Neural ODE based Control of Multi-Functional Heatpump Systems

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Battery electric vehicles (BEVs) are one of the most promising candidates for green individual mobility. On the one hand, lithium-ion-based batteries provide an efficient storage capability for energy from renewable resources, on the other hand, electric drives are known for their remarkable overall energy efficiency, especially when compared to internal combustion engines.

However, thermal management of BEVs is a hard challenge since the electric drive should not exceed a peak temperature limit at any time. At the same time, battery lifetime and passenger comfort require the temperatures of the high-voltage battery and the cabin to respect corresponding lower and upper limits. Since all actions for heating or cooling come with a cost in terms of electric energy consumption and therefore an unwanted impact on the remaining driving range, we are seeking intelligent solutions to fulfill the requirements above while minimizing the overall electric energy consumption. On the system design level, the introduction of fully integrated multi-functional heat pumps has been a key enabler to bring battery electric vehicles to the next level. Recent advances on predictive algorithms help on the software side to fully exploit the potential of these new complex system designs (see [1]).
In addition to the challenge of minimal electric energy consumption, we are looking for further improvements in terms of performance (e.g., reduced time for cabin heating or cooling) or system cost efficiency (e.g,. use of waste heat recovery), enabling unique selling points for Bosch as a system provider. However, to solve these challenges with optimal control methods, a mathematical description of the system dynamics is required. Due to complex nonlinearities in the system, i.e., the refrigerant circuit and heat exchangers, a description with classical differential equations is difficult, especially since the model has to allow for low computational efforts in online optimization. Therefore, a data-based approach using Neural ODEs (see [2]) is used in our work to model the temperature dynamics of the various components. This technique uses a neural network NN to approximate the right-handed side of the differential equation, i.e.

$$\dot{\mathbf{x}} = NN(\mathbf{x}, \mathbf{u}).$$

This allows for the approximation of complex dynamics that are difficult to capture in equations, while still allowing the use of classical methods from control engineering and optimization, such as numerical integration with well-known numerical algorithms, e.g., Euler-forward:

$$\mathbf{x}_{k+1} = \mathbf{x}_k + \Delta t \cdot N(\mathbf{x}_k, \mathbf{u}_k) \qquad \forall k = 0, ..., N-1.$$

Our goal is to obtain an accurate prediction

$$\mathbf{X} = \begin{bmatrix}\mathbf{x}_0 & \mathbf{x}_1 & \mathbf{x}_2 & \cdots & \mathbf{x}_N\end{bmatrix}$$

of the component temperatures over a time horizon

$$\mathbf{t} = \begin{bmatrix}t_0 & t_1 & t_2 & \cdots & t_N\end{bmatrix}$$

for a specific control input

$$\mathbf{U} = \begin{bmatrix} \mathbf{u}_0 & \mathbf{u}_1 & \mathbf{u}_2 & \cdots & \mathbf{u}_{N-1} \end{bmatrix}.$$

For this prediction to be accurate enough, the training data must contain the input space of the later evaluation. The DOE must therefore be carefully planned to cover this input space sufficiently. In the next step, the trajectories are used for training the neural network. For this purpose, a feedforward neural network (FNN) is used, although there are also more advanced architectures in the literature [3]. Since there is a large number of parameters for the training process, a hyperparameter analysis must be performed. This allows, for example, a suitable number of layers or neurons per layer to be determined. In addition, various methods such as batch learning, learning rate adaptation, or early stopping are used to improve the training process and must be calibrated for an accurate model.

In our work, we exemplarily investigate the optimal control of the cabin temperature. In a simple model with only one thermal mass T_{Cab}, three input variables significantly influence the temperature of the cabin. These are the ambient temperature T_{Amb}, as well as the inlet temperature T_{In} and blower speed u_{Blwr} of the air into the cabin at the outlet of the HVAC system.

$$\dot{T}_{\mathrm{Cab}} = NN(T_{\mathrm{Cab}}, T_{\mathrm{In}}, \dot{m}_{\mathrm{air}}, T_{\mathrm{Amb}}).$$

After a successful training, the model is used in an optimizer to compute the control input signals $\mathbf{U}_{\mathrm{Opt}}$. The most important goal of the control strategy is to keep the cabin temperature within a temperature window. This is achieved by switching between two different system modes. In Mode 1, the cabin can be heated with a constant inlet temperature $\bar{T}_{\mathrm{In}}$. In Mode 2, the blower is switched off, i.e., $u_{\mathrm{Blwr}} = 0$, so no energy is transferred. The goal of the optimization is to find the switching times to switch between modes 1 and 2, whereby the temperature window must not be violated and energy consumption shall be minimized. In order to compensate for prediction errors of the learned model, the optimizer is used in an MPC scheme with a shorter horizon and fewer mode switches.

In our talk, we will discuss the possibilities and challenges of the entire pipeline. This includes a suitable data collection, the training process, and the application of a NeuralODE in an optimizer/MPC scheme.

Literatur

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