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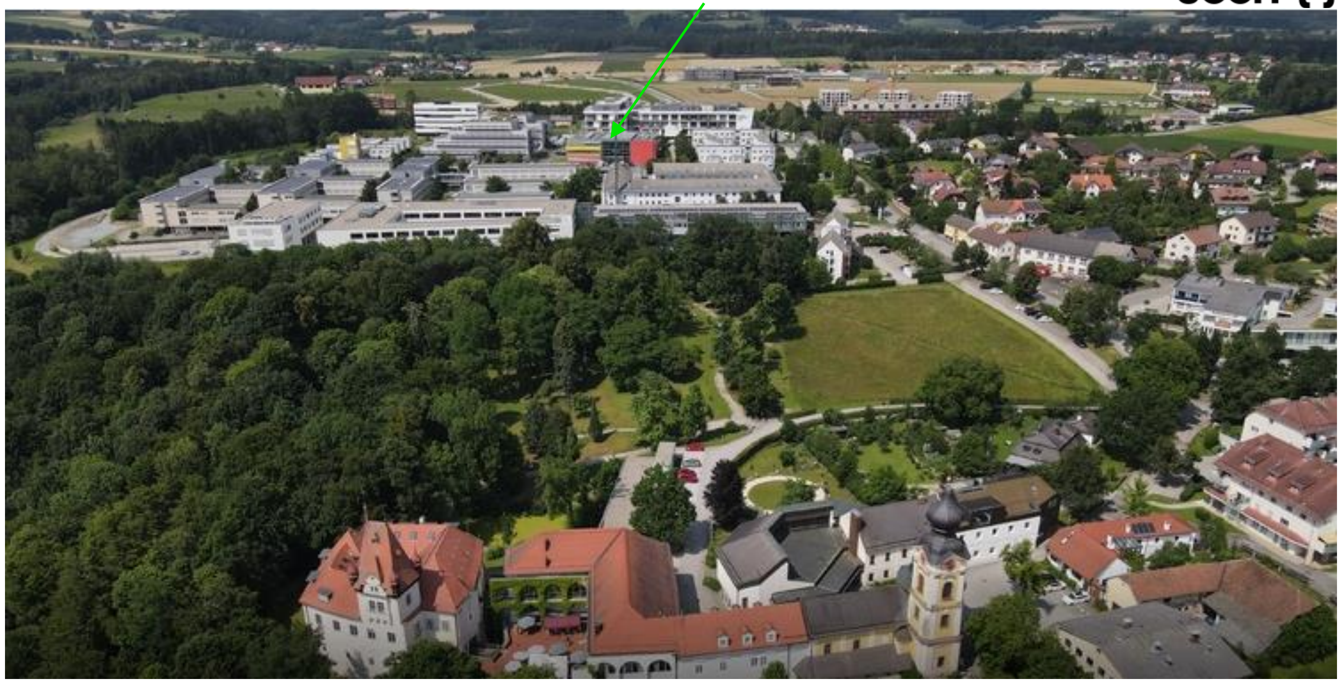
# Prescriptiveness in Maintenance of Domestic Heat Management

11.11.2023

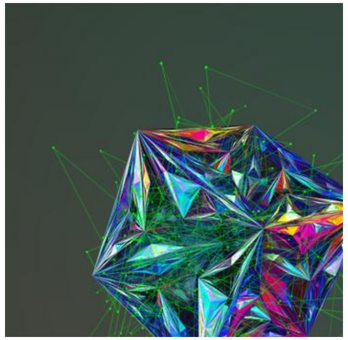
Florian Sobieczky

# Agenda

1. What is Prescriptiveness in Maintenance?
2. Domestic Heat Management
3. Realising Explanations with ODEs
4. Prescriptions from Explainable AI



Software Competence Center Hagenberg:
SCCH ~130 Employees, established 1999
31 running Projects, 13 Research Foci,
4 Areas (among which: Data Science)
Research and project work in cooperation
with companies from service & production



M. Pichler, M. Meisel, A. Goranovic, K. Leonhartsberger, C. Lettner, G. Chasparis, H. Vallant, S. Marksteiner, H. Bieser (2019). Decentralized Energy Networks Based on Blockchain: Background, Overview and Concept Discussion. In: Abramowicz, W., Paschke, A. (eds) Business Information Systems Workshops. BIS 2018. Lecture Notes in Business Information Processing, vol 339. Springer, Cham. https://doi.org/10.1007/978-3-030-04849-5_22

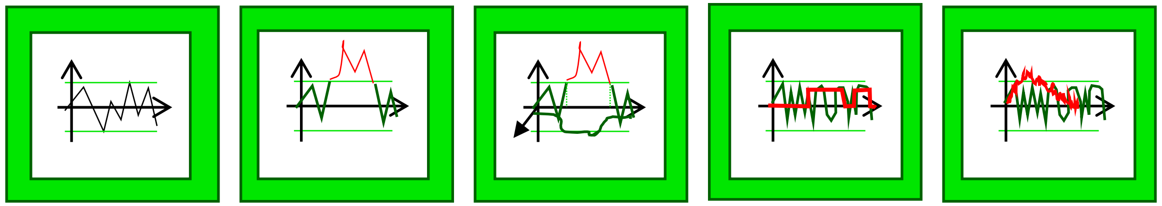
F. Sobieczky, C. Lettner, T. Natschläger, P. Traxler. Adaptive heat pump and battery storage demand side energy management, E3S Web Conf. 22 00162 (2017) https://doi.org/10.1051/e3sconf/20172200162

# Prescriptiveness

…in Predictive Maintenance

# Prescriptiveness in Predictive Maintenance

- Predictive Maintenance
  1. Collecting Information about Regular Case (‘Phase 1’)
  2. Collecting Information about Anomalies & extracting Features
  3. Selecting Features which are relevant Health Indicators (HI)
  4. Predictive Modeling of State of Health and
  5. Remaining useful lifetime (RUL).



- Prescriptive Maintenance
  - Collect Information about the quality of maintenance cycles (e.g.: optimal cost/time of maintenance, length of cycle, ….)
  - Extracting and Selecting Features relevant for best cycles
  - Choosing parameters for **initiating optimal maintenance cycles**


[1] Maqbool Khan; Arshad Ahmad; Florian Sobieczky; Mario Pichler; Bernhard A. Moser; Ivo Bukovský: A Systematic Mapping Study of Predictive Maintenance in SMEs, IEEE Access vol. 10 2022

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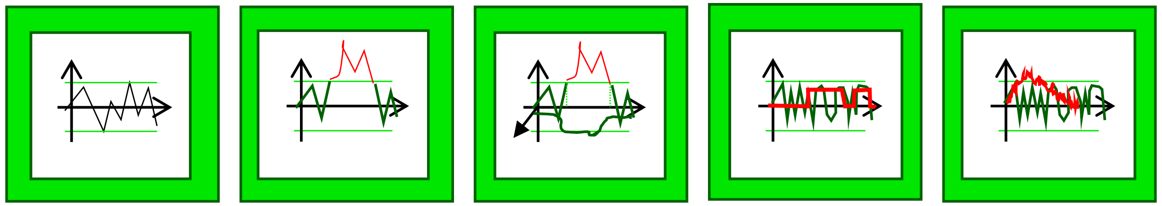

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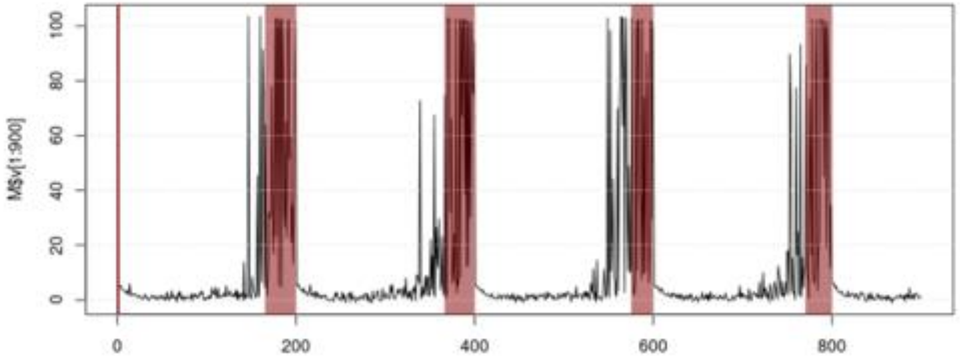


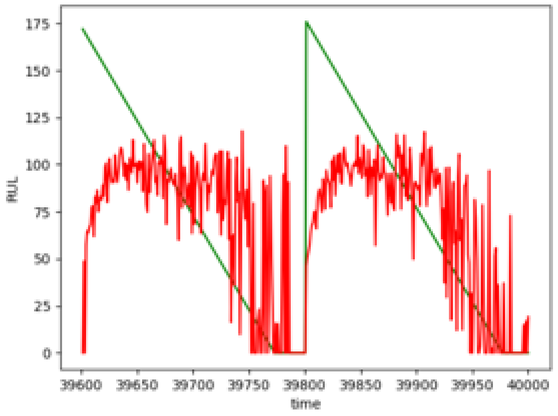


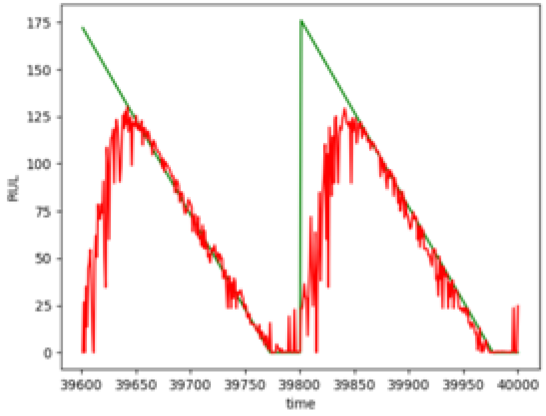


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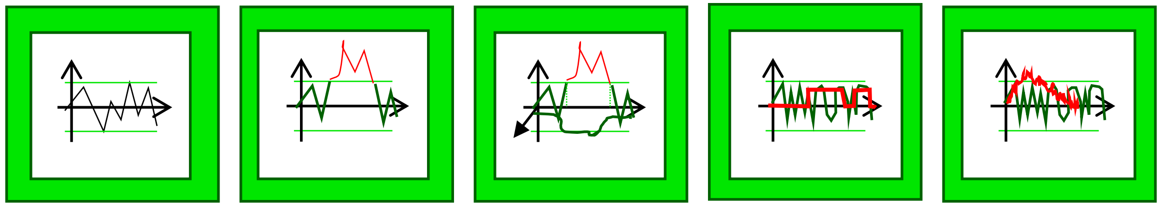

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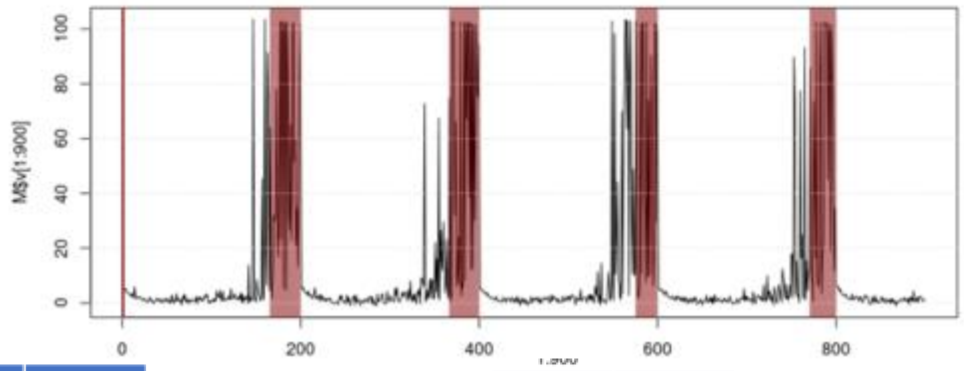


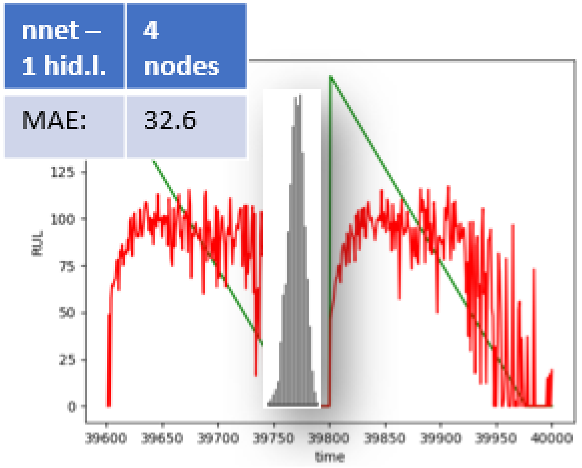


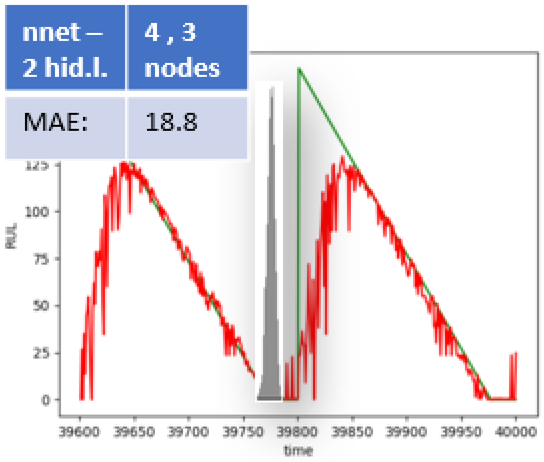



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# Case Study: Ball-screw health under high load

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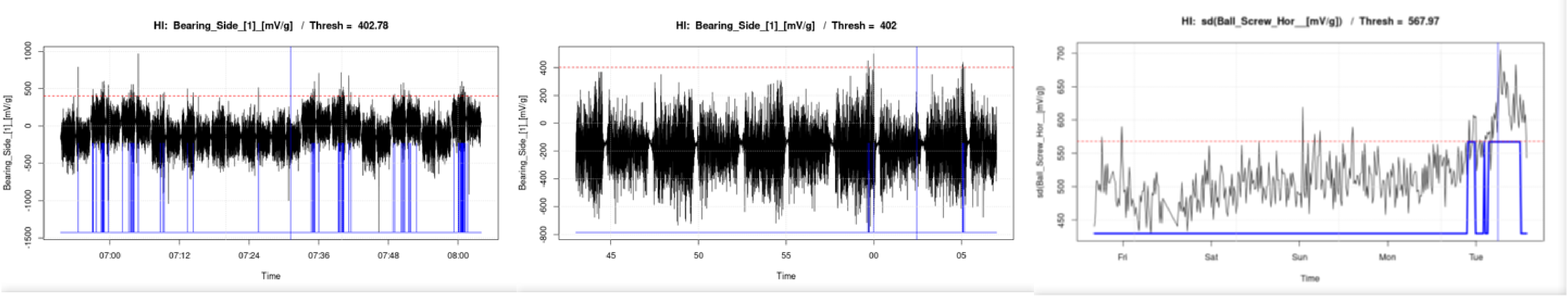
Long Short-Term Memory Based Semi-Supervised Encoder-Decoder for Early Prediction of Failures in Self-lubricating Bearings

Vigneashwara Pandiyan [a,*], Mehdi Akeddar [a], Josef Prost [b], Georg Vorlaufer [b], Markus Varga [b], Kilian Wasmer [a]

[a] Laboratory for Advanced Materials Processing (LAMP), Swiss Federal Laboratories for Materials Science and Technology (Empa)-CH-3602 Thun, Switzerland

[b] AC2T research GmbH, Viktor-Kaplan-Strasse 2/C, 2700 Wiener Neustadt, Austria

Data from the Experiment:




**Left**: Offline - threshold is largest limit for which exceedence-times are ‚uniformly distributed‘ - **Mid**: Online Use of threshold enables early anomaly detection – **Right:** Different Feature used for health-indication with more expressive indication of critical wear phase.

- Health indicating feature is used in beginning of maintenance cycle to set threshol
- First appearance of concentrated exceedences sets state to ‚unhealthy‘
- Automatic labelling of data -> Training of Predictive Model.

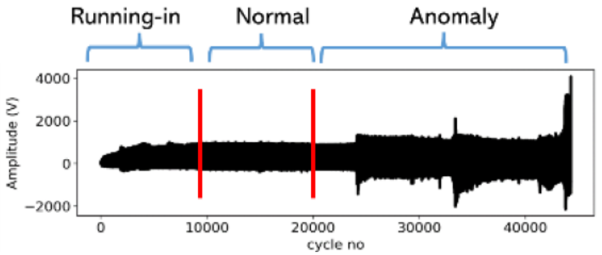



Fig. 3 from Pandiyan et. al.(2020): Axial Force

Pandiyan et. Al. Long Short-Term Memory Based Semi-Supervised Encoder-Decoder for Early Predictions in Self-lubricating Bearings, (2020)

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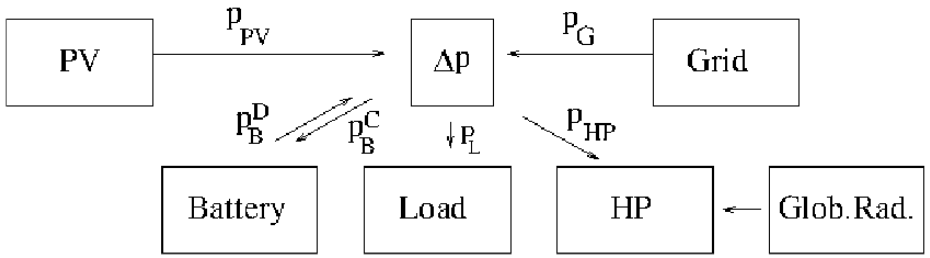
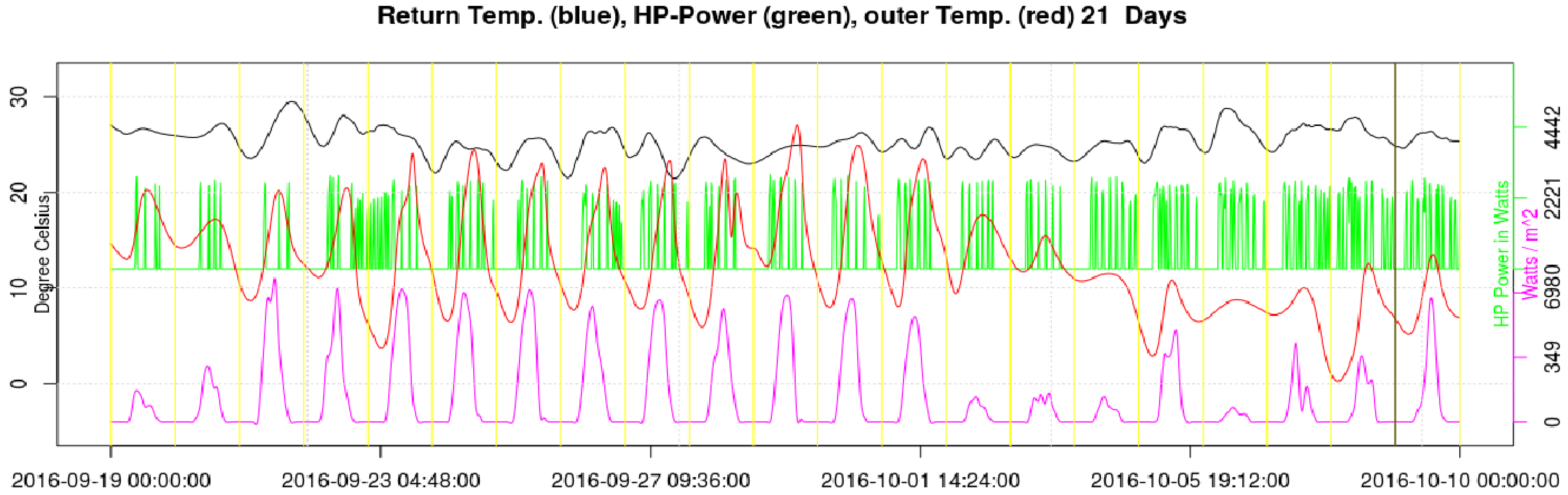
# Domestic Heat Management

…and Predictive Maintenance

# PV, Battery, ASHP, Global radiation, Grid – What is the ideal charging schedule?

$$\Delta p(i) = P_L(i) + p_{HP}(i) + p_B^C(i) - p_B^D(i) - P_{PB}(i)$$





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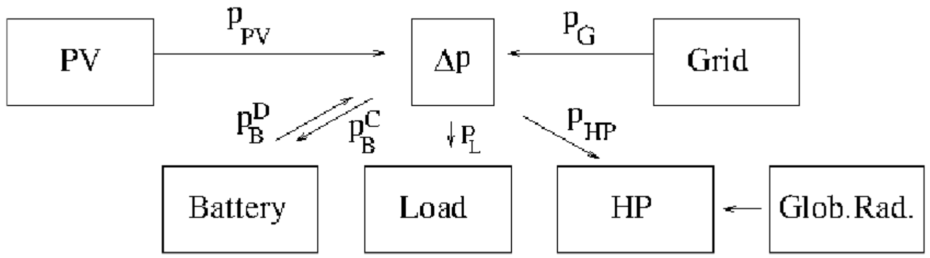
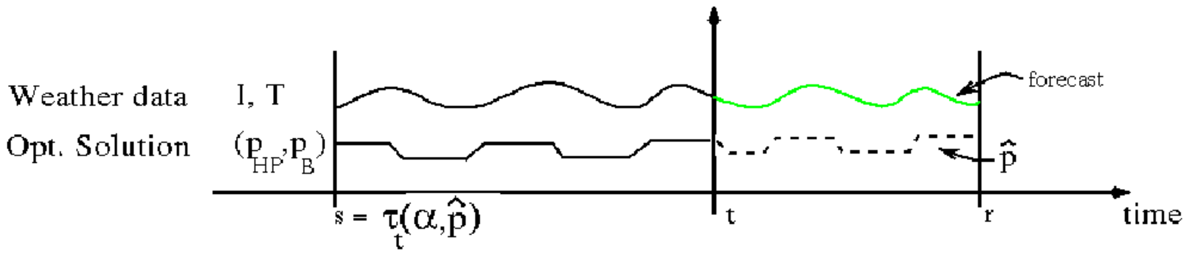
# PV, Battery, ASHP, Global radiation, Grid – What is the ideal charging schedule?




$$H_0 : \widehat{\theta}_{s,t} = \widehat{\theta}_{t,r}$$

$$\theta = \langle a, b, c \rangle$$

$$\tau_t(\alpha) = \sup\{\ s < t :\ \mathrm{H}_0 \text{ is rejected under significance level } \alpha\ \}$$

$$T'(t) = a\ (T_a(t) - T(t)) + b\ \epsilon(T_a(t))\ p_{HP}(t) + c\ I(t)$$

$$\tilde{F}(\Delta p, T, SOC) = \sum_i^n \left(\Delta p(i)\xi_P(i)\chi_{\Delta p(i)>0} + \Delta p(i)\xi_S\chi_{\Delta p(i)<0} + \lambda\,|T(i) - T_{exp}(i)|\right)$$

[2] F. Sobieczky, C. Lettner, T. Natschläger, P. Traxler. Adaptive heat pump and battery storage demand side energy management, E3S Web Conf. 22 00162 (2017) https://doi.org/10.1051/e3sconf/20172200162

# PV, Battery, ASHP, Global radiation, Grid – What is the ideal charging schedule?

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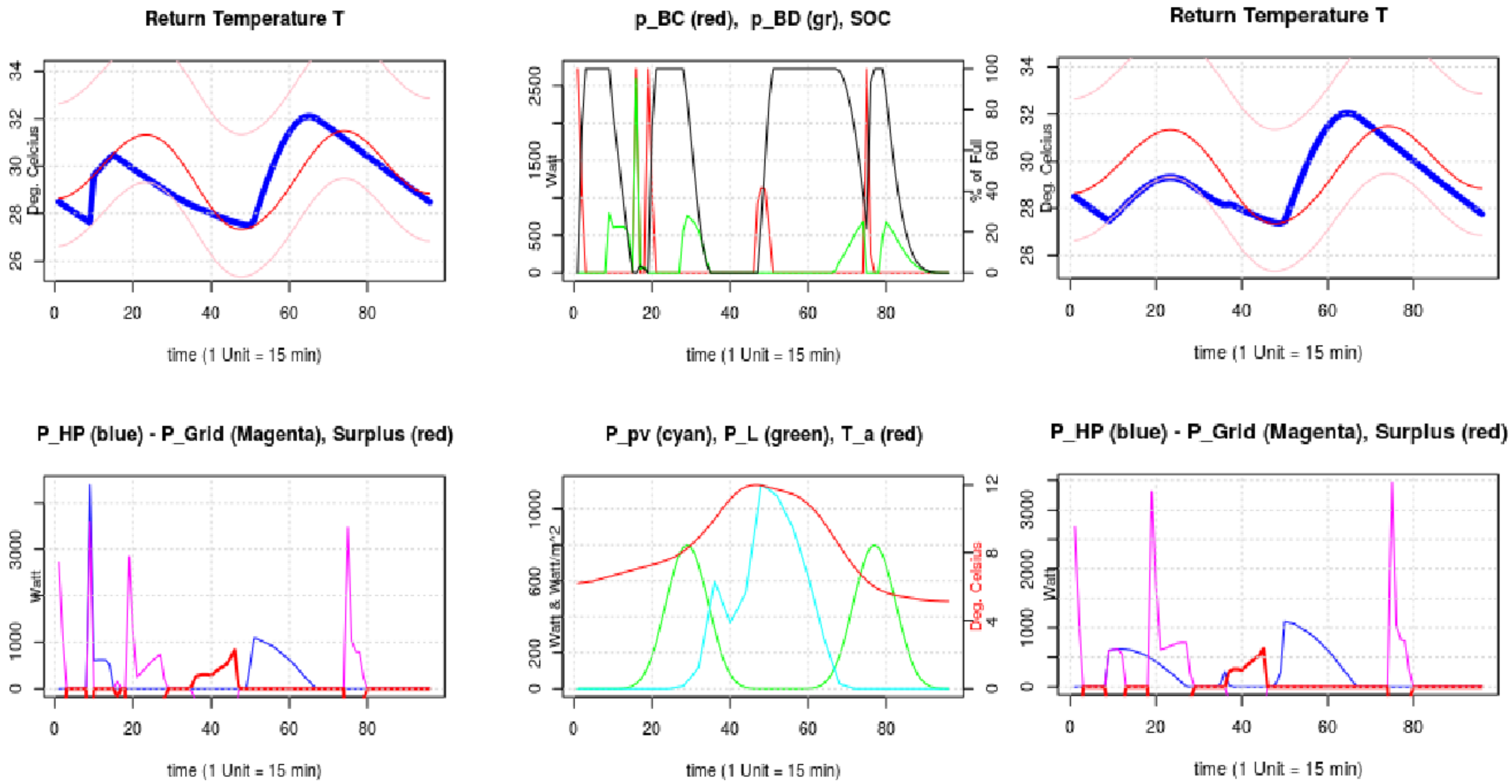
One can see realised return tempereature (thick blue) to be close to an expected temperature (thick red), realised by discharging battery after initially using (early) grid-power.  Third column: Effect of Increase of variable *a* (building‘s cool-off-rate) by a factor of 1.2: Heat Pump is only heated up in the morning to the minimum, as it cannot achieve overcoming of later morning minimal demand without grid-power, as high demand cannot be reached with battery.

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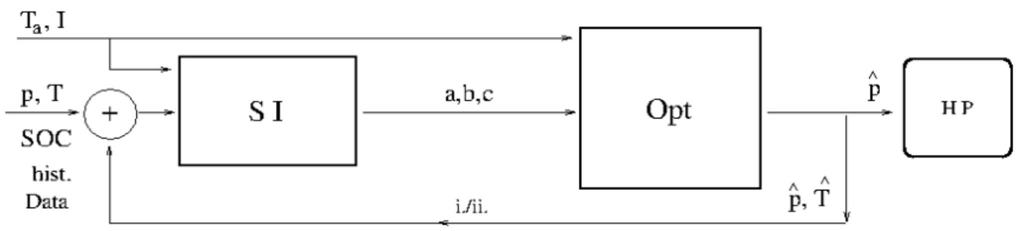
# PV, Battery, ASHP, Global radiation, Grid – Results: Amount Saved in comp. to fixed $\tau(\alpha)$




| | i.) Without I | | i.) With I | | ii.) Without I | | ii.) With I | |
|---|---|---|---|---|---|---|---|---|
| $\alpha$ | Days \| Cost/ % | | Days \| Cost/ % | | Days \| Cost/ % | | Days \| Cost/ % | |
| 0.00 | 21 | 605/ 0 | 21 | 600/ 0 | 21(0) | 605/0 | 21 | 600/0.0 |
| 0.001 | 21 | 605/ 0 | 21 | 600/ 0 | 18(2) | 347/43 | 18(2) | 344/**42** |
| 0.002 | 20 | 443/27 | 21 | 600/ 0 | 14(4) | 374/38 | 12(2) | 378/**37** |
| 0.01 | 16 | 420/31 | 17 | 378/37 | 13(3) | 377/38 | 12(2) | 370/38 |
| 0.02 | 15 | 427/29 | 15 | 424/29 | 11(3) | 326/46 | 11(3) | 324/**46** |
| 0.05 | 13 | 377/38 | 13 | 379/37 | 11(2) | 326/46 | 11(2) | 324/**46** |
| 0.1 | 12 | 349/42 | 12 | 346/42 | 12(1) | 349/42 | 12(1) | 345/42 |
| 0.2 | 11 | 326/**46** | 11 | 324/**46** | 11(1) | 326/46 | 11(1) | 324/46 |
| 0.3 | 10 | 372/39 | 10 | 369/39 | 8(2) | 372/39 | 8(2) | 344/**43** |

**Conclusions**:

- Model predictive control enables interpretation of lack of desired effect.
- Model-Accuracy of predicted charging schedule has significant impact on savings!

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# Realising Explanations

…with Ordinary Differential Equations

# Predicting the effect of external heat sources: A Heat Management Problem

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Newton‘s Cooling Law: $T' = -a(T - T_a)$
$a$ = coefficient of heat transfer

Consider the following problem:

*Assume you are entering an over-heated room in which you plan to remain for a longer while:*

- *At first, you completely turn off the radiator to reach quickest cool-off.*
- *Then, after realising ‘it has got cold‘, you re-invoke the heating cycle to let the temperature reach a desired stationary value.*

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If there is an external heat source:

$$T' = -a(T - T_a) + b$$

$b$ = a rate of temperate change.

… a linear inhomogeneous ODE:

$$y' = a_t y + b_t$$

where $a_t$ = cons. and $b_t$=step-function.

[3] F. Sobieczky, E. Dudkin, J. Zenisek. Learning the inhomogeneous term of a linear ODE. 5th Int. Conf. on Industry 4.0 and Smart Manufacturing, 2023, Elsevier Procedia Computer Science

# Predicting the effect of external heat sources: A Heat Management Problem

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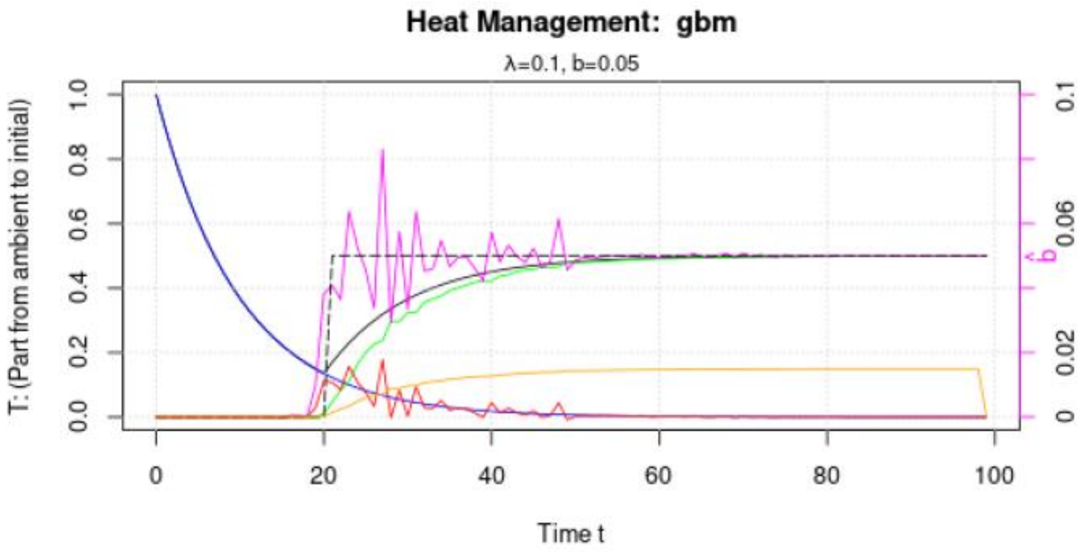


- Assume at first only homogeneous solution (maybe $a$ identified 'online'): $\hat{a}$ (estimate).
- Use observations to train model taking $\hat{a}$ and initial points to estimate temperature line as it is progressing from user's handling the thermostat [3].
- Predict: $\hat{T}_t$ as $T_0 e^{-\hat{a}t} + \hat{\epsilon}_t$

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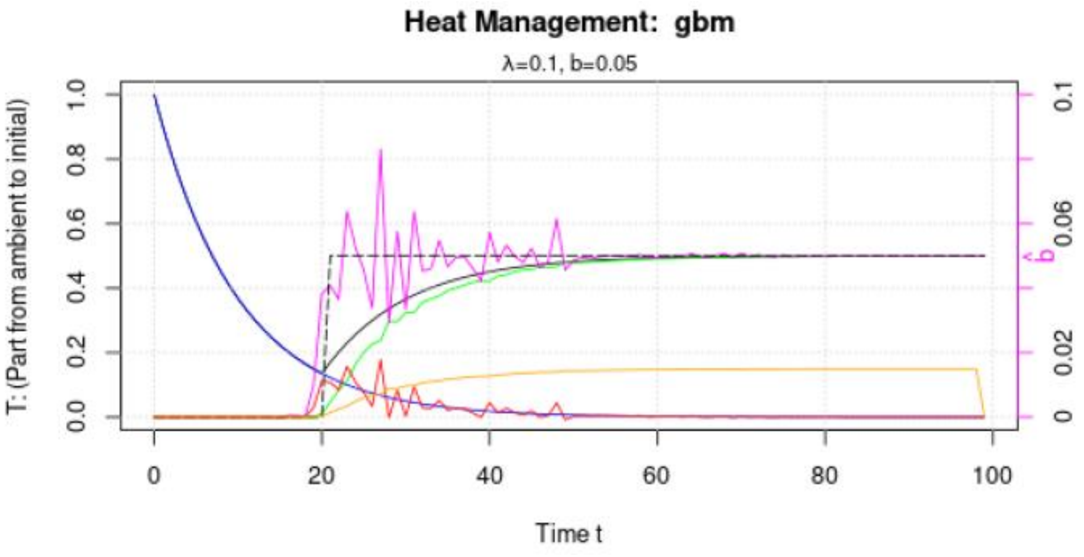


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Realise that difference of homogeneous solution and real value is result of presence of **inhomogeneous term** $b_t$ [3]:

$$\hat{b}_t = \widehat{\varepsilon_t'} + \hat{a} \cdot \widehat{\varepsilon_t}$$

- In this way the AI-prediction received an **explanation!**
- Estimate of step function is magenta-curve for XGB.

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# Predicting the effect of external heat sources: A Heat Management Problem

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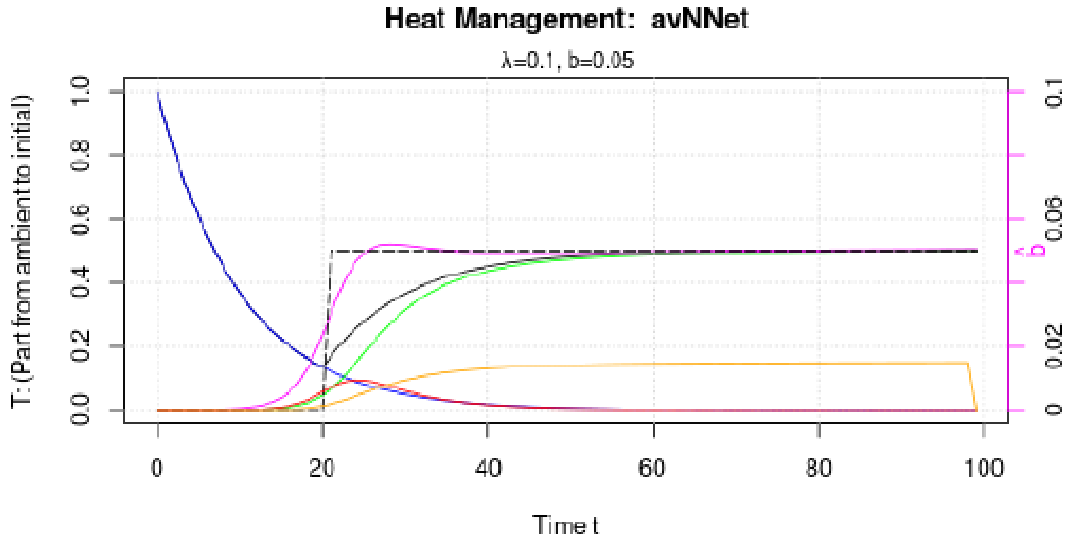


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# Predicting the effect of external heat sources: A Heat Management Problem

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Table 1. Results of the Experiment of Section 3 - CV with ten (training) folds to one (testing). Parameters tuned for same value of $\widehat{p}$.

| Predictive Model | RMSE( $b_t - \widehat{b_t}$ ) | RMSE( $S - \widehat{S}$ ) | $\widehat{p}$ |
|---|---|---|---|
| Random Forest (rf) | $0.438 \pm 0.004$ | $1.07 \pm 0.44$ | $0.098 \pm$ 4.6e-05 |
| Stochastic Boosted Trees (gbm) | $0.457 \pm 0.112$ | $1.43 \pm 0.69$ | $0.098 \pm$ 9.4e-05 |
| Averaged Model Neural Network (avNNet) | **0.346** $\pm$ 0.036 | **0.89** $\pm 0.74$ | $0.098 \pm$ 2.88e-04 |

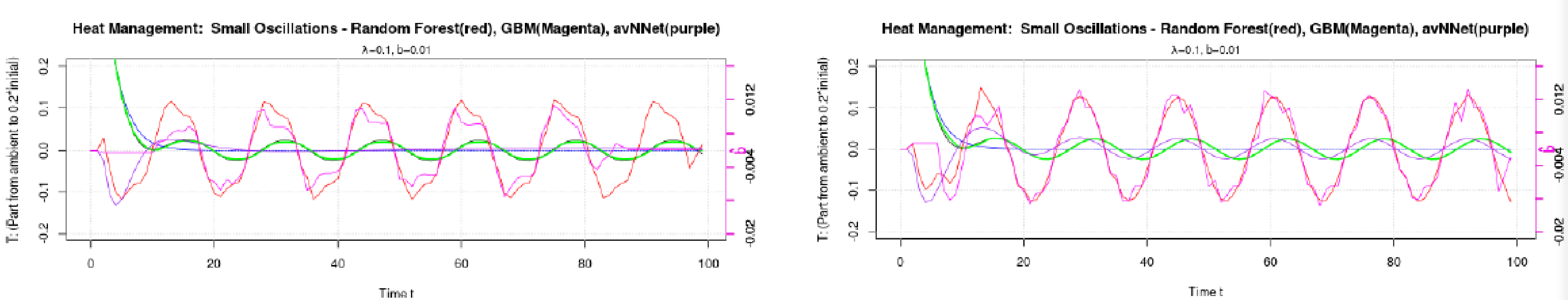


Fig. 2. Left: Modelling the residual error as a function of $t_i$ and $Y^{(h)}_{t_i}$. - Right: Modelling $\widehat{\varepsilon}_t$ over pairs of data $\langle t_i, Y_{t_i} \rangle$. The green curve is the full prediction $\widehat{Y}_t$ given by Step 5 of X-ODE, seen to almost completely cover the (black) observed raw data.

[3] F. Sobieczky, E. Dudkin, J. Zenisek. Learning the inhomogeneous term of a linear ODE. 5th Int. Conf. on Industry 4.0 and Smart Manufacturing, 2023, Elsevier Procedia Computer Science

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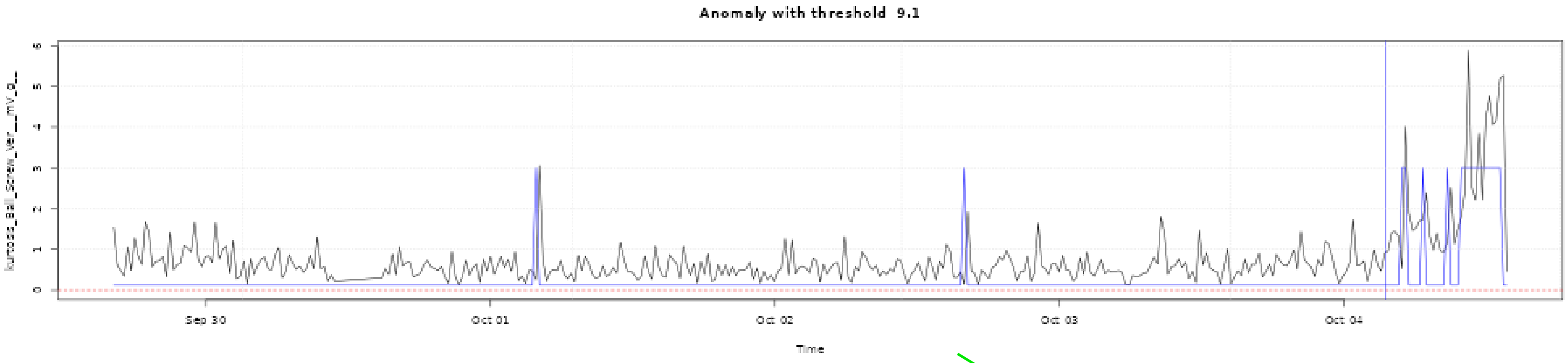
# Prescriptions

…for Predictive Maintenance

# Prescriptions




- **Proposition**:

*Prescriptive Maintenance refers to the quality of the predictive model used to relate the input variables to the qualitative aspects of the application.*

- **Example**: If an RUL-predictor includes an indication of its result‘s dependence on a physical parameter allowing to maximize this value then it is prescriptive.

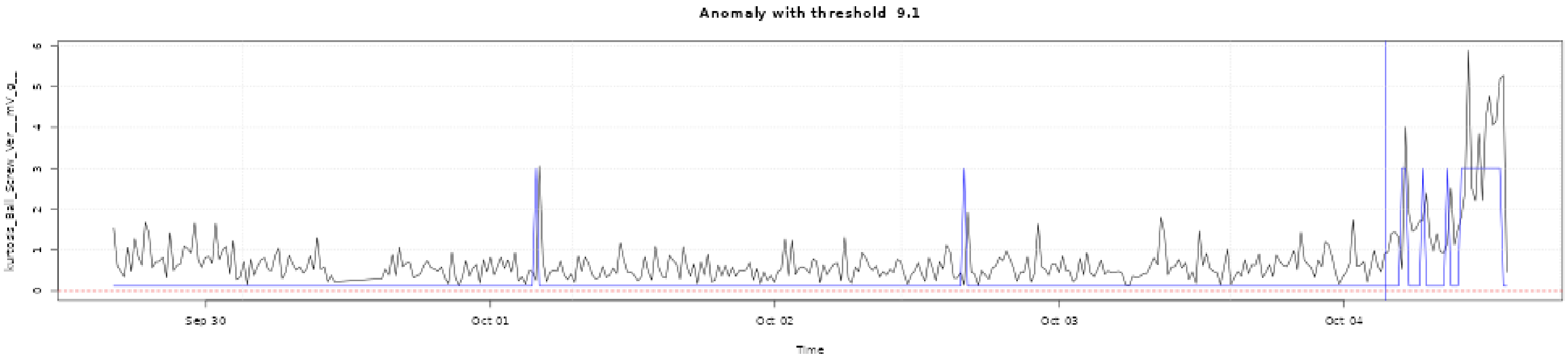
In other words: *Ignorance about the features‘ effects as they are changed makes a predictive model non-prescriptive.*

In this example, the ball-screw‘s vertical acceleration was measured for each cycle, and it was discovered that the kurtosis of the empirical measure is a good HI. It also allows to give the ‘Prescription‘:

*Look for ways to prevent the **kurtosis** to rise, as long as possible – this may increase the RUL!*

# Prescriptions

*-> Since with prescriptiveness the features' tendencies to improve some quality is looked for, it is possible that **Explainable AI** will play an important role to develop Prescriptive Analytics.*




## *Literature:*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*Thank you for your interest!*