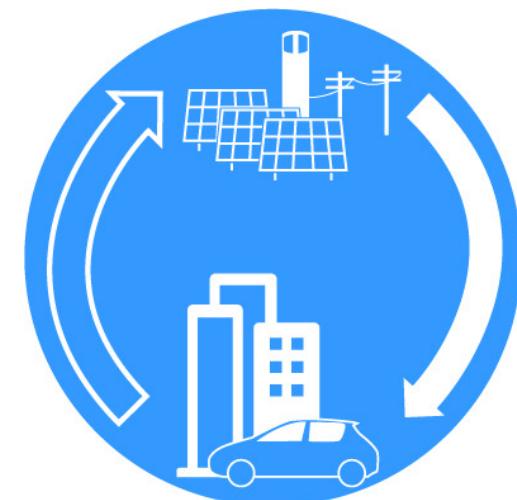


Estimating Household's Physical Parameters Using Neural Ordinary Differential Equations

Davud Topalović and Dušan Gabrijelčič
Jožef Stefan Institute

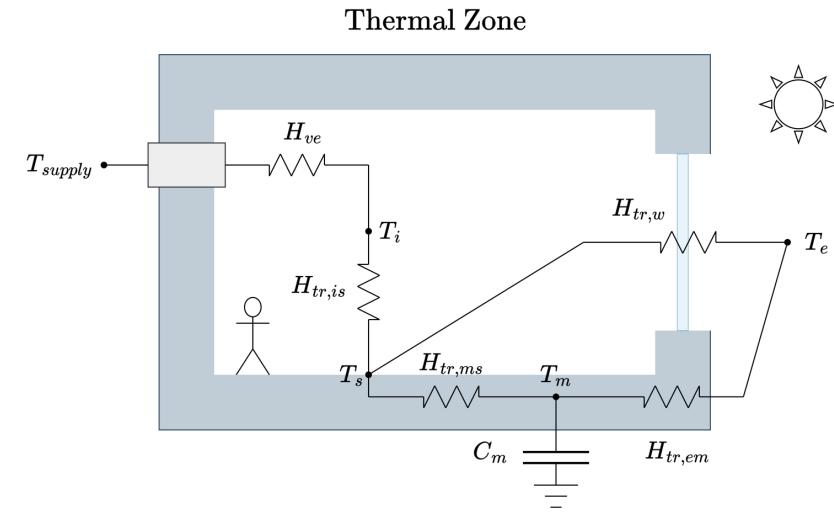
Motivation

- The integration of renewable energy sources into the power grid presents unique challenges due to the **varying nature of power generation and the decentralization of energy sources**.
- Grid stability and efficient energy consumption is crucial.
- DEMAND-SIDE FLEXIBILITY – controlling the electricity usage by consumers and prosumers to improve efficiency.



Motivation

5R1C thermal model, EN ISO 13790



Building – significant DSF potential

Thermal mass

&

HVAC system

$$C_m = A_f \cdot c_f$$

$$H_{ms} = 9.1 \cdot A_m$$

$$A_m = 2.5 \cdot A_f$$

$$A_t = 4.5 \cdot A_f$$

$$H_{em} = u_{walls} \cdot A_{walls}$$

$$H_w = u_{windows} \cdot A_{windows}$$

$$H_{is} = 3.45 \cdot A_t$$

$$H_{ve} = 1200 \cdot V_{room} \cdot ach_{tot}$$

$$T_m \cdot (H_{tr3} + H_{em}) + C_m \cdot \frac{dT_m}{dt} = \Phi_{mtot}$$

$$\Phi_{mtot} = \Phi_m + H_{em}T_e + \frac{H_{tr3}}{H_{tr2}}(\Phi_{st} + H_wT_e + H_{tr1}T_{sup} + \frac{H_{tr1}}{H_{ve}}(\Phi_{HC} + \Phi_{ia}))$$

$$\Phi_{ia} = 0.5 \cdot \Phi_{int}$$

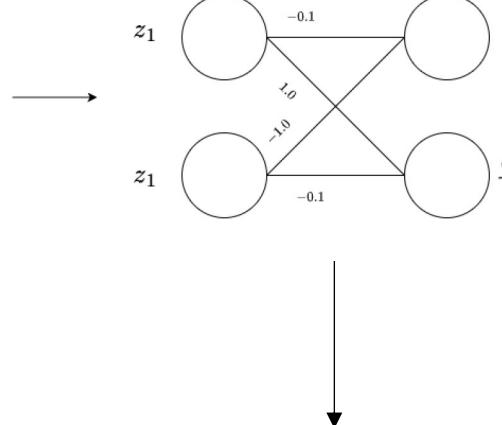
$$\Phi_m = \frac{A_m}{A_t}(0.5 \cdot \Phi_{int} + \Phi_{sol})$$

$$\Phi_{st} = \left(1 - \frac{A_m}{A_t} - \frac{H_w}{9.1 \cdot A_t}\right)(0.5 \cdot \Phi_{int} + \Phi_{sol})$$

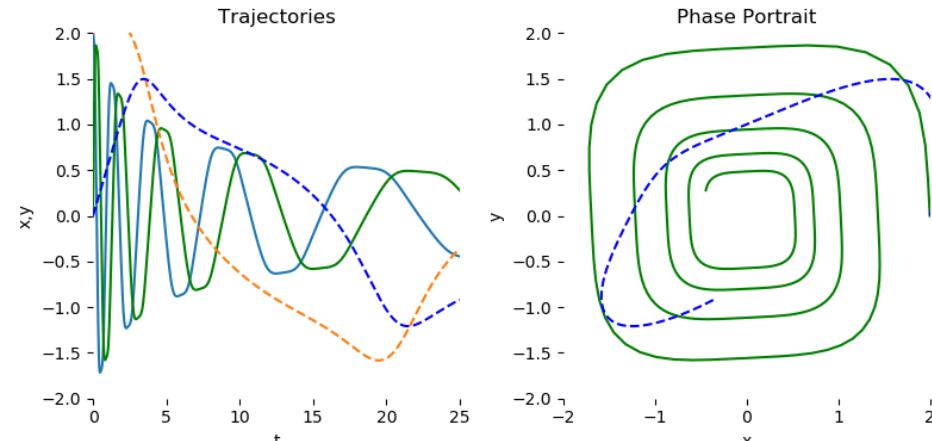
Neural Ordinary Differential Equations

- powerful deep algorithm that utilizes Neural Networks for inferring the dynamics of the system.

$$\frac{d}{dt} \begin{bmatrix} z_1 \\ z_2 \end{bmatrix} = \begin{bmatrix} w_{11} & w_{12} \\ w_{21} & w_2 \end{bmatrix} \begin{bmatrix} z_1 \\ z_2 \end{bmatrix}$$

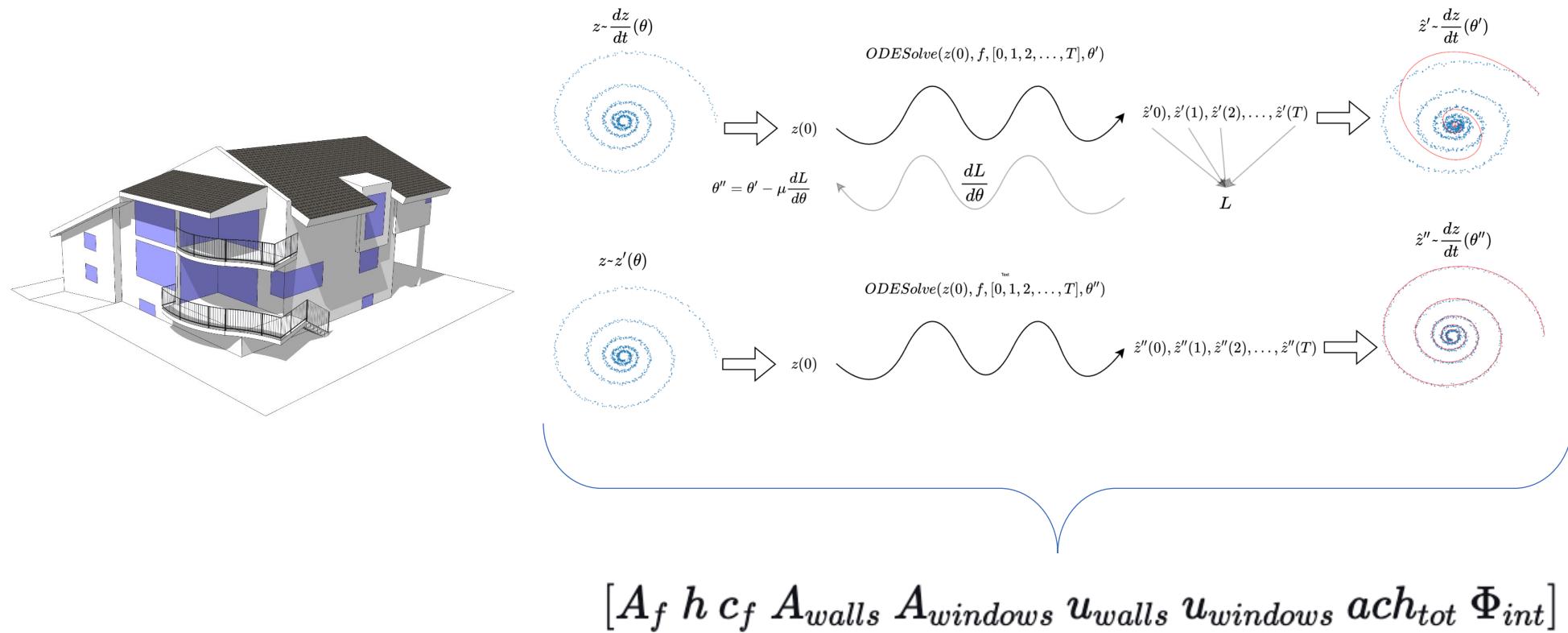


$$\frac{d}{dt} \begin{bmatrix} z_1 \\ z_2 \end{bmatrix} = \begin{bmatrix} -0.1 & 1.0 \\ 1.0 & -0.1 \end{bmatrix} \begin{bmatrix} z_1 \\ z_2 \end{bmatrix}$$

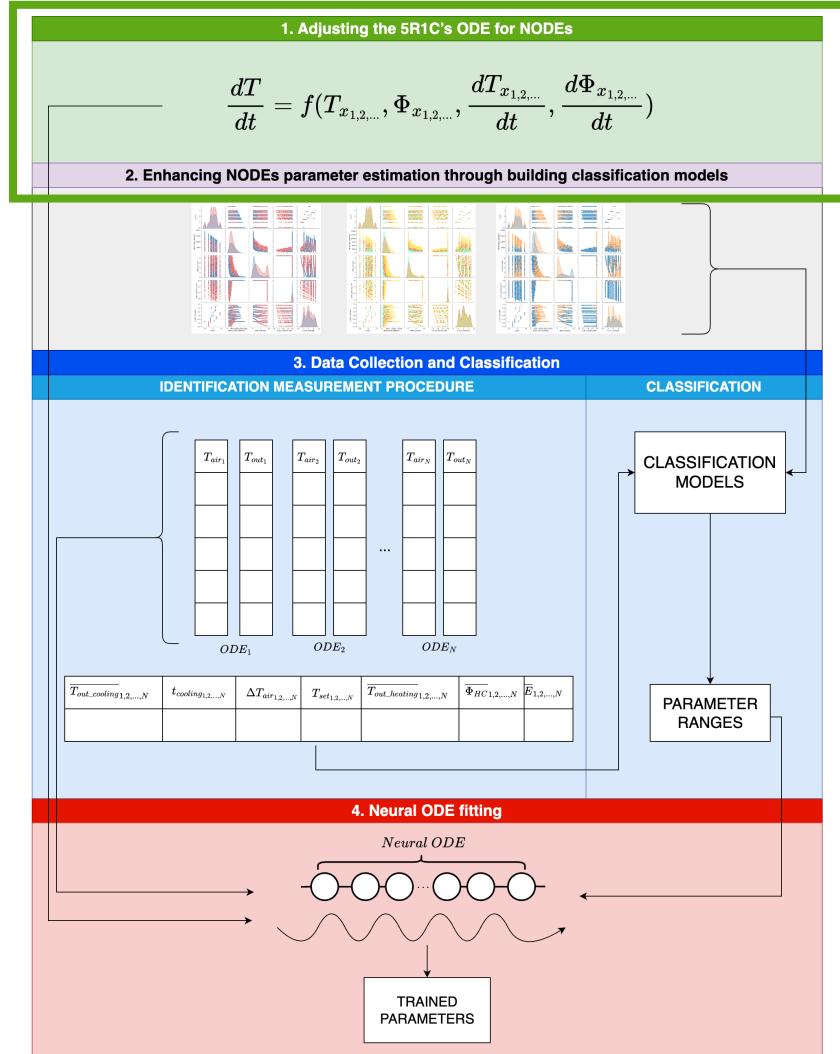


<https://github.com/rtqichen/torchdiffeq>

Neural Ordinary Differential Equations



Methodology



$$T_m \cdot (H_{tr3} + H_{em}) + C_m \cdot \frac{dT_m}{dt} = \Phi_{mtot}$$

$$\frac{dT_{air}}{dt} = \frac{H_{is}}{(H_{is} + H_{ve}) \cdot (H_{ms} + H_{tr2})} \cdot \left(H_{ms} \cdot \frac{dT_m}{dt} + H_{tr2} \cdot \frac{dT_e}{dt} + \frac{H_{tr1}}{H_{ve}} \cdot \frac{d(\Phi_{ia} + \Phi_{HC})}{dt} + \frac{d\Phi_{st}}{dt} \right) + \frac{1}{H_{is} + H_{ve}} \cdot \left(H_{ve} \cdot \frac{dT_e}{dt} + \frac{d(\Phi_{ia} + \Phi_{HC})}{dt} \right) \quad (22)$$

where:

$$\frac{dT_m}{dt} = \frac{1}{C_m} \cdot (\Phi_{mtot} - T_m \cdot (H_{tr3} + H_{em})) \quad (23)$$

$$\Phi_{mtot} = \Phi_m + H_{em} \cdot T_e + \frac{H_{tr3}}{H_{tr2}} \cdot \left(\Phi_{st} + H_w \cdot T_e + H_{tr1} \cdot T_e + \frac{H_{tr1}}{H_{ve}} \cdot (\Phi_{ia} + \Phi_{HC}) \right) \quad (24)$$

$$T_m = \frac{H_{ms} + H_{tr2}}{H_{ms}} \cdot T_s - \frac{1}{H_{ms}} \cdot \left(\Phi_{st} + H_w \cdot T_e + H_{tr1} \cdot (T_e + \frac{\Phi_{ia} + \Phi_{HC}}{H_{ve}}) \right) \quad (25)$$

$$T_s = \frac{H_{is} + H_{ve}}{H_{is}} \cdot T_{air} - \frac{H_{ve} \cdot T_e + \Phi_{ia} + \Phi_{HC}}{H_{is}} \quad (26)$$

$$\Phi_{ia} = 0.5 \cdot \Phi_{int} \quad (27)$$

$$\Phi_m = \frac{A_m}{A_t} \cdot (\Phi_{ia} + \Phi_{sol}) \quad (28)$$

$$\Phi_{st} = \left(1 - \frac{A_m}{A_t} - \frac{H_w}{9.1 \cdot A_t} \right) \cdot (\Phi_{ia} + \Phi_{sol}) \quad (29)$$

night-time case

$$\frac{dT_{air}}{dt} = \frac{H_{is}}{(H_{is} + H_{ve}) \cdot (H_{ms} + H_{tr2})} \cdot \left(H_{ms} \cdot \frac{dT_m}{dt} + H_{tr2} \cdot \frac{dT_e}{dt} \right) + \frac{H_{ve}}{H_{is} + H_{ve}} \cdot \frac{dT_e}{dt} \quad (31)$$

where:

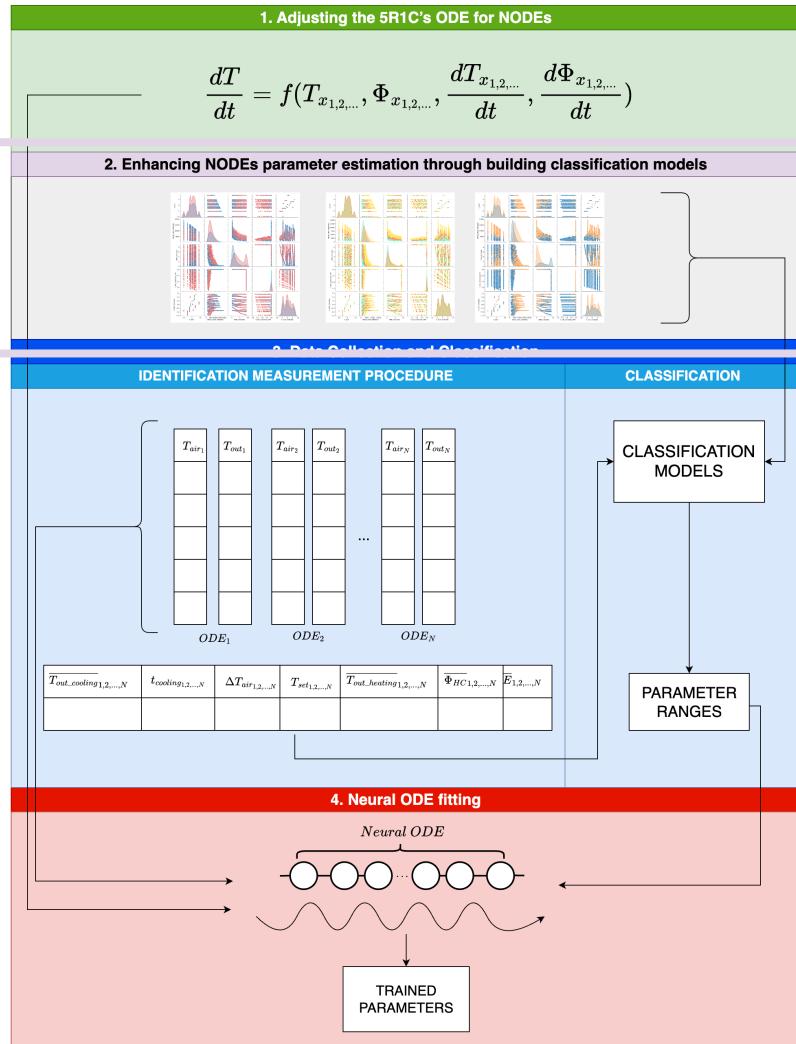
$$\frac{dT_m}{dt} = \frac{1}{C_m} \cdot (\Phi_{mtot} - (H_{em} + H_{tr3}) \cdot T_m)$$

$$\Phi_{mtot} = (H_{em} + H_{tr3}) \cdot T_e + \frac{H_{tr3}}{H_{tr2}} \cdot \frac{H_{tr1}}{H_{ve}} \cdot \Phi_{HC}$$

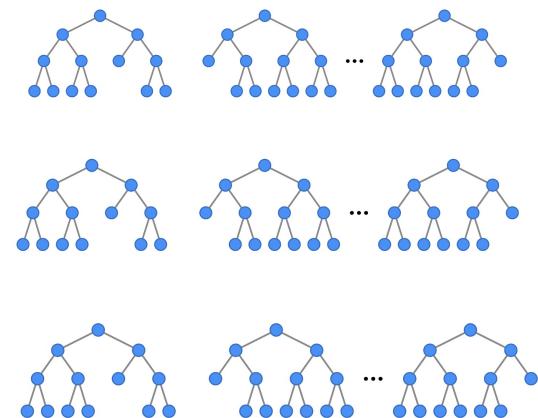
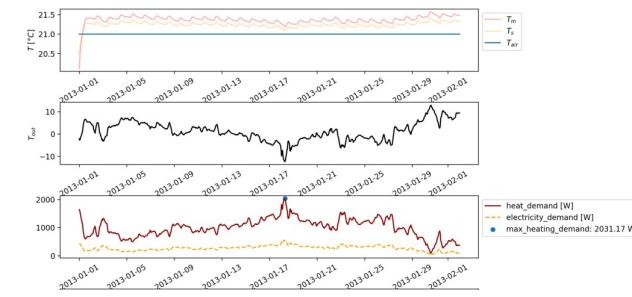
$$T_m = \frac{H_{ms} + H_{tr2}}{H_{ms}} \cdot T_s - \frac{H_{tr2}}{H_{ms}} \cdot T_e + \frac{H_{tr1} \cdot \Phi_{HC}}{H_{ve} \cdot H_{ms}}$$

$$T_s = \frac{H_{is} + H_{ve}}{H_{is}} \cdot T_{air} - \frac{H_{ve} \cdot T_e + \Phi_{HC}}{H_{is}}$$

Methodology



→ BUILDING CLASSIFICATION MODELS with synthetic dataset



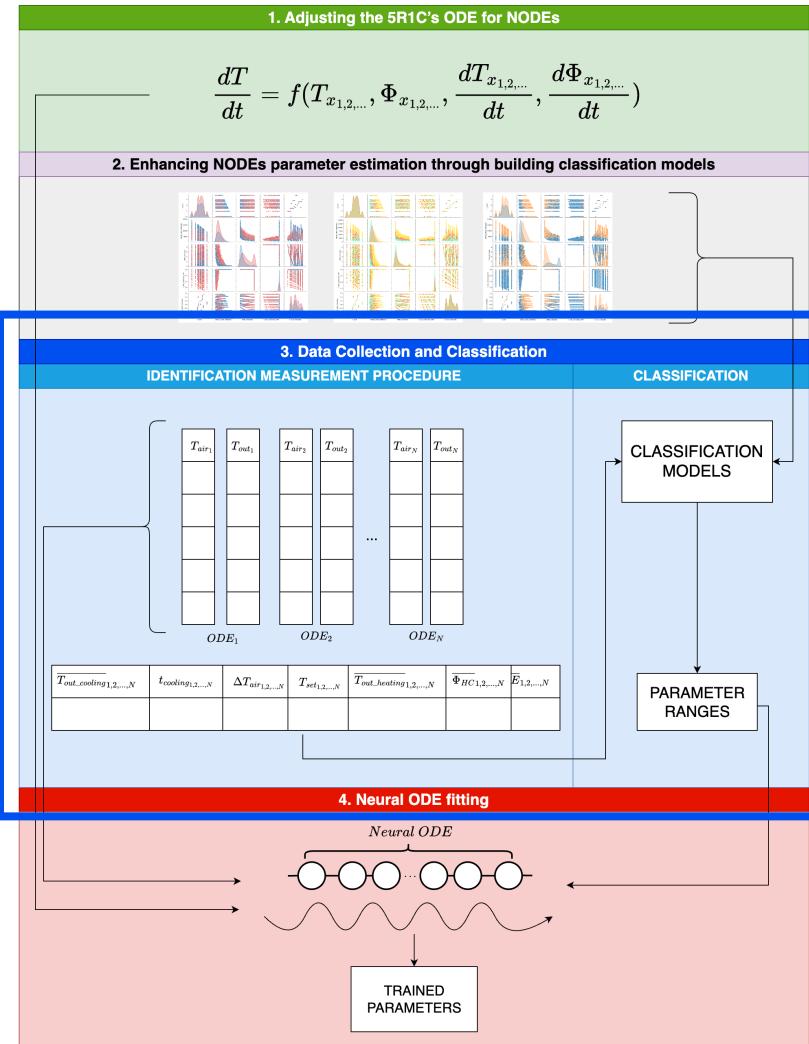
$$A_f \in [50, 100], [100, 200], [200, 300]$$

$c_f \in$ light, medium, heavy

$$u_{walls} \in [0.1, 1], [1, 2]$$

Predict the range for individual parameters and use them as constraints.

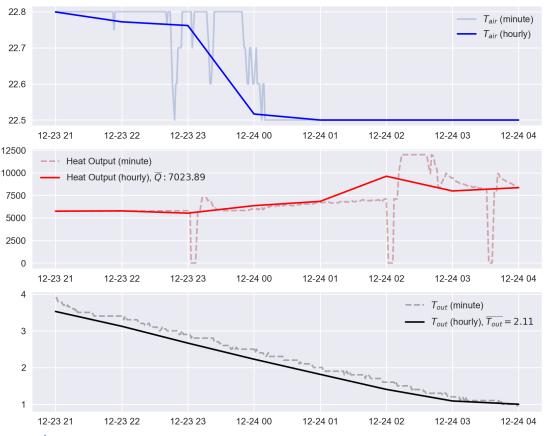
Methodology



Data collection – Identification Measurement Procedure

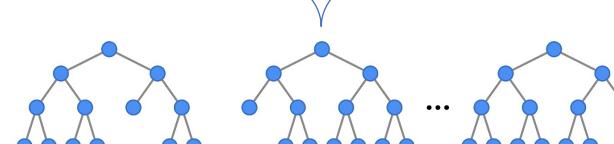
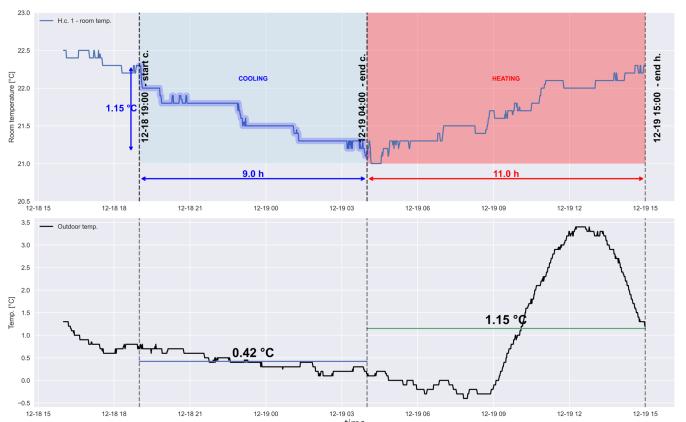
Normal operation night

2023-12-23

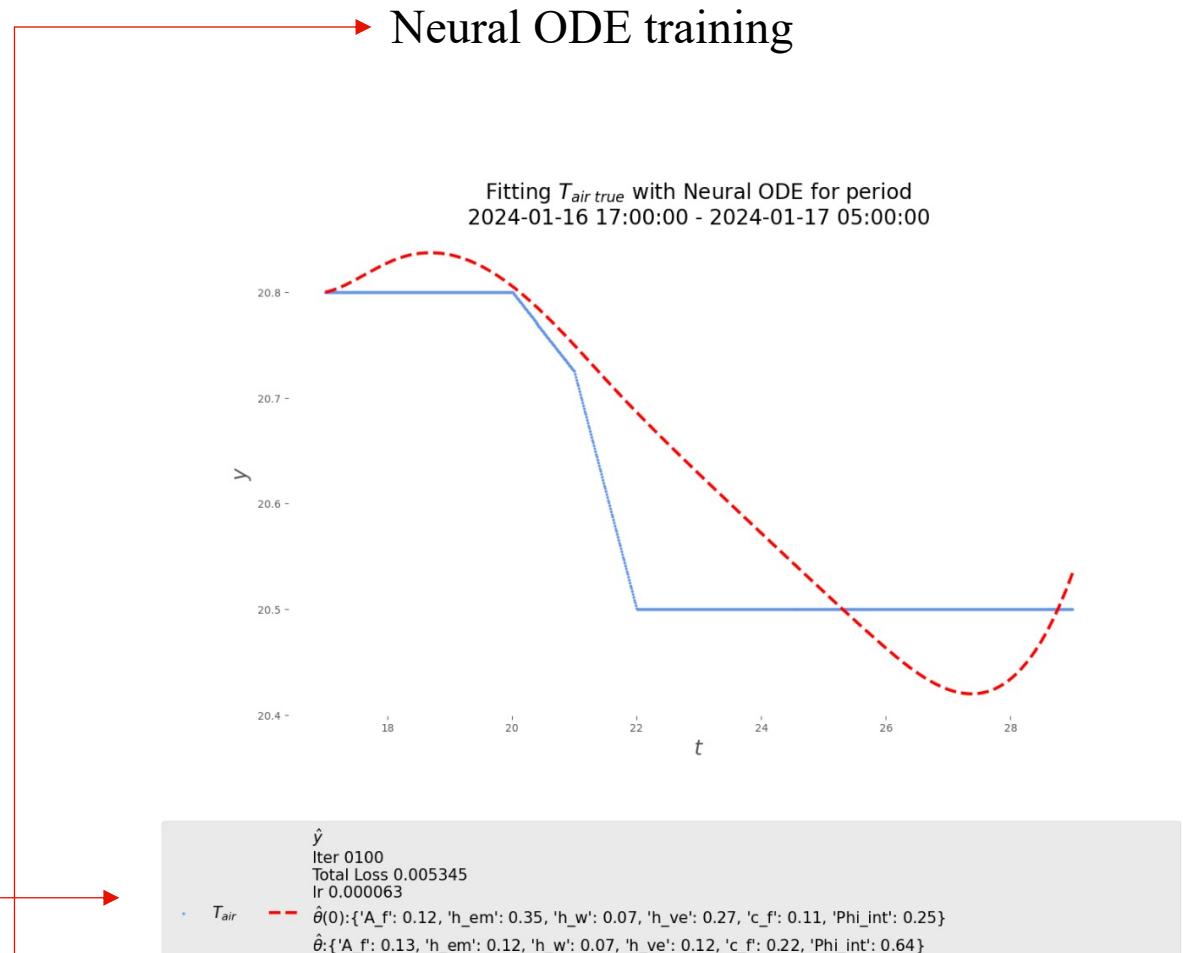
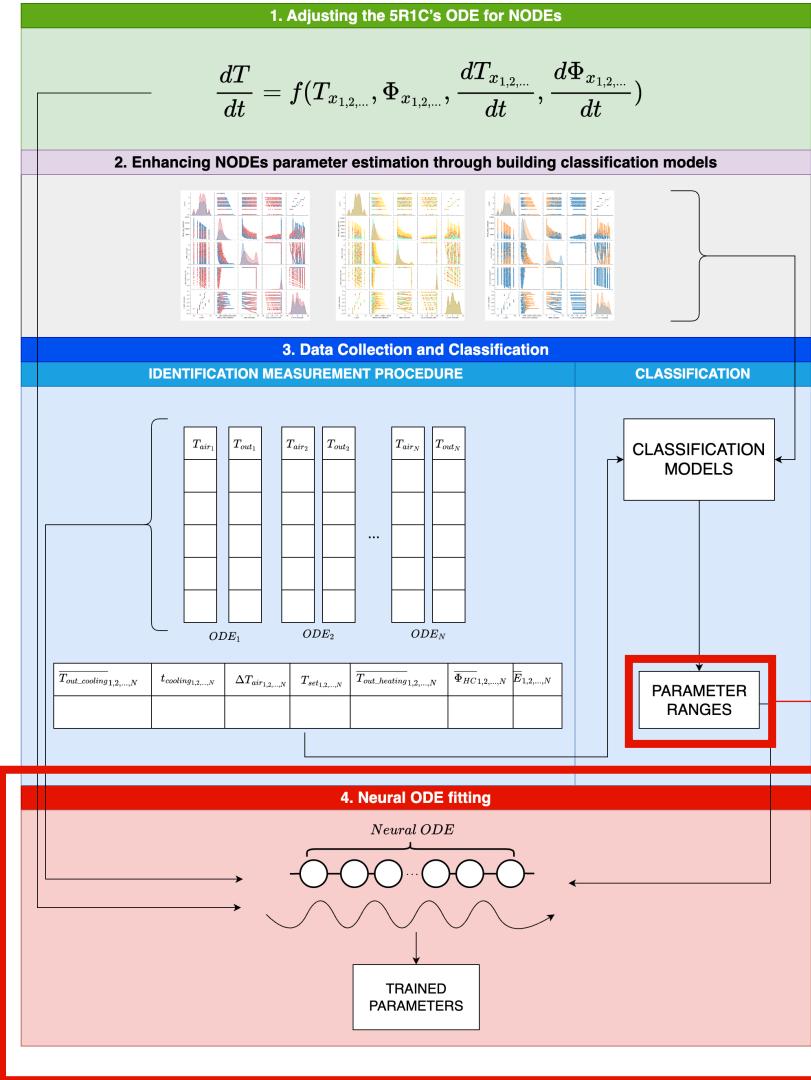


Constrained heating night

Night time cooling test on 18.-19. December 2023.



Methodology



Case Study – results



Results on classification models

We generated 900 virtual households by varying physical parameters such as floor area, walls height, thermal capacity and u-values.

We come up with a dataset of shape 35100x8 (with 35,100 instances and 8 features). From the generated data, we were able to train random forest model for A_f , c_f , u_{walls} .

TABLE III
CLASSIFICATION RESULTS USING RANDOM FOREST

Parameter	Parameter Range	Training Accuracy	Test Accuracy
A_f	(60, 100)		
	(100, 200)	93%	87%
	(200, 300)		
c_f	LIGHT (0.8 – 1.65)	85%	78%
	HEAVY (1.65 – 3.7)		
u_{walls}	(0.2 – 1.0)	86%	84%
	(1.0 – 2.0)		

Case Study – results



Data collection and Classification

IMP procedure - conducted in December, 2023 and January, 2024.

Constrained heating operation was performed twice and normal operation nights were taken only from January.

$$A_f : (200, 300)$$

$$c_f : \text{HEAVY} - (1.65 - 3.7)$$

$$u_{walls} : (0.2 - 1.0)$$

TABLE IV
PARAMETER COMPARISON

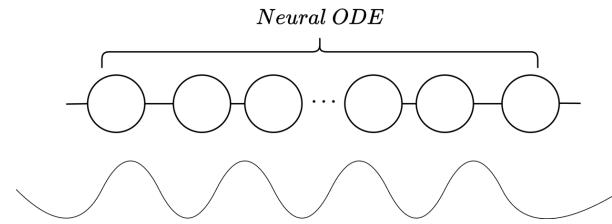
Parameter	True Value	Trained Value	Relative Error (%)
A_f	250.00	294.56	17.82
h	5.2	4.79	7.88
walls_area	263.10	256.01	2.70
windows_area	65.78	73.89	12.34
c_f	3.70	3.23	12.70
u_{walls}	0.60	0.72	20.00
$u_{windows}$	3.50	3.31	5.43

TABLE V
EVALUATION OF THE TRAINED PARAMETER VALUES

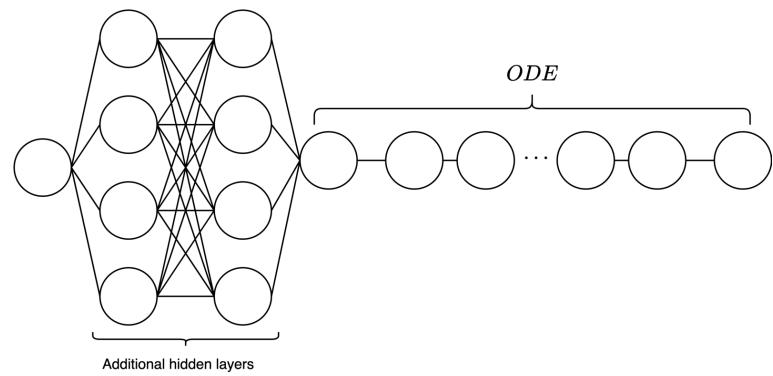
	November	December	January
ΔQ_{total} (kWh)	6.05	10.61	9.85
ΔQ_{power} (kW)	0.756	1.33	1.23
ϵ (%)	18.65	20.17	19.22

Future work

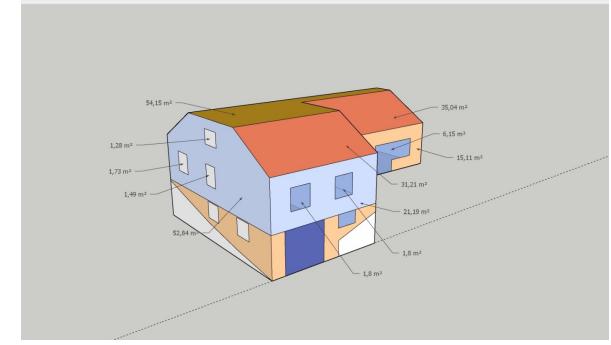
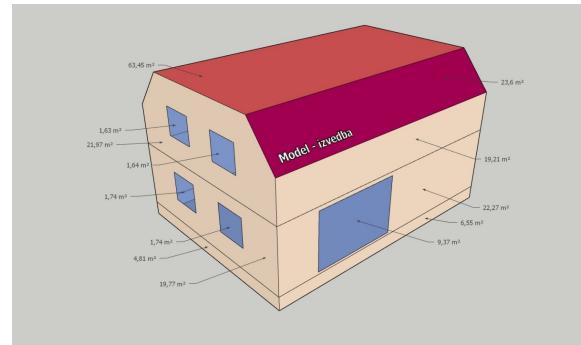
1. Experiment with more complex architectures



Include hidden layers that will not disturb the underlying physics of the system.



2. Apply the solution on multiple households and refine the solution



3. Include internal gains, solar gains and air ventilation

$$\Phi_{st} = \left(1 - \frac{A_m}{A_t} - \frac{H_w}{9.1 \cdot A_t}\right) \cdot (\Phi_{ia} + \Phi_{sol})$$

Thank you ☺

Questions?