State of charge estimation in latent thermal energy storage for domestic hot water applications

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Introduction

Thermal energy storage (TES) in residential buildings promotes the integration of renewables by shifting energy demand related to space heating, cooling and domestic hot water (DHW) to periods of favorable energy supply conditions. Latent thermal energy storage (LTES) leverages phase change materials (PCM) to enable higher energy densities, making it particularly advantageous for residential applications. Despite potential benefits, the development of LTES systems faces challenges in achieving economic feasibility and effortless integration into existing heating and cooling systems. One such challenge is posed by determining the state of charge (SoC), i.e., the amount of available energy in the LTES, which is required for reliable and efficient system operation. Contrary to sensible storage systems, the highly nonlinear thermal behavior of PCMs hinders straightforward SoC estimation from temperature measurements. Alternative approaches proposed in literature often require the addition of new, potentially expensive equipment.

Goal and approach:

This study investigates real-time SoC estimation for a LTES with practical approaches that do not rely on signals from costly measurement equipment. The works focuses on demonstrating a data-driven method, developed in two main steps:

- ❑ Conducting a series of controlled experiments on a LTES using a laboratory setup for charging and discharging under a variety of realistic operating conditions. The evolution of its SoC is computed with an energy balance as the storage undergoes repeated cycling.
- ❑ Training and testing a data-driven model to estimate the calculated SoC evolution in real time, but only relying on a subset of the measured quantities as inputs, restricted to five or less temperature signals.

Experimental data collection

Experiments were conducted on a laboratory setup, a simplified depiction can be seen in figure 1. The LTES features a finned tube heat exchanger (HEX) immersed in an inorganic PCM with a melting Temperature of 58°C. Since the storage is primarily designed for DHW application, it is fitted with two hydraulically separate circuits. The charging circuit was controlled to mimic the behavior of a heat pump, the mass flow was set constant for individual cycles and as long as the temperature was below a defined setpoint (65°C), the heating element supplied nominal power. As the storage inlet temperature T3 reached the setpoint, the power started reducing to maintain the setpoint temperature, and charging terminated when the outlet temperature T4 was sufficiently close to T3. Three combinations of charging flow rate and nominal power were tested, on at least three cycles each.

Various discharging profiles were used, ranging from uninterrupted discharge with constant flow rate, to operation with a synthetically generated DHW demand profile. Discharging with four constant flow rates ranging 3 - 10 kg/min were measured, lasting until the sensor T8 recorded a value below 51°C. A second group of cycles included periodic interruptions, defined by the amount of energy discharged at once and the frequency of discharging events. Resulting periods of standstill allowed for thermal equilibration inside the storage. The third group of cycles represented more realistic operation of a DHW storage, with no strict separation of charging and discharging segments. A synthetic DHW demand profile determined discharging power at any given time, and recharging of the storage occurred independently whenever the temperature threshold was reached, meaning both circuits were often active simultaneously.

Observations:

From the measurement results – see example in figure 2 – it is apparent that no straightforward relationship can be established between the SoC and the temperatures to be use as predictors for the data-driven model. However, several patterns appear to indicate certain storage states. For example, SoC influences the outlet temperatures T4 and T6 along with their derivatives when the respective circuit is active, while T8 provides insight into the progression of phase change along the height. When there is no flow through one or both circuits, the recorded temperatures still provide valuable insight. T5 consistently increases whenever there is no flow, while the rate of this increase also seems to correlate with SoC. Additionally, the beginning of discharging evens can clearly be identified by a sudden drop of this temperature.

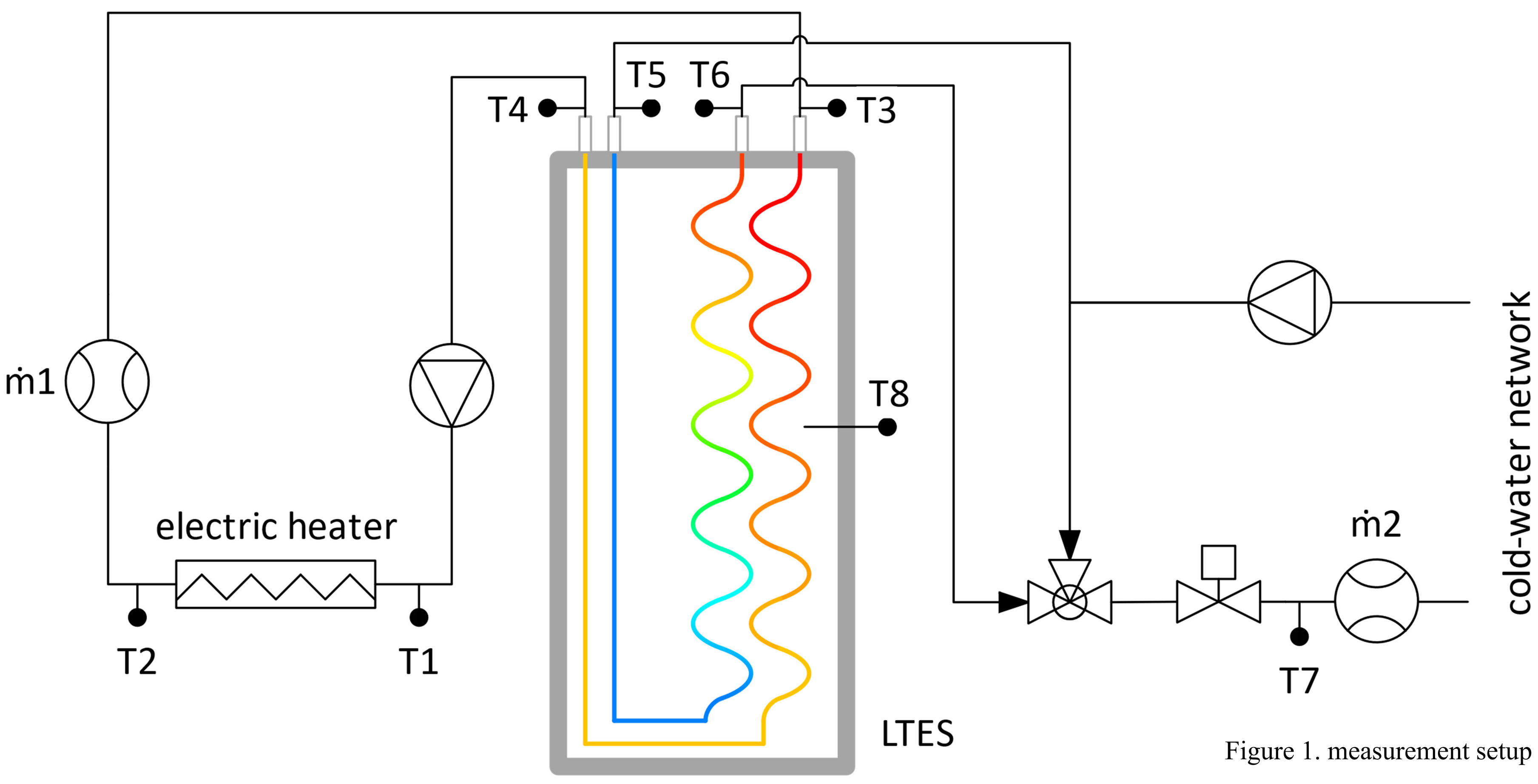

Figure 1. measurement setup

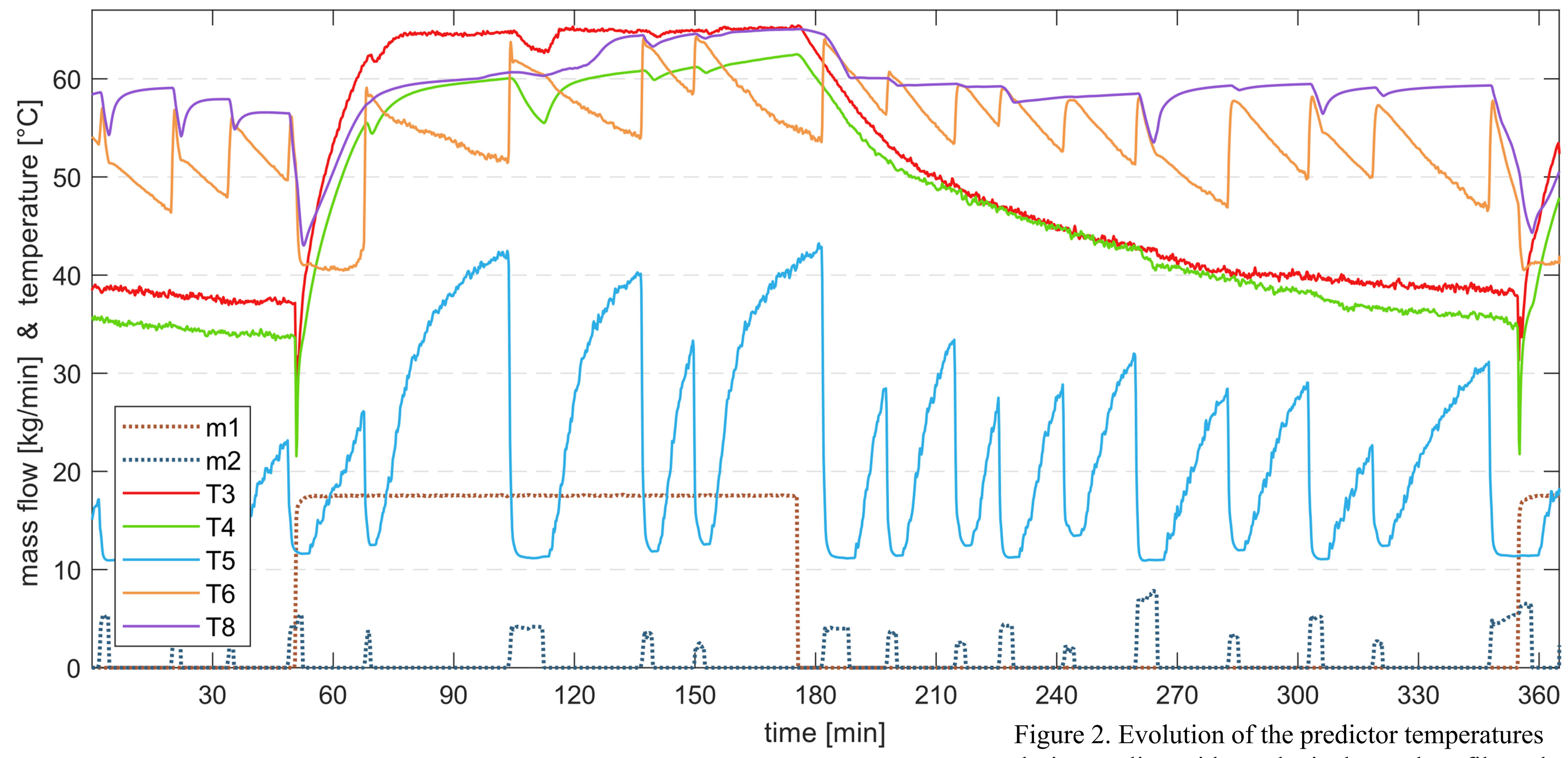

Figure 2. Evolution of the predictor temperatures during cycling with synthetic demand profile and simultaneous recharging

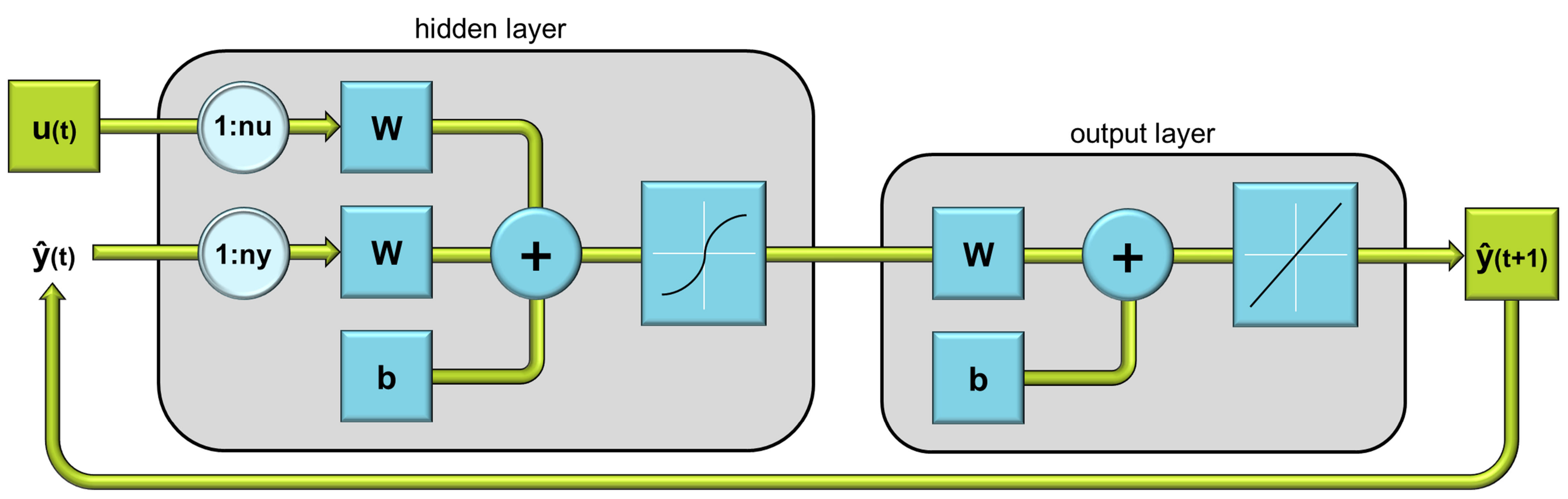

Figure 3. Recurrent NARX network architecture

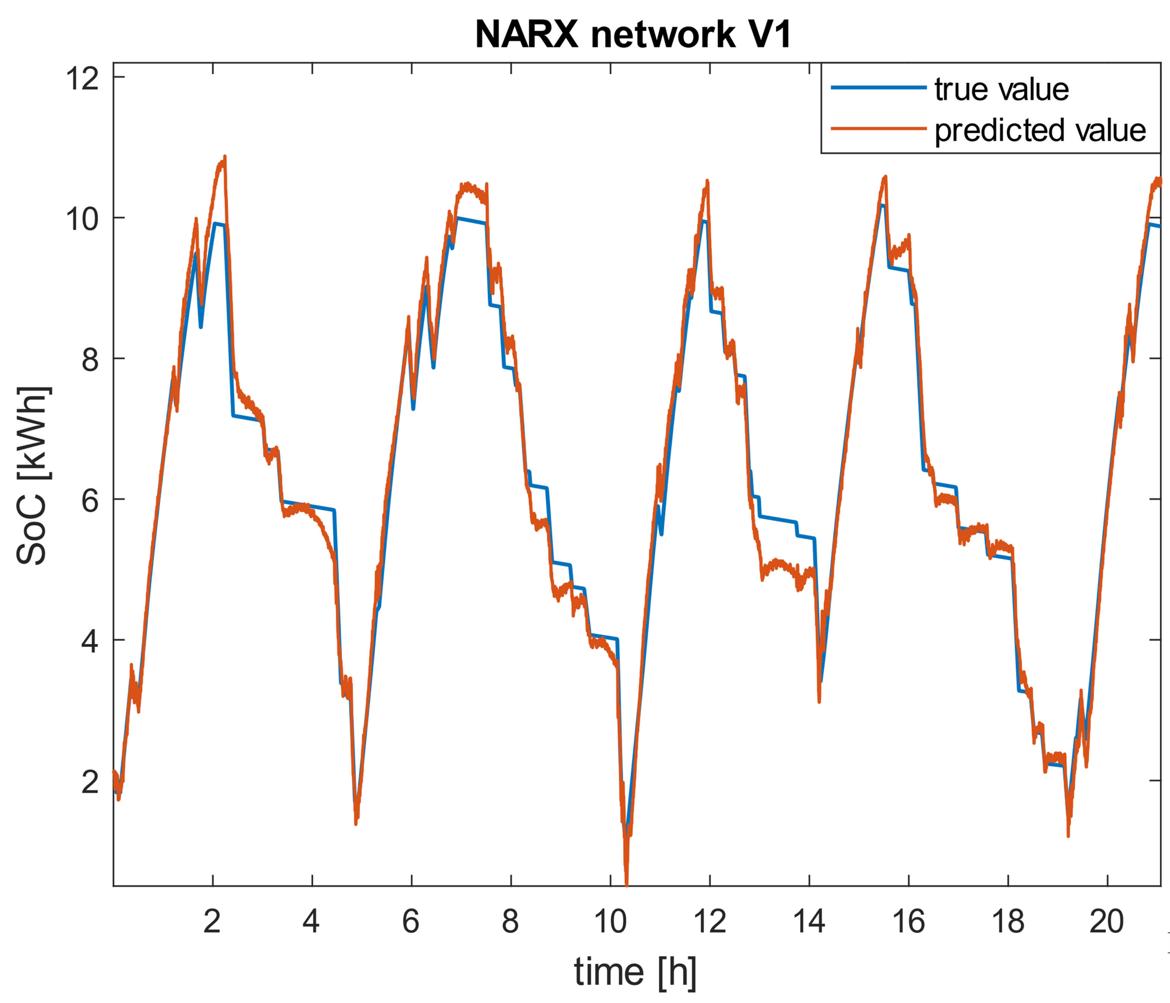

Figure 4. Test performance of NARX model version 1

NARX network V1 parameters & results

inputs	T3, T4, T5, T6, T8
input lags	all up to 5 min
output lags	10, 20, 30, 50, 80, 120, 180, 240, 300 sec
hidden layer(s)	1 layer, 20 neurons
regularization	L2, weight 0.1
training epochs	16
RMSE training	0.238 kWh
RMSE testing	0.326 kWh

Data-driven modelling

The laboratory measurements enabled energy balancing over the LTES to calculate the progression of SoC during repeated cycling. The calculated SoC weas then used as the ‘true’ value to be replicated through data-driven modeling. It must be noted that some error was still present in these values resulting from the numerous calculation steps.

The choice of data-driven modeling framework was nonlinear autoregressive model with exogeneous input (NARX). This approach makes use of multiple previous values of the system’s output u, along with previous values of one or more external input y to predict the current output value, as described by the equation below:

$$\hat{y}_{(t)} = F\left(y_{(t-1)}, y_{(t-2)}, \dots, u_{(t-1)}, u_{(t-1)}, \dots\right) + e_{(t)}$$

An artificial neural network was trained to approximate the function F, relying in part on its own previous predictions, making the network architecture (figure 3) recurre . Since frequent resets are impractical in the foreseen application, the network must also learn to compensate any systematic errors accumulating over time. Models were developed iteratively, exploring different numbers of hidden neurons in one or two layers, as well as changes in available predictor temperatures and their considered lags (previous values).

Results:

The performance of NARX models were tested on separate data not used for training. The best-performing versions, such as V1 depicted in figure 4, are able to track the SoC with an RMSE below 0.4 kWh on both training and test data, and the largest deviations in the range of 1kWh. Model versions employing a small network (<10 neurons) show limited capacity to capture the system’s complexity, while an excessive number of hidden neurons (>30) or input lags leads to overfitting. Model V1 (see specifics in table on the left) represent a suitable level of complexity for the amount and quality of training data available in this study. Reducing the number of available predictor temperatures resulted in noticeably worse performance on both training and test data, with deviations in excess of 2 kWh.

Conclusion

- Laboratory measurements revealed complex relationship between the progression of the recorded predictor temperatures and calculated SoC, but several patterns indicative of certain storage states could be identified.
- Several NARX network versions showed promising training and test results, while limitations posed by the quantity and quality of training data was acknowledged.
- The viability of the presented approach could be established, as models relying only on a set of temperature signals demonstrated sufficient prediction accuracy to support effective energy management in buildings.

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