Optimization of Energy and Transport Systems

Alessio Trivella

Zurich, May 31st, 2024

Background

University of Milan
BSc & MSc in Mathematics
(2007-2012)

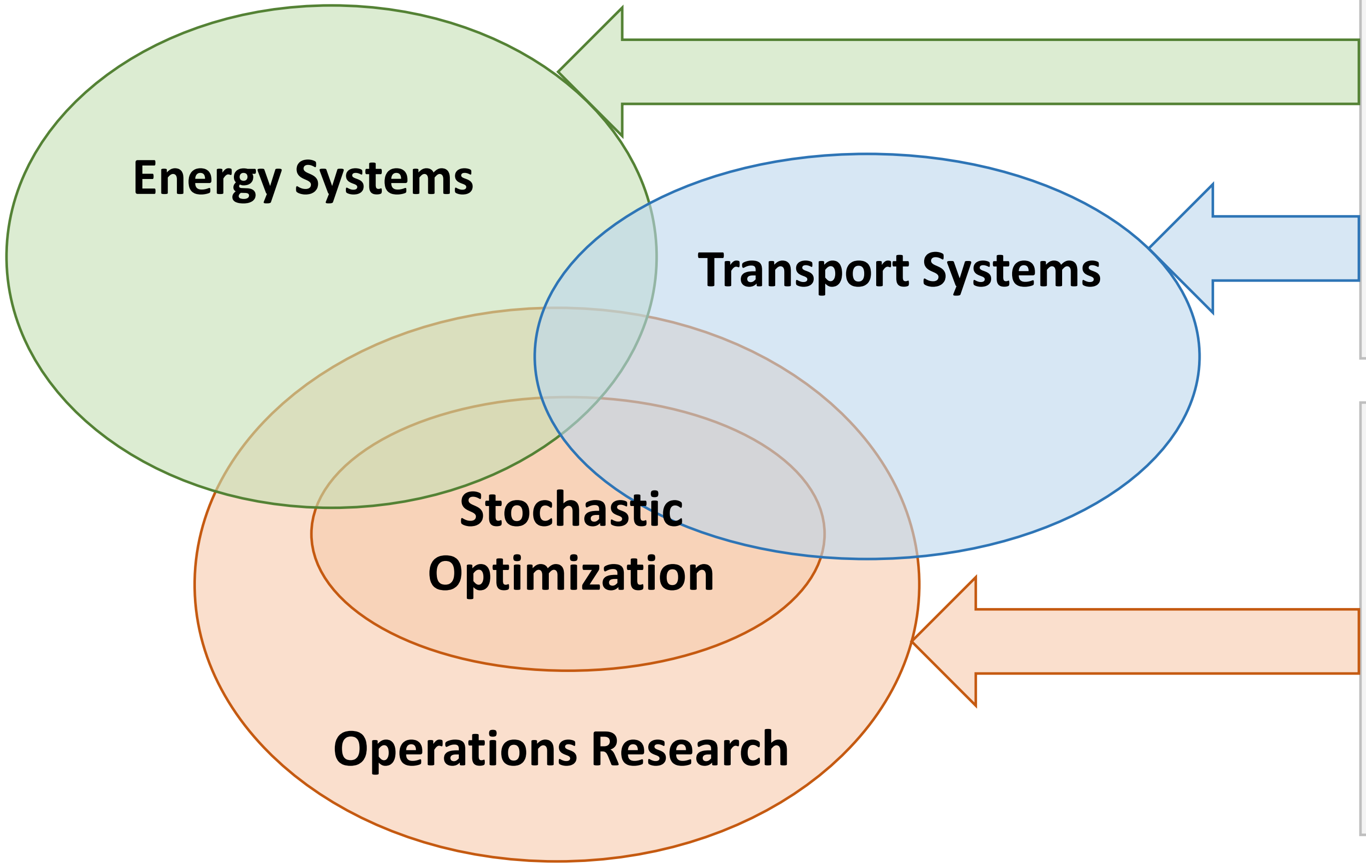
Bip. Consulting
Management Consulting
(2012-2015)

Technical Univ. of Denmark
PhD in Operations Research
(2015-2018)

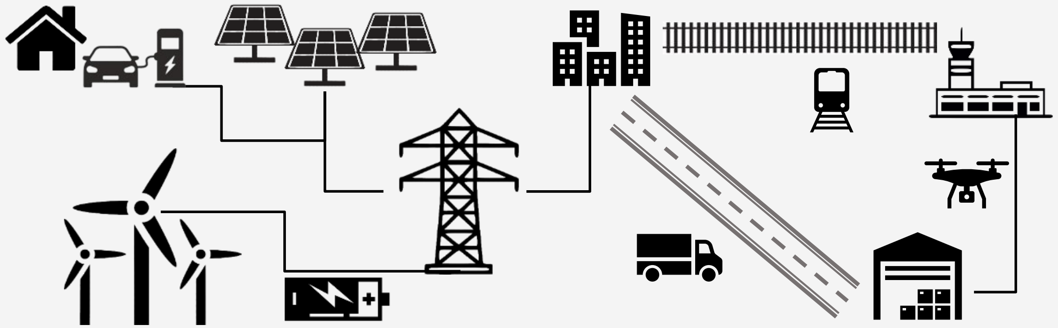
ETH Zurich, IVT, TS
Postdoc
(2019-2021)

University of Twente
Assistant Professor of Operations Research
(2022-)

Research interests

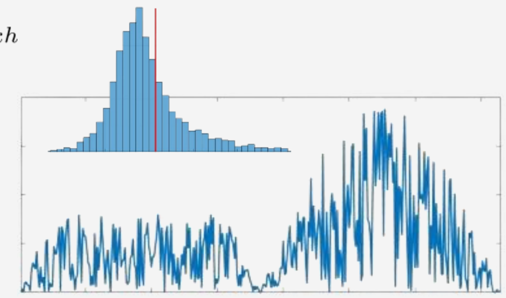


Domain



Methodology

$$
\begin{aligned}
\min \ & \sum_{j \in \mathcal{J}_i} \beta_{ij} y_{ij} + \sum_{k \in \mathcal{K}} \sum_{h \in \mathcal{H}_{ik}} z_{ikh} \\
\text{s.t.}: \ & F y_{ij} \geq \sum_{k \in \mathcal{K}} \sum_{h \in \mathcal{H}_{ik}} w^*_{ijkh} \\
& G_k z_{ikh} \geq \sum_{j \in \mathcal{J}_i} w^*_{ijkh} \\
\text{var.}: \ & y_{ij}, z_{ikh} \in \{0, 1\}
\end{aligned}
$$



Problem-driven research

VATTENFALL

Ahold Delhaize

simacan

Italmondo
Itlm group

bol.com

NS

BOLK
TRANSPORT

MAERSK

ProRail

arriva
a DB company

Twence®

HYDRO

THALES

voortman
STEEL GROUP

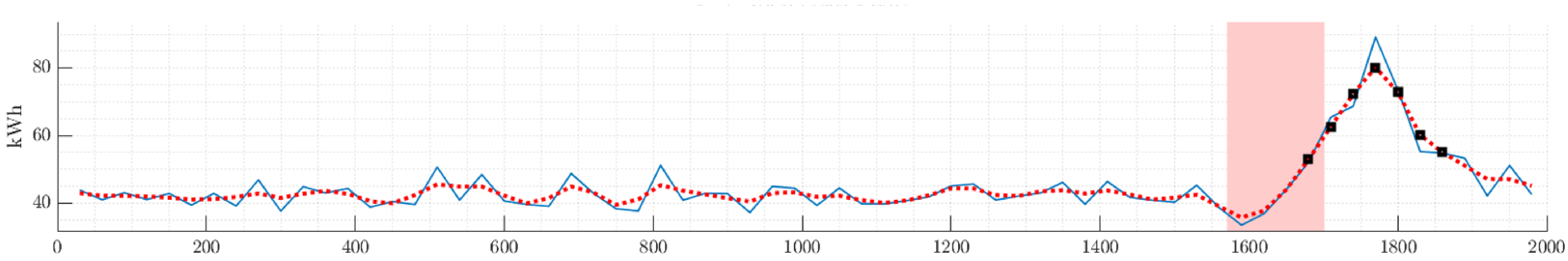
flaschenpost.de

SBB CFF FFS

Firan

DISTRIBUTE

RhB Rhätische Bahn



Improving energy efficiency in railway traffic and speed profiles under uncertainty

Alessio Trivella

Joint works with Francesco Corman

Zurich, May 31st, 2024

Problems considered

- **Microscopic** railway models, involving **uncertainty**, and including **energy use**

Railway traffic flow modeling

- Stochastic process in railway traffic flow: Models, methods and implications.

  F.Corman, **A.Trivella**, M.Keyvan-Ekbatani

  Transportation Research Part C (2021) + ISTTT

- Modeling system dynamics of interacting cruising trains to reduce the impact of power peaks

  A.Trivella, F.Corman

  Expert Systems with Applications (2023)

Train trajectory optimization

- The impact of wind on energy-efficient train control

  A.Trivella, P.Wang, F.Corman

  EURO Journal on Transportation and Logistics (2021)

- Traintrajectory optimization for improved on-time arrival under parametric uncertainty

  P.Wang, **A.Trivella**, R.Goverde, F.Corman

  Transportation Research Part C (2020)

Railway traffic flow modeling

Railway traffic

Much effort devoted to model **car traffic**: Describe traffic characteristics based on individual drivers' behavior (e.g., car-following and lane-changing)…

…but little exchange of ideas filtered to/from the similar problem for track-based transportation

We wanted to develop novel **railway traffic flow models** based on driver behavior modeling by:

- extending key ideas from car traffic
- considering the specific/different aspects of railway, e.g.,
  - Safety system
  - Common energy consumption
  - Technologies like ATO

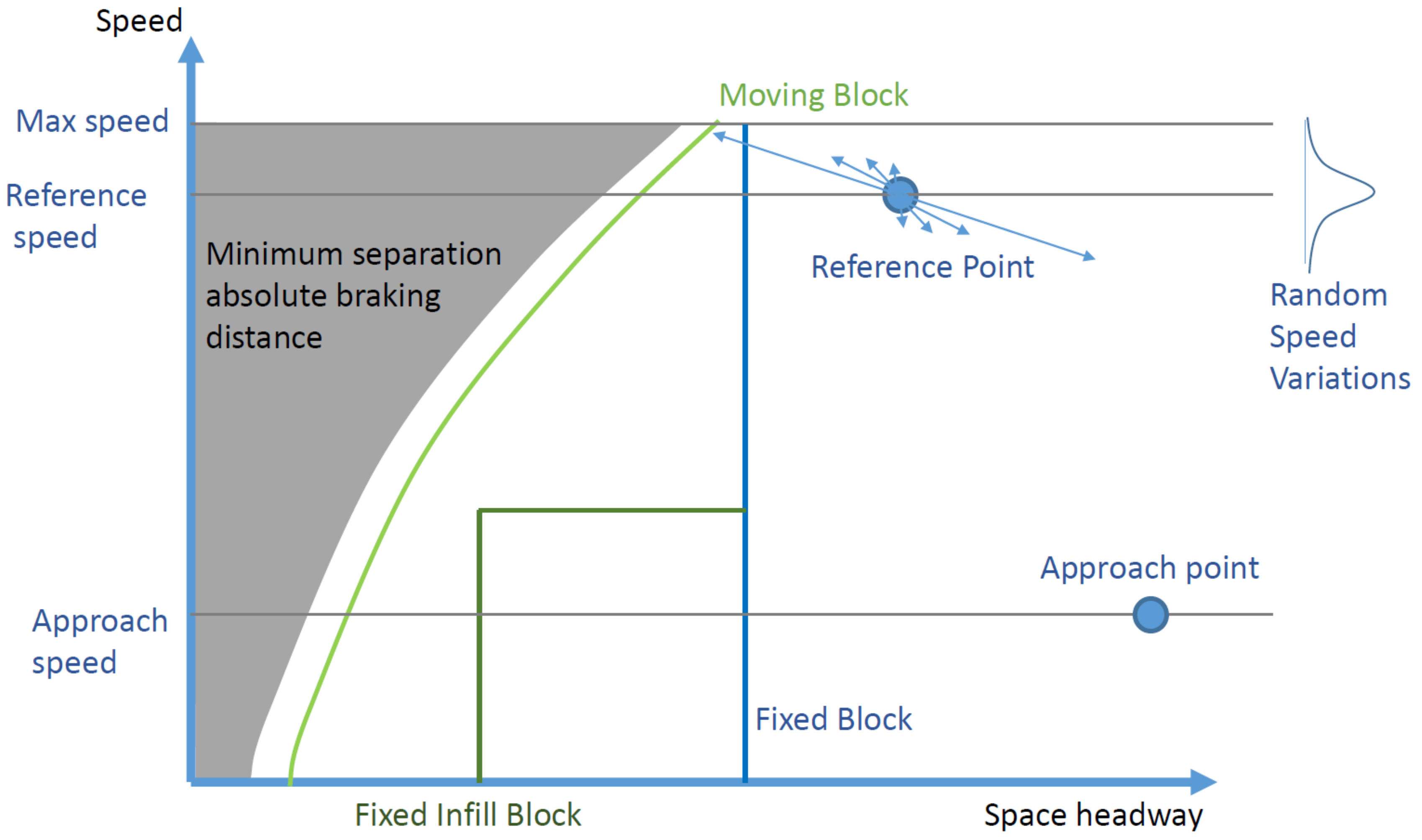
Goal is to formalize the relation between train driver characteristics, including behavior, vehicle's technology, signaling system, and the **aggregate performance** of the system

Problem description

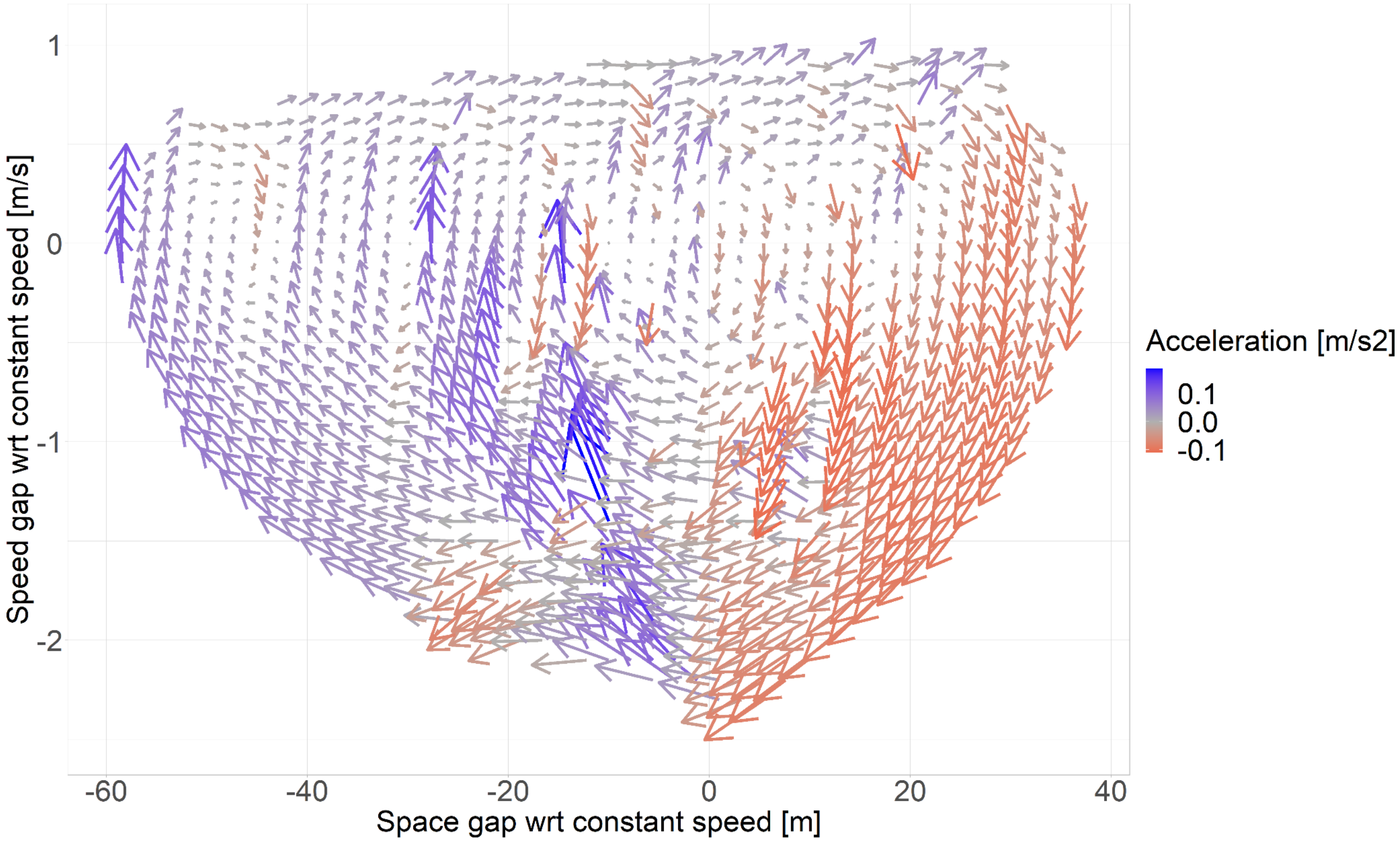
Leader-follower model

Follower is subject to speed variations

Yellow signals force the follower to decelerate



Analysis on recorded data from the Swiss network (50 trains)



Stochastic process models

We define **4 stochastic processes** of increasing complexity that model different situations

1. Speed follows an Ornstein-Uhlenbeck process **(OU)**

$$\textbf{[OU]:} \quad \begin{cases} \mathrm{d}v(t) = \beta(v_{\text{CRUISE}} - v(t))\mathrm{d}t + \sigma \mathrm{d}W(t) \\ \mathrm{d}s(t) = v(t)\mathrm{d}t \end{cases}$$

→ Mean-reverts to v_{CRUISE}

It can represent the process of a **human train driver** who knows the planned speed and continuously controls the train speed to be as close as possible

2. Doubly mean-reverting, doubly bounded process (**DMR**)

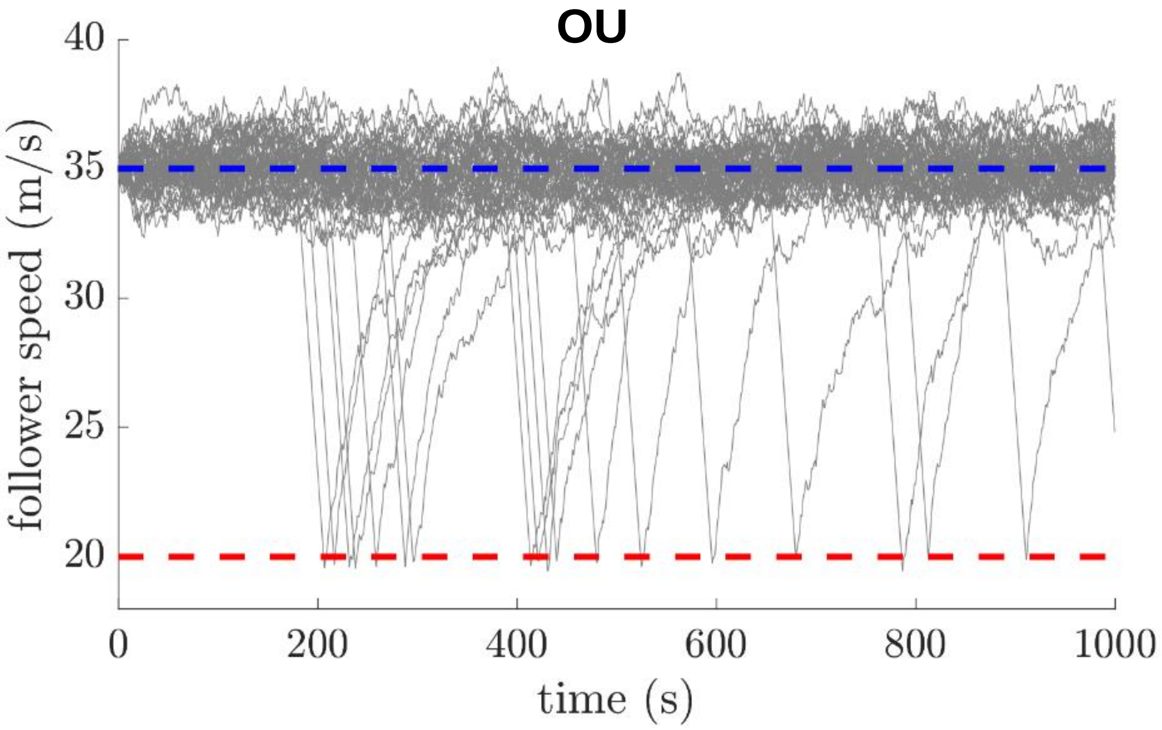
$$\textbf{[DMR]:} \quad \begin{cases} \mathrm{d}v(t) = \left[\beta(v_{\text{CRUISE}} - v(t)) + \alpha\left(v_{\text{CRUISE}}\, t - s(t)\right)\right]\mathrm{d}t + \widehat{\sigma}(v(t))\, \mathrm{d}W(t) \\ \mathrm{d}s(t) = v(t)\mathrm{d}t \end{cases}$$

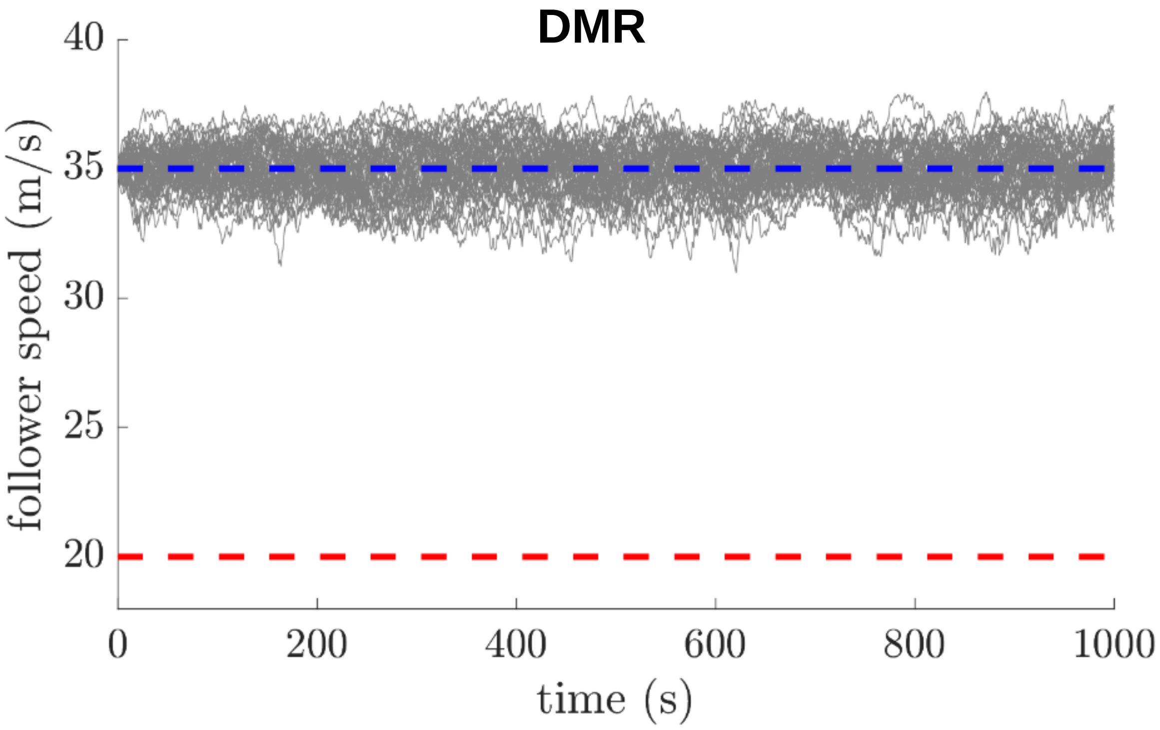
It can model how a **computer**, aware of precise position of current and ahead vehicle, can steer the system towards a desired space headway

Time-speed trajectories

We can study the system with two approaches:

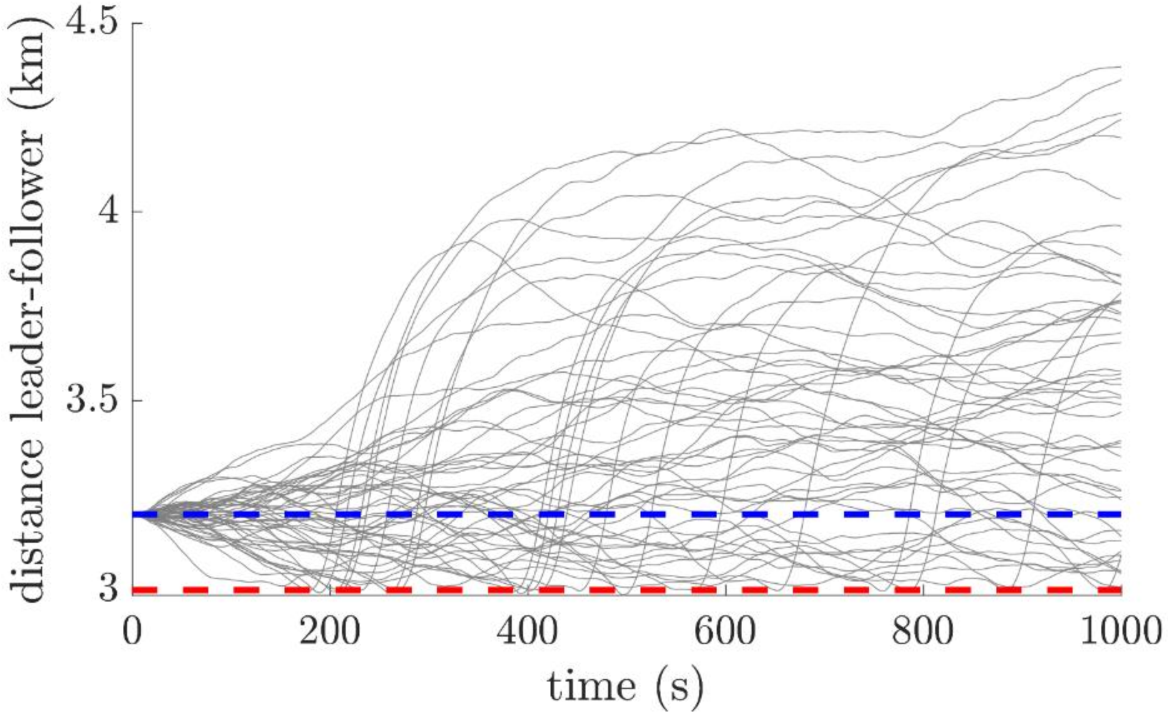
1. by adapting **theoretical results** on stochastic processes
2. by **Monte Carlo simulation** of multiple stochastic process trajectories



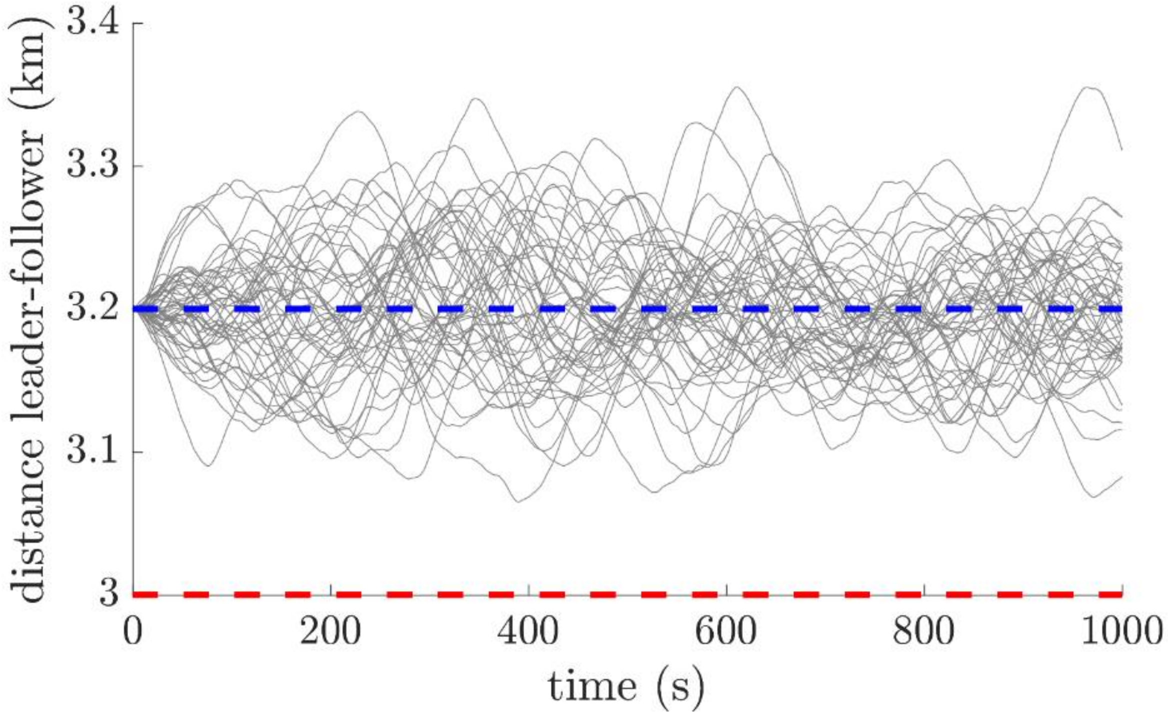


Time-space trajectories

OU

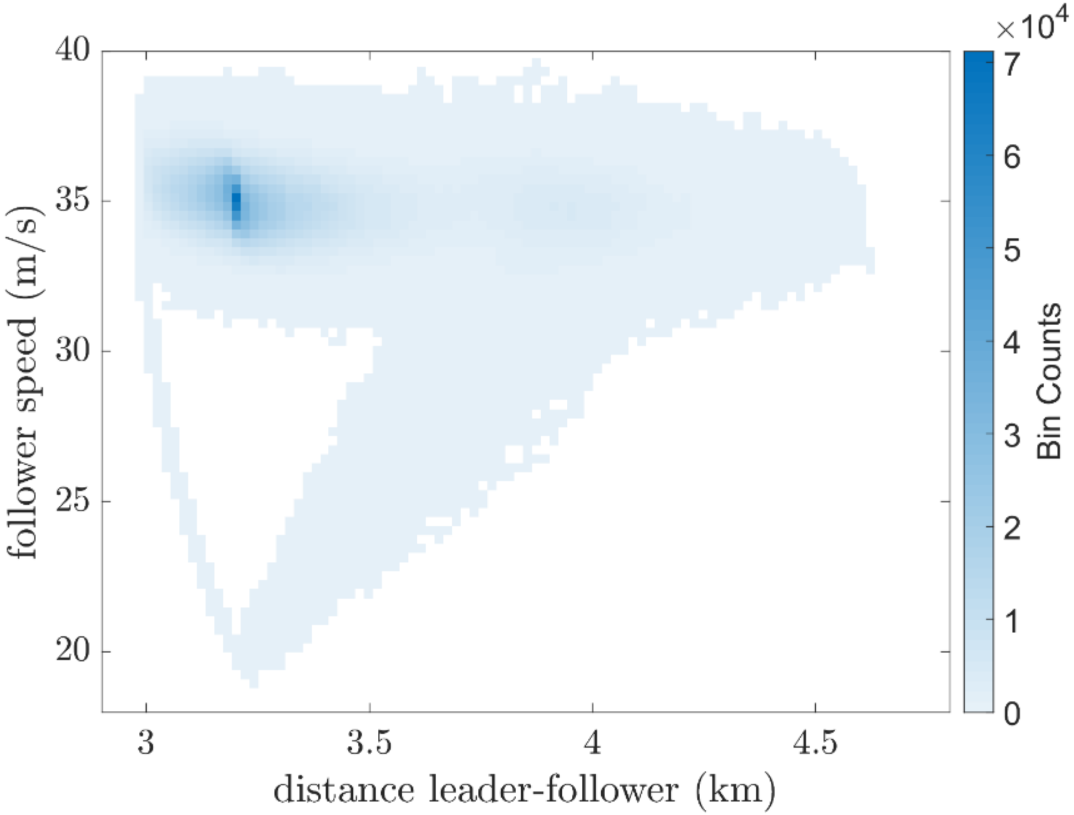


DMR

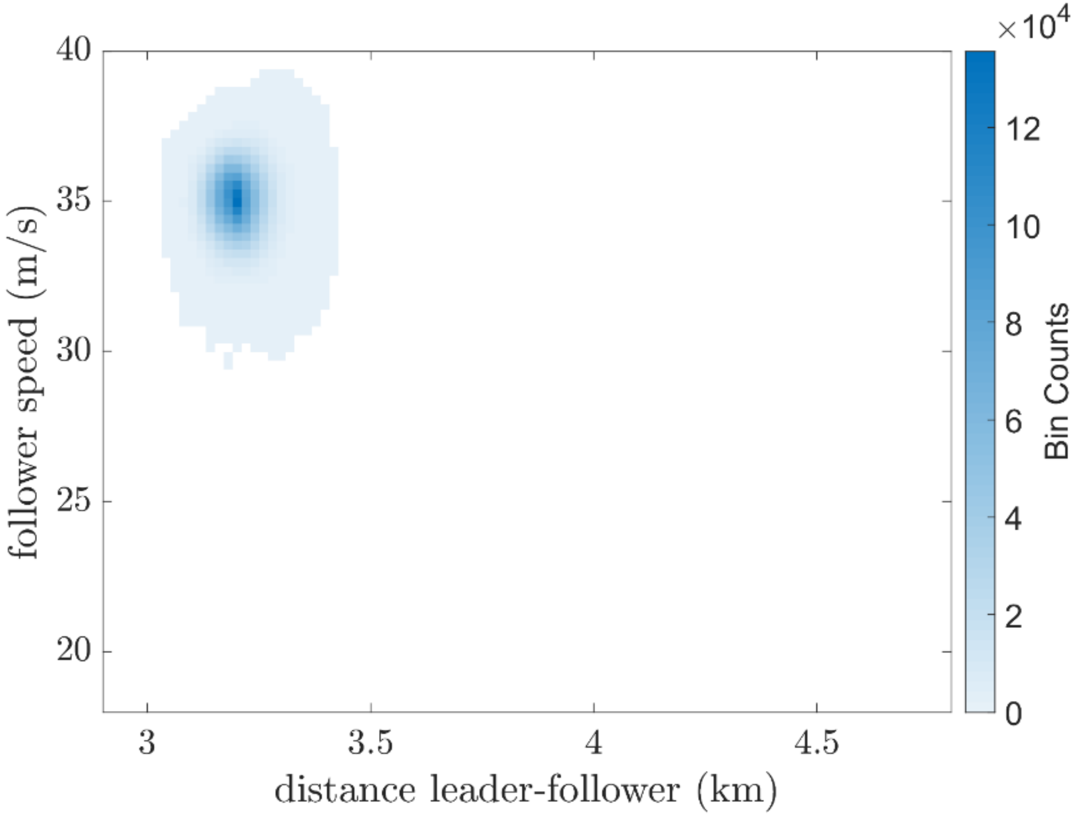


Space-speed trajectories

OU



DMR



System performance (5000 trajectories)

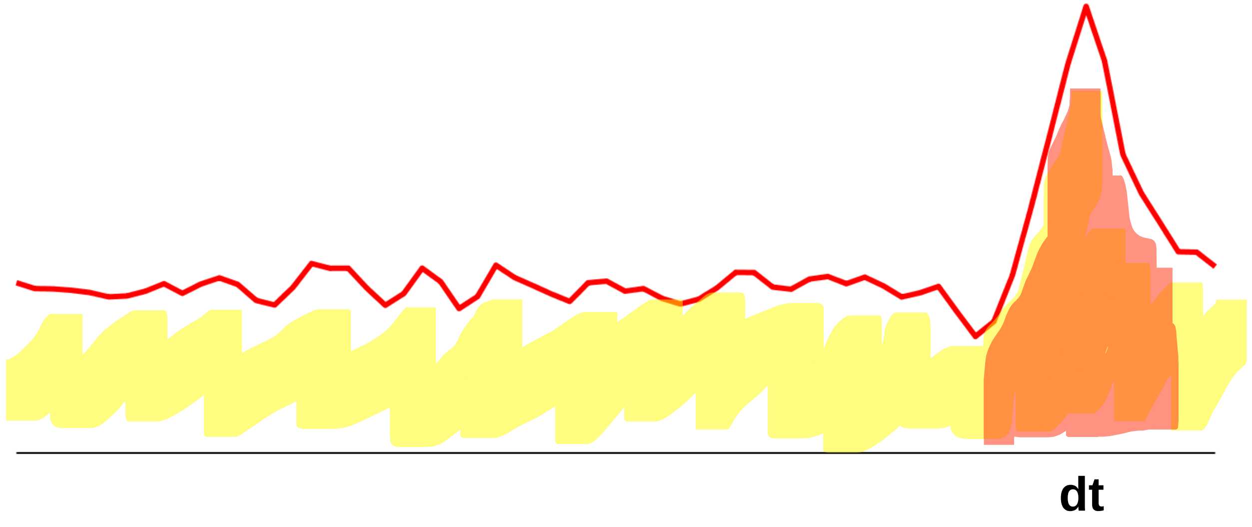
Table 1: Analysis of aggregate properties from the four stochastic process models (horizon 1 hour).

Performance indicator		Unit	BM	OU	CIR	DMR	DET_0	DET_+
Trajectories with at least one yellow signal		[%]	70.4	65.2	65.9	0.0	0.0	100.0
Yellow signals per 1000 seconds		[-]	0.20	0.19	0.19	0.00	0.00	2.50
Time to first yellow	average	[s]	1474	1962	1941	>3600	>3600	105
	50th percentile	[s]	536	1627	1563	>3600	>3600	105
	5th percentile	[s]	104	214	230	>3600	>3600	105
Space headway	average	[km]	20.25	3.66	3.66	3.20	3.20	3.33
	50th percentile	[km]	15.14	3.62	3.62	3.20	3.20	3.33
	95th percentile	[km]	55.24	4.41	4.43	3.28	3.20	3.64
Speed follower	average	[m/s]	24.24	34.81	34.81	35.00	35.00	34.88
	50th percentile	[m/s]	24.19	34.94	35.00	35.03	35.00	37.00
	95th percentile	[m/s]	37.08	36.60	36.51	36.59	35.00	37.00
System throughput (vehicles/hour) →			15.8	34.2	34.2	39.8	42.0	

Account for energy consumption

- Despite railway is an efficient transport mode, much effort is devoted to reduce its consumption to cope with **high energy prices** and meet the **ambitious climate targets**

- Railway operators are concerned with both **energy use and peaks** in power needed: such peaks affect both grid stability and the energy bill



- Goal: Analyze the performance of railway traffic in a corridor in terms of **regularity**, **energy use** and **power peaks**, depending on the assumptions on the processes

Generalization to a string of trains

- Dynamics of follower *n* as a function of follower *n*-1

$$\textbf{[DMR]:} \quad \begin{cases} \mathrm{d}v_n(t) = [\beta_n(v_{\text{CRUISE}} - v_n(t)) + \alpha_n\left(s_{n-1}(t) - s_n(t)\right)]\,\mathrm{d}t + \widehat{\sigma}(v_n(t))\,\mathrm{d}W(t), \\ \mathrm{d}s_n(t) = v_n(t)\mathrm{d}t \end{cases}$$

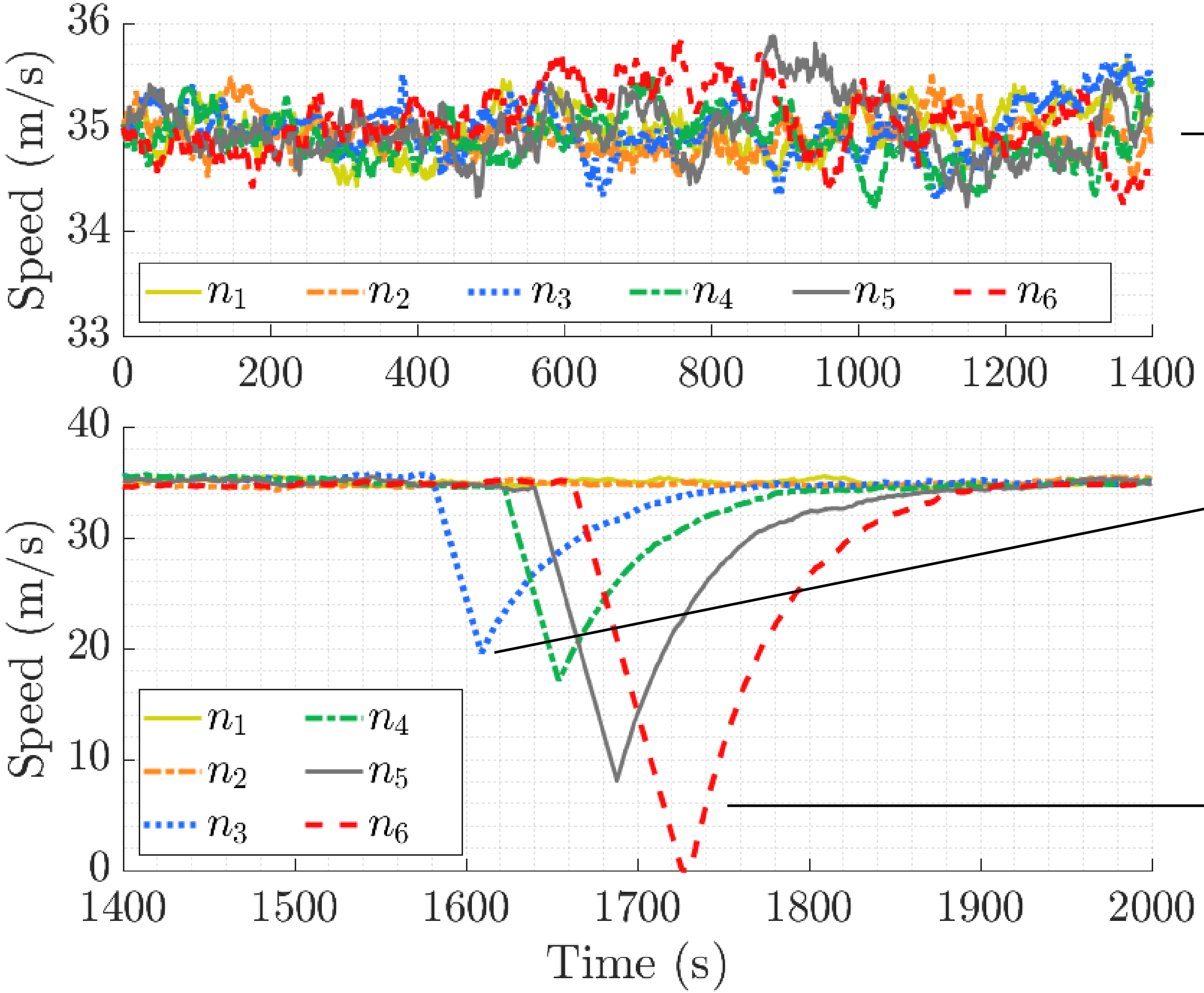
- Compute energy consumption of each train and of the entire system

$$E_{s_1}^{s_2} = \int_{s_1}^{s_2} \max\{f(s), 0\}\, ds$$

where the traction force fulfills

$$\begin{cases} \dfrac{dv(s)}{ds} = \dfrac{f(s) - R_{line}(s) - R_{train}(s)}{\rho \cdot m \cdot v(s)} \\ \dfrac{dt(s)}{ds} = \dfrac{1}{v(s)} \end{cases}$$

Analysis of a trigger event (OU process)

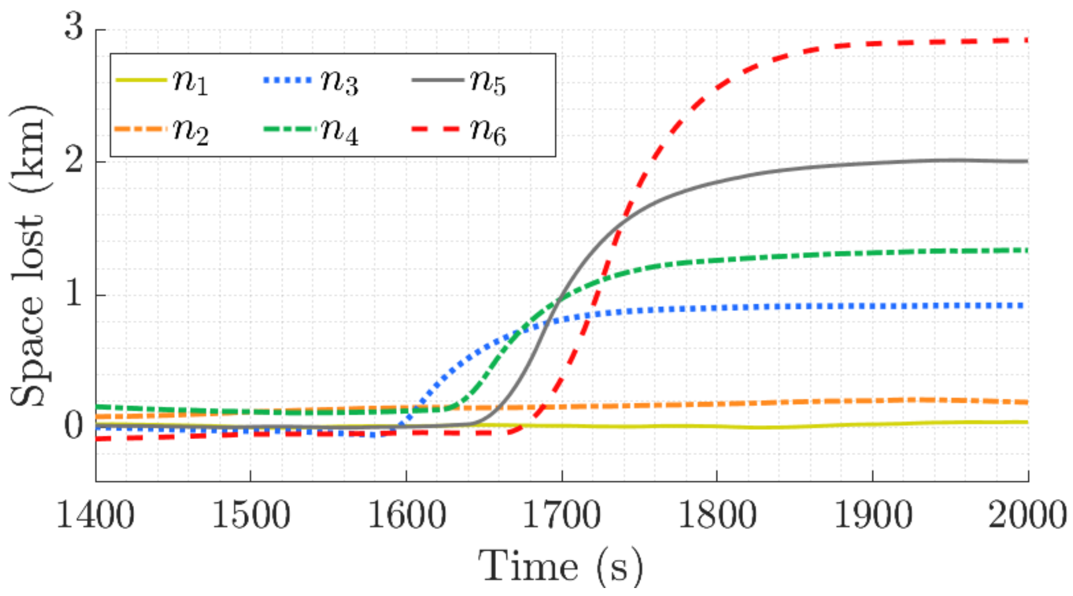


Speed fluctuations ±0.5 m/s for all trains due to stochastic process model (no yellow signal)

The third train triggers a yellow signal and decelerates until 20 m/s (approach speed given as input)

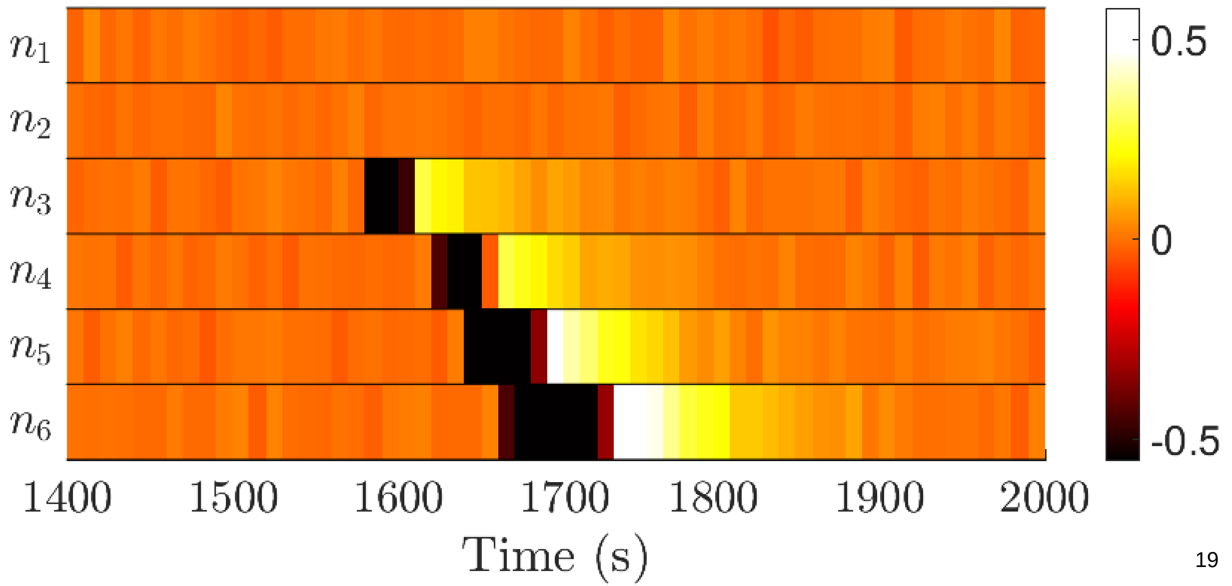
More downstream trains may have to decelerate more (or even stop) in order for the headway to be restored

Analysis of a trigger event (OU process)

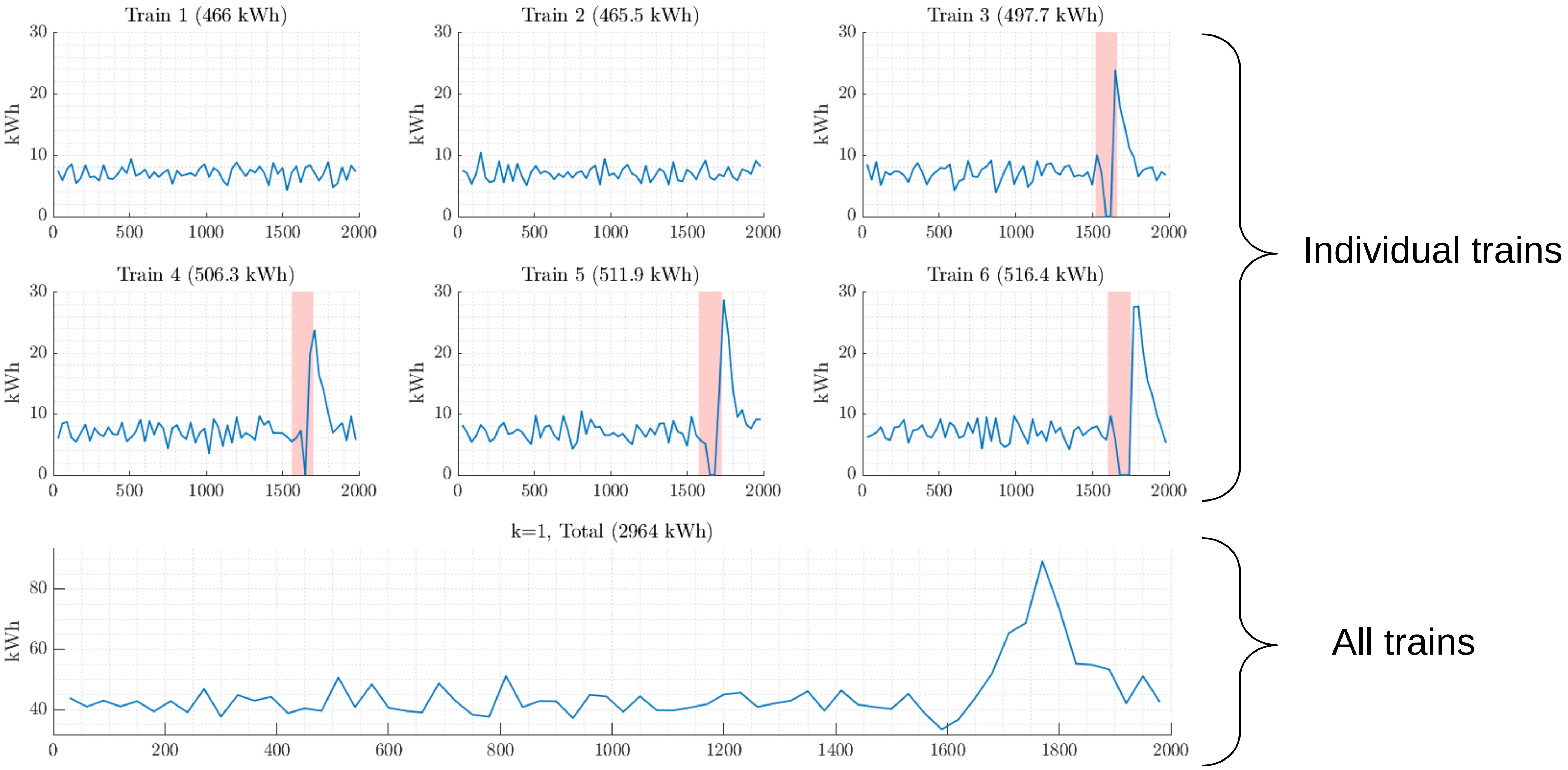


- Space lost w.r.t. a fixed speed benchmark
- The space lost increases the more the train is downstream

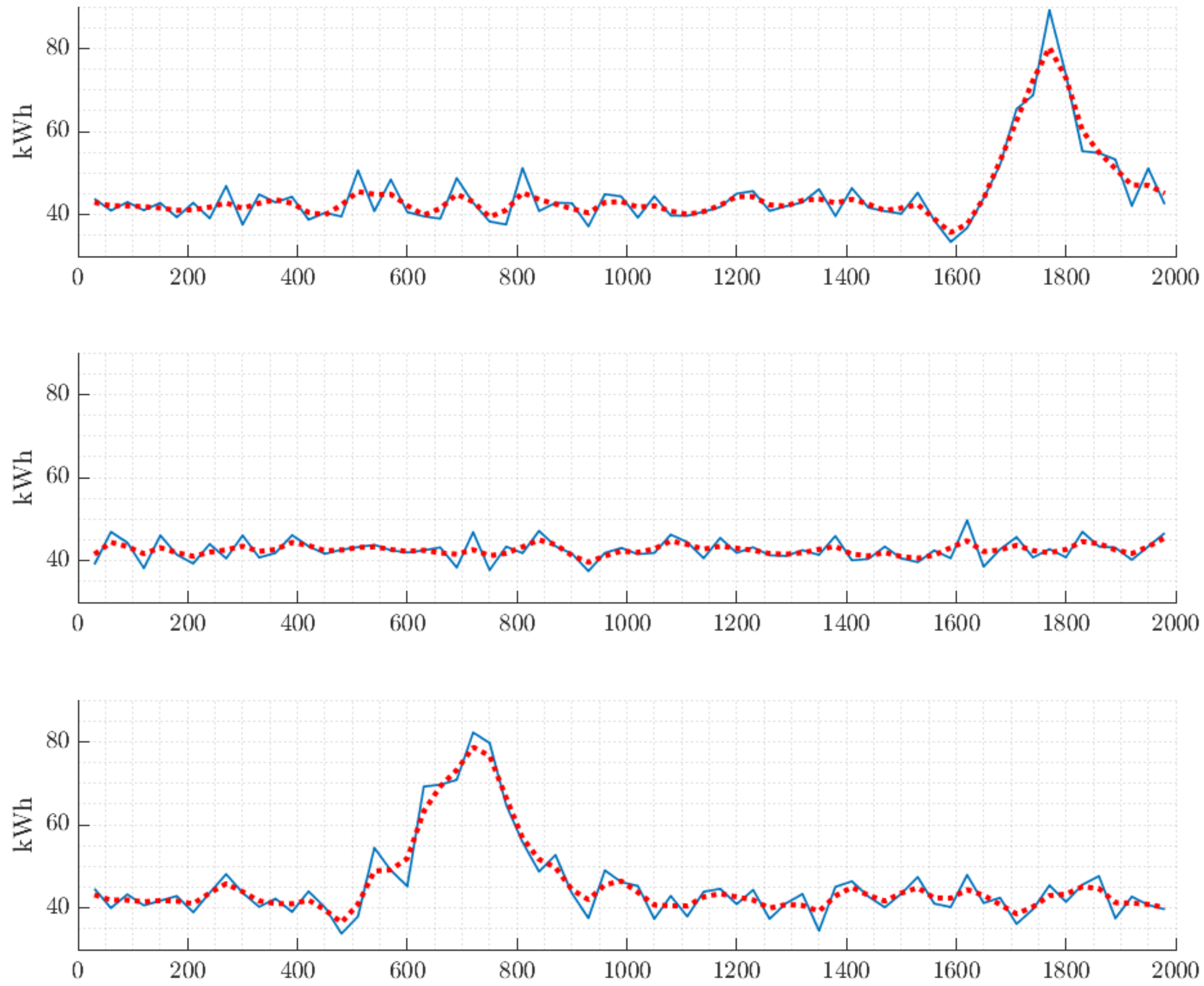
- Small changes in acceleration due to stochastic process (shades of orange)
- Deceleration and acceleration phases are longer the more the train is downstream



Energy consumption (1 trajectory)

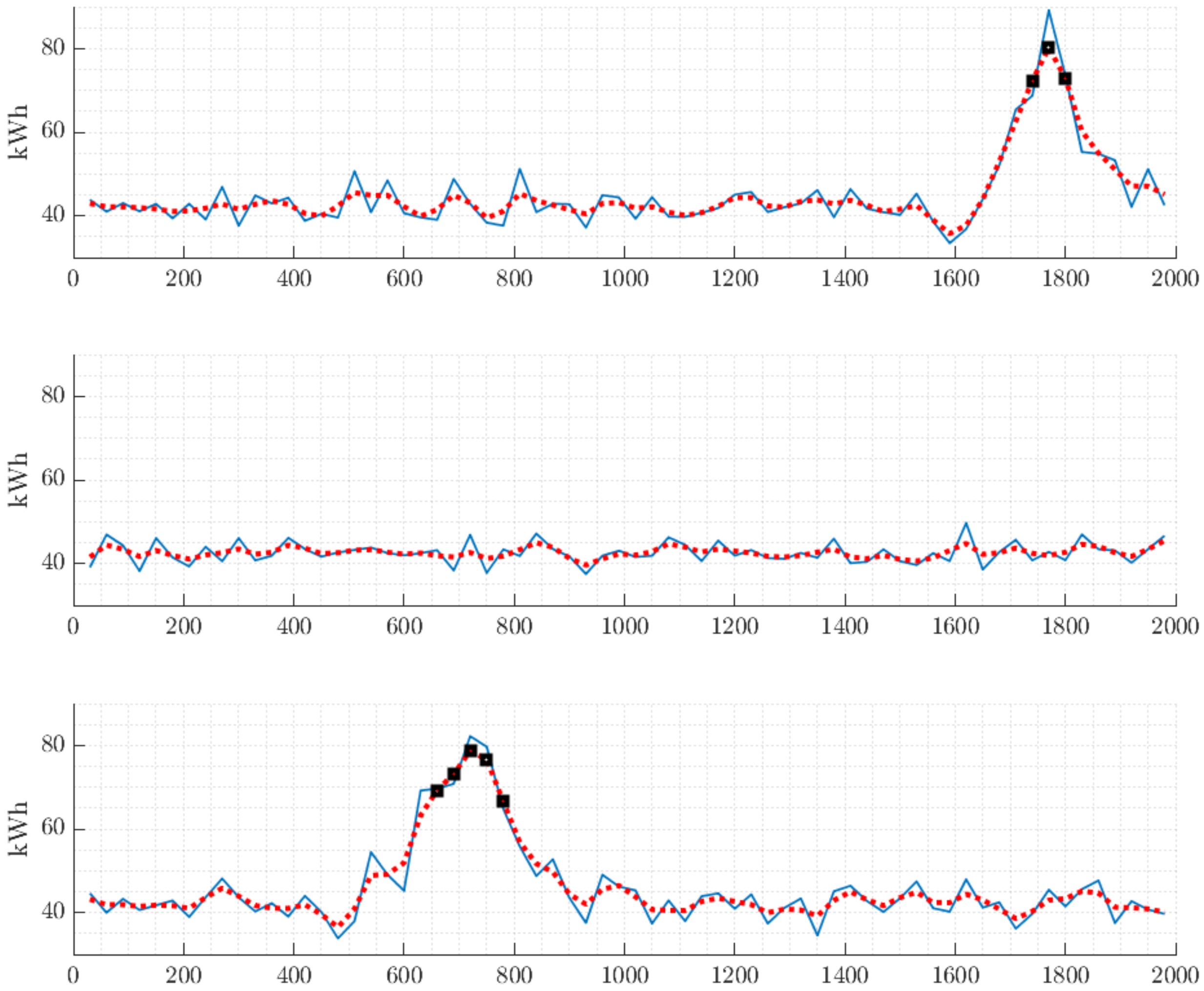


Peak detection in energy profiles



1. Exponential smoothing

Peak detection in energy profiles

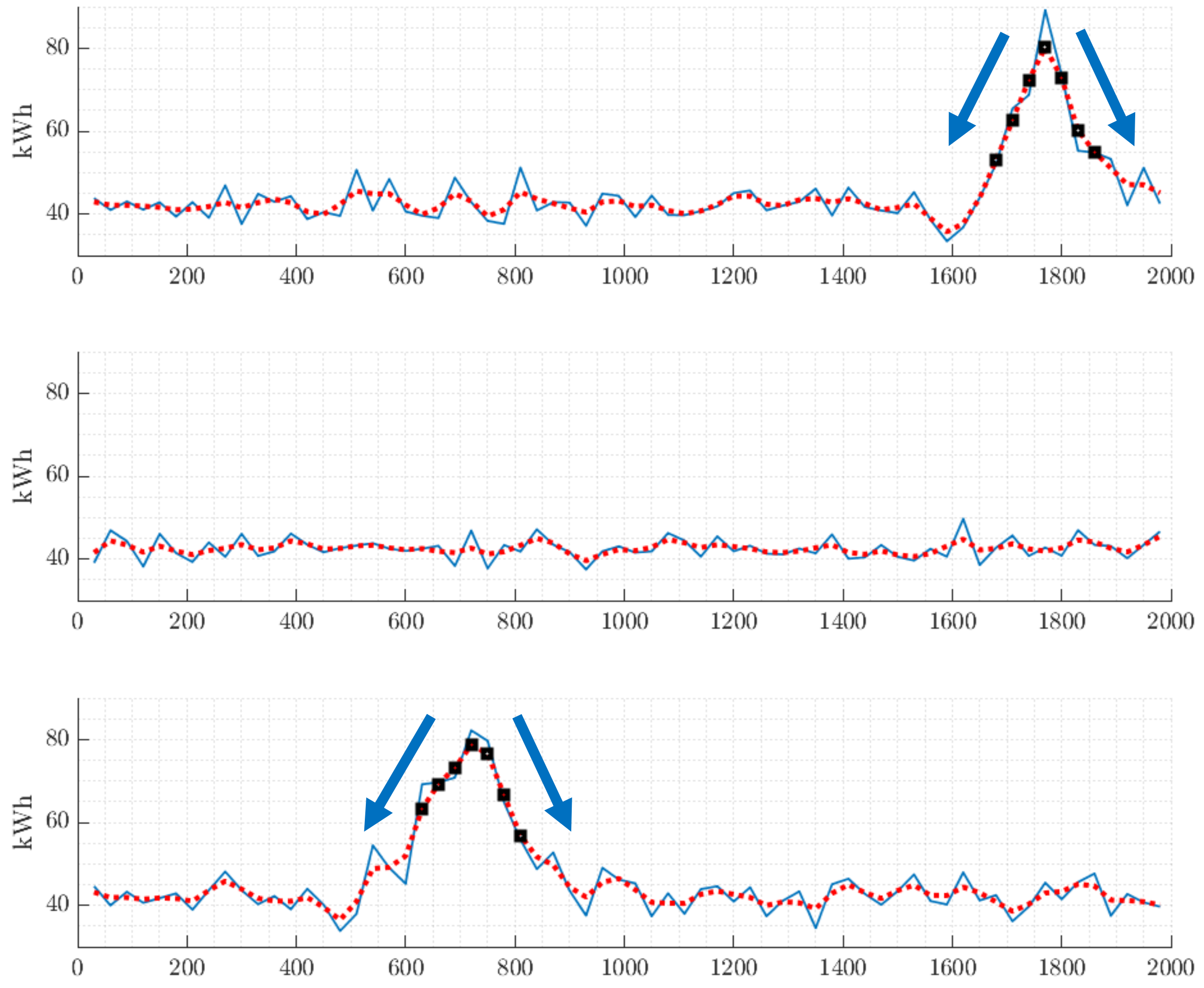


1. Exponential smoothing

2. Select points *t* such that

$$E_t \geq \alpha \cdot \mathrm{mean}(E) + \beta \cdot \mathrm{std}(E)$$

Peak detection in energy profiles



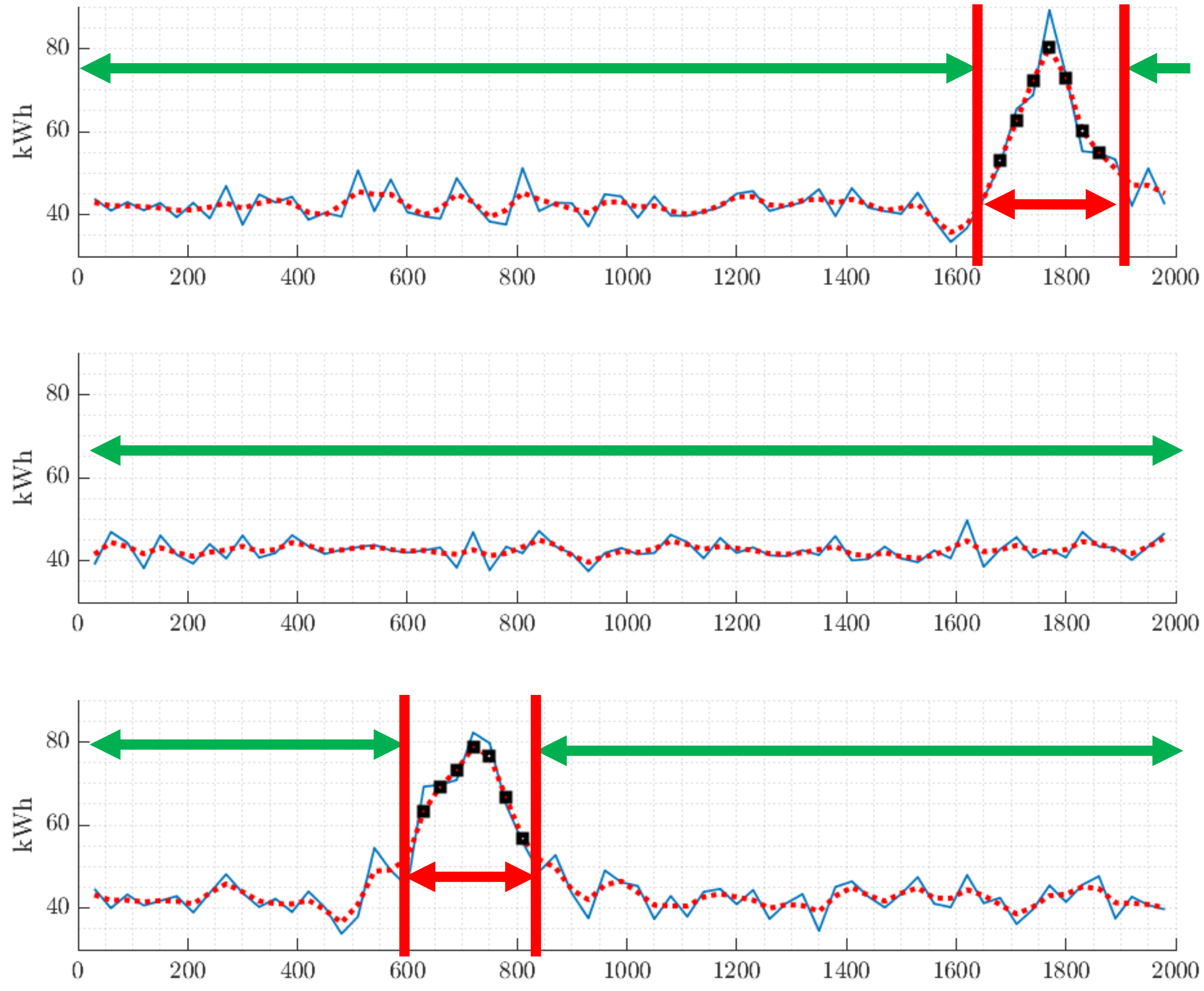
1. Exponential smoothing

2. Select points *t* such that

$$E_t \geq \alpha \cdot \text{mean}(E) + \beta \cdot \text{std}(E)$$

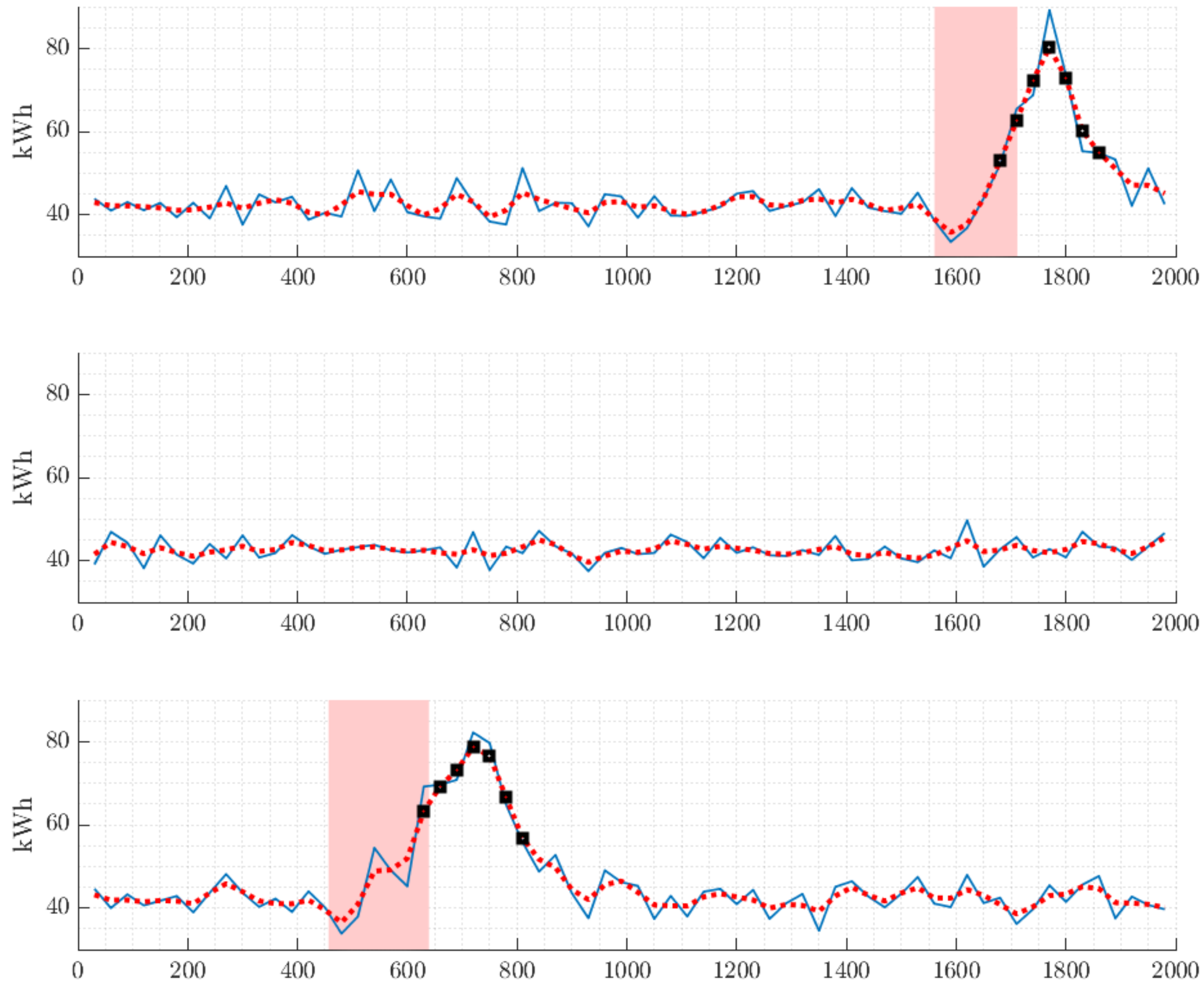
3. Reconstruct the peak

Peak detection in energy profiles



1. Exponential smoothing
2. Select points *t* such that
   $$E_t \geq \alpha \cdot \mathrm{mean}(E) + \beta \cdot \mathrm{std}(E)$$
3. Reconstruct the peak
4. Separate peaks from non-peaks and examine the two regions

Peak detection in energy profiles



1. Exponential smoothing

2. Select points *t* such that

   $$E_t \geq \alpha \cdot \mathrm{mean}(E) + \beta \cdot \mathrm{std}(E)$$

3. Reconstruct the peak

4. Separate peaks from non-peaks and examine the two regions

Peaks correspond to multiple trains accelerating after a yellow signal

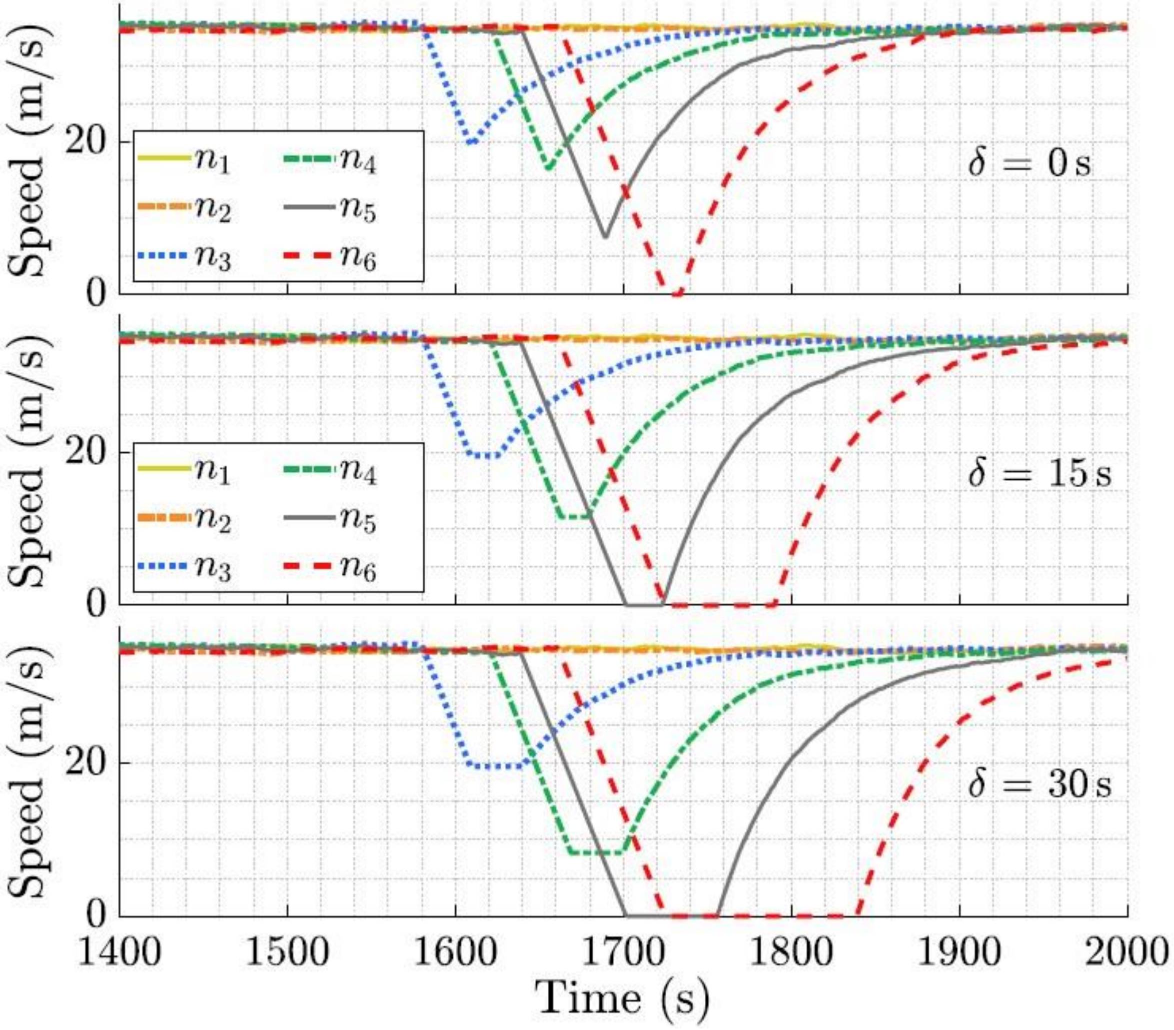
Average system performance

	Regularity	Energy
OU	Speeds (m/s) : 35 34.94 34.84 34.71 34.54 34.34 Space (km) : 35 35 34.9 34.8 34.7 34.6 Distance (km): 3.24 3.27 3.28 3.31 3.33 Triggers (%) : 0 12.4 29.4 42.6 52 57.2 FTTY (s) : 2000 1925 1807 1701 1627 1579	Mean out (kWh) : 42.52 Mean in (kWh): 63.02 Max (kWh) : 76.34 Extra (kWh) : 128.25 Total (kWh) : 2875.6
DMR	Speeds (m/s) : 35.01 35.01 35.01 35.01 35.01 35.01 Space (km) : 35 35 35 35 35 35 Distance (km): 3.2 3.2 3.2 3.2 3.2 Triggers (%) : 0 0 0 0.2 1.8 5.2 FTTY (s) : 2000 2000 2000 2000 1991 1965	Mean out (kWh) : 42.07 Mean in (kWh): 56.04 Max (kWh) : 63.88 Extra (kWh) : 54.38 Total (kWh) : 2821.5

Smoothing the peaks

	Assumptions	Impact on dynamics
Account for regenerative energy	Technology (electrical system) Energy recovered	-
Regenerative energy + energy storage	Technology (storage system)	Added storage operations
Fixed waiting rules	-	Update dynamics after trigger

Fixed waiting rules



0 seconds

10 seconds

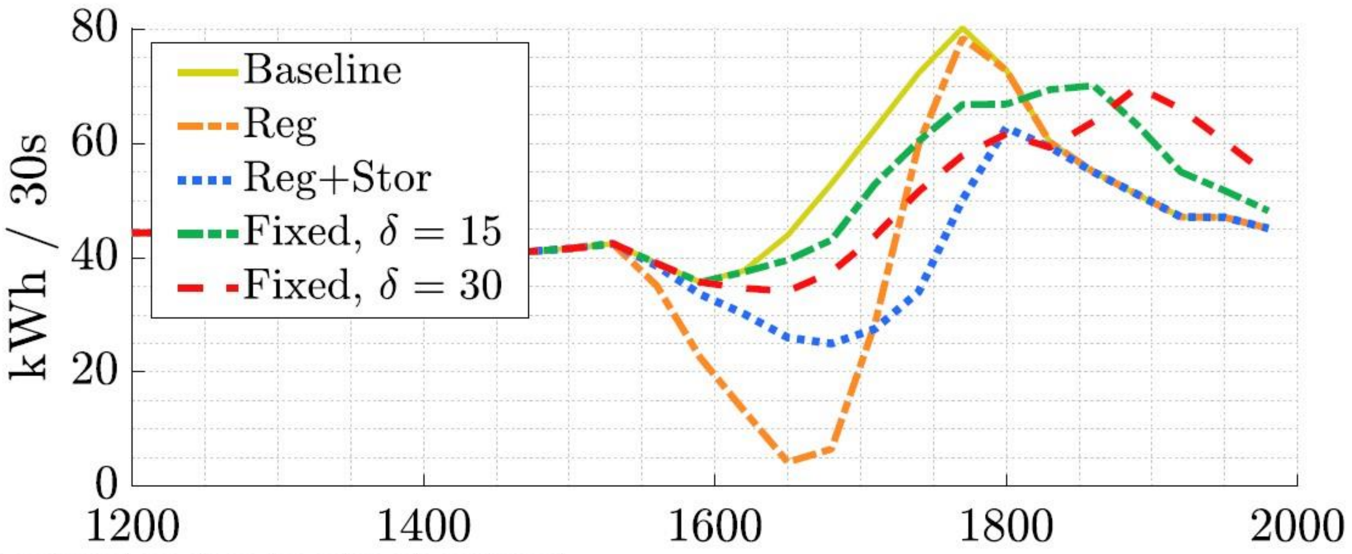
20 seconds

- The waiting time propagates downstream

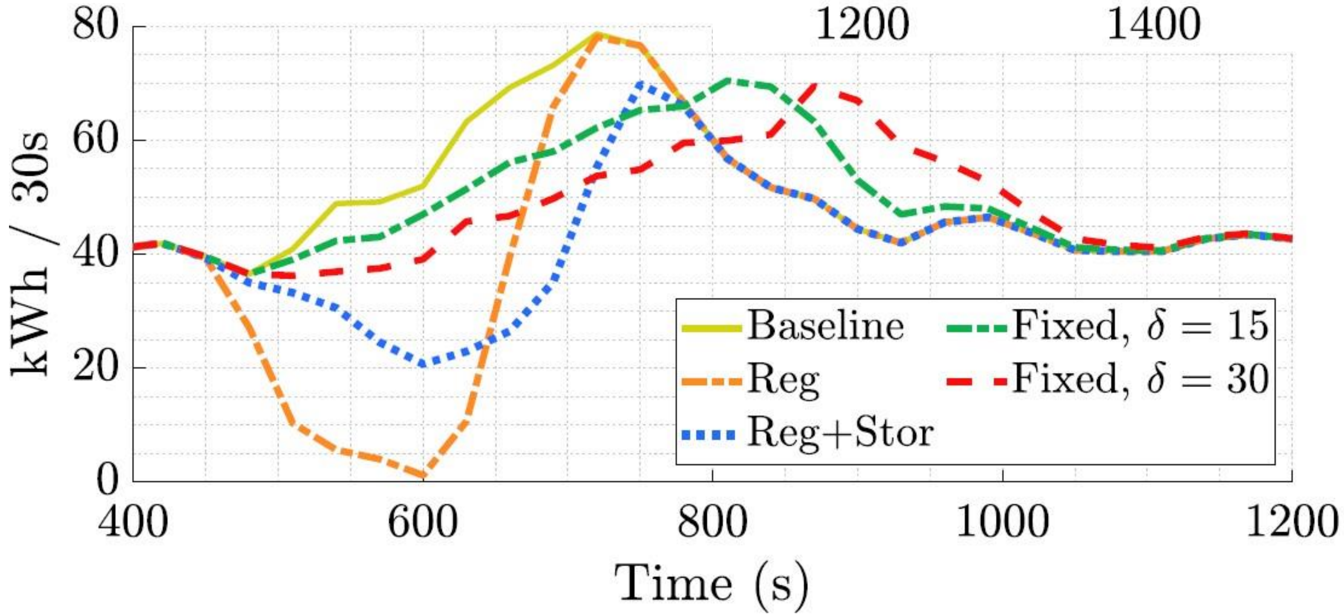
- Does it improve energy KPIs?
- Impact on regularity?

Energy profiles under different strategies

Example 1



Example 2



- Unclear what strategy performs best in general
- Trade off between objectives?

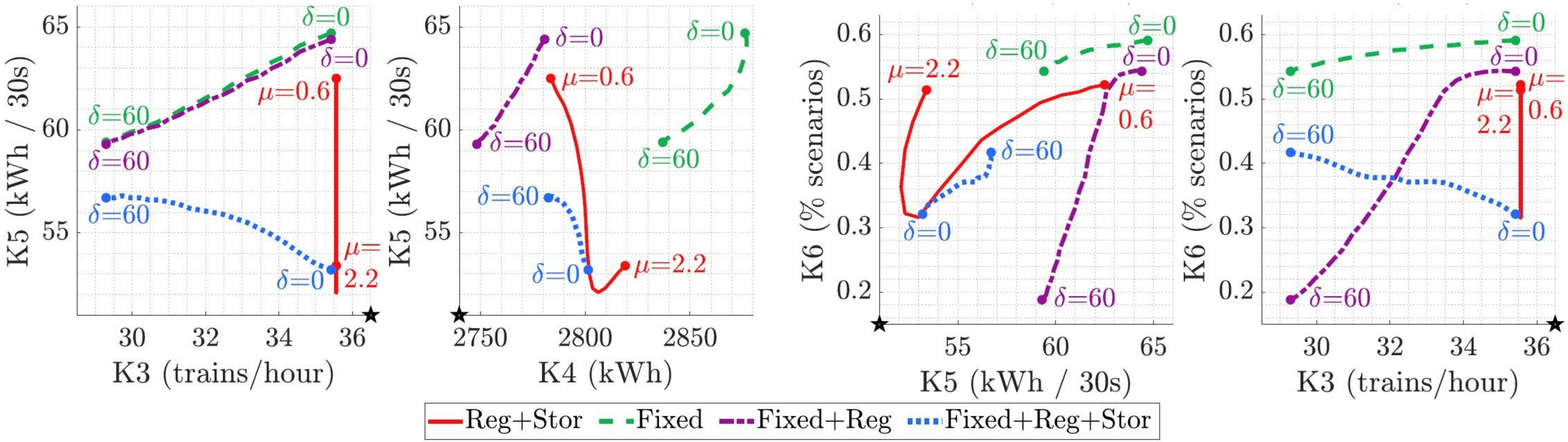
Trade-off between KPIs (Regularity, Energy, Peak)

KPIs of the system under different peak reduction strategies.

Technology	KPI	Fixed waiting time δ (s)						
		0	10	20	30	40	50	60
–	R	35.4	34.0	33.0	31.7	30.6	30.1	29.3
	E	2876	2877	2870	2864	2856	2845	2837
	P	64.7	63.6	62.2	61.6	60.6	59.7	59.2
Reg	R	35.4	34.0	33.0	31.7	30.6	30.1	29.3
	E	2781	2773	2768	2761	2757	2753	2748
	P	64.4	63.3	62.0	61.4	60.5	59.6	59.2
Reg+Stor ($\mu = 1$)	R	35.4	34.0	33.0	31.7	30.6	30.1	29.3
	E	2795	2788	2780	2775	2769	2765	2763
	P	59.3	59.5	59.1	58.6	58.1	57.7	57.4

R = Regularity / throughput **E** = Total energy consumption **P** = Maximum energy profile value

Trade-off between KPIs (Regularity, Energy, Peak)



- No strategy dominates the others in managing all KPIs

Conclusion

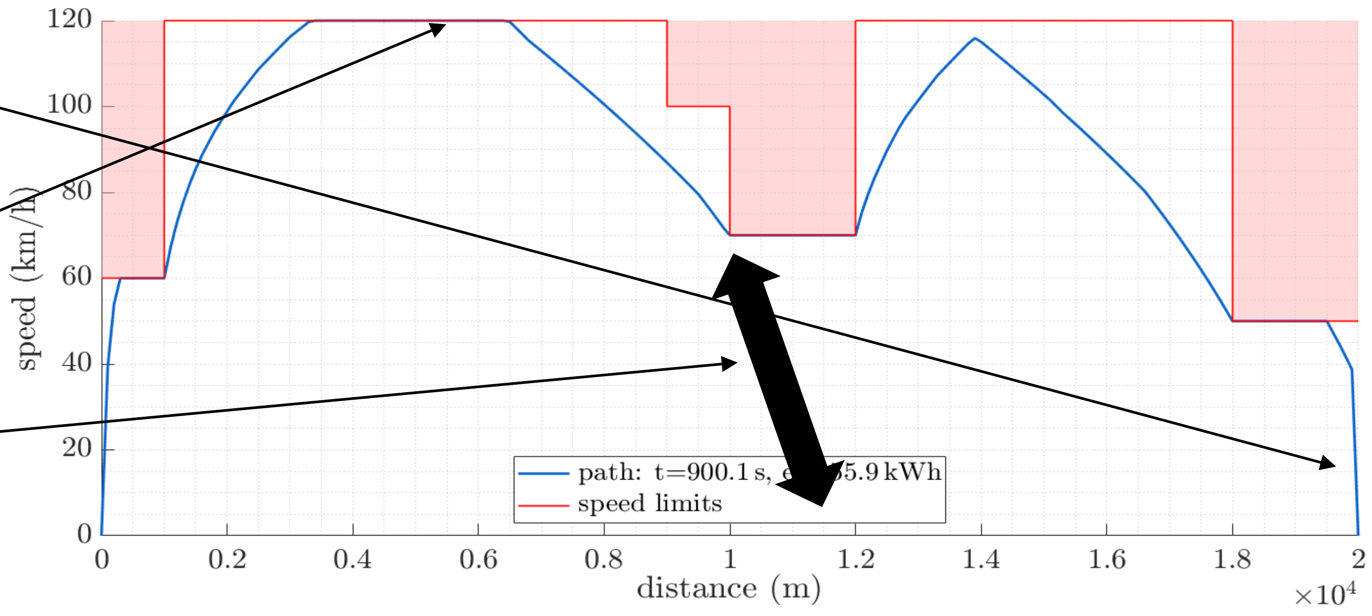
- We developed a novel railway traffic flow model based on stochastic processes
- We quantified the system benefit resulting from **automated train operation (ATO)** in terms of added regularity, reliability, and energy metrics compared to a **human driver**
- We assess the impact of different strategies **to shave the peaks in consumption**
- There is a **trade-off** between traffic regularity (e.g., measured as average train speed) and energy performance (e.g., average height of peaks) that need to be accounted for carefully

Train trajectory optimization

Train Trajectory Optimization Problem

Goal: Determine energy-efficient trajectories for trains driving between two stations while fulfilling:

- Scheduled arrival time
- Speed limits
- Train Path Envelope (TPE): time and/or speed windows



Relevant as it allows to:

- Save energy in the range of 5–20% (Hansen and Pachl 2014)
- Reduce costs for the operators, no particular investments in infrastructure

Uncertainty in train control

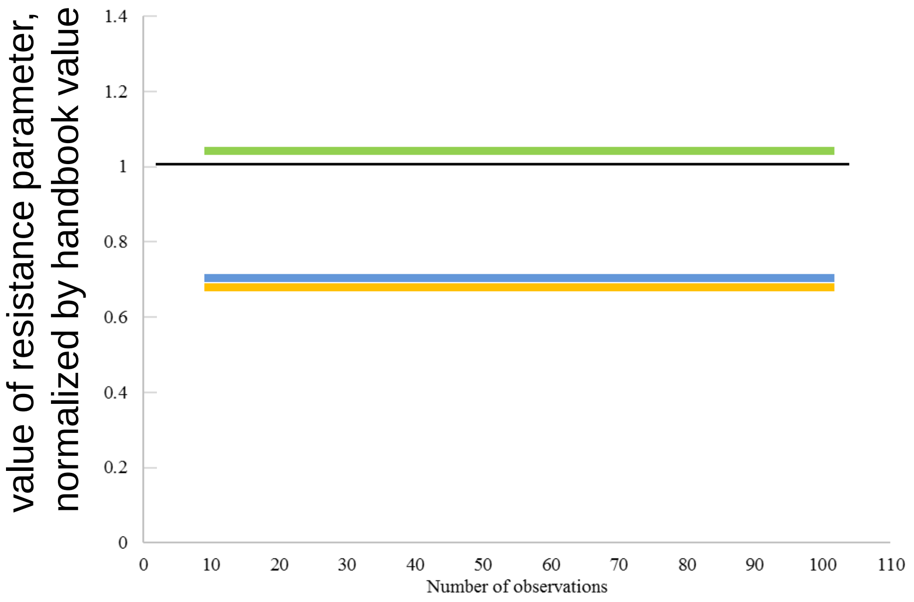
Much of the literature considers static parameters for motion / resistance
(Howlett 2000, Howlett and Pudney 2012, Ko et al. 2004, Wang and Goverde 2016, 2017, Haahr et al. 2017, Zhou et al. 2017, De Martinis and Corman 2018)

Parameters differ from the handbook!

And vary within the trip!

Parameters:

- Train mass (passengers, goods)
- Maximum traction force/power (voltage, current)
- Maximum braking force (speed, weather, friction)
- Train resistance (weather: wind, snow, track wet)



MDP and DDP formulation

Markov decision process

$$\min_{\pi \in \Pi} \mathbb{E}\left[\sum_{i \in \mathcal{I}} \delta^i c_i(x_i^\pi, w_i, Z_i^\pi(x_i^\pi, w_i)) + \delta^I c_I(x_I^\pi, w_I) \,\middle|\, (x_0, w_0)\right]$$

- Conditional expectation
- Sum over stages
- costs we incur when following a policy
- We want to find the best "policy"
- Endogenous part of the state
- Endogenous part of the state
- Decision we take at this stage and state

Stochastic dynamic program

$$V_I(x_I, w_I) = c_I(x_I, w_I), \ \forall (x_I, w_I) \in \mathcal{X}_I \times \mathcal{W}_I,$$

$$V_i(x_i, w_i) = \min_{a_i \in \mathcal{A}_i(x_i)} \left\{ c_i(x_i, w_i, a_i) + \delta \mathbb{E}\left[V_{i+1}\left(f_i(x_i, w_i, a_i), w_{i+1}\right) \middle| w_i\right] \right\}$$

$$\forall (i, x_i, w_i) \in \mathcal{I} \times \mathcal{X}_i \times \mathcal{W}_i$$

- Best action
- Immediate cost
- Continuation function

Train trajectory optimization as an MDP

- **Stages**: discretized locations
- **States**: train speeds and times at each location
- **Uncertainty**: train resistance, max traction effort, braking effort
- **Actions**: control decision in {MT, SH, CO, MB}
- **Transition**: equations determining the train motion

$$\frac{dv(s)}{ds} = \frac{f(s) - R^{\text{train}}(v) - R^{\text{line}}(s)}{\rho \cdot m \cdot v(s)}, \quad \frac{dt(s)}{ds} = \frac{1}{v(s)}$$

- **Cost function**: energy incurred from state to next state

$$E = \int_{s_d}^{s_{d+1}} \max\{f(s), 0\}\ ds$$

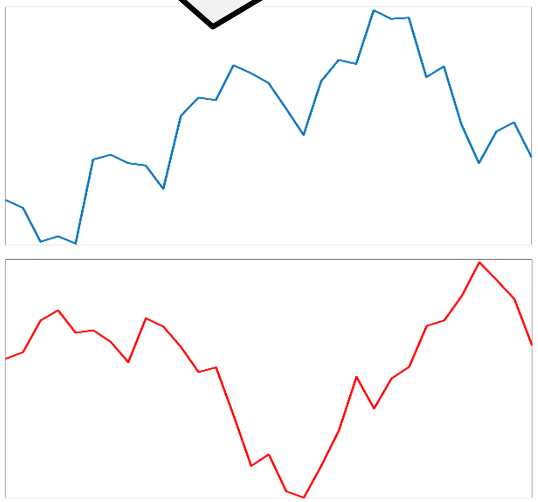
(analytic expression is available)

Approximate dynamic programming (ADP) algorithm

Double-pass algorithm based on Monte Carlo simulation (Mes and Rivera 2017)

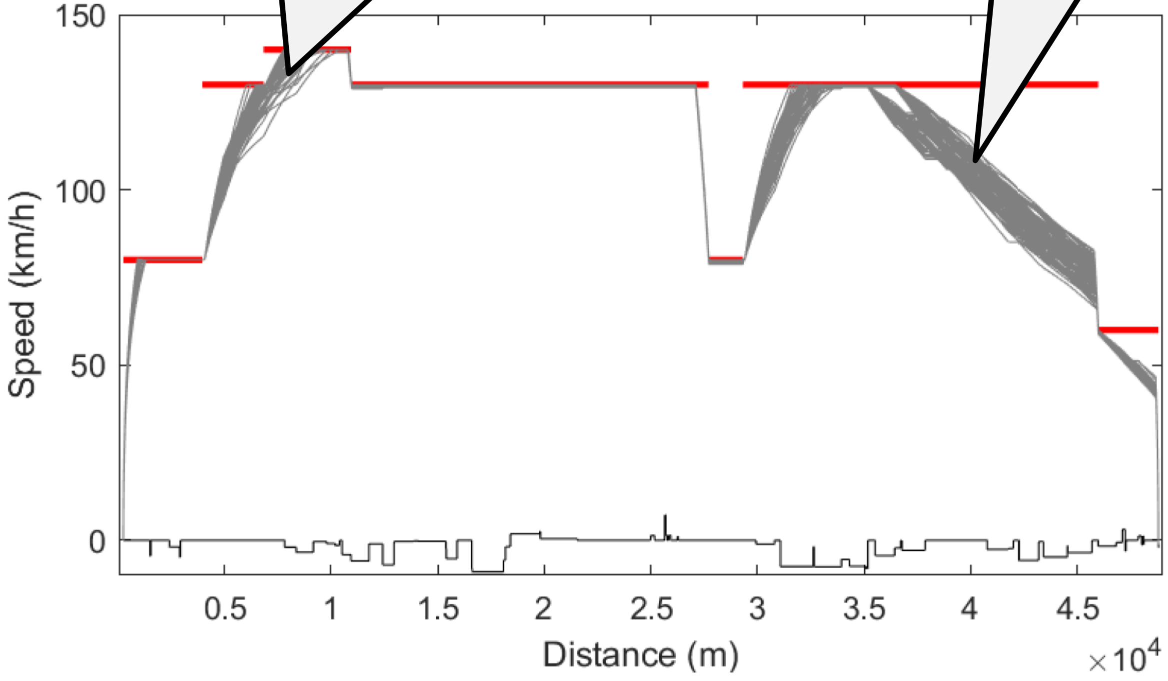
Goal: **Learn** MDP value functions and time/energy cost functions

1 Iteration n: Monte Carlo sampling



2 **Forward pass:** Take actions based on previous (n-1 th) estimates

3 **Backward pass:** Update value function approx., energy, time



Approximate dynamic programming (ADP) algorithm

Algorithm 1: DOUBLE-PASS ADP

Inputs: Initial value function approximation $V_d^{x,0}(S_d^x)$, $\forall\, d \in \mathcal{D}$, $S_d^x \in \mathcal{S}_d$; Initial MDP state S_0^1; Number of sampling iterations N.

For iteration $n = 1$ to N **do**:

Step 1. Generate a sample path of uncertainty w^n.

Step 2. Forward pass:

For $d = 0$ to $D-1$ **do**:

(a) Compute decision $X_d^n(S_d^n) = \underset{x_d^n \in \mathcal{X}_d(S_d^n)}{\operatorname{argmin}} \left\{ E_d^{n-1}(S_d^n, x_d^n) + \overline{V}_d^{x,n-1}(S_d^{x,n}) \right\}$;

(b) Find post-decision state $S_d^{x,n}$ and new pre-decision state S_{d+1}^n with transition functions;

(c) Compute the observed time and energy cost using $\psi(S_d^n, S_{d+1}^n)$ and $\chi(S_d^n, x_d^n, W_{d+1}(w^n))$.

Step 3. Backward pass:

Initialize $\overline{V}_D^{x,n}(S_D^{x,n}) = 0$, $\forall\, S_D^{x,n} \in \mathcal{S}_D$.

For $d = D-1$ to 0 **do**:

(a) Update approximations of time $t_d^n(S_d^n, x_d^n)$ and energy $E_d^n(S_d^n, x_d^n)$ by

$$t_d^n(S_d^n, x_d^n) = \frac{\sum_0^n \psi(S_d^n, S_{d+1}^n)}{n}, \quad E_d^n(S_d^n, x_d^n) = \frac{\sum_0^n \chi(S_d^n, x_d^n, W_{d+1}(w^n))}{n};$$

(b) Compute $V_d^n(S_d^n) = E_d^n(S_d^n, X_d^{\pi,n}(S_d^n)) + \overline{V}_d^{x,n}(S_d^{x,n})$;

(c) Compute $\overline{V}_{d-1}^{x,n}(S_{d-1}^{x,n}) = (1-\delta)\overline{V}_{d-1}^{x,n-1}(S_{d-1}^{x,n}) + \delta V_d^n(S_d^n)$.

Outputs: $\forall\, d \in \mathcal{D}$ and sampled state $S_d \in \mathcal{S}_d$: Time cost $t_d^N(S_d^N, x_d^N)$, energy cost $E_d^N(S_d^N, x_d^N)$, value function approximation $\overline{V}_d^{x,N}(S_d^{x,N})$, and action $X_d^N(S_d^N)$.

Framework

Offline (ADP or deterministic DP) + online phases

OFF-LINE

ADP

Double-pass algorithm based on:

- Monte Carlo sampling
- Forward pass: actions
- Backward pass: update values

DDP as benchmark

Deterministic dynamic programming:

- Future variability is neglected
- Space-speed network
- Backward DP algorithm

ON-LINE

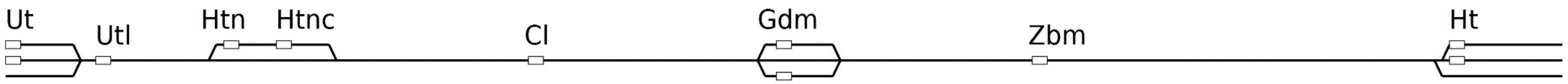
Policy update

Model to fulfill TPE constraints:

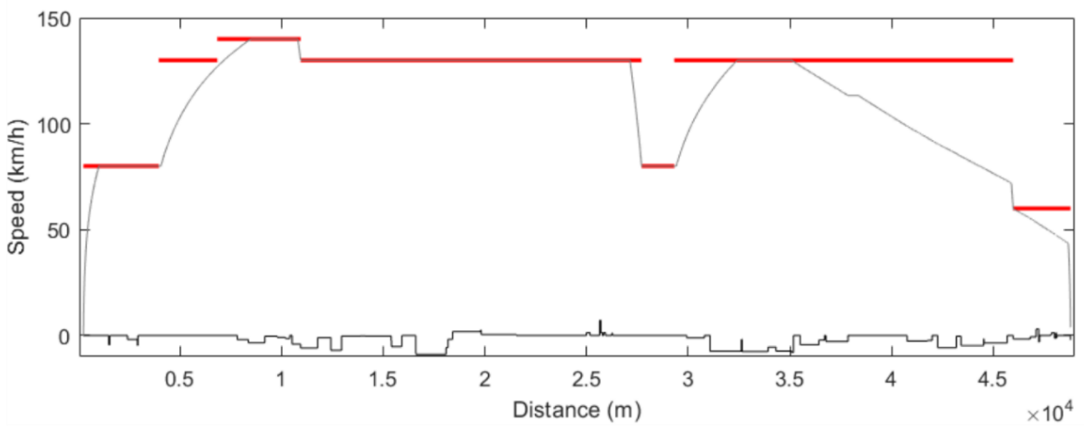
- Estimate EE running time
- Real-time policy adjustments
- Penalty-based rules

Case study: Instance

Experiments using deterministic detailed data for the Dutch railway network (Utrecht 's-Hertogenbosch)



- **Infrastructure**: 50km, track sections, speed signs, gradients, signals
- **Train**: mass, length, traction and braking rates, base resistance, speed
- **Uncertainty**: modeled using truncated normal random variables

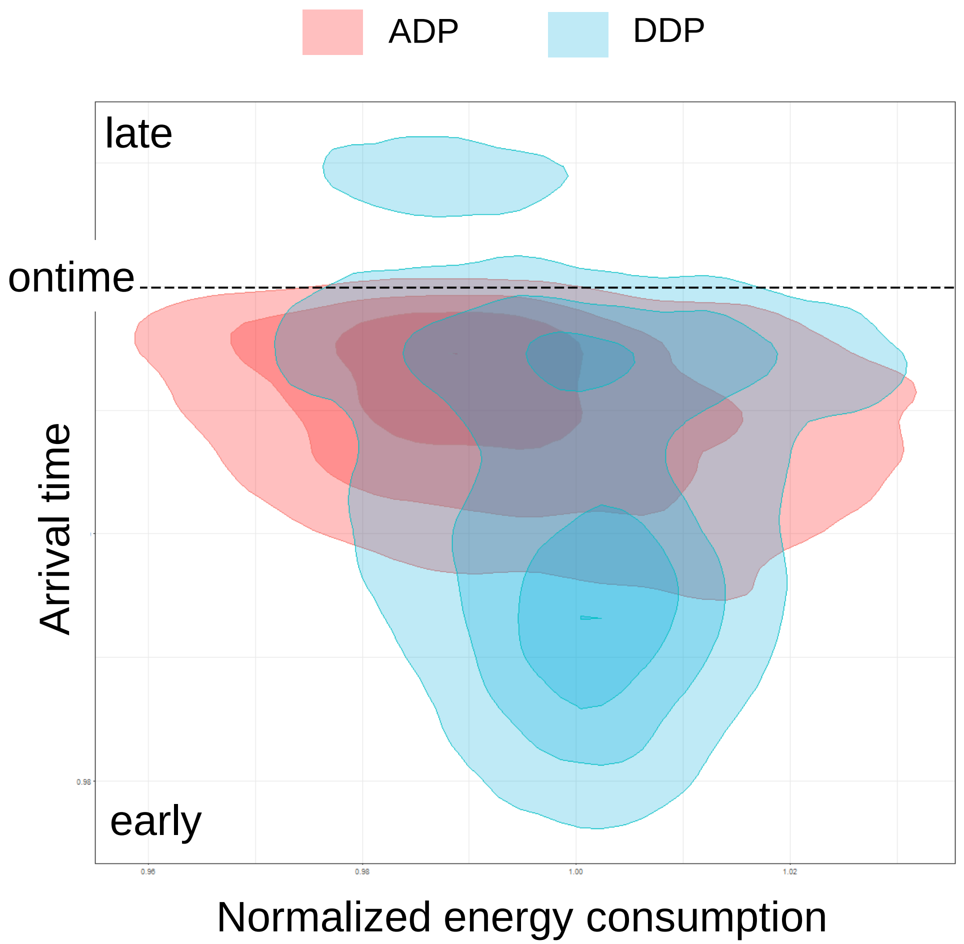


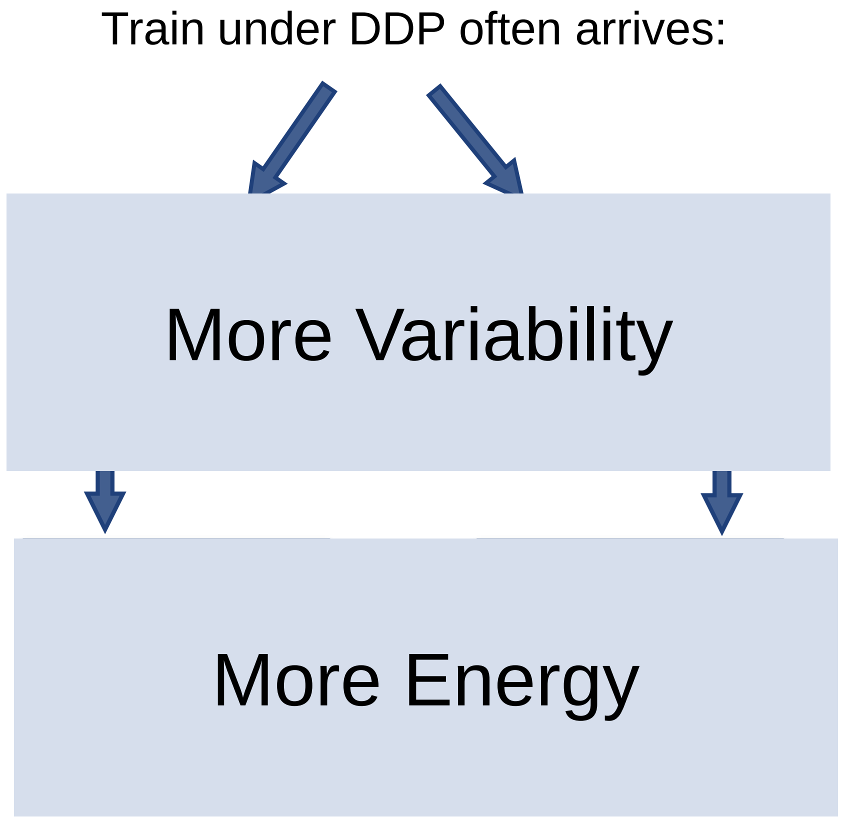
$$\tilde{F}^{\max}(s) \sim \mathcal{TN}(\mu_f, \sigma_f^2, a_f, b_f) \equiv \mathcal{N}(\mu_f, \sigma_f^2) \mid [a_f, b_f]$$

$$\tilde{P}^{\max}(s) \sim \mathcal{TN}(\mu_p, \sigma_p^2, a_p, b_p) \equiv \mathcal{N}(\mu_p, \sigma_p^2) \mid [a_p, b_p]$$

$$\tilde{R}^{\text{train}}(s) \sim \mathcal{TN}(\mu_r, \sigma_r^2, a_r, b_r) \equiv \mathcal{N}(\mu_r, \sigma_r^2) \mid [a_r, b_r]$$

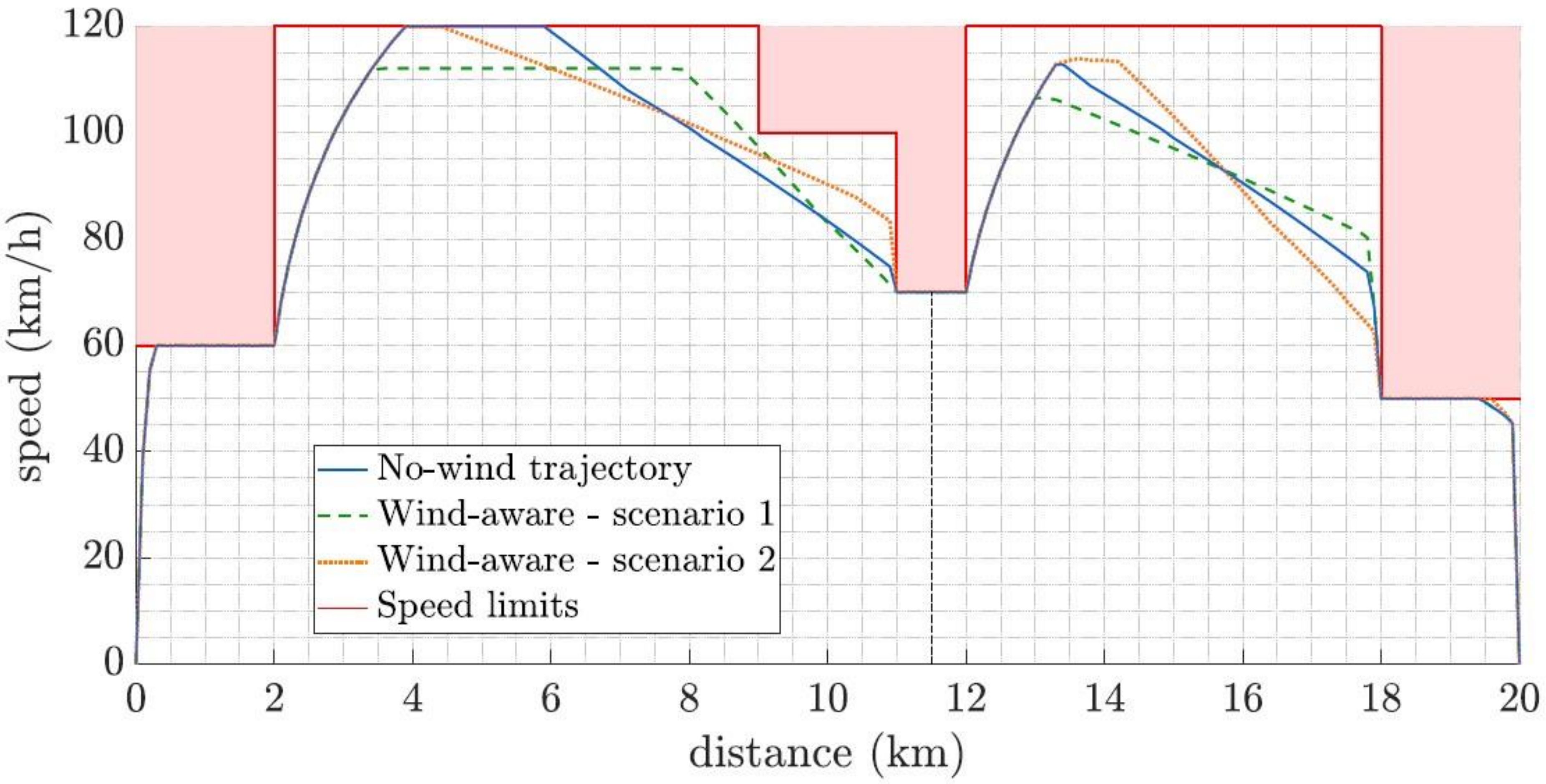
A few results (more in the paper)



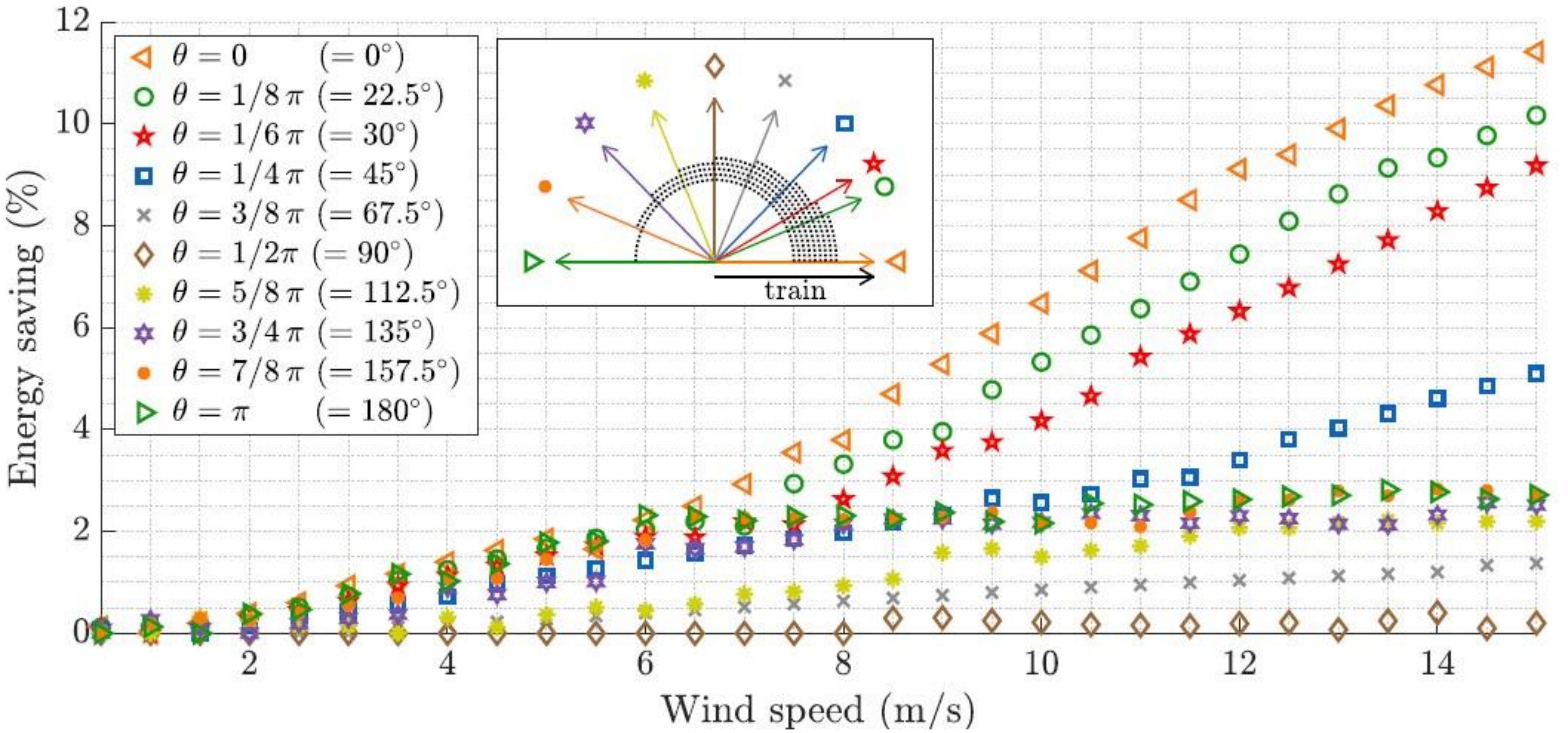


The impact of wind on energy-efficient train control

We computed wind-aware train trajectories that account for wind conditions



Energy savings in different instances



Method: Line-search based shortest path algorithm

Algorithm 1: Line search DP for train trajectory optimization

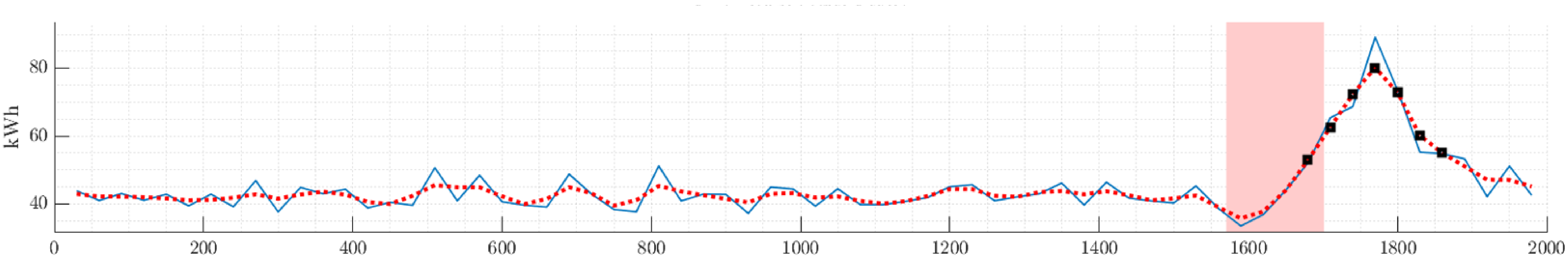
Inputs: Graph $\mathcal{G}$; Wind (w, θ); $\eta^{\text{MAX}} > 0$ (high value); Maximum iterations I; Arrival time tolerance ϵ.

Initialization: $T(w,\theta) = +\infty$, $E(w,\theta) = +\infty$, $\eta^{\text{MIN}} = 0$.

For iteration $i = 1$ to I **do**:

1. Set $\eta := (\eta^{\text{MAX}} + \eta^{\text{MIN}})/2$ and $c_b(\eta, w, \theta) := t_b + \eta\, e_b(w,\theta)$, $\forall b \in \mathcal{A}$, obtaining graph $\mathcal{G} = \mathcal{G}(\eta, w, \theta)$;
2. Solve shortest path as a DP on $\mathcal{G}(\eta, w, \theta)$, resulting in trajectory X_η, travel time T_η, and energy E_η;
3. **If** $|T_\eta - T^{\text{S}}| < |T(w,\theta) - T^{\text{S}}|$, update current best solution $X(w,\theta) = X_\eta$, $T(w,\theta) = T_\eta$, $E(w,\theta) = E_\eta$;
4. **If** $T_\eta < T^{\text{S}}$, redefine $\eta^{\text{MIN}} = \eta$, **else**, redefine $\eta^{\text{MAX}} = \eta$;
5. **If** $|T(w,\theta) - T^{\text{S}}| < \epsilon$, **break**.

Outputs: Optimized train trajectory $X(w,\theta)$, time $T(w,\theta)$, and energy consumption $E(w,\theta)$ for wind scenario (w,θ).



Thanks to SNF, DADA, Francesco

Zurich, May 31^{st}, 2024