

Improving User Experience in Interactive Job Scheduling

Johannes Varga^a

Supervisors: Günther R. Raidl^a, Tobias Rodemann^b

Advisor: Christiane Wiebel-Herboth^b

^aInstitute of Logic and Computation, TU Wien, Vienna, Austria

^bHonda Research Institute Europe, Offenbach, Germany

September 12, 2024

April 2022

Today

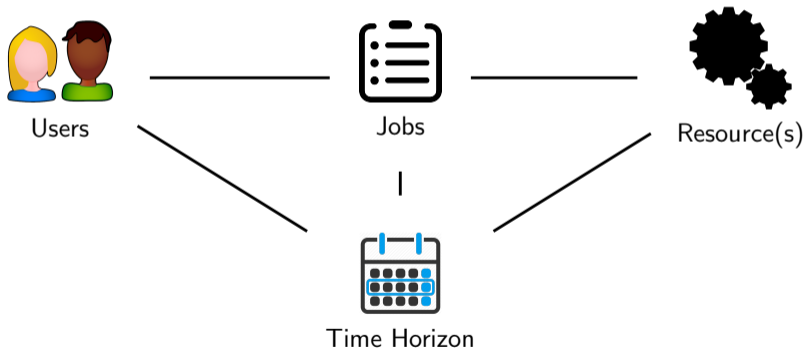
March 2026



General Problem Setting

How to organize processes best that involve humans?

Formulate as scheduling problem

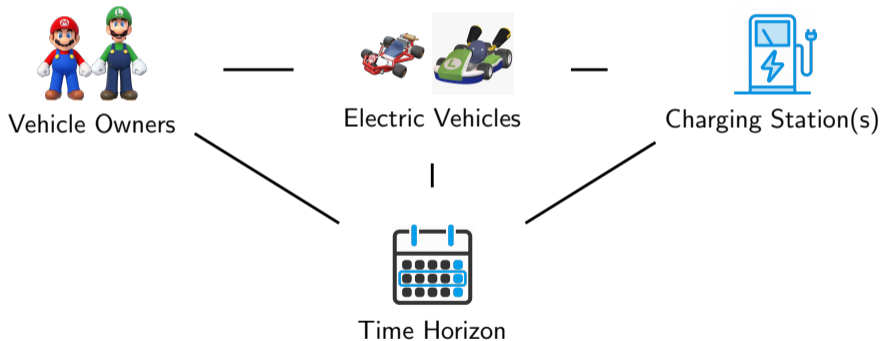


Scheduling the Charging of EVs¹

Time-dependent **electricity prices**

Limited number of charging stations

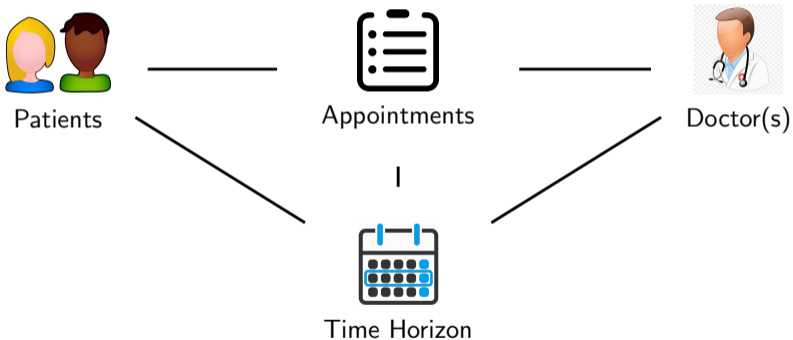
E.g. **weekly schedule**



¹Johannes Varga, Günther R. Raidl, and Steffen Limmer (2022). "Computational Methods for Scheduling the Charging and Assignment of an On-Site Shared Electric Vehicle Fleet". In: *Access 10*, p. 105786.

Scheduling Doctors Appointments

Rolling time horizon



Timetabling Classes

Semester-wise schedule



Lecturers



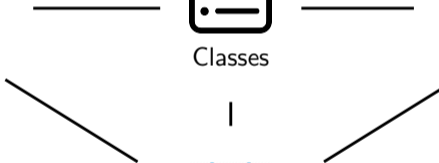
Classes



Lecture Room(s)



Time Horizon



Classical Approaches

EV Charging Scheduling:

- Users specify preferences beforehand
- **Optimization approach** computes schedule

Doctors appointments: **Secretary** coordinates appointments with patients

Timetabling classes: **Expert** coordinates access to lecture rooms

Common **disadvantages**:

- Labour intensive
- Annoying for users
- Suboptimal results

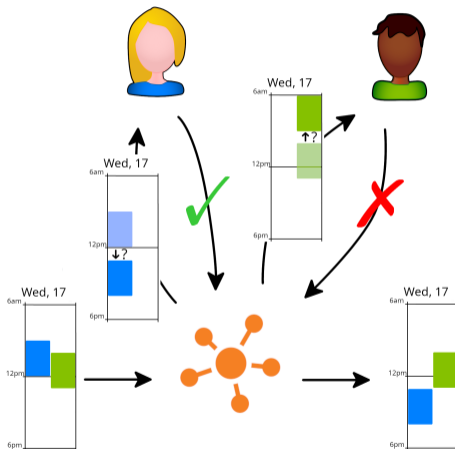
Cooperative Approach

Central unit: **Scheduler**

- **Coordinates** schedule among users
- Interacts with users to find out about their most relevant preferences

Advantages:

- Automated
- Low effort for users
- Optimized results

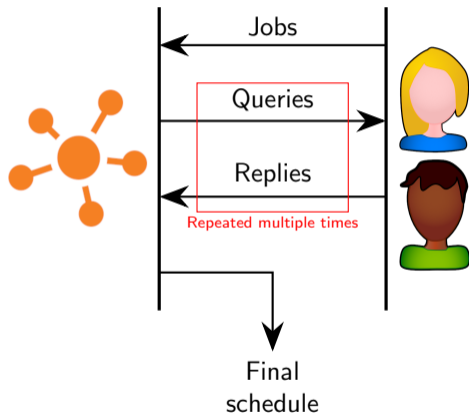


User Interaction

Key requirement: Do not annoy users

→ Limit **user frustration**

- Low number of queries
- Low effort
- Only queries, where positive feedback is likely
- Queries make sense to the user



Algorithmics Behind the Scenes

Integer Linear Programming (ILP)

- Technique to solve **optimization problems**
- Formulate with **decision variables**, **linear constraints** and **linear objective**
- State-of-the-art solvers: Gurobi, CPLEX
- Advanced techniques: Stochastic Programming, (Logic-based) Benders decomposition

Bayesian Learning and Probabilistic Programming

- Based on Bayes theorem: $\overbrace{p(\text{Parameters}|\text{Observed})}^{\text{Posterior}} \sim \overbrace{p(\text{Observed}|\text{Parameters})}^{\text{Likelihood}} \cdot \overbrace{p(\text{Parameters})}^{\text{Prior}}$
- Sample from posterior with e.g. Markov Chain Monte Carlo methods
- Advantages: **Sample efficient**, **flexible**, **uncertainty measure** of prediction

User Model

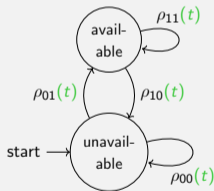
Task: **Predict reply** to query (\rightarrow acceptance probability)

Assumptions:

- Availabilities change slowly
- Users behave similar

Markov-Model:

- Two states
- Time-independent vs. **time-dependent**



Interval model:

- User is available in 2-3 intervals throughout the day
- Normally distributed start- and endpoints

Learn parameters from user interaction of previous instances²

²Johannes Varga, Günther R. Raidl, and Tobias Rodemann (2025). "Learning to Predict User Replies in Interactive Job Scheduling". [submitted to AAAI].

Approaches

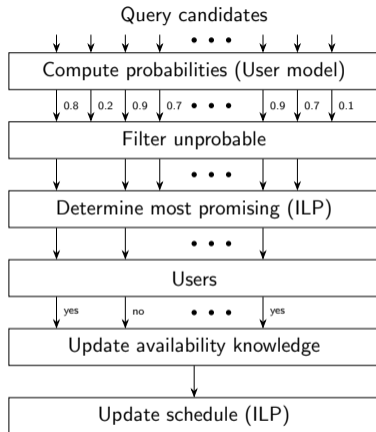
Query candidates: Move any job to any other time

Threshold approach³⁴:

- Discard queries below **probability threshold**
- Select queries that minimize costs

Stochastic Programming approach⁵:

- Prefer queries more that are likely accepted
- Minimize **expected** costs



³Johannes Varga et al. (2023). "Interactive Job Scheduling with Partially Known Personnel Availabilities". In: *OLA 2023: Optimization and Learning*. Ed. by B. Dorransoro et al. Vol. 1824. Communications in Computer and Information Science. Springer, pp. 236–247

⁴Johannes Varga et al. (2024). "Scheduling jobs using queries to interactively learn human availability times". In: *Computers & Operations Research* 167, p. 106648

⁵Johannes Varga, Günther R. Raidl, and Tobias Rodemann (2024). "Selecting User Queries in Interactive Job Scheduling". [to appear]

Approaches

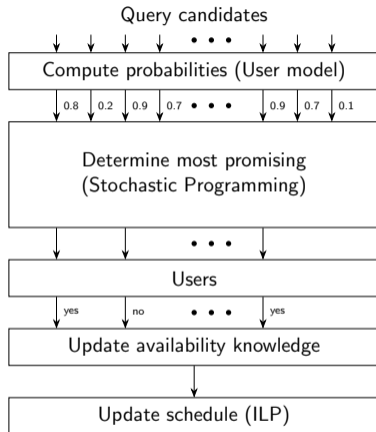
Query candidates: Move any job to any other time

Threshold approach³⁴:

- Discard queries below **probability threshold**
- Select queries that minimize costs

Stochastic Programming approach⁵:

- Prefer queries more that are likely accepted
- Minimize **expected** costs



³Johannes Varga et al. (2023). "Interactive Job Scheduling with Partially Known Personnel Availabilities". In: *OLA 2023: Optimization and Learning*. Ed. by B. Dorransoro et al. Vol. 1824. Communications in Computer and Information Science. Springer, pp. 236–247

⁴Johannes Varga et al. (2024). "Scheduling jobs using queries to interactively learn human availability times". In: *Computers & Operations Research* 167, p. 106648

⁵Johannes Varga, Günther R. Raidl, and Tobias Rodemann (2024). "Selecting User Queries in Interactive Job Scheduling". [to appear]

Simulation Results⁶

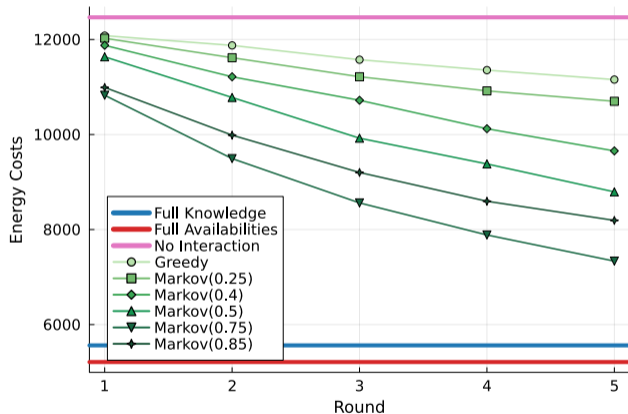
Setting: Employees of company want to use **expensive machine**

5 machines, 30 users

5 rounds of user interaction, 30 queries per round

Threshold approach with different thresholds

Cost reduction after five rounds:
12400 \rightarrow 7300 (41%)



⁶Johannes Varga et al. (2024). "Scheduling jobs using queries to interactively learn human availability times". In: *Computers & Operations Research* 167, p. 106648.

Currently: Psychological Factors

Cooperation with **Christiane Attig**

Plan: submit at Conference on Intelligent User Interfaces (IUI)

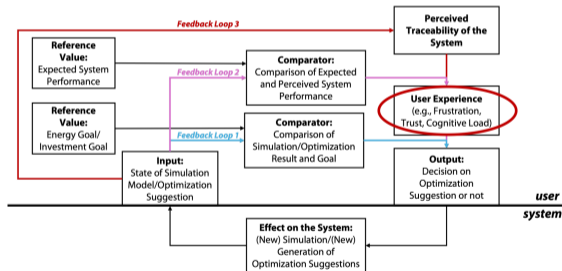


Idea: Model user **frustration** with system

Consider in the scheduler

Important aspects we plan to consider in the future:

- **Cognitive Load**⁷
- **Explainability/Traceability**⁸



⁷Paul Slovic et al. (2013). "Risk as analysis and risk as feelings: Some thoughts about affect, reason, risk and rationality". In: *The feeling of risk*. Routledge, pp. 21–36

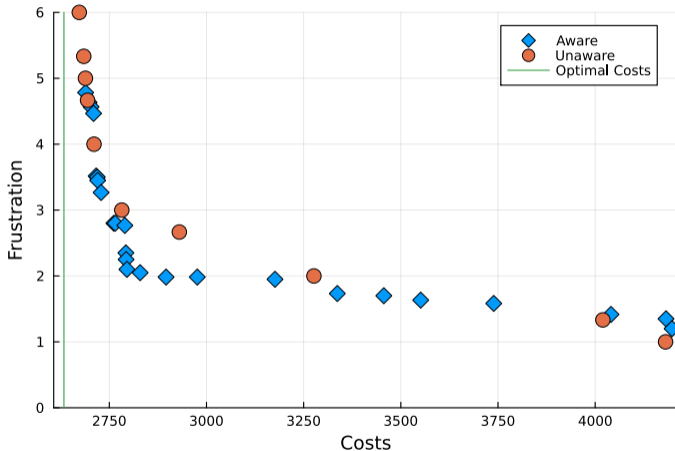
⁸Serge Thill et al. (2018). "Driver adherence to recommendations from support systems improves if the systems explain why they are given: A simulator study". In: *Transportation research part F: traffic psychology and behaviour* 56, pp. 420–435

Currently: Psychological Factors

Frustration: linear with number of queries

Approaches

- **Unaware:** Minimizing only costs
- **Aware:** Multi-objective optimization considering frustration and costs



First insight: Better tradeoff between frustration and costs when considering frustration

Outlook: Fairness¹⁰

Differences in frustration between users → unfair?

“Min–max fairness: The primary objective for distribution is to ensure an allocation of resources that **maximizes the minimum benefit** received by any user.”⁹

Benefit (aka utility) depends on frustration and time of the scheduled jobs

Potential research questions:

- How much does fairness cost?
- How can incentives be used to increase fairness?

⁹João Soares et al. (2024). “Review on fairness in local energy systems”. In: *Applied Energy* 374, p. 123933.

¹⁰Violet Xinying Chen and John N Hooker (2023). “A guide to formulating fairness in an optimization model”. In: *Annals of Operations Research* 326.1, pp. 581–619.

Conclusion

Optimization important when **scheduling human activities**

Works better when **coordinating cooperation**






Also important:

- Optimization approach
- User frustration
- Fairness





We implemented and evaluated: **efficient scheduling system**

Cost reduction after five rounds: 41%

References I

-  Slovic, Paul et al. (2013). “Risk as analysis and risk as feelings: Some thoughts about affect, reason, risk and rationality”. In: *The feeling of risk*. Routledge, pp. 21–36.
-  Soares, João et al. (2024). “Review on fairness in local energy systems”. In: *Applied Energy* 374, p. 123933.
-  Thill, Serge et al. (2018). “Driver adherence to recommendations from support systems improves if the systems explain why they are given: A simulator study”. In: *Transportation research part F: traffic psychology and behaviour* 56, pp. 420–435.
-  Varga, Johannes, Günther R. Raidl, and Tobias Rodemann (2025). “Learning to Predict User Replies in Interactive Job Scheduling”. [submitted to *AAAI*].
-  Varga, Johannes, Günther R. Raidl, and Steffen Limmer (2022). “Computational Methods for Scheduling the Charging and Assignment of an On-Site Shared Electric Vehicle Fleet”. In: *Access* 10, p. 105786.

References II

-  Varga, Johannes, Günther R. Raidl, and Tobias Rodemann (2024). “Selecting User Queries in Interactive Job Scheduling”. [to appear].
-  Varga, Johannes et al. (2023). “Interactive Job Scheduling with Partially Known Personnel Availabilities”. In: *OLA 2023: Optimization and Learning*. Ed. by B. Dorransoro et al. Vol. 1824. Communications in Computer and Information Science. Springer, pp. 236–247.
-  Varga, Johannes et al. (2024). “Scheduling jobs using queries to interactively learn human availability times”. In: *Computers & Operations Research* 167, p. 106648.
-  Xinying Chen, Violet and John N Hooker (2023). “A guide to formulating fairness in an optimization model”. In: *Annals of Operations Research* 326.1, pp. 581–619.