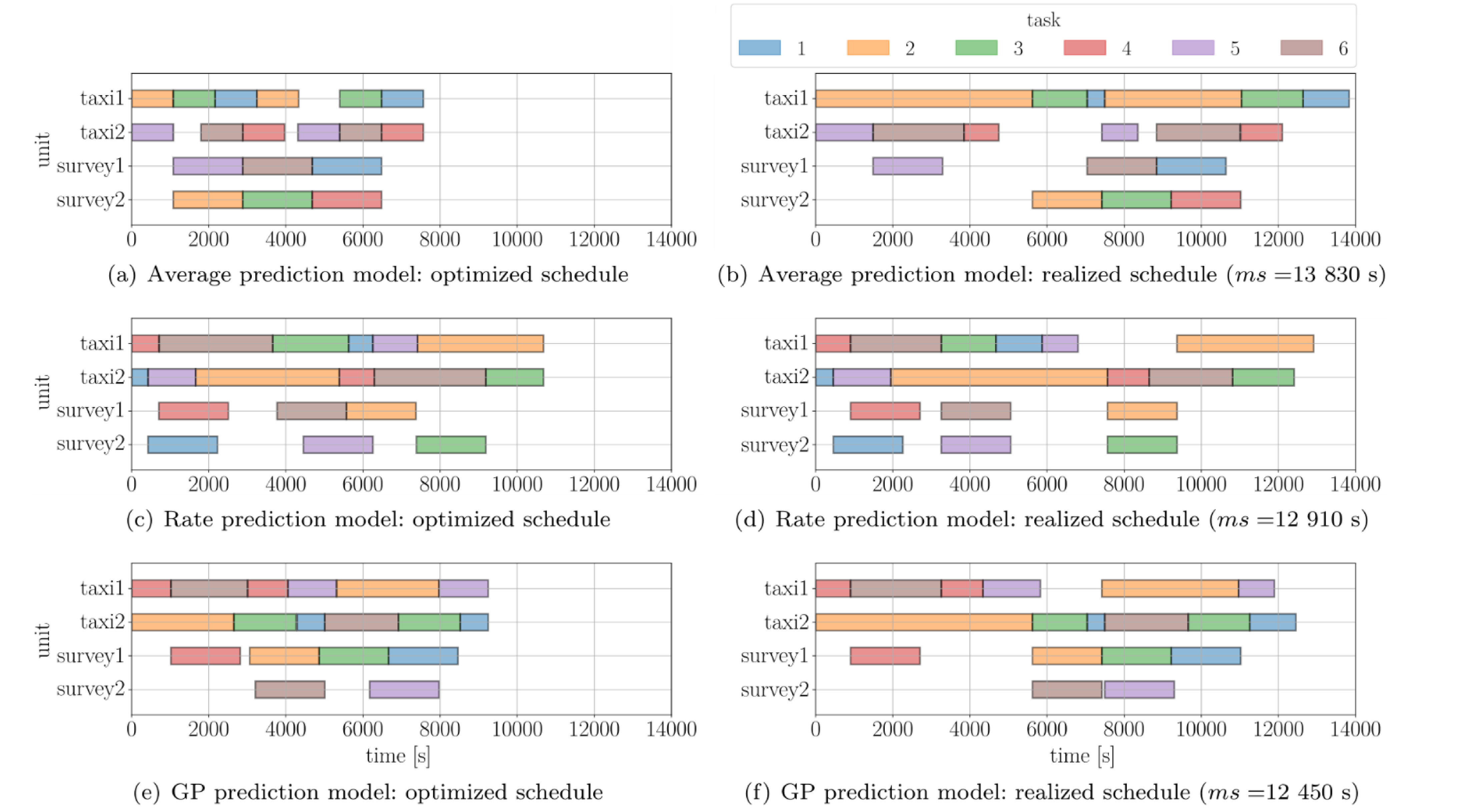

Figure 5

Results

A single optimization problem (Fig. 5):

- In both optimized and realized schedules, each task consists of the outbound taxi trip, survey, and inbound taxi trip, in this chronological order.
- The realized make span is longer than the optimized make span for all prediction methods.
- The main cause for this is the significantly longer realized duration for the outbound taxi trip to site 2 in comparison to its predicted values.

A set of 30 optimization problems:

- The use of GP prediction model yielded, on average, 5.8% and 1.8% shorter realized make spans in comparison to using the low and medium-fidelity prediction models, respectively (Fig. 6).

- The computational cost of solving the scheduling problem with predictions from the GP and rate prediction models (variable taxi durations) is an order of magnitude higher than with those obtained from the average model (fixed taxi durations).

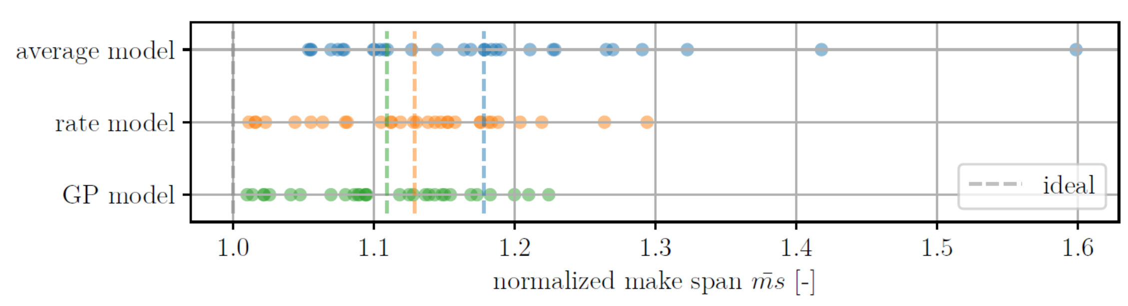

Figure 6

Conclusions

- Duration prediction models are incorporated into scheduling optimization
- The highest fidelity prediction model yields 5.8% shorter make spans than the lowest fidelity prediction model
- However, the solution time of the scheduling model with variable task durations is an order of magnitude higher than with fixed task durations

Acknowledgements

Financial support is gratefully acknowledged from the Academy of Finland project ''SINGPRO'', Decision No. 313466.

References

[1] Kaggle Inc (2017). New york city taxi trip duration [accessed on the 15th of June, 2018]. URL https://www.kaggle.com/c/nyc-taxi-trip-duration.