KU LEUVEN

Dynamic thermal models with the Filter-EWM-MBE (FEM) correction approach

…or linear regressions everywhere

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Making equation-based models reliably dynamic

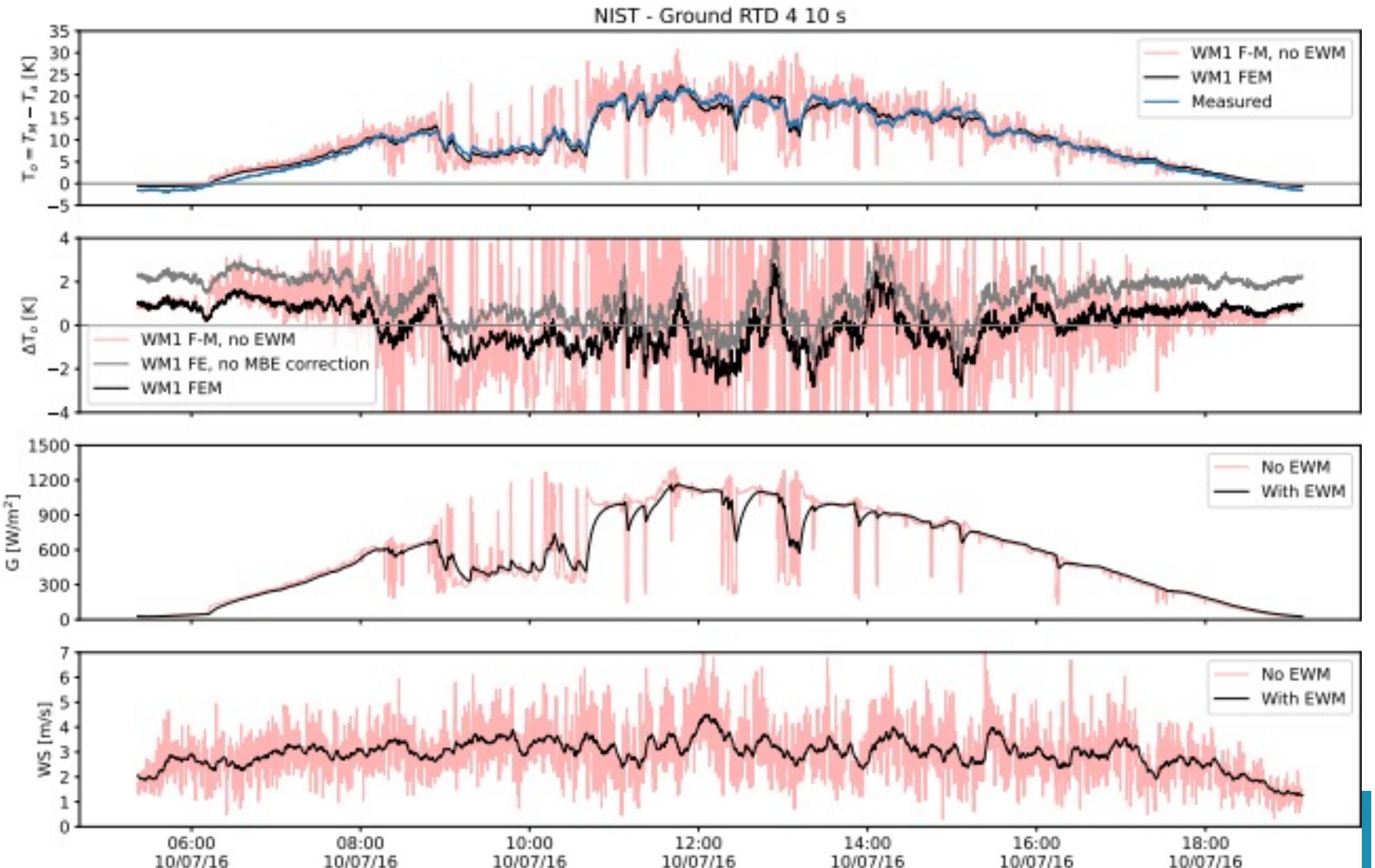
- After irradiance, temperature estimation is the most important factor
- Thermal models were (implicitly) steady-state ⇒ better RMSE, MAE, MBE for dynamic models
- Previous methods for dynamic models laborious or physics-intensive, e.g. Lobera et al, 2013: 10.1016/j.solener.2013.03.028
- First step-change: Prilliman et al "Transient Weighted Moving-Average Model of Photovoltaic Module Back-Surface Temperature", IEEE J PV, 2020 & pvlib implementation
  - Requires Finite Element Analysis (FEA) ⇒ labour intensive
  - Still too much physics!

Our solution: what if you can find what you need from measured data? ⇒ Investigating methods to improve photovoltaic thermal models at minute-to-second timescales, Solar Energy, 2023

- Inspired by Armstrong & Hurley (A thermal model for photovoltaic panels under varying atmospheric conditions, Applied Thermal Engineering 2010) + PhD (2016) ⇒ Find τ from data
- Process for reliable coefficients: filters, linear regressions, corrections
- Tested on 15 sites, 24 datasets, from 1 s to 1 h

FEM in practice

- **Filter** step gives “ideal” coefficients.
  - 2 linear regressions instead of 1
    (1 for irradiance, 1 for wind)
- **EWM** step maintains time resolution, and **smooths** output in the ***right way***.
  - Python pandas (built-in), or custom numpy or cython
- $\mathbf{MBE}_{\mathbf{train}}$ shifts output for MBE ≈ 0
  (and improves RMSE & MAE)



Filter-EWM-MBE (FEM) correction steps

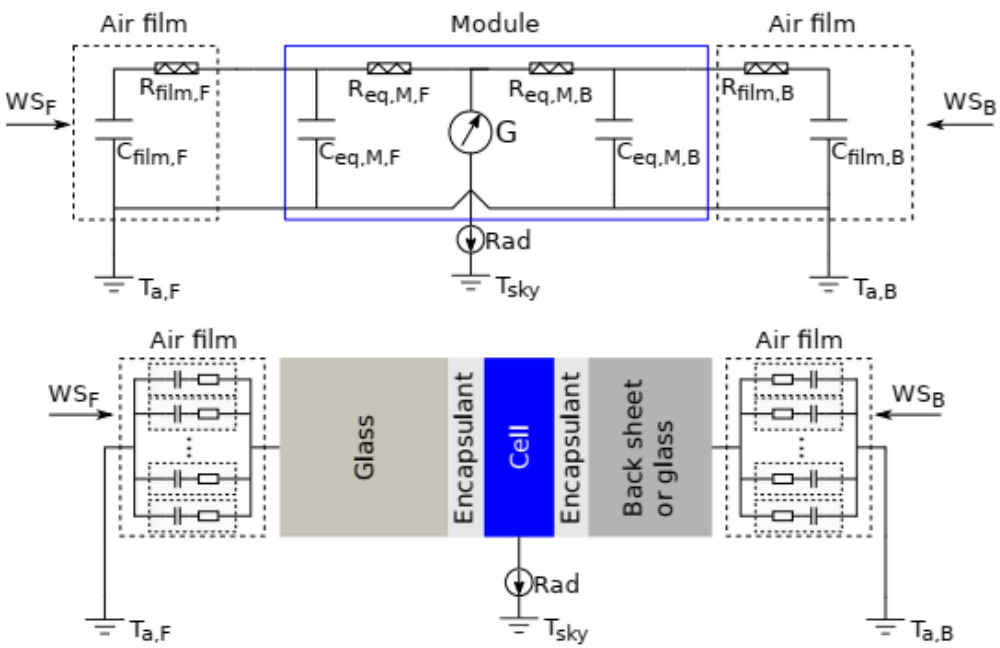
- Filter(s): to get steady-state model coefficients + thermal time constant $\boldsymbol{\tau}$
  - Ross/heating coefficient: low WS, variable G
  - WS convective cooling coefficient: high, constant G, variable WS
  - $\boldsymbol{\tau}$: how fast is ΔT, for given ΔG
- Exponential weighted mean (**EWM**), using $\boldsymbol{\tau}$ & time resolution Δt.
  Makes model dynamic.
  - Smoothing coefficient $\boldsymbol{\alpha}$: $\alpha = 1 - e^{-\frac{\Delta t}{\tau}} \Rightarrow$ **link $\boldsymbol{\tau}$ & Δt** $\Rightarrow$ EWM adapts to different Δt
  - Apply in python pandas (or numpy, or…).
- Mean Bias Error (MBE) correction: use FE steps on training dataset, calculate $\mathbf{MBE_{train}}$, use on testing or production dataset
  - Basically, don't stop at (first) MBE calculation; instead use as "free lunch" for improved RMSE, MAE and MBE.
- FEM is sequence of (mostly) independent steps: FE-, -EM, F-M, F-- all possible

Models & notation

Use only G, T_{amb}, WS ⇒ wide implementation

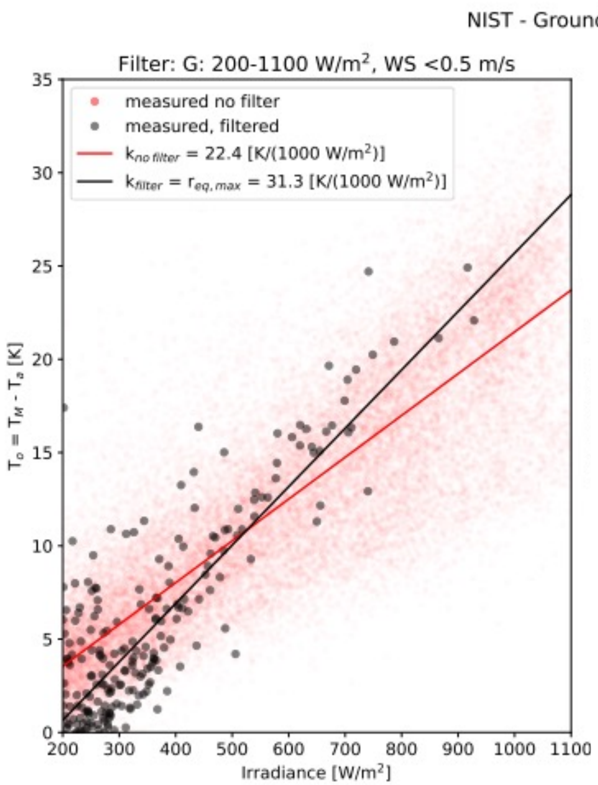
- **Over-temperature T_o:** $\boldsymbol{T_o = T_M - T_{amb}}$
- Ross: $T_{o,Ross} = k \cdot G$
- King or SAPM: $T_{o,King} = G \cdot e^{a+b \cdot WS}$
- Faiman: $T_{o,Faiman} = \frac{G}{U_0 + U_1 \cdot WS}$
- Wind model 1 (**WM1**): $\boldsymbol{T_{o,WM1} = k \cdot G \cdot e^{-WS/d}}$
- Wind model 2 (WM2): $T_{o,WM2} = G \cdot (k - h \cdot WS|_{WS \le 8})$
- Note: When WS = 0, (nearly) all models become Ross
    - **k = R-value r_{eq} [K/(W/m²)]** ⇒ easiest @ G_{STC}: $k = 30 \left[\frac{K}{1000 \frac{W}{m^2}}\right]$ ⇒ T_o = 30 K @ G_{STC}
    - $\boldsymbol{k = e^a = \frac{1}{U_0}}$ ⇒ model bridge Ross – King/WM1/WM2/Faiman
    - King/SAPM = WM1 when using same coefficients.

Modified RC-equivalent network



- Air films: *series* RC-networks, in *parallel* to each other, impacted by WS.
  - Low WS: high r_{eq}, low(er) c_{eq}
  - High WS: lower r_{eq}, higher(er) c_{eq}
  - Explanatory link theory-data
- RC network ⇒ **thermal time constant τ**
  - From material properties
  - From outdoor measured data: look for irradiance *step changes*
- **τ** used for Exponential Weighted Mean (EWM) calculation ⇒ make model dynamic

Filter: determining *k* & *d* for WM1



- To find ***k***:
  - Δt = 5 min (resample data)
  - Filter: G = 200-1100 W/m^2, WS < 0.5 m/s
  - Linear regression T_o vs G
  - k gives T_o @ G_{STC} & WS ≈ 0 m/s.

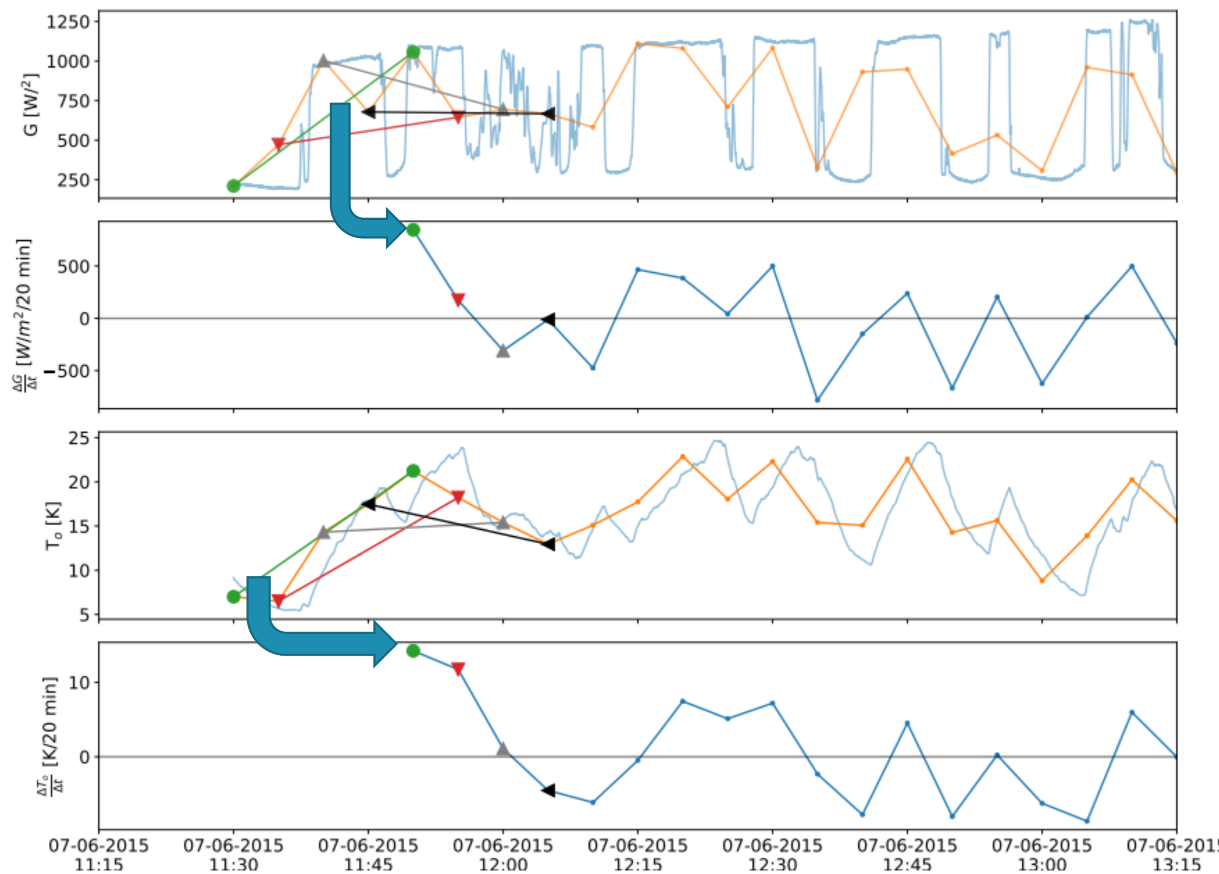
  $k = 31.3 \frac{mK}{W/m^2}$ gives 31.3 K above T_{amb}

  - $U_0 = \frac{1}{k} = \frac{1}{31.3/1000} = 31.9 \frac{W/m^2}{K}$

To find ***d***:
  - Δt = 5 min (resample data)
  - Filter: G = 1000 ± 100 W/m^2, WS = 0-8 m/s
  - Linear regression **ln(T_o/G)** vs WS
  - Faiman **U_1**: **G/T_o** vs WS

Determining the thermal time constant τ from measured data

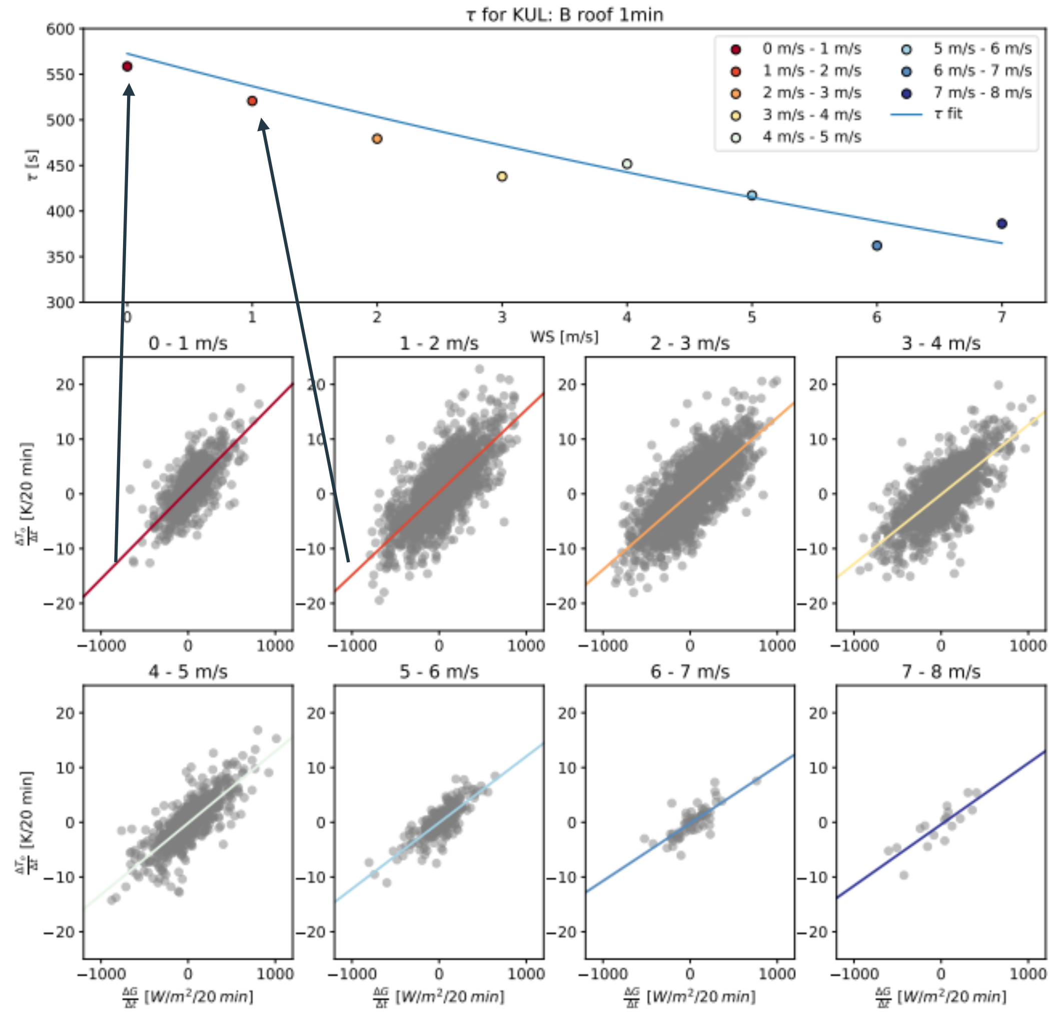
- Find $\frac{\Delta G}{\Delta t}$ & $\frac{\Delta T_o}{\Delta t}$ for 5 min data, and 4 periods (20 min total).
- 20 min: longest time window with sufficient frequency of sustained irradiance step changes
- Sort $\frac{\Delta G}{\Delta t}$ & $\frac{\Delta T_o}{\Delta t}$ by WS bins (0-1, 1-2, …, 7-8 m/s).
- Linear regression of $\frac{\Delta T_o}{\Delta t}$ vs $\frac{\Delta G}{\Delta t}$ per WS bin ⇒ get τ



τ from measured data II

$$T_{o,WM1} = k \cdot G \cdot e^{-WS/d} \equiv r_{eq} \cdot G \cdot e^{-WS/d}$$

$$\begin{aligned}
\tau(WS) &= \frac{\Delta T_o/\Delta t}{\Delta G/\Delta t} / r_{eq,max} \cdot \Delta t \\
&= \frac{r_{eq} \cdot (\Delta G \cdot e^{-WS/d})/\Delta t}{\Delta G/\Delta t} / r_{eq,max} \cdot \Delta t \\
&= \frac{(\cancel{\Delta G} \cdot e^{-WS/d})/\cancel{\Delta t}}{\cancel{\Delta G}/\cancel{\Delta t}} \cdot \underbrace{r_{eq} \cdot \frac{\Delta t}{r_{eq,max}}}_{\tau_0} \\
&= \tau_0 \cdot e^{-WS/d} \equiv \tau_0 \cdot e^{-WS/f} \ [s].
\end{aligned}$$



$\tau_0 = \frac{r_{eq}}{r_{eq,max}} \cdot \Delta t$, i.e. τ at WS = 0 m/s

Note: f ≥ d (smaller effect)

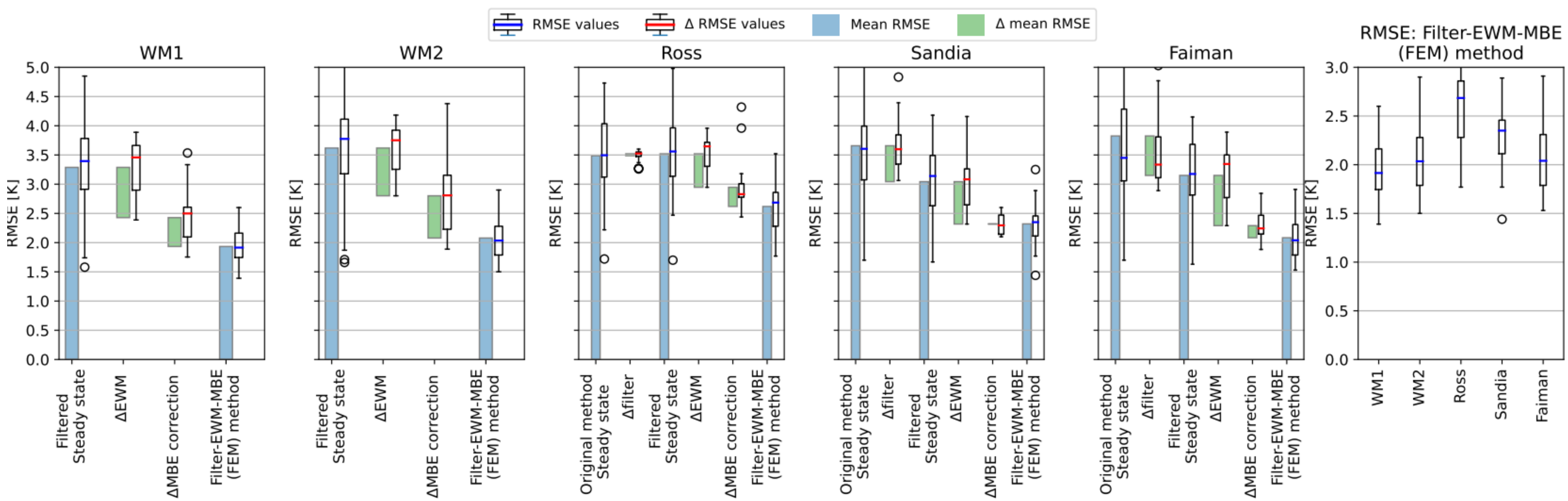
e.g. Δt = 20 min: $\tau_0 = \frac{16.96}{35.7} \cdot 1200 = 570\ s$ (9.5 min)

The EWM step

- $\tau = \ 6.3 \pm 1\, min$ (378 ± 60 s)
  - Works quite good for ~ all systems (design phase + evaluation after)
  - Better results possible from measured data
  - Impact on RMSE by choosing "wrong" (± 60 s) τ is typ. 0.1 K ~ 0.3 K (e.g. 2.0 K w/ ideal τ, 2.3 K w/ non-ideal τ)
- <u>Important</u>: **Δt and τ** must have **same time units**: $\alpha = 1 - e^{-\Delta t/\tau}$
- EWM step in python pandas is *fast* (<1 s for 1 y @ 1 s modelling)
- **df['G'] ⇒ df['G'].ewm(alpha=alpha_EWM).mean()**

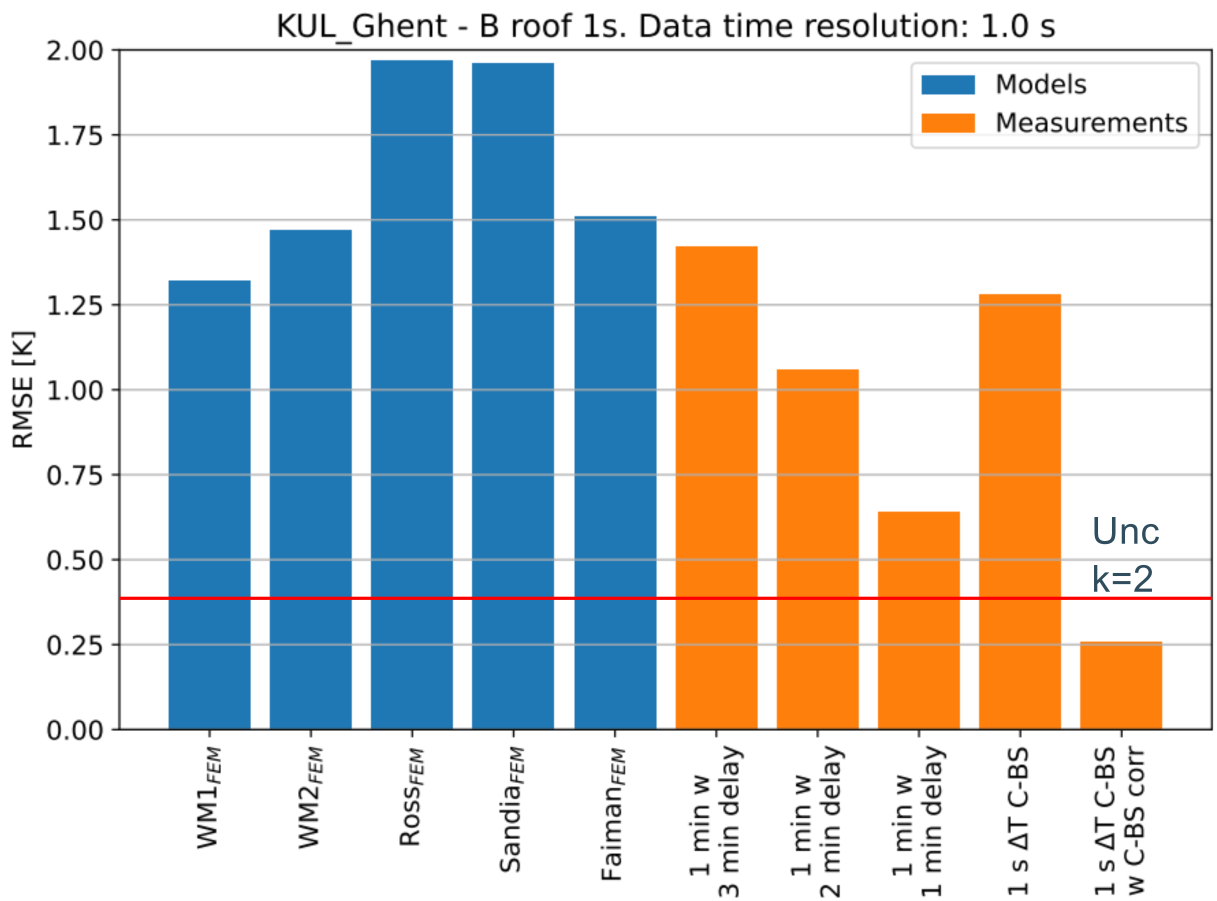
Impact of each step in FEM

Impacts typically add (compounding effect): F ⇒ FE ⇒ FEM
Filter & EWM largest impact, MBE correction can be meaningful (~ 0.5 K RMSE)



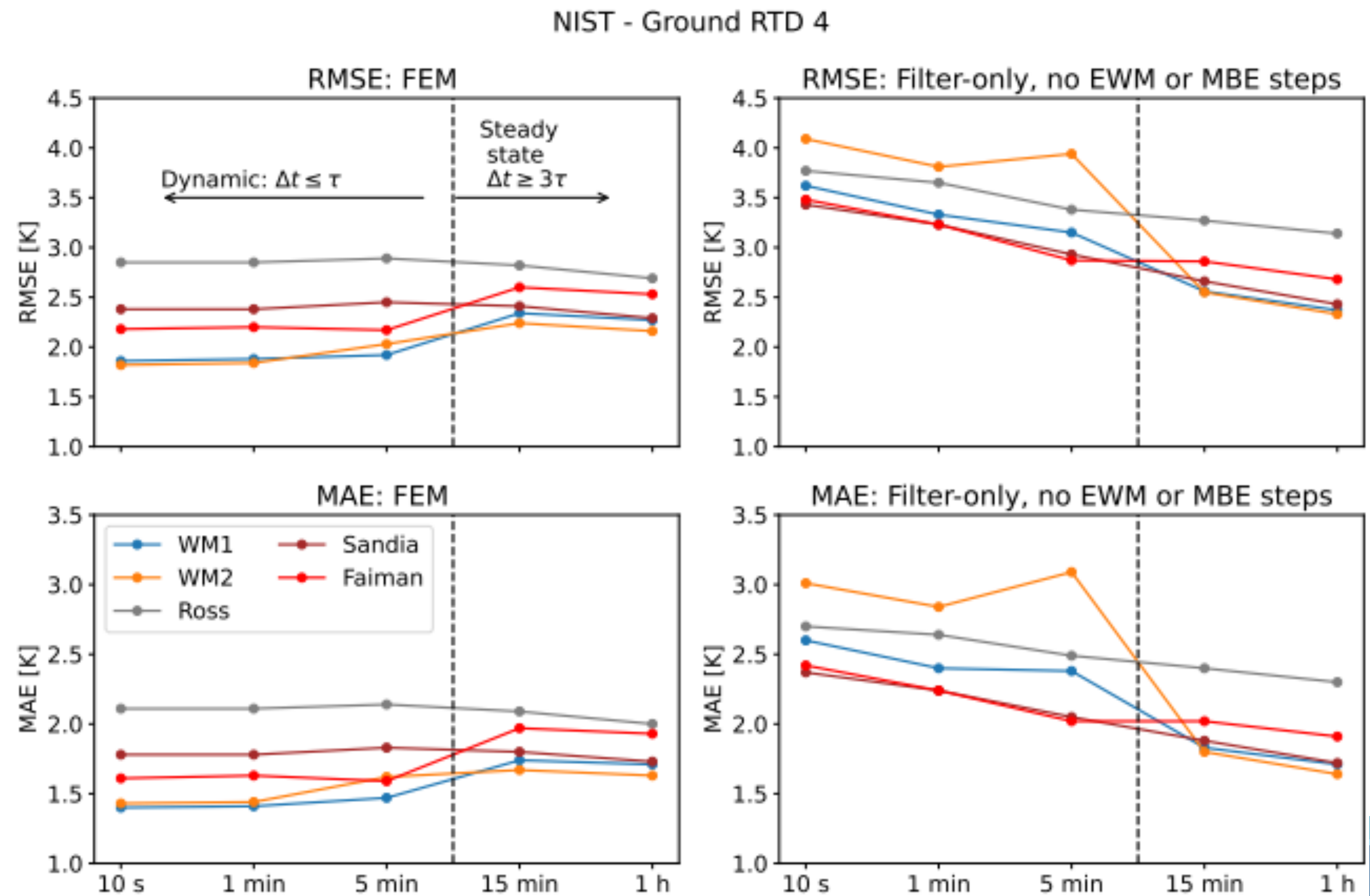
Contextualisation

- Best model results ≈ 1 min data w/ 3 min signal delay
- BS w/ BS-to-cell correction (with EWM) ≈ identical to measured data (within meas. uncertainty)
- ***Accurate and well-installed and well-maintained (backsheet) sensors still (way) better than models***



FEM with changing time resolution

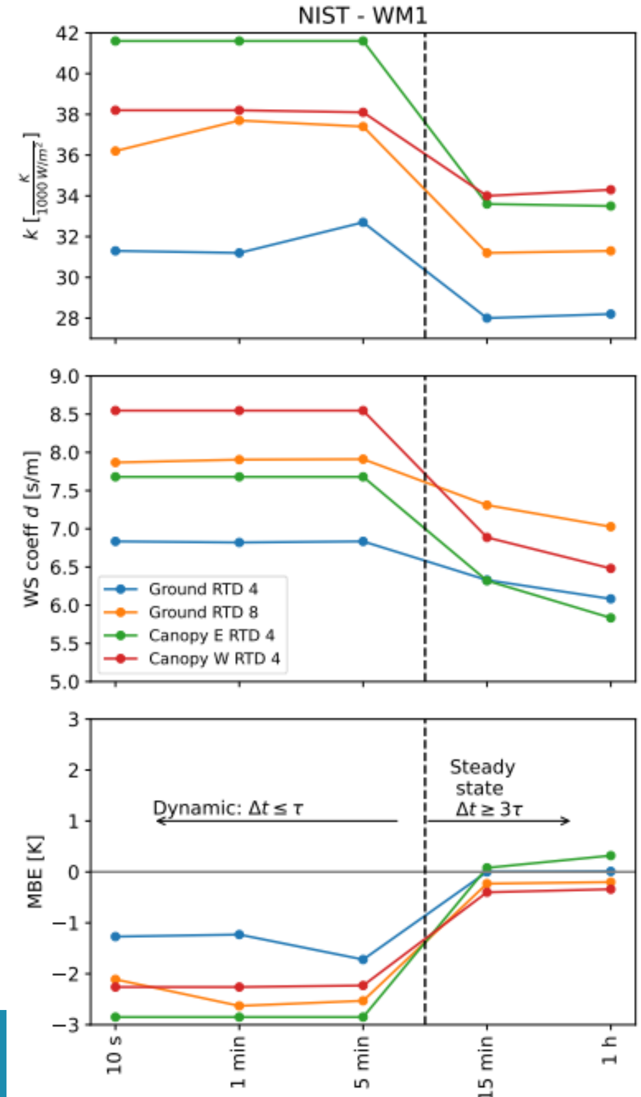
FEM: better or constant KPIs as Δt → 0



Impact of time resolution

Difference between steady state & dynamic coefficient values can lead to important model errors

- Error: Use thermal model steady state coefficient values at dynamic time scales (e.g. PVsyst U_0 and U_1, or WM1 k & d) erroneously for data analysis
  - E.g. PR calculation & weather correction, using 5 min data *and* the contract model coefficients (@ 1 h).
- $MBE_{steady\ state,\ training} \approx 0$ K, $MBE_{dynamic,training} \approx -1$ K to -3 K
- As $\Delta t \rightarrow 1\ s$ k & d increase (or $k_{dyn} > k_{steady\ state}$)
- PR impact ~0.5% to 1.0% points (γ = -0.35%/K). ⇒ EPC warranty envelope…



Conclusions

- FEM approach gives better, more stable (repeatable) coefficients ⇒ KPIs (RMSE, MAE, MBE) better or stable as $\Delta t\colon\ 1\ h \rightarrow 1\ s$
- EWM step makes (any) model dynamic; fast, easy & simple use in python pandas
- Thermal time constant τ linked to material properties (τ_0), affected by mounting conditions (wind access)
- Module sensors (if accurate + well-installed + well-maintained) still much better than models
- Careful using coefficients: distinction between steady-state & dynamic needed
    - ~ **5-20% difference** for k & d (or U_0 & U_1) between steady state & dynamic ⇒ source of error when comparing design (PVsyst/pvlib/…) @ 1 h resolution with measured data at 1 s to 5 min

Thank you

- Many thanks to those who have shared their data:
  - NIST: https://doi.org/10.18434/M3S67G
  - IEA PVPS Task 13 PLR group: https://doi.org/10.17605/OSF.IO/VTR2S
  - University of Heidelberg: https://doi.org/10.5281/zenodo.3958820
  - KU Leuven: https://doi.org/10.48804/RVTSD4

Call to action: please share more data!

Contact: bert.herteleer@kuleuven.be
⇒ interest in evaluating FEM approach on 1-axis systems & different system types