Estimating Household's Physical Parameters Using Neural Ordinary Differential Equations

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***Abstract*—Integrating renewable energy sources into power grids introduces challenges due to the decentralization and variability of power generation. Demand-side flexibility (DSF) is one solution for optimizing power consumption. Buildings in particular offer significant DSF potential due to their large thermal mass and controllable HVAC (Heating, ventilation, and air conditioning) systems. Maximizing DSF benefits requires accurate energy consumption and heat demand prediction. Therefore, the development of robust thermal models for consumer/prosumer households that adhere to international energy standards is needed. Thermal models are based on Ordinary Differential Equations (ODE) and explain the thermal behavior in view of the household's physical parameters, e.g. floor area or thermal capacity. Since measuring these parameters is often impractical, this paper introduces a novel approach for household's parameters identification. Our methodology involves adapting the model's ODE for air temperature observations and enhancing parameter estimation through a comprehensive synthetic dataset. We then classify households into parameter ranges based on collected data, facilitating Neural ODEs training to fit measured temperatures to the ODE for parameter inference. The major contribution of our work is in providing a scalable solution that eliminates the need for individual parameter measurements, enhancing the feasibility of implementing DSF strategies in a broader context.**

Keywords*—Demand-side flexibility; Power consumption; Thermal model; Identification; NODEs

I. INTRODUCTION

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. As technology advances and more smart devices integrate into the grid, ensuring grid stability and efficient energy consumption become crucial. One promising approach is demand-side flexibility, which focuses on controlling and optimizing electricity usage by consumers and prosumers to improve efficiency.

To make progress in harnessing demand-side flexibility, it is essential to understand the needs of consumers, especially in residential buildings where a significant portion of electricity is used, particularly for heating. Our goal is to create a model that predicts electricity consumption based on the predictions of heat demand. This requires the development of a robust thermal model.

In our work, we rely on a well-known and standardized thermal model - the 5R1C model, defined within the EN ISO 13790 Standard [1]. However, obtaining the parameters for this model presents a practical challenge, particularly in the context of large-scale implementation, where measuring these parameters for every household becomes infeasible. Our aim is to automate the identification of the household's parameters with minimal data requirements, a task that has been tackled in various ways in previous research. The identification of a simplified thermal model was carried out through the observation of external mean wall temperatures and the application of optimization methods in the research conducted by [2]. Similarly, [3] proposed a two-step identification framework based on the least square method and statistical analysis, considering factors such as air exchange rates and other thermal characteristics. Additionally, studies such as [4] focus on identifying various models using likelihood estimations and a likelihood-test based forward strategy that selects the most suitable model. Another relevant study, [5], utilized an optimization model that employs the Reflective Newton algorithm, excluding consideration of heat transfer through glaze surfaces. However, many of these studies require substantial data inputs for accurate estimation of model parameters.

To address some of the issues related to parameter estimation, Neural Ordinary Differential Equations (NODEs) have emerged as a class of neural network models that extend traditional deep learning by using differential equations to define the behavior of the models. Important paper by [6] introduced the groundbreaking concept of the adjoint sensitivity method. This method significantly improved the training efficiency of NODEs by efficiently computing gradients, making them a powerful tool for continuous-time modeling and dynamic system analysis in machine learning.

Our approach exploits the advancements brought about by the NODEs and takes a distinctive path to thermal model identification. Firstly, in addition to estimating the thermal parameters (like thermal capacity or heat transfer coefficients), we also account for the physical parameters, such as floor area or walls height. Secondly, rather than relying on traditional optimization techniques, we leverage the thermal behavior of the building itself to classify measured data into parameter ranges. Moreover, we utilize the NODEs algorithm, which enables us to learn the system's ODE (therefore its parameters) by constraining the search space with the classified parameter ranges.

Notably, our approach requires relatively small amount of easily measurable night-time data: indoor/outdoor temperature observations and output heat power from the HVAC system, effectively eliminating the need for modeling solar gains.

This paper introduces a novel approach for physical parameters estimation by extending and validating the 5R1C simple hourly method, with a particular focus on night-time calculations. To do that, the paper is structured as follows: first, we provide a general overview of the 5R1C simple hourly method in order to set the theoretical background for the study; then, we define the general methodological framework in terms of four major steps - two at a conceptual and two at an empirical level; finally, in order to demonstrate the practical feasibility of the proposed methodology, we apply it to a real-world use case of a Slovenian household. In the end, we conclude and provide potential future directions to pursue in our research.

II. The 5R1C Simple Hourly Method

One of the key components of ISO 13790:2008 is the 5R1C model. The 5R1C model is an Ordinary Differential Equation (ODE)-based framework that captures the thermal behavior of a building on hourly level. This involves the calculation of heating (or cooling) demand for each hour, based on the environmental conditions and temperature setpoint. The model, as presented in Figure 1, is based on an equivalent resistance-capacitance (R-C) circuit, where resistors (R or H in Figure 1) represent the heat transfer characteristics of the building envelope and the capacitor represents the thermal mass of the interior (C).

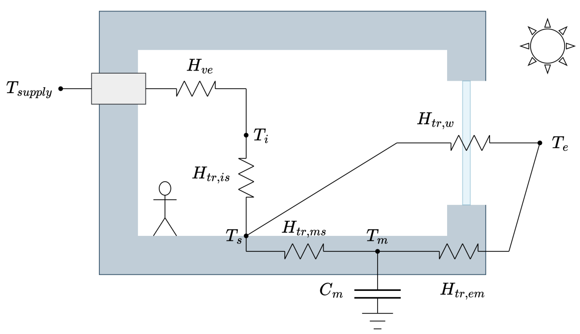

Fig. 1. 5R1C Model

Denoting by T_m, temperature of the thermal mass in the room, the ODE for the R-C circuit in Figure 1 is given by:

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

with Φ_{mtot} representing an equivalent thermal heat flux based on the solar heat gains, internal heat gains, external air temperature and the thermal conductance of the building elements.

To obtain the hourly calculations, the ODE 1 is discretized and can be solved numerically as:

$$T_{m_{k+1}} = \frac{\Phi_{mtot_{k+1}} + T_{m_k}\left(\frac{C_m}{\Delta t} - 0.5 \cdot (H_{tr3} + H_{em})\right)}{\frac{C_m}{\Delta t} + 0.5 \cdot (H_{tr3} + H_{em})} \tag{2}$$

Based on thermal mass temperature T_m, for the $k+1$-th hour we can calculate the temperature of the inside room surface, $T_{s_{k+1}}$, and the air temperature, $T_{air_{k+1}}$:

$$T_{air_{k+1}} = \frac{H_{is} \cdot T_{s_{k+1}} + H_{ve} \cdot T_{\text{supply}_{k+1}} + \Phi_{ia_{k+1}} + \Phi_{HC_{k+1}}}{H_{is} + H_{ve}} \tag{3}$$

Ignoring the parameters that define the solar gains, Φ_{sol}, such as the position and orientation of the household, solar and light transmittance of the glazed surfaces, there are 9 different physical parameters that define 5 resistors and 1 capacitor of the 5R1C mode. These parameters are detailed in Table I.

TABLE I
Description of Physical Parameters for the 5R1C Model

Parameter name	Description, Unit
A_f	floor area, $[m^2]$
h	wall height, $[m]$
$walls\_area$	total area of all outside walls, $[m^2]$
$windows\_area$	total area of all windows, $[m^2]$
c_f	thermal capacitance of the room per floor area, $[10^5 J/m^2K]$
u_{walls}	U-value of opaque surfaces, $[W/m^2K]$
$u_{windows}$	U-value of glazed surfaces, $[W/m^2K]$
ach_{vent}	Air changes per hour through ventilation, $[1/m^3]$
ach_{infl}	Air changes per hour through infiltration, $[1/m^3]$

III. Methodology

Our methodology encompasses 2 steps to parameter estimation at a conceptual level and 2 steps at an empirical level. This is shown in Figure 2:

1. Adjusting the 5R1C's ODE for temperature observations to enable utilization of the NODEs.

2. Enhancing NODEs parameter estimation: Collecting a rich synthetic dataset enabling the design of a classification models for parameter ranges.

3. Data collection and classification: Real-world collected data is comprised of the recorded temperatures and the data obtained by applying the defined procedures within step 2. The later undergoes classification, which allows us to categorize households into specific parameter ranges. This effectively allows setting the boundaries for the parameters during NODEs training.

4. NODEs Training: Using classified parameter ranges and measured temperatures, we proceed to the NODEs fitting step. During this step, we fit the measured temperatures to the corresponding ODE, effectively inferring its parameters.

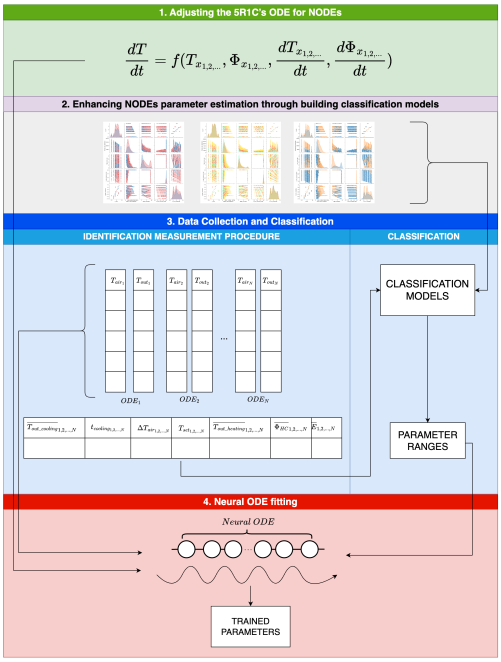

Fig. 2. Methodology steps for household's parameter estimation

A. Step 1: Adjusting 5RC1 ODE for NODEs

To utilize the NODEs algorithm we are required to derive the ODE for T_{air}, as it is the only measurable temperature calculated from the model. By applying the derivative with respect to time to equation 3, we obtain:

$$\frac{dT_{air}}{dt} = \frac{1}{H_{is} + H_{ve}} \cdot (H_{is} \cdot \frac{dT_s}{dt} + H_{ve} \cdot \frac{dT_e}{dt} + \frac{d}{dt} \cdot (\Phi_{HC} + \Phi_{ia})) \tag{4}$$

where:

$$\frac{dT_s}{dt} = f(\frac{dT_m}{dt}, \frac{d\Phi_{st}}{dt}, \frac{d\Phi_{ia}}{dt}, \frac{d\Phi_{HC}}{dt})$$

In theory we could model equation 4 into NODEs, train it and infer the parameters. However, this ODE presents significant complexity due to the presence of Φ_{ia} and Φ_{st} and their rates. These energy fluxes are challenging to directly measure, necessitating difficult approximations. To address this issue we choose to restrict ourselves on two nighttime cases: normal heating case and constrained heating case. The first scenario involves heating with a steady setpoint and heat output, while the latter involves heating interruption (referred to as cooling, despite no active cooling process taking place). For both specific cases, we encounter the following simplified conditions:

- Internal gain, in general, can be approximated as zero, and during the night, its rate of change over time is also zero. This gives us:

$$\Phi_{int} \approx 0 \rightarrow \Phi_{ia} \approx 0 \rightarrow \frac{d\Phi_{ia}}{dt} \approx 0$$

- Solar gain is effectively reduced to zero with the rate of change over time being zero as well. This gives us:

$$\Phi_{sol} = 0 \rightarrow \Phi_{st} \approx 0 \rightarrow \frac{d\Phi_{st}}{dt} \approx 0$$

In case of the normal heating, we approximate Φ_{HC} to be the mean value over the observed nighttime period, while $\frac{d\Phi_{HC}}{dt}$ is approximated as zero. This results in the following ODE for T_{air}:

$$\frac{dT_{air}}{dt} = \frac{H_{is}}{(H_{is} + H_{ve}) \cdot (H_{ms} + H_{tr2})} \cdot \left(H_{ms} \cdot \frac{dT_m}{dt} + H_{tr2} \cdot \frac{dTe}{dt}\right) + \frac{H_{ve}}{H_{is} + H_{ve}} \cdot \frac{dTe}{dt} \tag{5}$$

where:

$$\frac{dT_m}{dt} = \frac{1}{C_m} \cdot (\Phi_{mtot} - (H_{em} + H_{tr3}) \cdot T_m)$$
$$\Phi_{mtot} = (H_{em} + H_{tr3}) \cdot T_e + \frac{H_{tr3}}{H_{tr2}} \cdot \frac{H_{tr1}}{H_{ve}} \cdot \Phi_{HC}$$
$$T_m = \frac{H_{ms} + H_{tr2}}{H_{ms}} \cdot T_s - \frac{H_{tr2}}{H_{ms}} \cdot T_e + \frac{H_{tr1} \cdot \Phi_{HC}}{H_{ve} \cdot H_{ms}}$$
$$T_s = \frac{H_{is} + H_{ve}}{H_{is}} \cdot T_{air} - \frac{H_{ve} \cdot T_e + \Phi_{HC}}{H_{is}}$$

In the case of constrained heating, Φ_{HC} and $\frac{d\Phi_{HC}}{dt}$ converge to zero one hour after the constrained heating process has commenced. The approximation that is taken into account here is that emission systems stop emitting heat one hour after the HVAC system is turned off.

Therefore for $t \geq t_{start} + 1h$, the ODE for T_{air} becomes:

$$\frac{dT_{air}}{dt} = \frac{H_{is}}{(H_{is} + H_{ve}) \cdot (H_{ms} + H_{tr2})} \cdot \left(H_{ms} \cdot \frac{dT_m}{dt} + H_{tr2} \cdot \frac{dTe}{dt}\right) + \frac{H_{ve}}{H_{is} + H_{ve}} \cdot \frac{dTe}{dt} \tag{6}$$

where:

$$\frac{dT_m}{dt} = \frac{1}{C_m} \cdot (\Phi_{m_{tot}} - (H_{em} + H_{tr3}) \cdot T_m)$$
$$\Phi_{mtot} = (H_{em} + H_{tr3}) \cdot T_e$$
$$T_m = \frac{H_{ms} + H_{tr2}}{H_{ms}} \cdot T_s - \frac{H_{tr2}}{H_{ms}} \cdot T_e$$
$$T_s = \frac{H_{is} + H_{ve}}{H_{is}} \cdot T_{air} - \frac{H_{ve}}{H_{is}} \cdot T_e$$

B. Step 2: Enhancing NODEs Parameter Estimation

This section delves into a critical aspect of our approach that precedes NODEs fitting. While NODEs algorithm offers a potent tool for inferring physical parameters specific to a household, it is imperative to address the challenge of ensuring accurate parameter value estimations. NODEs, if left unconstrained during training, can potentially converge to incorrect parameter values that nonetheless fit the temperature observations. This poses a significant issue as our objective is to ascertain the precise parameter values crucial for defining the household's thermal model.

We propose two key strategies to mitigate the risk of NODEs learning inaccurate parameters:

1. Imposing Physical Boundaries: One approach involves setting explicit physical boundaries for each parameter. By restricting parameter values within their valid physical domains during the training process, we ensure that the NODEs cannot converge to values outside these bounds. However, even with this constraint, as we contend with seven distinct parameters, the model might still identify various parameter combinations that fit the temperature observations. To tackle this challenge effectively, we introduce a novel solution:

2. Identification Measurement Procedure (IMP): Leveraging the explicit 5R1C thermal model's capability to precisely simulate hourly thermal behavior based on physical parameters, environmental conditions and temperature setpoint, we create a diverse set of virtual households, each defined by distinct parameter set. These virtual households undergo a testing process known as the Identification Measurement Procedure (IMP), designed to gather data that elucidates their thermal behavior. This data collection serves as the foundation for building classification models that classify households into parameter ranges. Such parameter ranges are used as an parameter constraint input to NODEs training process.

The IMP encompasses the following steps:

a. Determining Operating Temperature Range: We identify a comfort temperature range (ΔT) in which we can operate. We test for different ranges but this is typically within a 1°C variation around the temperature setpoint (T_{set}).

b. Observing Constrained Heating Patterns: For multiple nights the household is cooled from the upper limit ($T_{max} = T_{set} + \Delta T$) to the lower limit ($T_{min} = T_{set} - \Delta T$) or for a preferred, predefined period of time. The observed data from this process includes:

- T_{air} - observations of the indoor temperature
- T_{out} - observations of the outside temperature
- $\overline{T_{out}}$ - average outside temperature
- $t_{cooling}$ - cooling time
- ΔT_{air} - indoor temperature drop

c. Observing Normal Heating Patterns: For multiple nights the household is maintained on various temperature setpoints, defined inside the temperature comfort range. The observation period is from 22:00 to 5:00, as heating power is only used for supplying the temperature (excluding sanitary water). The observed data from this process includes:

- T_{air} - observations of the indoor temperature
- T_{out} - observations of the outside temperature
- T_{set} - temperature setpoint
- $\overline{Q_{HC}}$ - mean heat power

What IMP provides us is twofold:

1. Classification Data: The IMP collects data that enables the classification of households into distinct parameter ranges. These ranges serve as crucial input boundaries for NODEs during training.

2. Temperature Observations: For every observed night, whether it involves cooling or heating/maintaining the temperature set point, we extract air temperature observations. These observations serve as the key input for modeling by the NODEs algorithm.

As the next two steps are devised at an empirical level, we will demonstrate their application through the real-world case study.

IV. Case Study: Determining the Physical Parameters of a Slovenian Household

This section provides the preliminary results of a case study conducted on a household in Slovenj Gradec, Slovenia. The household is equipped with a Kronoterm heat pump and smart metering capabilities. This smart meter can measure indoor and outdoor temperatures, export heat power, and import active power.

To justify the suitability of applying the 5R1C hourly method to the particular use case, we first perform some validation tests as pre-preparation for applying the methodology. It is worth noting that the first step of the methodology is a theoretical adjustment of the model, which is why it is also integrated into this step.

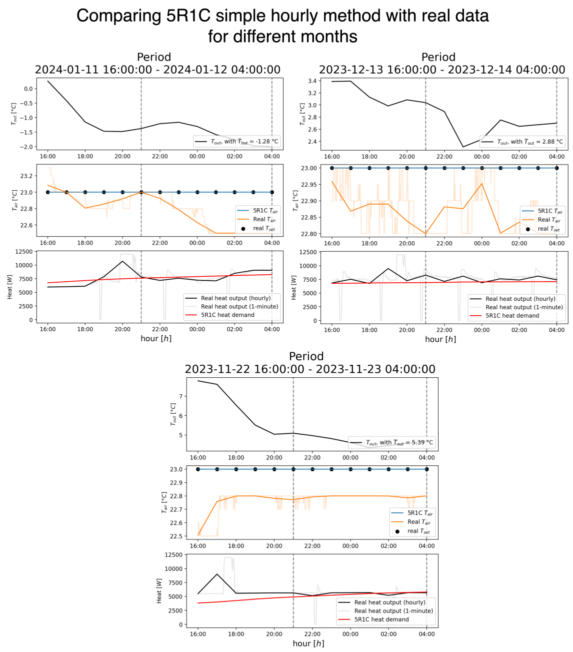

Fig. 3. Multi-dimensional Validation of the 5R1C Model Across Different Months: The figure presents a month-by-month validation of the 5R1C simple hourly method for 3 subsequent months. The first subplot in each set displays the outside temperature. The second subplot compares the modeled indoor air temperature with the actual measurements, and the third contrasts the modeled heat demand with the actual heat output.

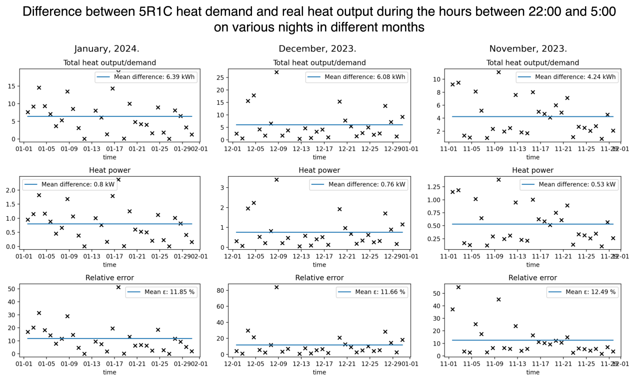

Fig. 4. Validation of the 5R1C simple hourly method applicability: Displayed here are the deviations between the 5R1C model's predicted heat demand and the actual heat output of the heat pump during the nighttime period, from 22:00 to 5:00, when the demand is primarily for space heating.

The validation of the 5R1C simple hourly method was performed through a comparison of the calculated heat demand against the actual heat output recorded with smart metering. The household's physical parameters were determined based on information provided by the household's owner and publicly available data from *Javni vpogled Republike Slovenije*. The comparative analysis for both hourly and total aggregated values was conducted for months spanning from November 2023 to January 2024. Figure 3 shows the close agreement between the model's hourly predictions and the real data, demonstrating that the model can accurately reflect the household's thermal behavior on an hourly level.

TABLE II
VALIDATION OF THE 5R1C SIMPLE HOURLY METHOD APPLICABILITY

	November	December	January
$\overline{\Delta Q_{total}}$ (kWh)	4.24	6.08	6.39
$\overline{\Delta Q_{power}}$ (kW)	0.53	0.76	0.8
ϵ (%)	12.50	11.66	11.85

Figure 4 focuses on the comparison of the model's heat demand prediction with the actual heat output during the nighttime, from 22:00 to 5:00. This interval was strategically selected to exclude the heat pump's output for domestic hot water usage, thereby isolating its heating function. The results, as also detailed in Table II, show a small average difference between model's and real heat power ($\overline{\Delta Q_{power}}$) and model's and real total heat demand ($\overline{\Delta Q_{total}}$) for nighttime period for multiple months. The difference between the average total energy demand for the span of 7 hours does not cross 7kWh and the difference for the mean heat power does not cross 1 kW. In terms of relative error, the model's estimation is off by approximately 12%, which confirms the model's ability to estimate the household's heating demands accurately enough.

A. Building Classification Models

This section presents the results of training classification models, which represents the second step of the methodology.

We generated 900 virtual households by varying physical parameters: A_f, c_f, h, u_{walls} and $u_{windows}$. The parameters for ventilation and infiltration were approximated to be very small or zero, specifically $ach_{vent} = 0$ and $ach_{infl} = 0.01$. This resulted in 900 different houses. Each household underwent the IMP procedure (as defined in subsection III-B) for 15 different days, with different days for constrained heating operation and normal operation. On top of that the normal operation was tested for three temperature setpoints: 22, 23 and 24 °C. This resulted in a dataset of shape 35,100x8 (with 35,100 instances and 8 features). From the generated data, we were able to train classification models for A_f, c_f, and u_{walls}. Different parameter ranges and different classification algorithm were tested and for every parameter, Random Forest algorithm was the most suitable. The results summarizing the selected parameter ranges and the accuracy of the models are presented in Table III.

TABLE III
CLASSIFICATION RESULTS USING RANDOM FOREST

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

B. Data collection and classification

Collecting the data through IMP procedure (as defined in subsection III-B) was done with the following settings:

1. Preferred temperature range was $\Delta T = 1.5$°C T .

2. Preferred constrained heating time was from 22:00 to 5:00. The household was cooled down twice, once in December, 2023 and once in January, 2024.

3. The heating patterns of normal operations were observed for multiple nights in January, 2024. The data obtain from IMP was classified into the following parameter ranges:

- $A_f : (200, 300)$
- $c_f : \text{HEAVY} - (1.65 - 3.7)$
- $u_{walls} : (0.2 - 1.0)$

With that, we complete step 3 from the methodology.

C. NODEs Training

Estimated ranges of the parameters were used as a constraint input to NODEs training. The equations 6 and 5 were modeled in the form of a neural network and trained with NODEs algorithm for the constrained heating night and multiple nights of normal heating. Trained parameter values were then averaged across all training nights. Table IV shows the trained parameter values and the relative error compared to the true parameter values. The best estimated

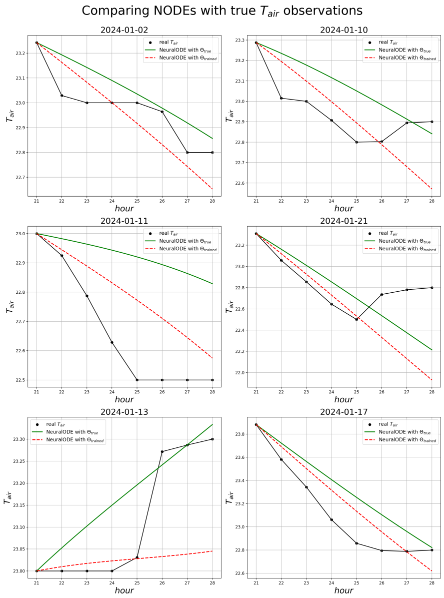

Fig. 5. Comparing the real T_{air} observations with the ones modeled by NODEs defined with true/trained parameters. The reason why the NODEs defined with true parameters (green) doesn't perfectly fit the real observations lies in taking various approximations.

parameter is the $walls\_area$, with relative error of 2.70% and the worse estimated parameter is the u_{walls}, with the relative error of 20.00 %. Figure 5 compares the true T_{air} observations with the one modeled by NODEs defined with true and trained parameters. We can see that the trained parameters, even not perfectly, do model the dynamics of the original system.

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
$\overline{\Delta Q_{total}}$ (kWh)	6.05	10.61	9.85
$\overline{\Delta Q_{power}}$ (kW)	0.756	1.33	1.23
ϵ (%)	18.65	20.17	19.22

Evaluation of the trained parameters was performed through a comparison of the real data and the calculations of the thermal model defined with the trained parameters. Table V shows the average difference between model's and real average heat power ($\overline{\Delta Q_{power}}$) and total heat demand ($\overline{\Delta Q_{total}}$) for a nighttime period for multiple months. The difference between the average total energy demand for the span of 7 hours does not cross 11kWh and the difference for the mean heat power does not cross 2 kW. In terms of relative error, the model's estimation is off by approximately 20%.

V. Conclusion

This paper presents a novel approach for identification of household's physical parameters. The accurate estimation of the physical parameters enabled us to define a more robust thermal model for a household without the need of using huge amounts of data. The viability and the practical utility of the proposed approach were demonstrated through a practical real-world use case, showing the effectiveness of the methodology for parameter estimation. Notably, the $walls\_area$ parameter emerged as the best-estimated parameter, boasting a relative error of just 2.70%. However, it is important to acknowledge the challenges encountered in practical application, exemplified by the 20.00% relative error observed for the parameter u_{walls}. This highlights not only the accuracy of our methodology but also the opportunity for further refinement.

Future work will include obtaining insights and data from more households, which will facilitate the refinement of the methodology through testing for different NODEs architectures and potentially integrating other time varying variables. This will allow us to improve the precision of parameter estimation, resulting in more accurate and robust thermal models.

Acknowledgment

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