UNIVERSITY OF PASSAU

MASTER SEMINAR: DATA SCIENCE & OPTIMIZATION

THE FUTURE OF MULTI-VARIANT PRODUCTION: CAR SEQUENCING

Aleksandra Petrenko & Ninh Tran

24th Jan 2024

Motivation: Why car sequencing?

- Customers require more customer-tailored products => the variety of product models is growing
- How to produce various model without cost-intensive work overloads?
- Common approaches: Car Sequencing (CS) and Mixed-Model Sequencing (MMS) => CS is easier to implement

AGENDA

UNIVERSITY OF PASSAU

INTRODUCTION TO SEQUENCING

- In production planning, sequencing **defines optimal orders** when various products are being produced at a production line in order to **minimize setup costs or avoid work overload**
- Assume there are 2 types of car (**orange** and **black**) processed intermixed in a line
- Comparing between 2 sequences, **which sequence** would not generate work overload?

[1]

[2]

INTRODUCTION TO SEQUENCING

- Sequencing theory is a **mathematical model** that turns manufacturing goals into **objective functions**, incorporating other **constraints** such as labor utility and capital capacity
- There are **two common approaches: car sequencing (CS)** and **mixed-model sequencing (MMS)**

MMS	• Derives **explicit method for calculating workload.** Therefore, objective function is to **minimize total work generated** • Tedious effort in collecting operation data
CS	• Based on an **implicit rule $H_0 : N_0$** which restricts the number of successive models with long processing time. Therefore, objective function is to **minimize total number of violations** in each subsequence • Easy to implement

RESEARCH QUESTIONS

Our work tries to answer the following research questions:

- What are the **advantages of car sequencing** compared to mixed-model sequencing?
- What are the **sequencing rules** that generate a result as good as mixed-model sequencing?
- What are the **recent trends** in literature about car sequencing?
- What are the **suggestions for future research**?
- In **which industries** could car sequencing still be applied?

MATHEMATICAL MODEL

Problem formulation

- Assume that there are 2 models of cars that are **processed intermixed** in a production line
  - Black model (a car ***without*** feature "O", with ***shorter processing time p = 2)***
  - Orange model (a car that ***requires a feature/option "O"***, with ***longer processing time p = 7)***

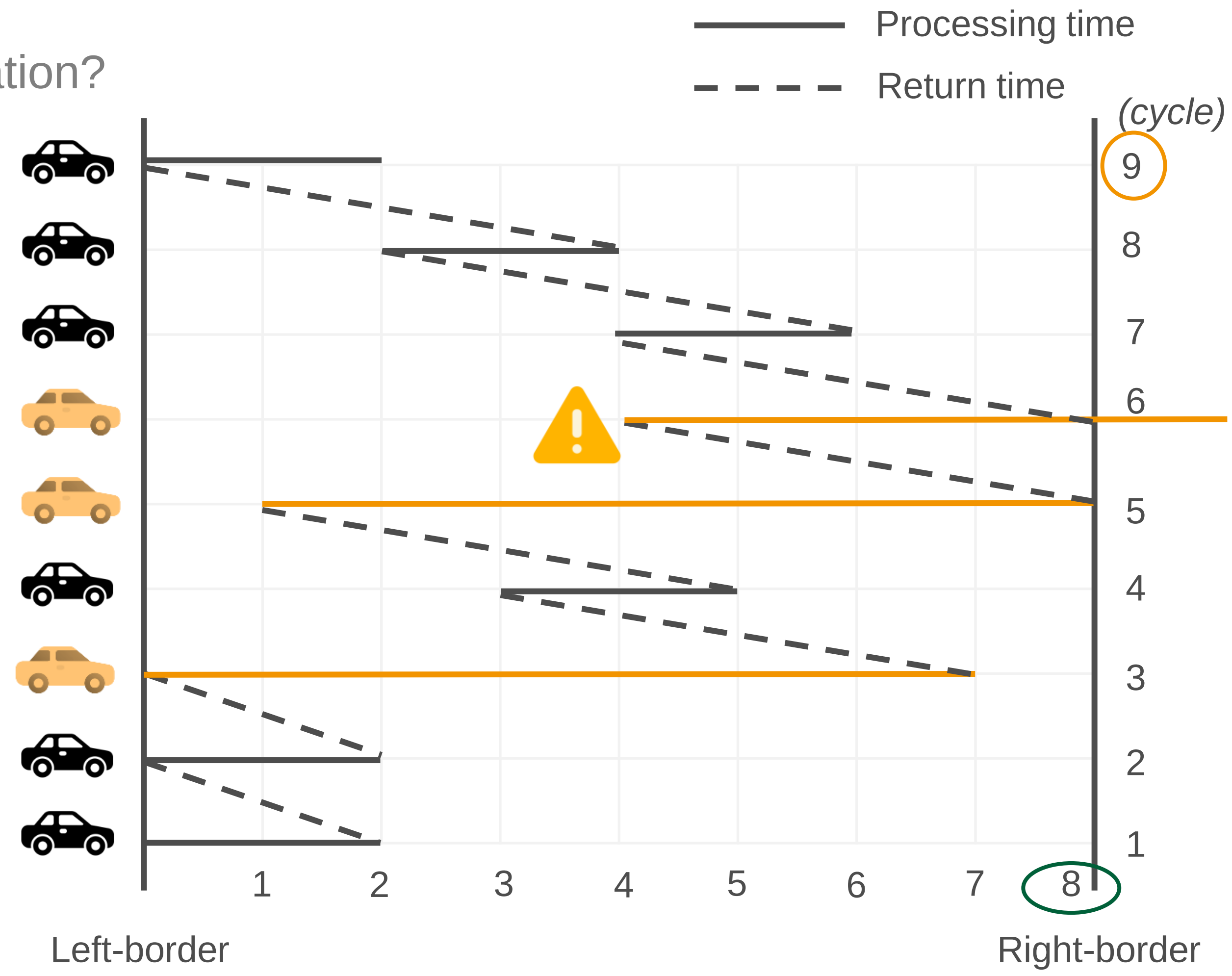
- The problem concerns the **order** of car to **avoid work overload**

- What is the design of one workstation on a production line?
  - Conveyor used to place the models **moves from left to right**
  - Operators return to the left border to proceed the next product

Left-border station **Right-border station**

Problem formulation

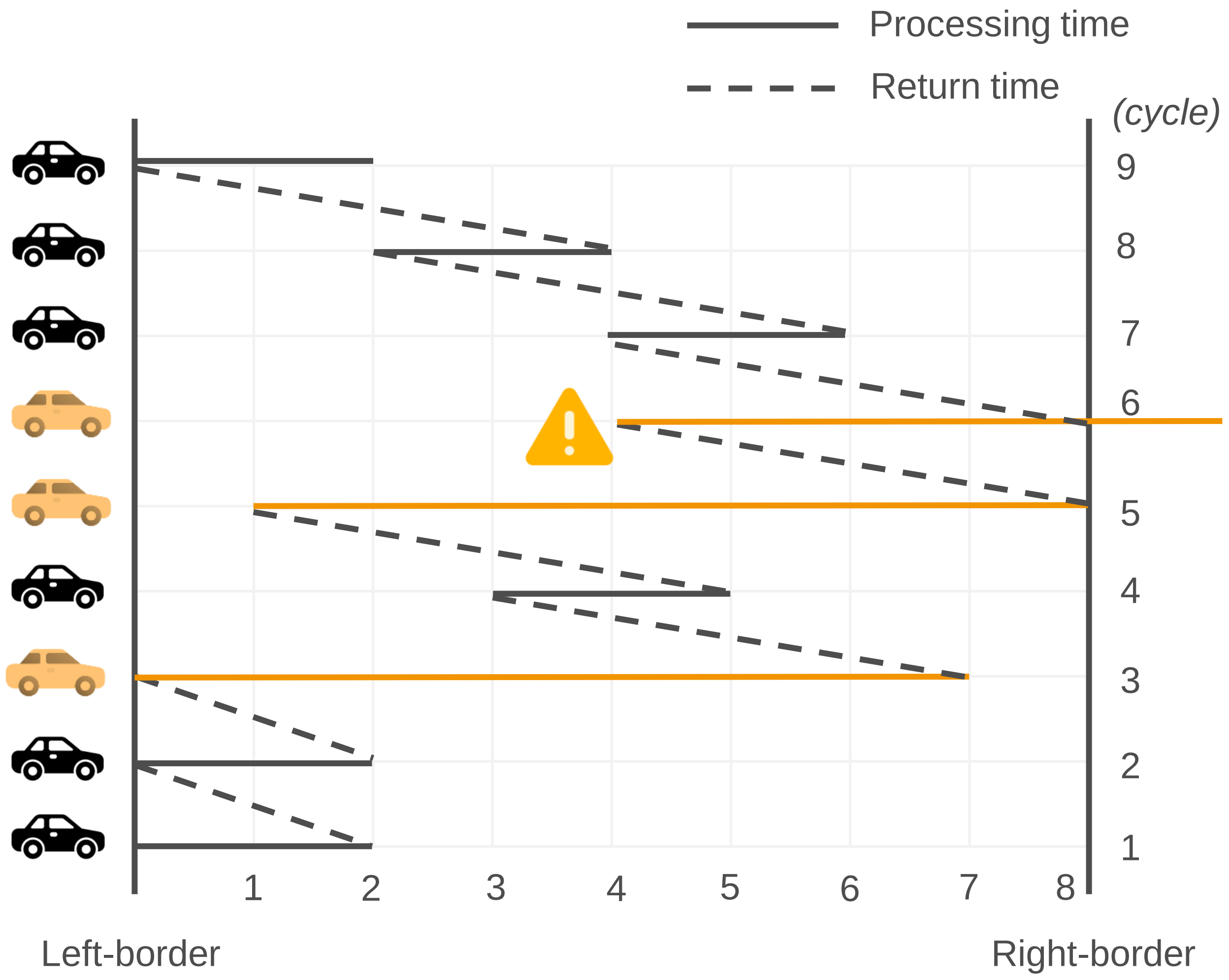
- How does work overload incur at the workstation?
  - A workstation is set up as described:
    - T cycles (T = 9)
    - Border length l_k (l = 8)
  - Movement of cars within the workstation:
    - A black car enters a station
    - After handling, operator comes back and continue until finish the 5th car
    - However, he **cannot finish the 6th** car and work overload incur
    - We assume it is compensated and the line continue until the end



MATHEMATICAL MODEL

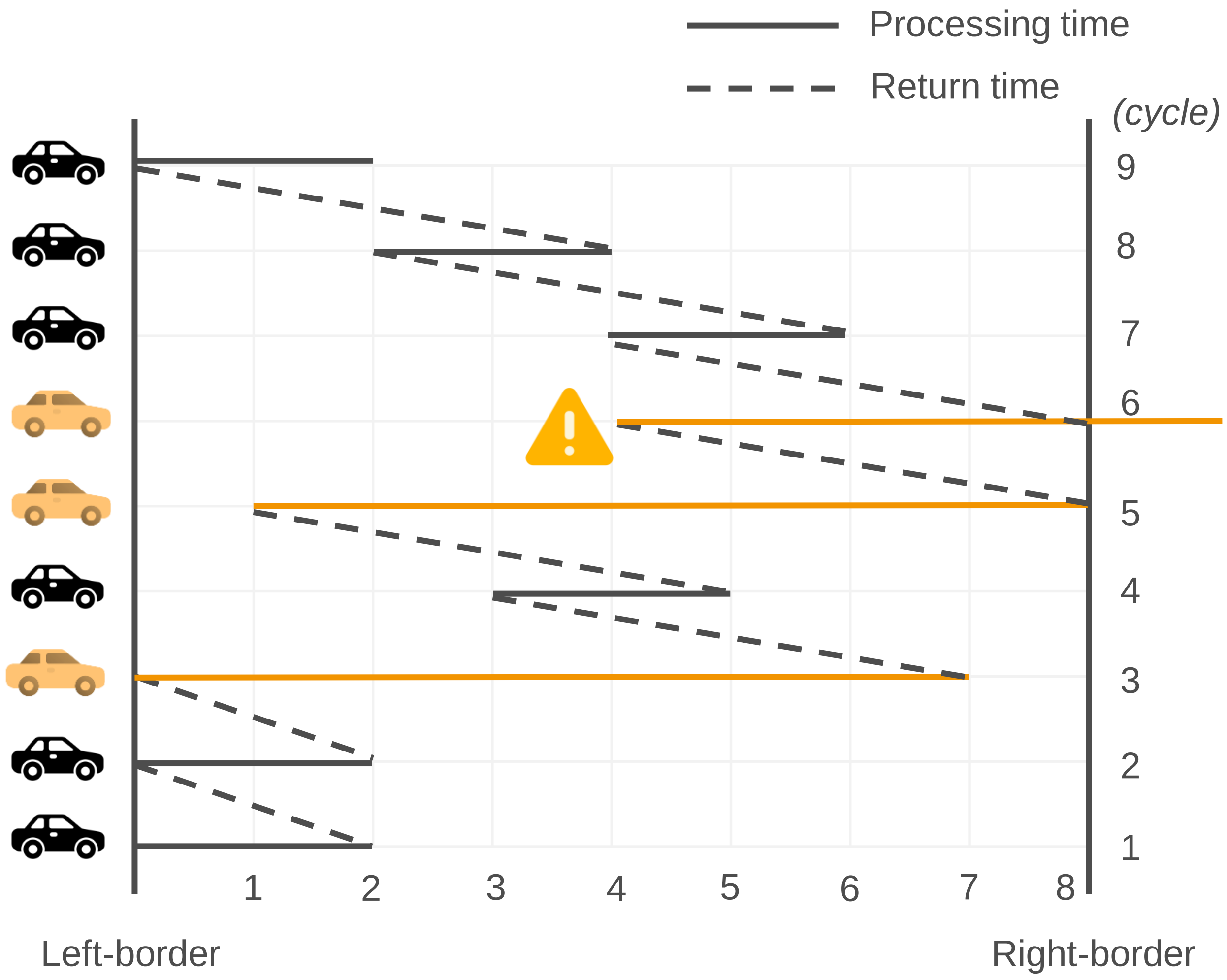
Problem formulation

- A feasible sequence
  - B – B – O – B – O – O – B – B – B is not feasible as work overload incurs
  - 2 orange models should not enter the line consecutively
- Car sequencing rule $H_o : N_o$
  - H_o restricts the number of models with option O that could be processed consecutively without generating work overload
  - N_o is H_o plus other models (w/o O) to get the operators back to left-border station



Assumptions of mathematical model

- Workflow is from left to right
- Operators can work only in their workstation
- Product models move at a constant speed
- All workstations are set up successively
- The products are processed as long as they meet the operators within the stations
- The operator has sufficient time to return to proceed next model
- **Demand** and **processing time** are **deterministic** and remain **constant**
- Work overload will be compensated and therefore **no line stoppage**

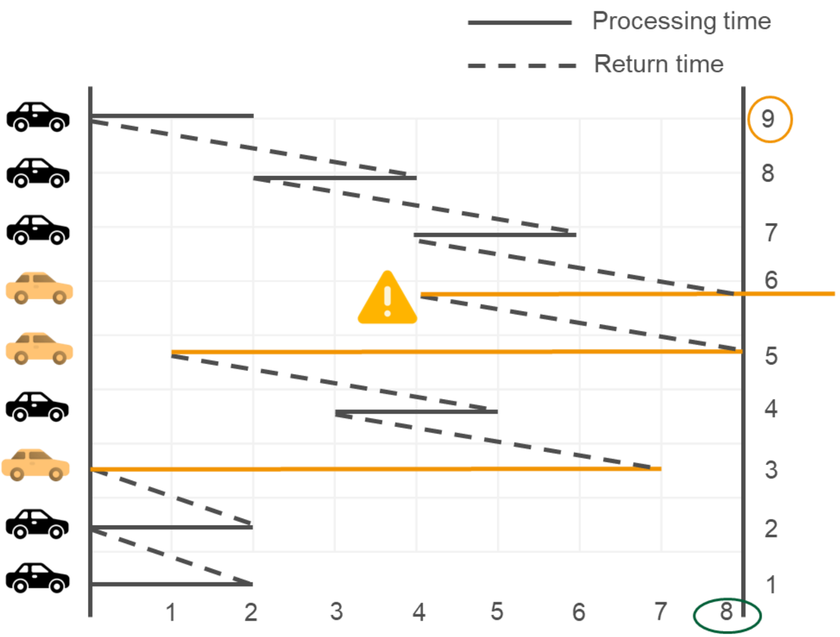


Introduction to variables of the mathematical models

- Settings: consider a production line with K workstations (index k), T cycle (index t), M models (index m) cycle time c and 2 models with **2 processing time**
  - p_o^+, **longer processing time**, for model with option O
  - p_o^-, **shorter processing time**, for model w/o O

- The model is based on Golle et. al., (2014) and describes a car sequencing model with **multiple sequencing rules** (MSR) in which **each rule is assigned a weighting factor λ_0**

$$\lambda_0 = p_o^+ - c$$



Introduction to variables of the mathematical models

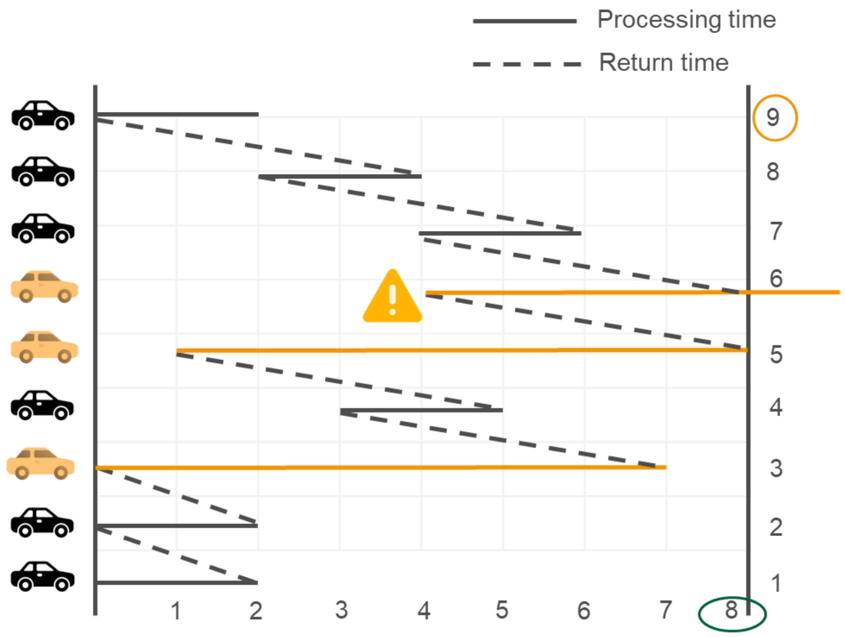
- v_0 calculates **the number of successive models with option O** in a sequence

$$v_0 = \sum_{t=1}^{T-N_o^q+1} \min\left\{1; \max\left\{\sum_{t'=t}^{t+N_o^q-1} \sum_{m \epsilon M} a_{om} \cdot x_{mt'} - H_o^q ; 0\right\}\right\}$$

$H_o^q : N_o^q$ is the rule in sequencing rule q^{th}

a_{om} is a binary variable. 1 if model contains option o, 0 otherwise

$x_{mt'}$ is a binary variable. 1 if model is produced in slot t, 0 otherwise



UNIVERSITY OF PASSAU

Introduction to variables of the mathematical models

- Define the number of rules (Q)

Q_o amounts to $q_o^{max} - q_o^{min} + 1$ with

$$q_o^{min} = \left\lfloor \frac{l_o - c}{p_o^+ - c} \right\rfloor \forall o \in O \quad (1)$$

$$q_o^{max} = \left\lfloor \frac{T(c - p_o^-) + (l_o - c)}{p_o^+ - p_o^-} \right\rfloor \forall o \in O \quad (2)$$

Then, $\forall q_o \in \left[q_o^{min}, q_o^{max}\right]$, MSR generates a rule $H_o^{q_o - q_o^{min}+1} : N_o^{q_o - q_o^{min}+1}$ with

$$H_o^{q_o - q_o^{min}+1} = q_o \ \forall o \in O \quad (3)$$

$$N_o^{q_o - q_o^{min}+1} = H_o^{q_o - q_o^{min}+1} + \left\lceil \frac{q_o \cdot (p_o^+ - c) + (l_o - p_o^+)}{c - p_o^-} \right\rceil \forall o \in O \quad (4)$$

q_o^{min}	*Maximum number of successive models containing option o without inducing work overload, equals H_o*
q_o^{max}	*Maximum number of models with option o that can occur in a sequence of length T without work overload*

- Numerical example:

Assume that l_o = 20 and there are two car models, with two processing time $p_o^+ = 15$ and $p_o^- = 5$ respectively. The cycle time is 10 and we assume that the length of the sequence T = 12

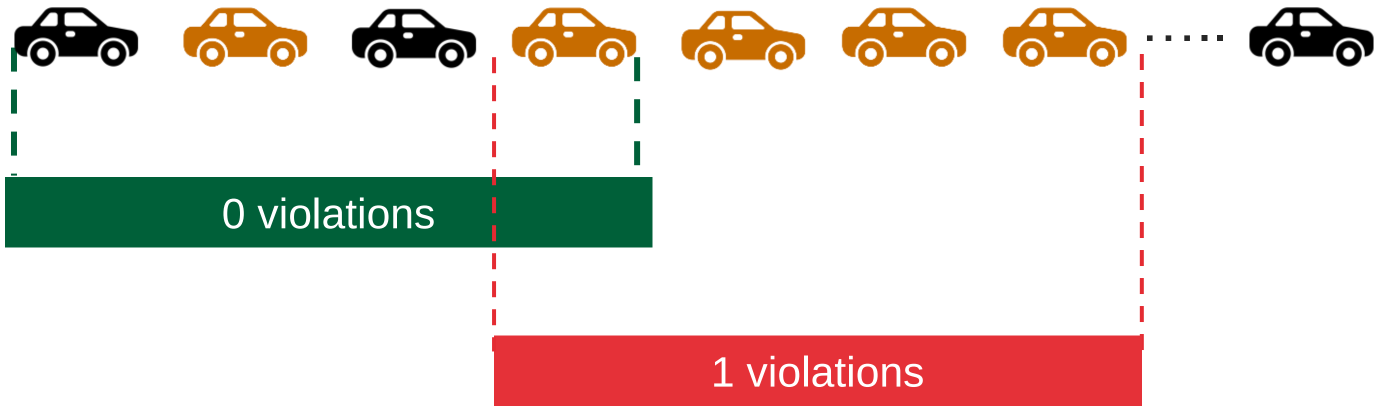
From (1) and (2) we derive $q_o^{min} = 2$ and $q_o^{max} = 7$, which indicates that we would have 6 sequencing rules

From (3) and (4), we get $H_o^1 : N_o^1 = 2 : 3$, $H_o^2 : N_o^2 = 3 : 4$, $H_o^3 : N_o^3 = 4 : 5$, $H_o^4 : N_o^4 = 5 : 6$, $H_o^5 : N_o^5 = 6 : 7$ and $H_o^6 : N_o^6 = 7 : 8$

Introduction to variables of the mathematical models

- How does multiple sequencing rules per station work?

  It follows sliding window. Assume we have a sequence of total 8 cars as and examine the rule of $H_o^2 : N_o^2 = 3 : 4$ *(under a subsequence of 4 cars, there are maximum of 3 orange cars that can be processed consecutively to avoid work overload)*



- Numerical example:

  Assume that l_o = 20 and there are two car models, with two processing time $p_o^+ = 15$ and $p_o^- = 5$ respectively. The cycle time is 10 and we assume that the length of the sequence T = 12

  From (1) and (2) we derive $q_o^{min} = 2$ and $q_o^{max} = 7$, which indicates that we would have 6 sequencing rules

  From (3) and (4), we get $H_o^1 : N_o^1 = 2 : 3$, $H_o^2 : N_o^2 = 3 : 4$, $H_o^3 : N_o^3 = 4 : 5$, $H_o^4 : N_o^4 = 5 : 6$, $H_o^5 : N_o^5 = 6 : 7$ and $H_o^6 : N_o^6 = 7 : 8$

UNIVERSITY OF PASSAU

Introduction to model objective functions

- Objective functions

$$\text{minimize } obj^{w} = \sum_{o\epsilon O} \lambda_o \frac{1}{Q_o} \sum_{q\epsilon Q_o} v_{oq}$$

(minimize total number of violations with weighting factors)

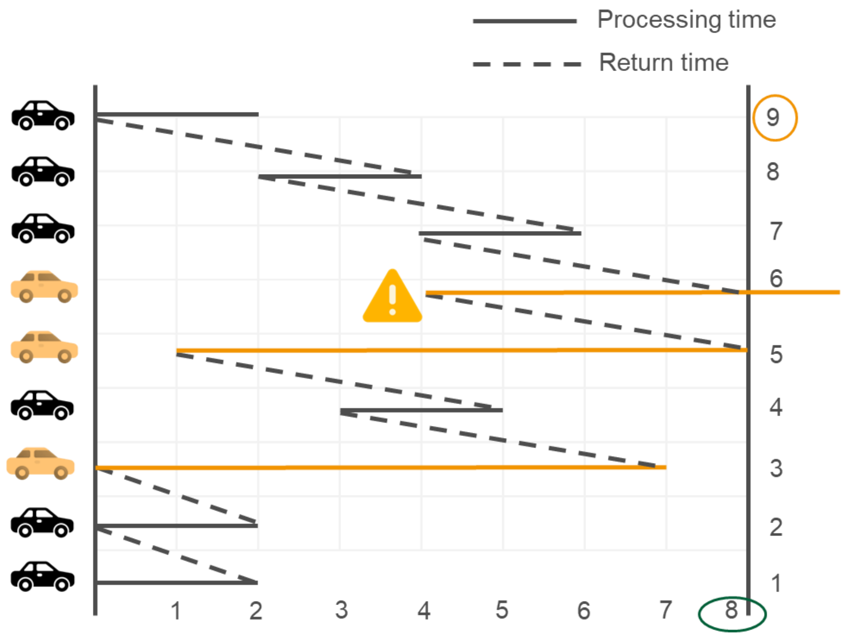
subject to

$$\sum_{t=1}^{T} x_{mt} = d_m$$

(d_m demand, total production output needs to meet demand)

$$\sum_{m\epsilon M} x_{mt} = 1 \;\forall t = 1, \dots, T$$

(each slot in the sequence contains exactly 1 model)



Advantages of car sequencing compared to mixed-model sequencing

- Based on Golle et. el., 2014 and Louis et. al., 2023 car sequencing are considered
  - **Easy** to apply and execute in practice
  - **Less effort** in constructing the mathematical model and data collection process
  - The evaluation of sequence is **faster**

- However, all previous studies shown that
  - **MMS generates less overload** than CS for assembly workers (using both real-case industry data and random instances)

UNIVERSITY OF PASSAU

Selection of sequencing rules

- Based on Golle et. al., 2014, there are 2 scenarios of misclassifying in CS
  - A sequence is **feasible in CS** but **not feasible in MMS**
    - Sequencing **rules are not strict** enough to eliminate circumstances where work overload would happen
    - **Additional costs** to deal with unforeseen work overload if it is incurred
  - A sequence is **infeasible in CS** but **feasible in MMS**
    - Car sequencing is **unnecessarily strict** that no sequence could fulfill
    - The elimination of feasible solutions would potentially lead to the removal of optimal solution or in the worst case, **no feasible sequences could be found**
- The quality of CS rules are based on the **percentage of misclassification**. The lower, the better

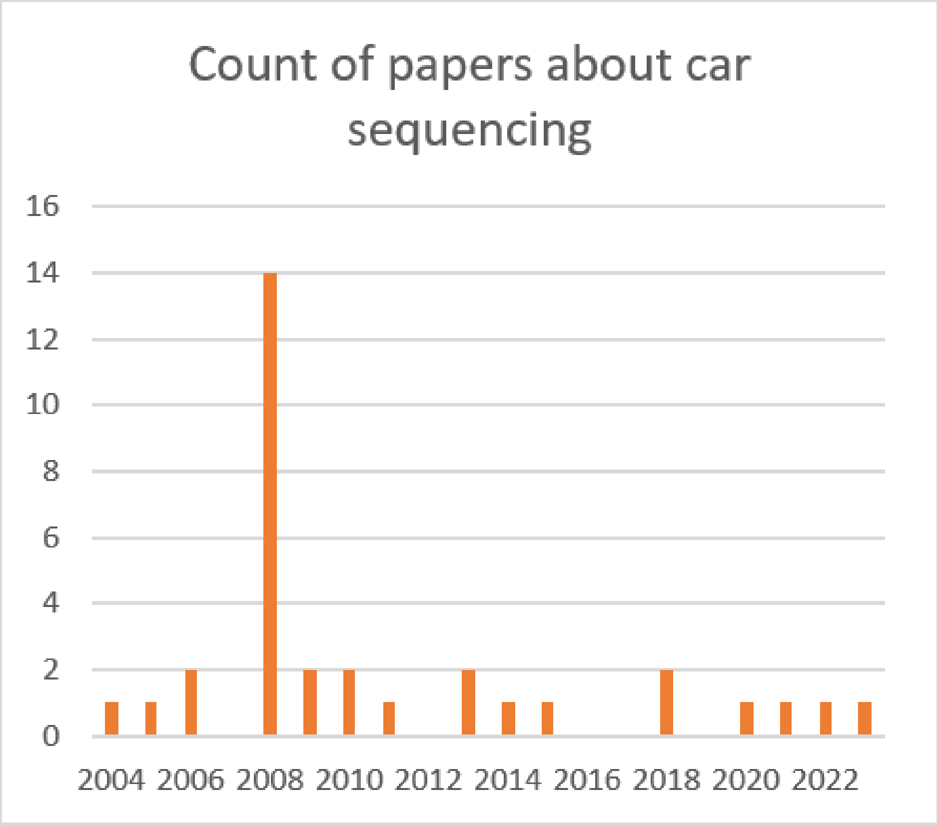
Selection of sequencing rules

- There are **3 sequencing rules** that have been used for previous research studies
  - **One** sequencing rule (introduced by Golle et al., 2014)
  - **Multiple** sequencing rules (MSR) per station (introduced by Golle et al., 2014)
  - **Unique** sequencing ratio (USR) per station (introduced by Lesert, Alpan, and Frein 2011)

- Finding from Louis et. el., 2023 and Golle et al., 2014
  - **MMS always achieve the best results** compared to CS
  - With industry real-case data:
    - CS with MSR method **are as good as MMS when cars on one sequence are limited**
    - Otherwise, **MMS helps achieve better results** than CS
    - Among 3 sequencing rules, **USR gave the best results**

Literature selection: Methodology

- SCOPUS database
- Journals with ranking from A+ to B according to VHB-JOURQUAL rating for operations research
- Period from 2004 to 2023 inclusively
- ROADEF’05 challenge in 2005 initiated by Renault company (mostly papers of 2008) => the period reduced to 2010-2023
- Excluding Estellon and Gardi (2013)
- **=> 12 highly rated papers**



Literature table (I)

Title		Problem formulation			Contribution					
Paper	**Year**	**Problem type**	**Objective function**	**Options per station**	**Solution method**	**Algorithm type**	**Bounds improved**	**Comparison of CS and MMS**	**Sequencing rules creation**	**Instance space analysis**
Giard and Jeunet	2010	CS with sequence-dependent setups and utility workers	minimize the cost function involving costs associated with additional utility workers and setup costs	2, colors	MIP solved with ILOG-Cplex 9.0	exact algorithm	-	-	-	-
Golle et al.	2010	CS	-	multiple	-	-	-	-	**X**	-
Lesert et al.	2011	CS	minimize the number of violations	multiple	sequencing tool of an automotive company	-	-	-	**X**	-
Yavuz	2013	combined CS and LS	minimize the sum of absolute differences between actual and ideal positions of variant copies	2	iterated beam search	both heuristic or exact algorithm	tight lower bounds, upper bounds	-	-	-

Literature table (II)

Title		Problem formulation			Contribution					
Paper	**Year**	**Problem type**	**Objective function**	**Options per station**	**Solution method**	**Algorithm type**	**Bounds improved**	**Comparison of CS and MMS**	**Sequencing rules creation**	**Instance space analysis**
Golle et al.	2014	CS	minimize the number of (weighted) violations with 3 objective functions: 1) sliding window (Gravel et al., 2005), 2) Fliedner and Boysen (2008) function, 3) Bolat and Yano (1992) function	2	MIP solved with CPLEX 12.2	exact algorithm	-	**X** CS is worse	-	-
Golle et al.	2015	CS	minimize the number of (weighted) violations with 3 objective functions: 1) sliding window (Gravel et al., 2005), 2) Fliedner and Boysen (2008) function	2	iterated beam search	both heuristic or exact algorithm	lower bounds improved	-	-	-
Jahren and Achá	2018	industrial CS	minimize the weighted sum of 2 objectives: ratio costs and paint changes	2, colors	column generation based algorithm	exact algorithm	lower, upper bounds improved	-	-	-

Literature table (III)

Title		Problem formulation			Contribution					
Paper	**Year**	**Problem type**	**Objective function**	**Options per station**	**Solution method**	**Algorithm type**	**Bounds improved**	**Comparison of CS and MMS**	**Sequencing rules creation**	**Instance space analysis**
Yavuz and Ergin	2018	combined CS and LS	minimize sum of absolute differences between actual and ideal positions of variant copies	2	constraint propagation, branch-and-bound	heuristic	-	-	-	-
Thiruvady et al.	2020	CS	min the sum of upper over- and under-assignments (see Bautista et al., 2008)	2	large neighborhood search	heuristic	-	-	-	-
Hottenrott et al.	2021	CS, robust against short-term sequence alterations	minimize the expected number of violations	2, colors	1) branch-and-bound for small instances, 2) a sampling-based adaptive large neighborhood search heuristic for large instances	1) exact algorithm 2) heuristic	lower bounds improved	-	-	-

Literature table (IV)

Title		Problem formulation			Contribution					
Paper	**Year**	**Problem type**	**Objective function**	**Options per station**	**Solution method**	**Algorithm type**	**Bounds improved**	**Comparison of CS and MMS**	**Sequencing rules creation**	**Instance space analysis**
Sun et al.	2022	CS	minimize the sum of upper over- and under-assignments (see Bautista et al. 2008)	2	adaptive large neighborhood search, MIP with lazy constraints solved with Gurobi	1) heuristic 2) exact algorithm	-	-	-	**X**
Louis et al.	2023	CS, industrial CS	minimize the number of violations	2 or multiple	-	-	-	**X** CS is worse	-	-

Literature trends and future research

Trends	Future research
Modifications of CS	Incorporating uncertainty (e. g. robust CS)
Multiple options: the early 2010-s, then less interest	Revisiting the topic
Case studies in automotive industry	Applications in other industries
Development of well-performing algorithms (e. g. ROADEF‘05)	Focus on other aspects
CS vs. MMS – MMS is better	Deployment of MMS in companies: cases
Sequencing rules generation – popularity in the early 2010-s, then less interest	Revisiting the topic
Instance space analysis	Further features of hard instances, new benchmark instances, improvement of existing algorithms

Industries selection: Methodology

- Google Scholar and SCOPUS databases
- Keywords “mixed-model assembly”, “sequencing”, “case study”, excluding keywords “car”, “automotive”, “truck”, “motorbike”
- No restriction on journals and paper ratings

Industries found

- Boiler manufacturing (Hwang and Katayama, 2010): E. g. various fan seals, fan motors, burners, air conditioners, etc.
- Food processing (Savsar et al., 2017): E. g. a salad line with different core and additional ingredients
- GPU cards (Wang et al., 2023)
- Hydraulic pumps (Rauf et al., 2020): E. g. different valves, levers
- Industrial air-dryers (Faccio et al., 2016)
- Industrial machines manufacturing (Rabbani et al., 2015)

Industries found

- Off-Highways systems manufacturing (Tiacci and Mimmi, 2018): E. g. the presence/absence of the Power Take Off (PTO) and/or quick couplers
- Plastic bag manufacturing (Mamun et al., 2012): E. g. presence/absence of different prints, various U-panels, etc.
- Turbocharger assembly (Yadav et al., 2020)
- Wooden furniture (Nouri and Abdul-Nour, 2019): E. g. presence/absence of reclining sofa backs, cabinet handles, different colors, etc.

Conclusion

- Sequencing is the task of defining the optimal job orders to minimize costs and work overload
- Mixed-model and car sequencing are the two common methods
- Among all sequencing rules, unique sequencing ratio per station delivered optimal results
- Methodology of searching papers was proposed
- Literature was classified by problem formulation and contribution
- Literature trends and future research directions were identified
- Industries where sequencing can be applied were identified

Thank you! Any questions?

References

Bautista, J., Pereira, J., & Adenso-Díaz, B. (2008). A beam search approach for the optimization version of the car sequencing problem. *Annals of Operations Research, 159*, 233-244.

Bolat, A., & Yano, C. A. (1992). A surrogate objective for utility work in paced assembly lines. *Production Planning & Control*, *3*(4), 406-412.

Estellon, B., & Gardi, F. (2013). Car sequencing is NP-hard: a short proof. *Journal of the Operational Research Society, 64(*10), 1503-1504.

Faccio, M., Gamberi, M., & Bortolini, M. (2016). Hierarchical approach for paced mixed-model assembly line balancing and sequencing with jolly operators. *International journal of production research*, *54*(3), 761-777.

Fliedner, M., & Boysen, N. (2008). Solving the car sequencing problem via branch & bound. *European Journal of Operational Research*, *191*(3), 1023-1042.

Giard, V., & Jeunet, J. (2010). Optimal sequencing of mixed models with sequence-dependent setups and utility workers on an assembly line. *International Journal of Production Economics*, *123*(2), 290-300.

Golle, U., Boysen, N., & Rothlauf, F. (2010). Analysis and design of sequencing rules for car sequencing. *European Journal of Operational Research*, *206*(3), 579-585.

Golle, U., Rothlauf, F., & Boysen, N. (2014). Car sequencing versus mixed-model sequencing: A computational study. *European Journal of Operational Research*, *237*(1), 50-61.

Golle, U., Rothlauf, F., & Boysen, N. (2015). Iterative beam search for car sequencing. *Annals of Operations Research*, *226*, 239-254.

Gravel, M., Gagne, C., & Price, W. L. (2005). Review and comparison of three methods for the solution of the car sequencing problem. *Journal of the Operational Research Society*, *56*(11), 1287-1295.

Hottenrott, A., Waidner, L., & Grunow, M. (2021). Robust car sequencing for automotive assembly. *European Journal of Operational Research*, *291*(3), 983-994.

References

Hwang, R., & Katayama, H. (2010). Integrated procedure of balancing and sequencing for mixed-model assembly lines: a multi-objective evolutionary approach. *International Journal of Production Research*, *48*(21), 6417-6441.

Jahren, E., & Achá, R. A. (2018). A column generation approach and new bounds for the car sequencing problem. *Annals of Operations Research*, *264*, 193-211.

Lesert, A., Alpan, G., Frein, Y., & Noire, S. (2011). Definition of spacing constraints for the car sequencing problem. *International Journal of Production Research*, *49*(4), 963-994.

Louis, A., Alpan, G., Penz, B., & Benichou, A. (2023). Mixed-model sequencing versus car sequencing: comparison of feasible solution spaces. *International Journal of Production Research*, *61*(10), 3415-3434.

Mamun, A. A., Khaled, A. A., Ali, S. M., & Chowdhury, M. M. (2012). A heuristic approach for balancing mixed-model assembly line of type I using genetic algorithm. *International Journal of Production Research*, *50*(18), 5106-5116.

Nouri, K., & Abdul-Nour, G. (2019). Optimization via Computer Simulation of a Mixed Assembly Line of Wooden Furniture-A Case Study. *Procedia Manufacturing*, *39*, 956-963.

Rabbani, M., Sadri, S., Manavizadeh, N., & Rafiei, H. (2015). A novel bi-level hierarchy towards available-to-promise in mixed-model assembly line sequencing problems. *Engineering Optimization, 47*(7), 947-962.

Rauf, M., Guan, Z., Sarfraz, S., Mumtaz, J., Shehab, E., Jahanzaib, M., & Hanif, M. (2020). A smart algorithm for multi-criteria optimization of model sequencing problem in assembly lines. *Robotics and Computer-Integrated Manufacturing*, *61*, 101844.

Savsar, M., Elsaadany, A. K., Hassneiah, R., & Alajmi, A. (2017). Analysis of a manual mixed-model assembly line in food processing industry: a case study. In *International Conference on Industrial Engineering and Operations Management* (pp. 5689-5695).

References

Sun, Y., Esler, S., Thiruvady, D., Ernst, A. T., Li, X., & Morgan, K. (2022). Instance space analysis for the car sequencing problem. *Annals of Operations Research*, 1-29.

Thiruvady, D., Morgan, K., Amir, A., & Ernst, A. T. (2020). Large neighbourhood search based on mixed integer programming and ant colony optimisation for car sequencing. *International Journal of Production Research*, *58*(9), 2696-2711.

Tiacci, L., & Mimmi, M. (2018). Integrating ergonomic risks evaluation through OCRA index and balancing/sequencing decisions for mixed model stochastic asynchronous assembly lines. *Omega*, *78*, 112-138.

Wang, K. J., Eunike, A., Kurniawan, I., Ardi, R., & Chiu, J. M. (2023). Autonomous agent-based simulation modelling – A case study on a flexible GPU-card final assembly line. *Robotics and Autonomous Systems*, *169*, 104511.

Yadav, A., Verma, P., & Agrawal, S. (2020). Mixed model two-sided assembly line balancing problem: an exact solution approach. *International Journal of System Assurance Engineering and Management*, *11*(Suppl 2), 335-348.

Yavuz, M. (2013). Iterated beam search for the combined car sequencing and level scheduling problem. *International journal of production research*, *51*(12), 3698-3718.

Yavuz, M., & Ergin, H. (2018). Advanced constraint propagation for the combined car sequencing and level scheduling problem. *Computers & Operations Research*, *100*, 128-139.