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Multi-fidelity modeling and control for building temperature control

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Learning Objectives

After this presentation, you will be able to:

1. Envision how a residential building can be more **efficiently** controlled
2. Understand how **shaping** and **shifting** building loads can play a crucial role in a more **effective** grid
3. Learn the benefits of a **multi-fidelity** approach to building control
4. Conceptualize a **Gaussian Process** as a surrogate for a high-fidelity dynamical model of a building

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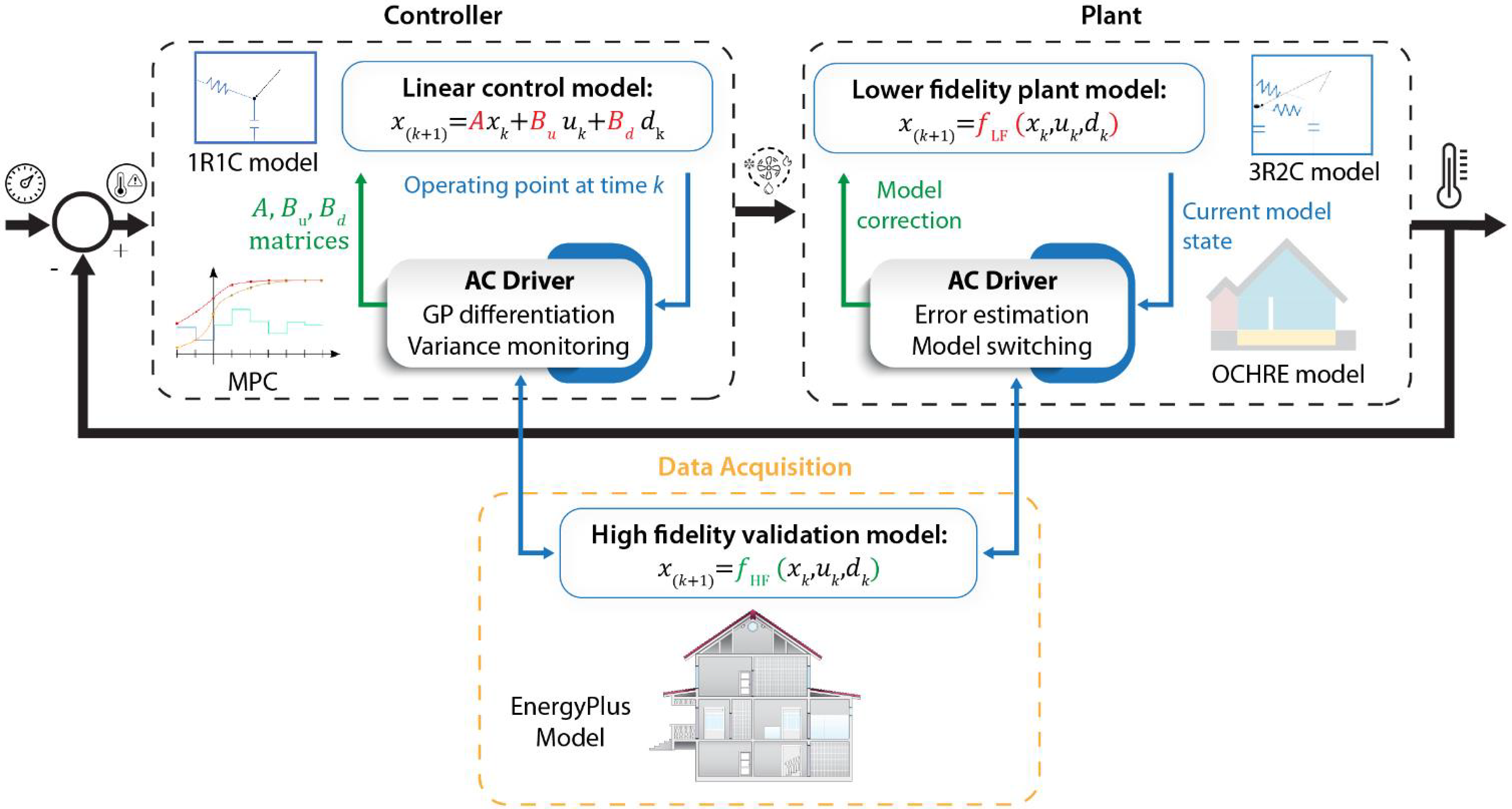
Outline

- Introduction
- Multi-fidelity linear model (MFLM)
- Learning on the fly
- Discussion
- Conclusion



Introduction: building control

Motivation:

- Increased electrification of **end uses**[1,2,3]
  - Demand is **higher**, but is more **flexible**
- Increased **renewable energy** generation[4]
  - Available power is more **intermittent**
- A **stable** grid: demand = generation
  - **Challenging** when generation is intermittent
  - So, what can be done on the demand side?

End use example: buildings

- **38%** of electrical demand in U.S. in 2022[1]
- Can **shift** and **shape** this flexible demand using advanced control techniques[5,6,7]
- Potential to benefit the grid if done at a **large scale**[8]
- Requires **computationally heavy** large-scale simulations

Introduction: model predictive control

Background:

- Model predictive control (MPC):
  - Popular method for HVAC control[9, 10, 11]
  - Optimize **objective**, include **constraints**, …
- Linear MPC:
  - Uses **linear model** to simulate trajectory and get optimal control actions
- Nonlinear MPC:
  - Uses **nonlinear model** to simulate trajectory and get optimal control actions

	Linear MPC	Nonlinear MPC
Benefits	**easy** and **cheap** to evaluate[12]	more **accurate** predictions (if system is nonlinear)
Challenges	**less accurate** predictions (if system is nonlinear)	**complex** and **expensive** to evaluate[12]

Building systems are typically **complex** and **nonlinear**[9]

Introduction: research goal

Goal:

Bridge the gap between **computational burden** and **accuracy** to **more effectively** control the HVAC system in a building or group of buildings

Proposed Solution:

- Exploit benefits of both MPC types:
  - **Preserve** linear model efficiency
  - **Approach** nonlinear model accuracy
- A **multi-fidelity** (MF) method[13]:
  - Update a **low-fidelity** (LF) model with **high-fidelity** (HF) information (a MF model)
- Adaptive computing[14]:
  - Update the MF model **on the fly**

Linear model (LM) with static parameters

Building as a 1-D LM:

- Control action: $u \in \mathbb{R}^1$
  - HVAC heat flow [kW]: Q_{HVAC}
- State: $x \in \mathbb{R}^1$
  - Internal temperature [C]: T_b
- Disturbances: $d \in \mathbb{R}^3$
  - Outdoor air temperature [C]: T_{oa}
  - Solar heat flow [kW]: Q_{sol}
  - Internal load [kW]: Q_{int}

image: Flaticon.com

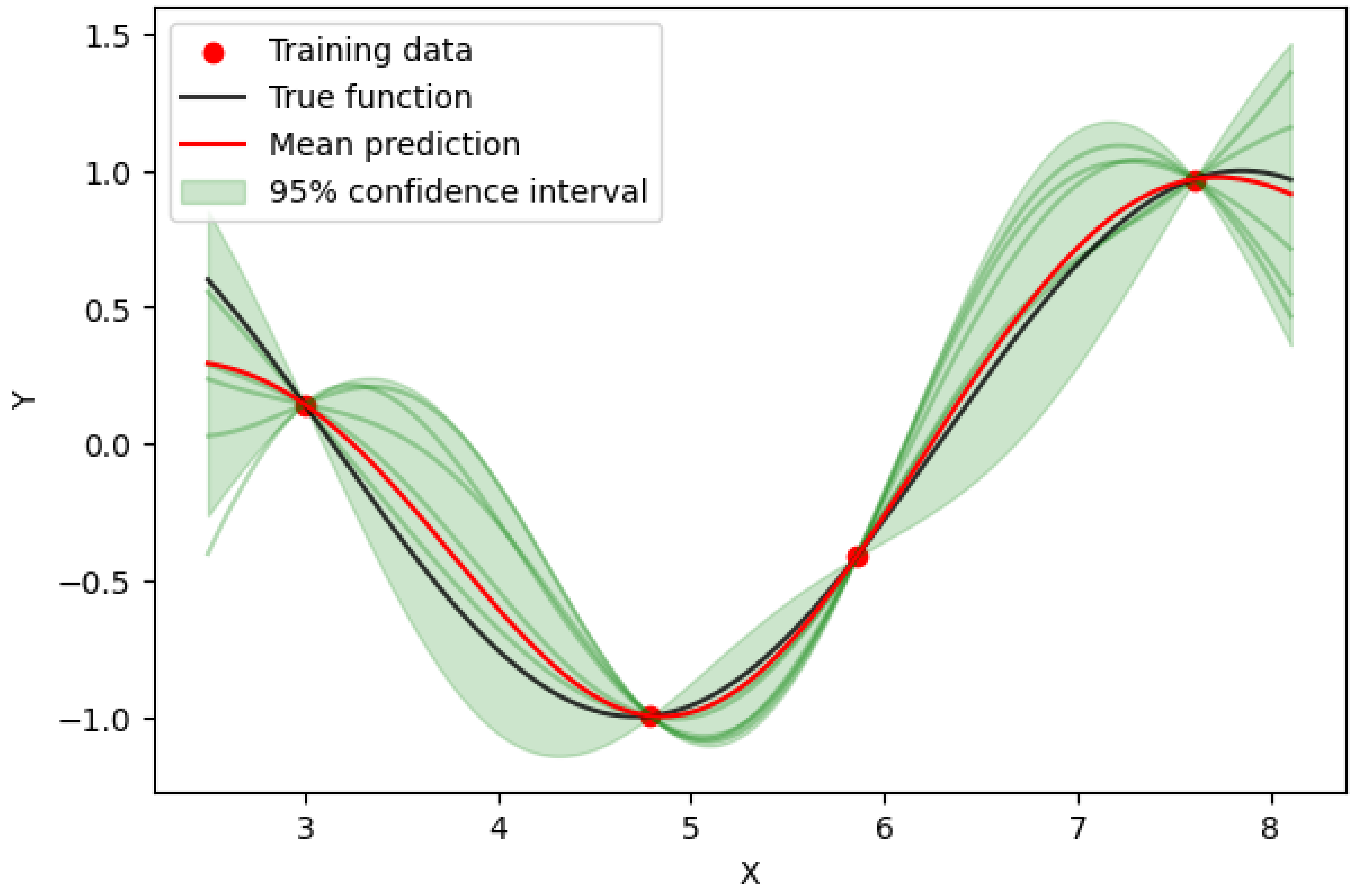
$$x_{k+1} = Ax_k + Bu_k + Ed_k$$

$$A \in \mathbb{R}^{1x1}$$
$$B \in \mathbb{R}^{1x1}$$
$$E \in \mathbb{R}^{3x1}$$

HF data driven model

A surrogate for a HF building model:

- Gaussian Process (GP) model: $f_{GP}(\cdot)$
  - Maps **HF** inputs (x_k, u_k, d_k) to **HF** outputs (x_{k+1})
- **Fast** to evaluate
- Captures **nonlinear** or **complex** dynamics
- Easy to **adapt** and **update** on the fly
- Provide **uncertainty** quantification



$$Y = f_{GP}(X)$$

$$|||$$

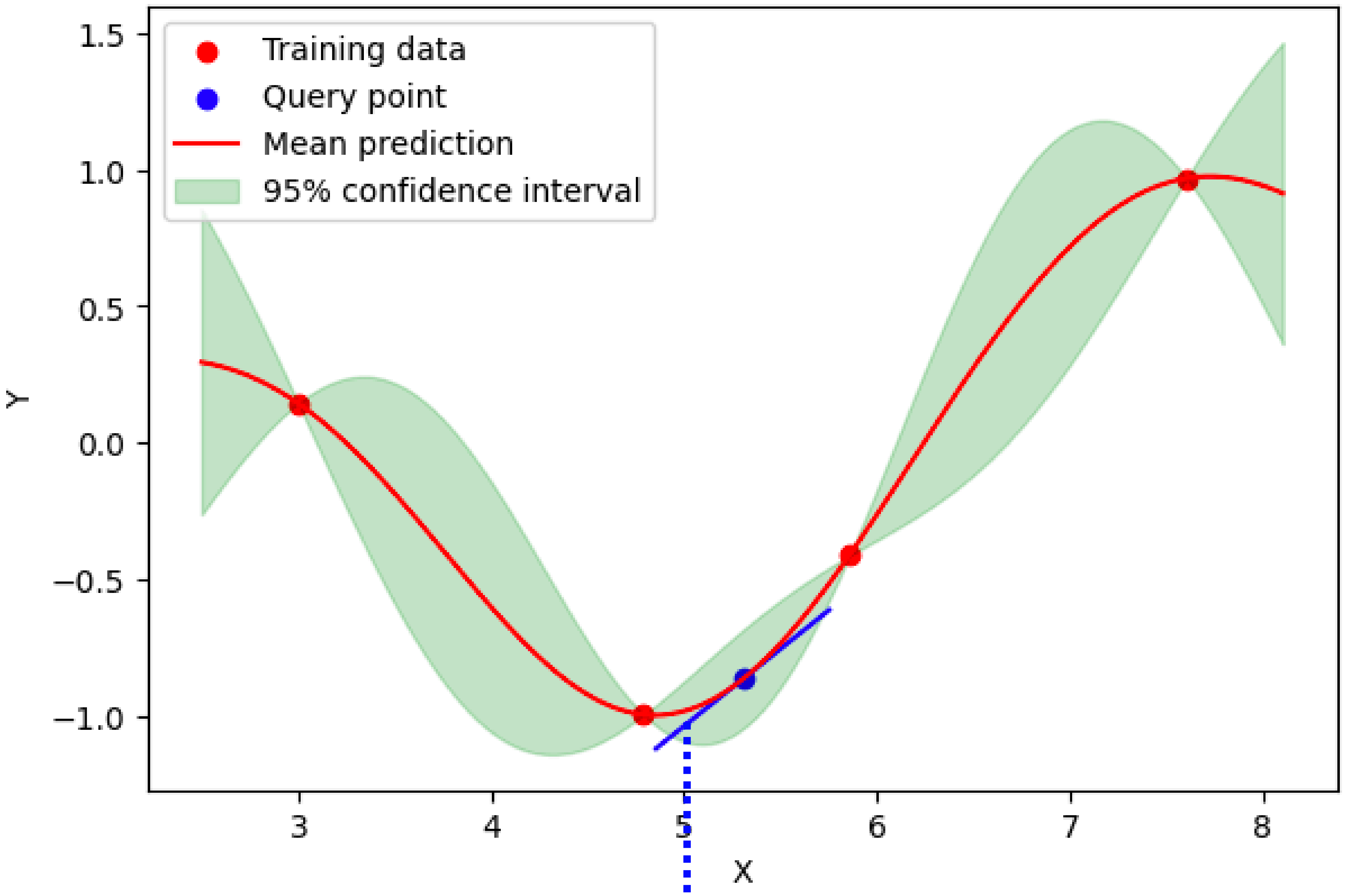
$$x_{k+1} = f_{GP}([x_k, u_k, d_k])$$

Multi-fidelity linear model (MFLM)

MFLM idea:

- Parameters are **time-varying**
- **Differentiate** the GP at current building conditions $\rho_k = [x_k \quad u_k \quad d_k]$

$$\hat{A} = \frac{\partial f_{GP}(\rho_k)}{\partial x_k} \quad \hat{B} = \frac{\partial f_{GP}(\rho_k)}{\partial u_k} \quad \hat{E} = \frac{\partial f_{GP}(\rho_k)}{\partial d_k}$$



$$x_{k+1} = \boxed{\hat{A}} x_k + \hat{B} u_k + \hat{E} d_k$$

MFLM – Learning on the fly

Possible challenges with MFLM:

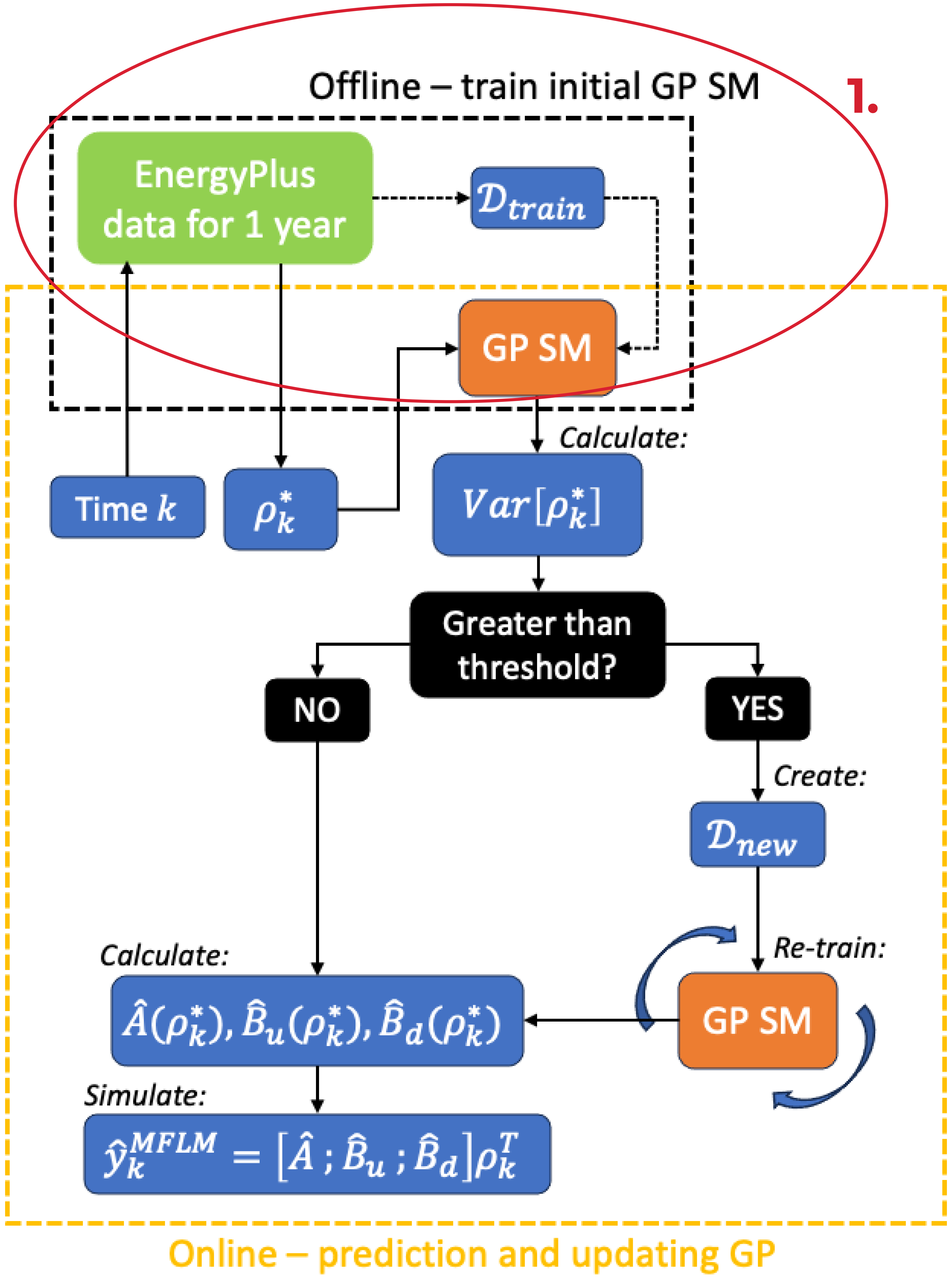
- GP Training
  - **Computation time** increases by $\mathcal{O}(N^3)$
  - Access to **limited data**
- High-performance computing
  - Certain computational **time/budget allocation**

Obtain **smallest** dataset that results in **best** GP/MFLM **performance**

MFLM – Learning on the fly

Process:

1. **Train** GP on **small** initial dataset
2. Track **variance** of current conditions
3. Learn on the fly
   a. If **Var**$[\boldsymbol{\rho_k}] \geq \overline{\boldsymbol{V}}$: add current condition to initial dataset, **re-train** GP with new dataset
   b. If **Var**$[\boldsymbol{\rho_k}] < \overline{\boldsymbol{V}}$: continue simulation
4. Compute MFLM parameters



MFLM – Learning on the fly

Process:

1. Train GP on **small** initial dataset
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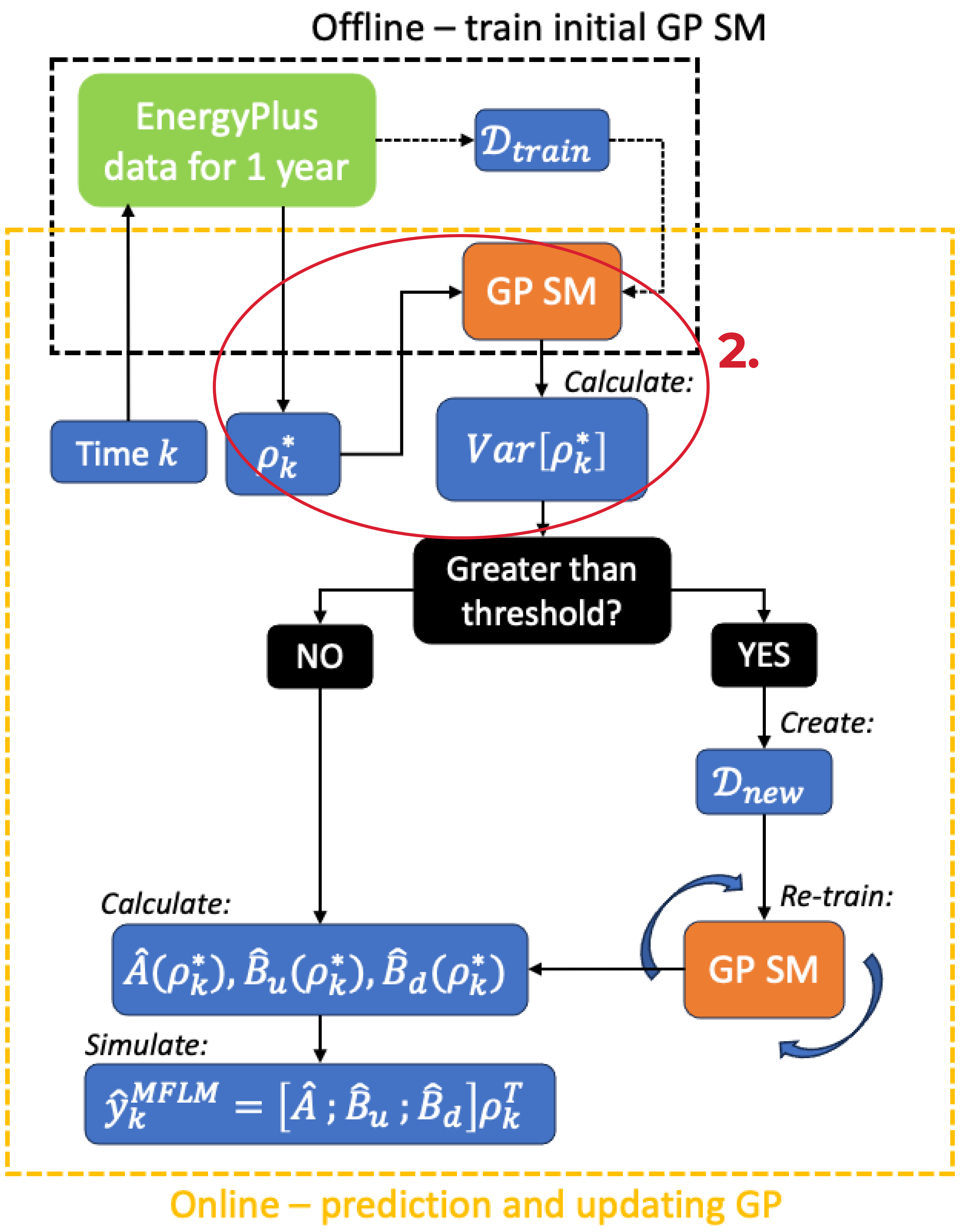

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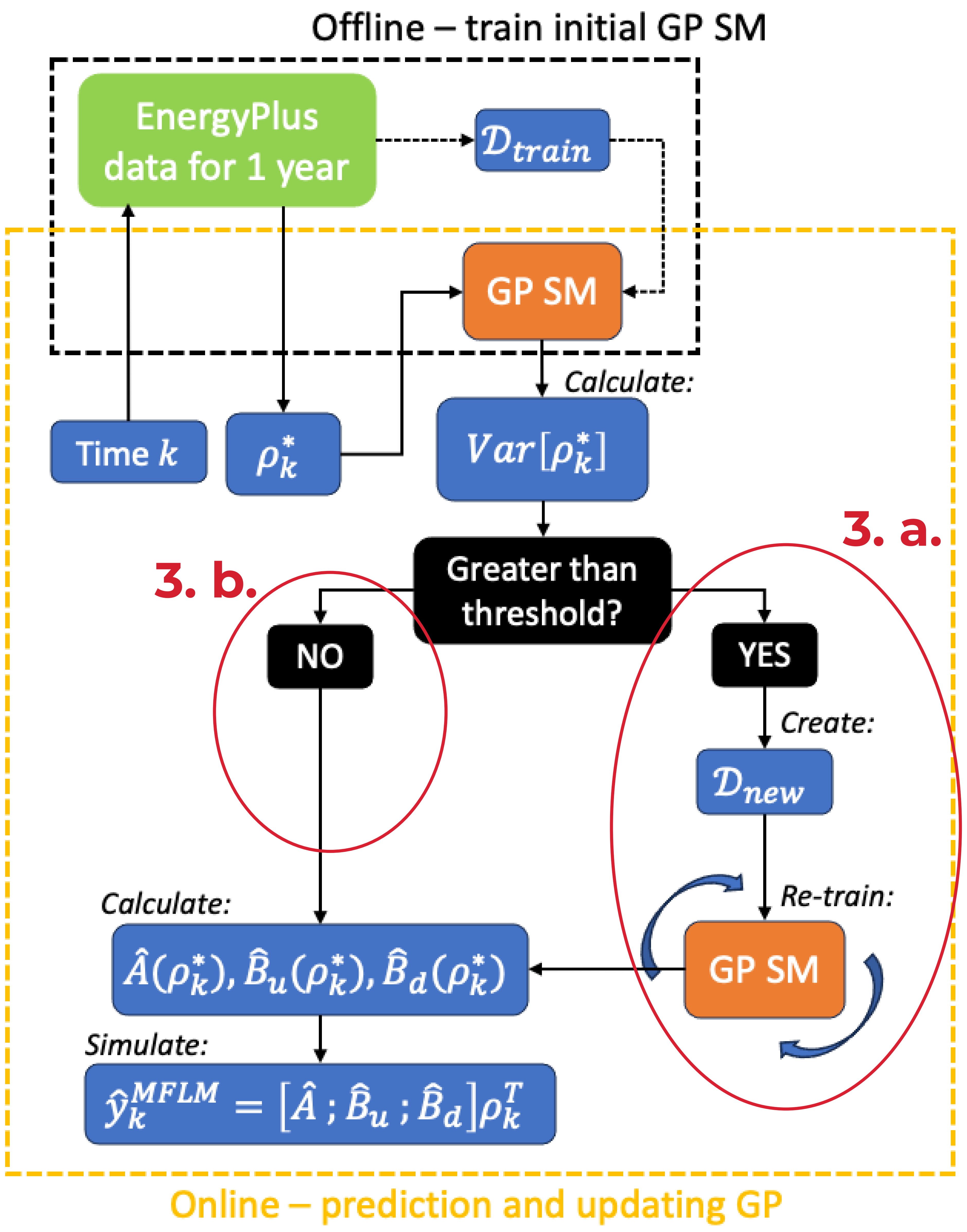

MFLM – Learning on the fly

Process:

1. Train GP on **small** initial dataset
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3. Learn on the fly
   a. If **Var**$[\boldsymbol{\rho_k}] \geq \overline{\boldsymbol{V}}$: add current condition to initial dataset, **re-train** GP with new dataset
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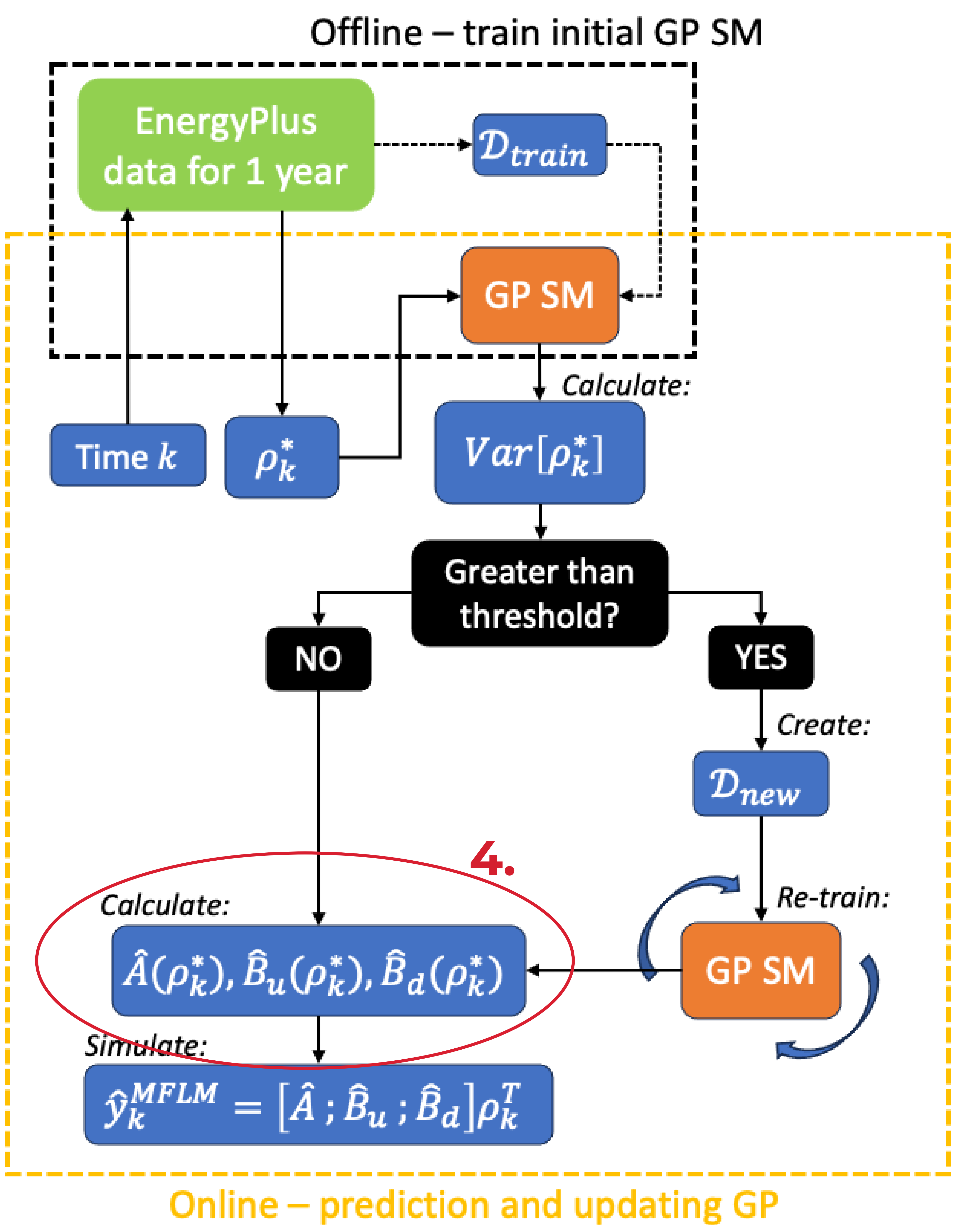
4. **Compute** MFLM parameters



Results: no learning on the fly

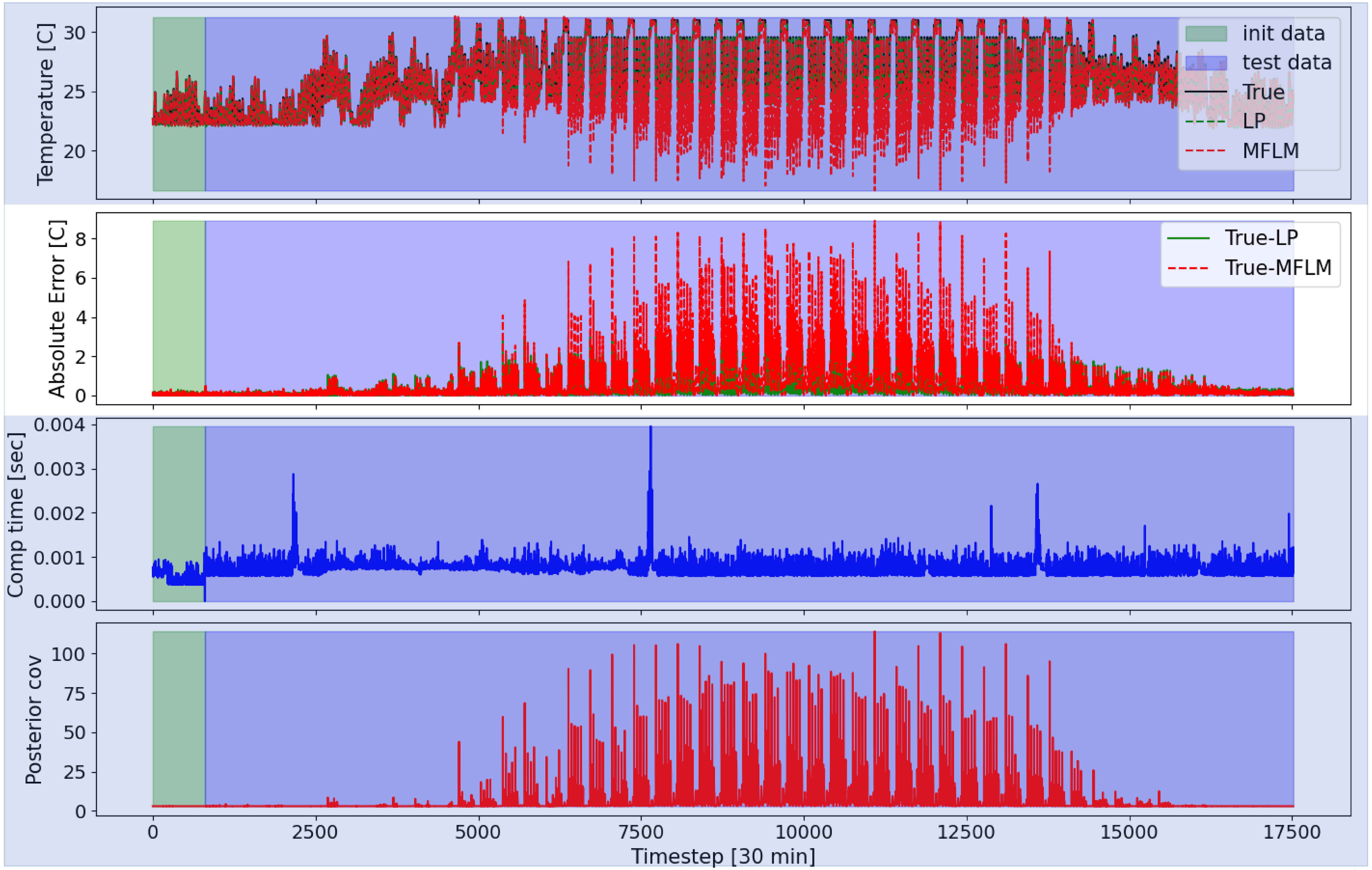
Mean Absolute Error [C]:

MFLM	LM
0.706	0.295

Comp. time [sec.]:

MFLM	LM
12.52	NA

In addition to LM



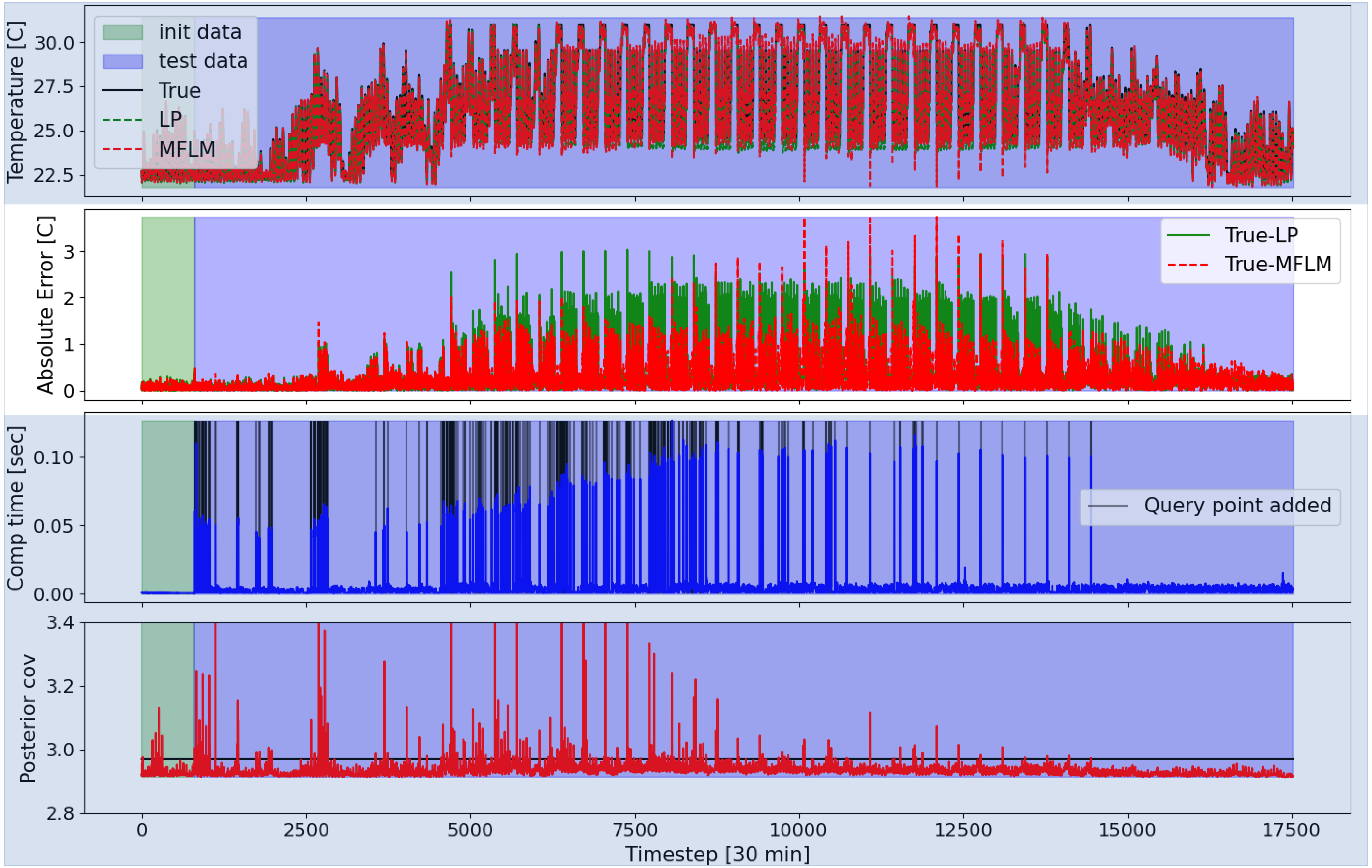
Results: learning on the fly

Mean Absolute Error [C]:

MFLM	LM
0.251	0.295

Comp. time [sec.]:

MFLM	LM
93.94	NA



Discussion

Accuracy:

- MFLM can make **more accurate** predictions than a LM in terms of MAE
- Given **adequate** training data

Computation time:

- MFLM **>** LM in general
- MFLM **w/ on-the-fly** learning takes **longer** to compute than **w/o** …
- **Much faster** than training on entire year

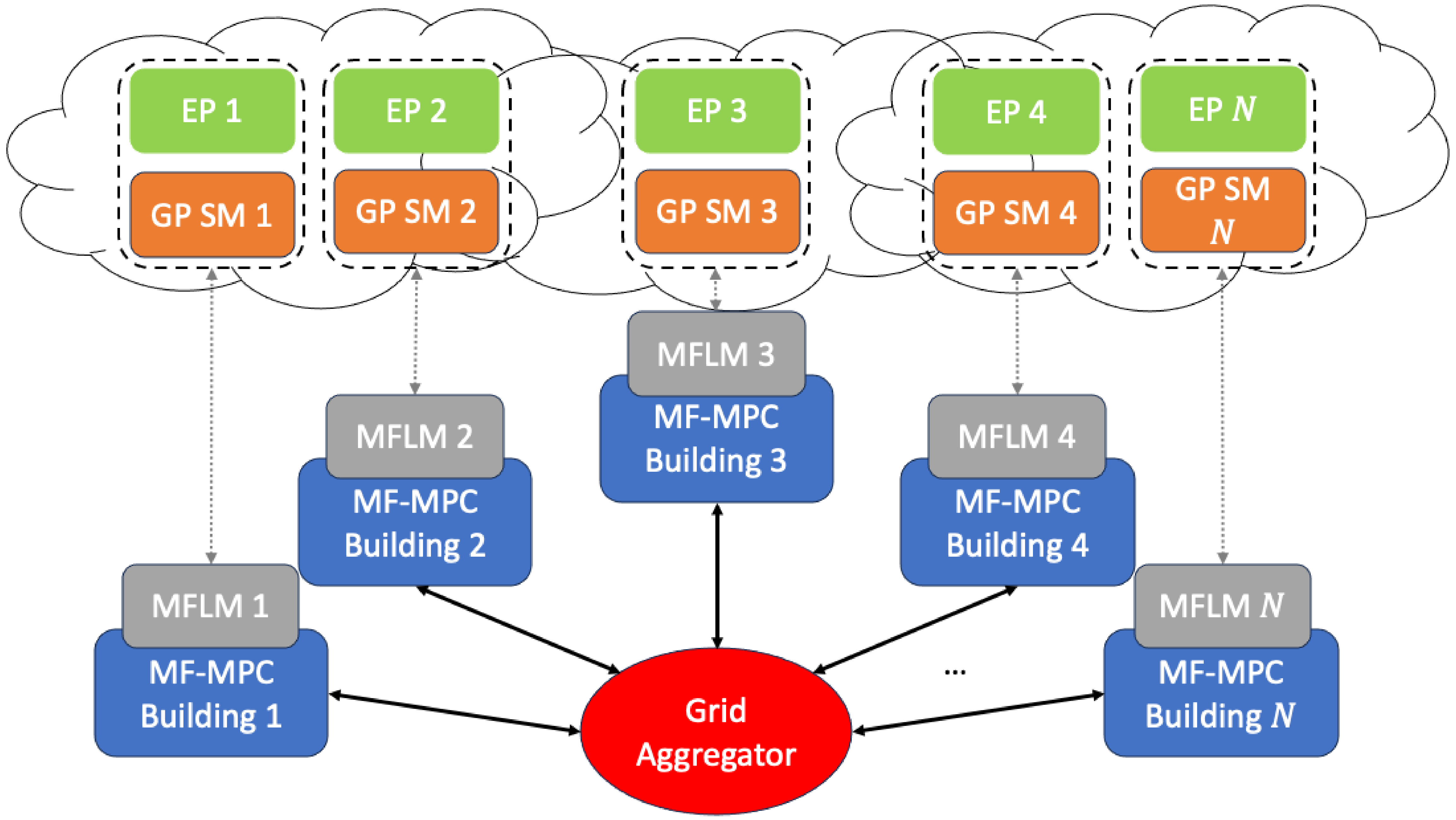
Result implications: Immediate benefit:

- MPC can use MFLM to get more **accurate** state **trajectory**
- MPC can then produce **more effective** control actions
- More efficient HVAC operation in a **single** building

Discussion

Result implications:

- Bigger picture benefit:
  - Objectives are **better met**
  - Many buildings, each more efficient, each communicating, can **benefit the grid**
- Possible applications:
  - A **neighborhood** or **community** of residential buildings
  - Different **building types** (commercial, industrial, …)
  - Different **end use devices** (EV charging, storage, …)



Conclusion

A multi-fidelity method can **bridge the gap** between computational **complexity** and **accuracy** to more effectively **control buildings** and provide **grid services**

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Team Members

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Kevin Griffin

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Thank you for listening!

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Building and data info

- **Building type**: single family home
- **Building location**: Phoenix, Arizona
- **Building specifications**:
  - HVAC: central AC, ducted heating
  - Natural gas heating
  - Southeast facing

- **HF simulator**: EnergyPlus
  - Simulation resolution: 1 minute
- **Gaussian Process model**: GPytorch
  - Data resolution: 5 minute (sampled, averaged across timestep)
  - Kernel: white noise + const * RBF

Future work

Current research:

- MF-MPC:
  - Currently working on linking the MFLM to an existing MPC controller
  - Will act as a supervisory controller (sends temperature setpoints to a building plant model)
  - Compare performance of MF-MPC to linear MPC (control action effectiveness)

Future research:

- MF-DMPC:
  - Create a distributed version of MF-MPC
  - Multiple buildings would communicate/coordinate to achieve global objective
  - Individual buildings still achieve local objectives
  - Analyze load shaping/shifting effectiveness

Surrogate Model Tuning

Purpose:

- Properly tuned hyperparameters crucial to GP performance
- Hyperparameters (HPs): noise prior, constant value, length scales
- Popular HP tuning method:
  - Maximize the marginal log likelihood (MLL) function
  - Has proven to be best method for HP tuning

Problem:

- Chooses HPs such that GP fits output very well
- Gradients of GP surface are highly variable
- MFLM thus does not perform well

Surrogate Model Tuning

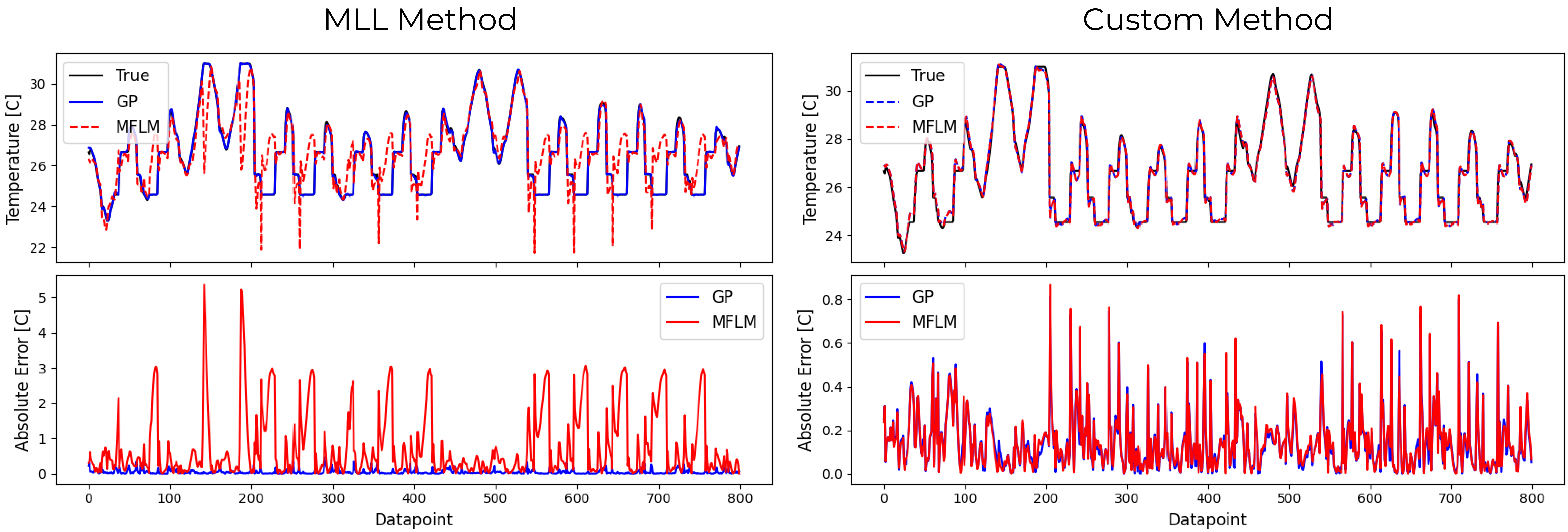
Process:

- Custom objective function using the Optuna hyperparameter tuning software

Purpose:

- Regularize the GP tuning process
- Smooth out gradients (smooth the GP surface)
- More conservative GP, but more accurate MFLM

Surrogate Model Tuning - Results



Introduction

Background:

- Model Predictive Control (MPC):
  - popular method for HVAC control[9, 10, 11]
  - Optimize **objective**, include **constraints**, …
- Linear MPC:
  - uses **linear model** to simulate trajectory and get optimal control actions
- Nonlinear MPC:
  - uses **nonlinear model** to simulate trajectory and get optimal control actions

Benefits:

- Linear MPC:
  - Computationally **cheap** to evaluate[12]
- Nonlinear MPC:
  - Highly **accurate** predictions

Challenges:

- Linear MPC:
  - **Less accurate** predictions (if true system is nonlinear)
- Nonlinear MPC:
  - Computationally **expensive** to evaluate[12]
- Building systems are typically **complex** and **nonlinear**[9]