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Application of Feedforward Neural Networks in Battery Electric Vehicle Air Conditioning System Simulations

Abhishek Jain

Nils Framke

Arpit Tiwari

Mihail Spasov

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Abhishek Jain[1]*, Nils Framke[2], Arpit Tiwari[1], Mihail Spasov[1]

[1] Gamma Technologies, LLC, Thermal and Fluid Solver Development,
Westmont, Illinois, USA
a.jain@gtisoft.com

[2]Gamma Technologies GmbH, Thermal and Fluid Applications,
Stuttgart, Germany

* Corresponding Author

ABSTRACT

Machine learning techniques have garnered extensive interest recently to reduce complicated physics-based models. This reduction enables a general speedup of simulations and allows the creation of plant models that can run substantially faster than the physics-based models while maintaining the same accuracy. One promising approach has been using feedforward neural networks (NNs) as a substitute for some of the physics-based sub-systems that make up the system model of a battery and/or fuel cell-powered electric vehicle. The thermal management systems in these vehicles are of utmost importance for component conditioning and obtaining higher efficiencies that translate into greater vehicle range. The two-phase circuit of a thermal management system is generally the bottleneck in the simulation speed of such a system due to complicated phase transitions. We start here with a two-phase circuit in a representative vehicle thermal management system and replace it with feedforward neural nets. We then assess the capabilities of neural nets to reproduce important physical quantities. A commercially available software GT-SUITE is used for model generation and neural-net training. We train the neural nets based on the compressor speed, component flow rates, and temperatures, and use the trained network as a proxy for the two-phase circuit. We found that good and valid assumptions are necessary at the interface between the NN metamodel and the remaining physical circuit to utilize NN. We also observe that static NNs generally perform well for circuits having relatively low thermal inertia. These findings are crucial for a user in assessing the applicability of these metamodels. One key application is the study of battery degradation where the degradation timescale is in making the traditional physics-based techniques infeasible. Another potential application of NNs is in controls law development in electric vehicles.

1. INTRODUCTION

The electric vehicle (EV) industry (IEA 2021) has seen significant growth in the past decade. With this growth in EVs, the thermal management of the vehicle components has gained great importance since they have a direct impact on vehicle range (Chan 2007). One of the major systems regulating this thermal behavior is the electric vehicle air conditioning (AC) system which consists of a refrigerant loop. The AC system is responsible for maintaining optimum battery temperature and providing occupant comfort in the cabin (Neapolitan & Hee Nam 2018). Designing this thermal architecture to optimally control the thermal behavior of the EV presents several

challenges when using physics-based models. Some specific challenges are caused by the complicated phase-transition behavior that needs suitable numerical techniques to model stably and accurately (Beshr et al. 2017).

While physics-based models have generally done a good job of predicting AC system performance they take a substantial amount of time when trying to solve the vapor-liquid equilibrium. One way of mitigating this behavior is the use of reduced-order models in the form of Artificial Neural Networks (ANN). ANNs have been used in a multitude of applications in AC systems to determine refrigerant charge (Hwang et al. 2020), assess the potential of low GWP refrigerant systems (Ghanbarpour 2021), analyze compressor (Ghorbanian & Gholamrezaei 2009) and heat exchanger (Mohanraj et al. 2015) performance, and understand system behavior (Datta et al. 2019). These ANNs serve as a reasonable substitute for traditional thermodynamics-based models that need a lot of geometrical parameters to define system components. However, a lot of these analyses are based on experimental data or steady-state models where transient thermal events do not occur. A good test of these ANNs would be for applications like EVs in select drive cycles with differing ambient conditions and transient behavior.

Therefore, in this study, we perform a comparison between a transient system-level model of an EV using traditional physics-based modeling and then substituting the AC loop with an ANN using training data from the physics model. This test will allow us to evaluate the effectiveness of the ANN in capturing correct system behavior in different conditions (heat-up and cool-down) over standardized drive cycle tests. We also discuss the pros and cons of using different kinds of neural network architecture and the various situations where these can be used.

2. SIMULATION METHODOLOGY

In this section, general flow infrastructure is discussed. GT-SUITE is a multi-physics simulation tool capable of analyzing devices consisting of flow, thermal, mechanical, and electrical parts. There are template libraries for different components with specific solutions for each. Since the focus of this paper is refrigerant modeling, we describe the flow and AC library in greater detail in this section.

2.1 Flow Solver and AC Components

The GT-SUITE flow solution models each pipe and juntions.in the system model as flow volumes with pipes being further discretized into multiple sub-volumes as required. Orifices connect different flow volumes and act as boundaries for these volumes. Heat exchangers are represented as compound objects made up of a collection of pipes, flow volumes, and thermal masses to model both the fluid and structure. The equations for mass, momentum, and energy conservation are solved for each flow volume in a 1D manner (all quantities are averaged across the flow direction).

Implicit and explicit time-stepping schemes are supported by the flow solver. Explicit time stepping is appropriate for capturing wave dynamics through smaller time steps that are restricted by the acoustic condition. The implicit solver allows bigger timesteps and is suitable for situations dealing with slower transients. AC systems typically fall in this category; hence the implicit solution is used in this study. More details of the flow solution can be found in the GT-SUITE Flow manual (GT-SUITE 2021).

The solver has an extensive library for general and flexible modeling of fluid properties; it supports different forms of the equation of state, including analytical formulations (such as ideal/real gas approximations and polynomial/algebraic correlations) and tabulated data. The solver fully supports multiple fluid species (Tiwari & Framke 2019, Zhong et al. 2021) and multiple phases with phase transition (Moore et al. 2019, Zhong et al. 2021). The routines for property calculation of pure refrigerants are built upon NIST REFPROP. Pre-tabulated property tables with interpolation to fill in the gaps are used to speed up refrigerant property calculations.

The other components that make up an AC system are the compressor and the expansion valve. Efficiency and speed maps are required to model the compressor performance. The efficiency map includes compressor speed, pressure ratio, and isentropic efficiency; and the speed map includes compressor speed, pressure ratio, and refrigerant mass flow rate. During the simulation of a transient operation, the pressure ratio is obtained from the flow solution. A combination of the compressor speed and the pressure ratio determines the mass flow rate and the isentropic efficiency of the compressor (Zhong et al. 2021). The expansion valve is modeled as a round hole with a

controllable diameter, i.e., an orifice connection for the portion in contact with the flow and a PID controller to target the superheat at the evaporator outlet of the AC system. The orifice is modeled as a planar object with no volume and the momentum equation is solved to compute the mass flow rate and the velocity (see GT-SUITE Flow Manual, GT-SUITE 2021).

2.2 Neural Network Description
Neural networks allow for the mathematical approximation of arbitrary functions, and they represent one method available in GT-SUITE to derive metamodels from physics-based system models.
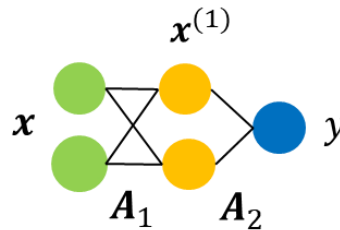

Figure 1: Layout of multi-layer perception network used for data-driven modeling heat exchanges across the two-phase system boundaries.

For this study, a multilayer perceptron (MLP) neural network (NN) approach is proposed. MLP neural networks are feedforward-style artificial neural networks that map the input vector to the output instantaneously using at least one hidden layer and arbitrary nonlinear functions. The nodes of input, hidden and output layers are connected via matrices of weights that get optimized during the training process to minimize the error between a known output and the NN prediction.

This technology has been shown to be capable of approximating the output of many complex non-linear dynamical systems (Sarkar et al. 2022) including systems and components of thermal management systems (Reynoso-Jardón et al. 2019). They allow the substitution of physical system models with a data-driven black-box type description based on rich datasets derived from time intensive numerical simulations or experimental measurements of the physical systems. Utilizing MLPs in transient simulations is straightforward and computationally inexpensive.

3. SYSTEM DESCRIPTION

3.1 Electric Vehicle Model
The model used for testing the efficacy of a neural network is a representative model of the sub-systems found in a Battery Electric Vehicle (BEV). The model consists of 5 major thermal-fluid circuits:
1. A high-temperature (HT) – cooling circuit
2. A low-temperature (LT) – cooling circuit
3. An indirect refrigerant circuit
4. A cabin air circuit
5. An underhood air circuit

R134a is used as the refrigerant fluid. The condenser and evaporator used in the refrigerant circuit are plate-type heat exchangers that are commonly found in BEV refrigerant loops (Amalfi et al. 2016). The heat exchangers have a plate length of 167.1 mm and a plate width of 87.1 mm with a thickness of 0.6 mm. Aluminum is used as the pate material and there are 9 and 8 channels on the main and secondary sides respectively. The compressor and expansion valve are also representative of standard components found in standard BEVs. Heat transfer correlations recommended for plate-type heat exchangers are used with the Yan, Lio, & Lin (1999) correlation used for condensation and a modified form of the Kandlikar (1990) correlation used for evaporation. The 2-phase pressure drop is evaluated using the Friedel (1979) correlation. Appropriate multipliers are used to calibrate these correlations to obtain heat transfer rates and pressure drops commensurate with actual operation.

The refrigerant circuit is indirectly connected to the other circuits and has two modes of operation – a cooling mode

and a heat pump mode depending on ambient conditions. The cooling mode is used to remove heat from the cabin and battery through the evaporator while the heat pump mode heats the battery back using heat from the environment which is transferred to the HT circuit using a radiator.

The powertrain components consisting of the electric motor, inverter, and DC-DC converter are placed in the HT cooling circuit in which the coolant temperature through the powertrain is regulated through a thermostat which can divert the complete flow from the main radiator if cold conditions are encountered. Through the use of electrically actuated valves, the battery is connected to the HT or LT circuits based on the ambient temperature. For this study, an ambient temperature of 18 °C is used to switch between the two circuits. A temperature above 18 °C means it is connected to the LT cooling circuit while a temperature below 18 °C means it is connected to the HT cooling circuit. This temperature is chosen because it ensures optimum operating conditions for the battery. The cabin air circuit rejects heat to the LT cooling circuit through a cabin cooler when in cooling mode and receives heat from the HT cooling circuit through a cabin heater when in heating mode. For cold start conditions, an electric cabin heater provides heat to the cabin until enough heat is available from the HT circuit.

The thermal management model manages the coupling between these circuits using multiple control elements to regulate and adjust inputs to the system components such as the electric flow devices (pumps, compressors, and fans) and control valves. The Worldwide Harmonized Light Vehicle Test Procedure (WLTP) drive cycles in heating and cooling mode are used for comparing the physical model results to the neural net. A representative diagram of the system is shown below in Figure 2.
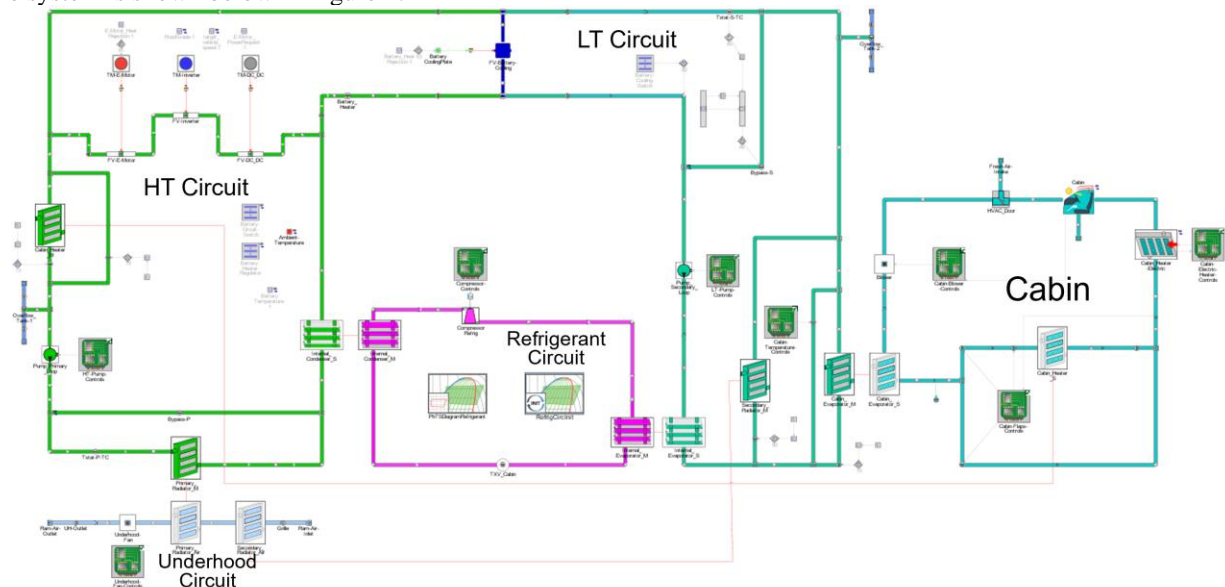

Figure 2: GT-SUITE set-up of the representative EV model. The refrigerant circuit is marked in purple, the HT circuit is green, the LT circuit is light green, and the cabin circuit is marked in blue.

3.2 Neural Network Setup
The specific neural network architecture chosen for this study is a four-layer MLP neural network with 2 hidden layers consisting of 10 and 5 neurons respectively. A sigmoid function is used as a transfer function between hidden layers and a linear transfer function for the output layer. Using a variant of the Levenberg-Marquardt algorithm the weights of the feed-forward MLP neural network are trained using GT-DOE POST

3.2.1 Design of experiments
The training was done on the standalone refrigerant circuit depicted in Figure 3 by varying the compressor speed, the HT and LT coolant flow, and temperature. A total of 20000 points were used for the training with the targets

being the heat transfer rate of the condenser and evaporator, compressor power, and time. The input parameters or experiments are selected using a Latin-Hyper cube approach with the ranges shown in Table 1 below. The refrigerant circuit is trained separately to conserve time compared to training by running the full model.

Table 1: Training parameters

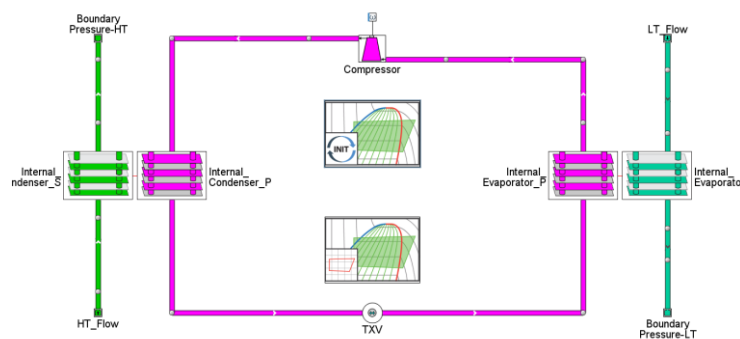| Parameter	Unit	Minimum	Maximum
HT Coolant Temperature	K	253.0	333.0
LT Coolant Temperature	K	253.0	313.0
HT Flow Rate	kg/s	0.0	0.6
LT Flow Rate	kg/s	0.0	0.6
Compressor Speed	RPM	500.0	7000.0

Figure 3: Standalone refrigerant circuit consisting of the condenser, evaporator, compressor, and expansion valve.

3.2.2 Model training and validation

The processing, analysis, and neural network training were performed using GT-DOE POST. The training and validation are performed against the results generated from the physics-based models. This is done to ensure a just comparison of the NN-based simulation to the physics-based one for the same set of parameters. During the selection of input parameter values, the technical and functional feasibility of all combinations is not considered or ensured. As a result, a limited number of experiments are invalid either because they will never exist during the actual operation of the refrigerant circuit or because they do not allow the simulation model to converge to a technically relevant steady-state operating point.

The results of those experiments are excluded from the result dataset reducing the total number of trainable operating points to 16510 of which 20% are used as validation dataset.
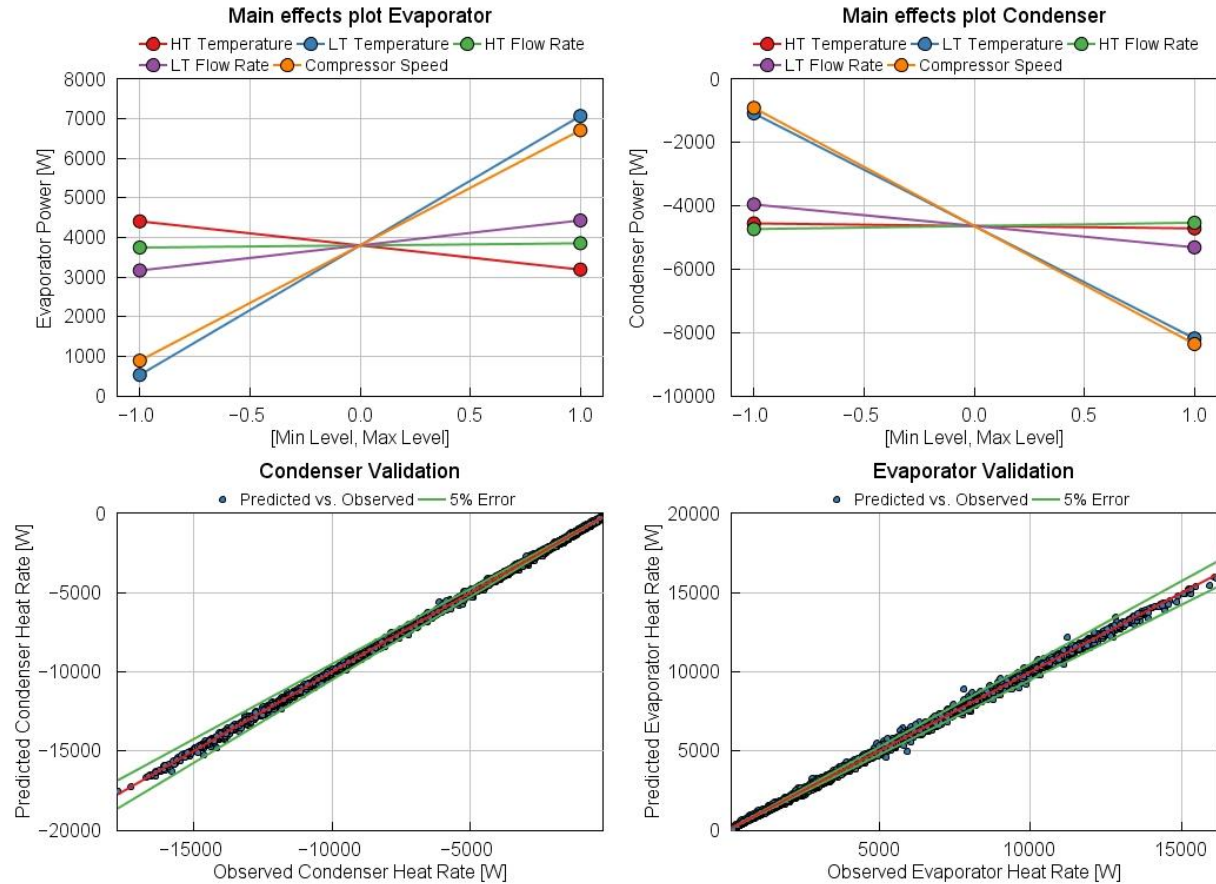
Figure 4: Main effects of NN factors in the response as well as training results. The red line in the validation plots is the regression line that is used to calculate the error of the trained NN model.

Figure 4 shows that both evaporator and condenser heat rates are influenced by the DOE parameters that will be the inputs to the neural network. Additionally, Figure 4 shows the results of the NN training for both heat exchangers by comparing the heat rate predicted by the NN with that obtained from the physics-based simulation model for steady-state points. The neural network training results in satisfactory heat rate prediction for both heat exchangers, especially for moderate and high heat rates.

To test the capability of the trained neural networks the full thermal management model is run by replacing the refrigerant circuit with the neural network for condenser and evaporator heat rate as shown in Figure 5. This allows the neural network to interact with all the other parts of the BEV circuit so that the cabin and battery thermal effects can be studied.
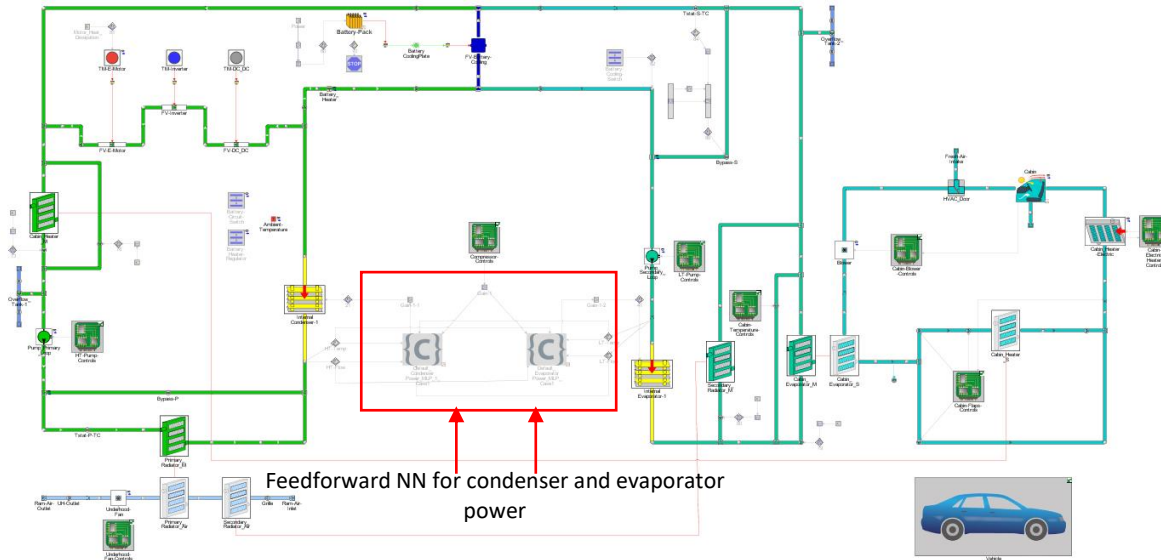
.

Feedforward NN for condenser and evaporator power

Figure 5: System design with refrigerant circuit replaced with the neural network.

4. RESULTS

Both the physical and neural net-based simulations are run with a time-step of 0.1 seconds. As mentioned previously two drive cycles are simulated to test the cooling and the heating modes.

4.1 WLPT drive cycle: cool-down

In this drive cycle, the ambient temperature is 30 °C and the refrigerant circuit is responsible for cooling the battery as well as the cabin during the drive cycle. We observe in Figure 6 that the transient cabin temperature, as well as the evaporator heat transfer rate and the condenser energy rate, are captured relatively well by the ANN. We also note some differences in the battery pack temperature (around 1 K at 1500 seconds). However, this difference is still insignificant considering the temperature ranges here. We also observe that the conditions for this drive cycle are relatively stable with all profiles smoothly changing and no significant thermal events occurring since all components are operating within their desired ranges.
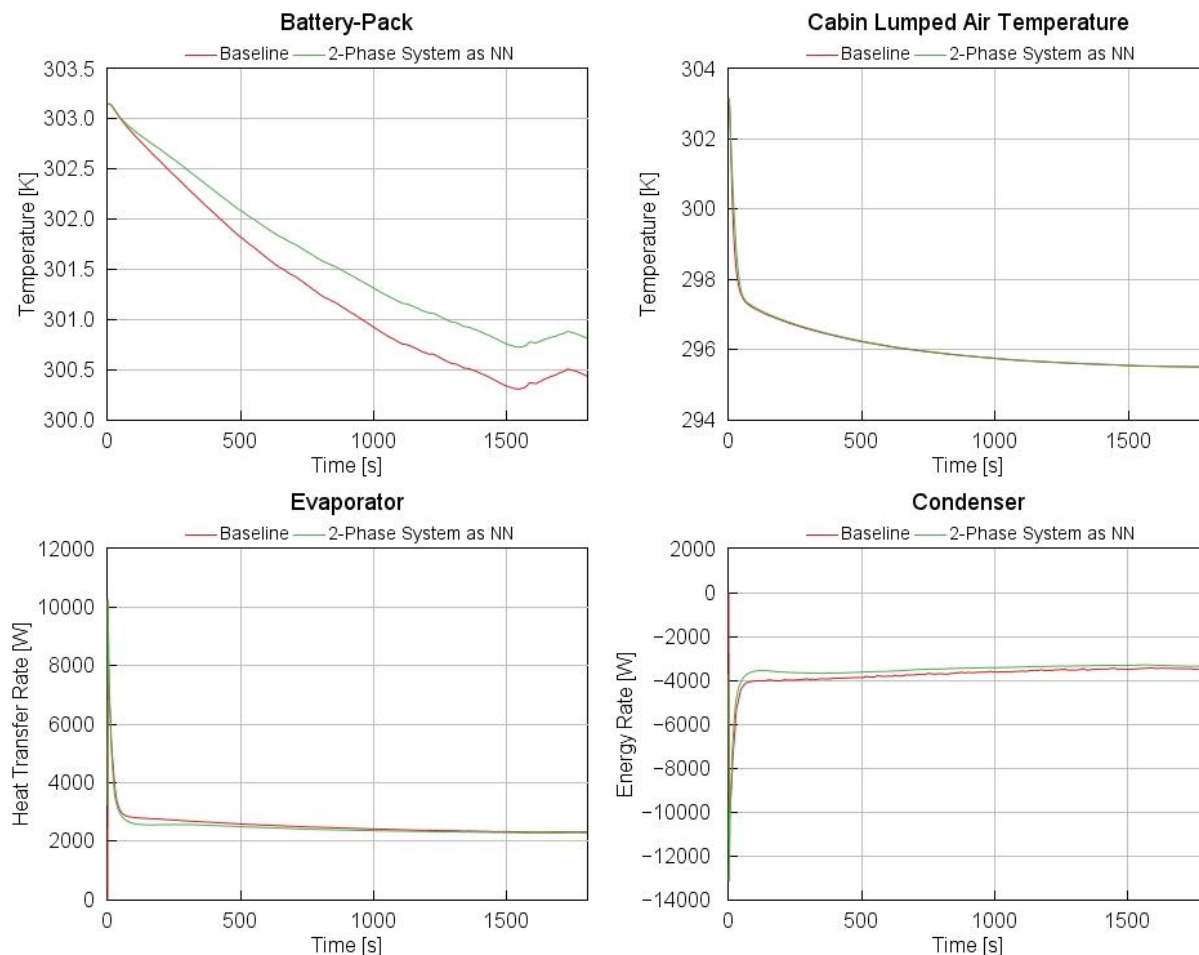
Figure 6: Comparison of physics-based simulation results (red) with neural network-based results (green) for cool-down. The parameters shown are battery temperature (top left), cabin temperature (top right), evaporator heat transfer rate (bottom left), and the condenser energy rate (bottom right).

4.2 WLPT drive cycle: heat-up

In this drive cycle, the ambient temperature is -10 °C and significant thermal energy is required to heat the battery to its ideal operating temperature and the cabin to 25 °C for human comfort. This can be seen in the plots for the heat and energy transfer rates for the heat exchangers in Figure 7 where significant thermal events occur throughout the drive cycle. We also observe that the neural network can capture the transient effects on the battery and cabin temperature very well. However, there is considerable underprediction in the evaporator heat transfer rate (~ 100 W) and condenser energy rate (~ 250 W) after 1000 seconds of simulation time. These may arise due to the nature of the neural network used in this study which is not able to capture transient behavior well since a feedback loop is not incorporated into its architecture. The reason for the selection of feedforward neural nets is discussed in the next section.
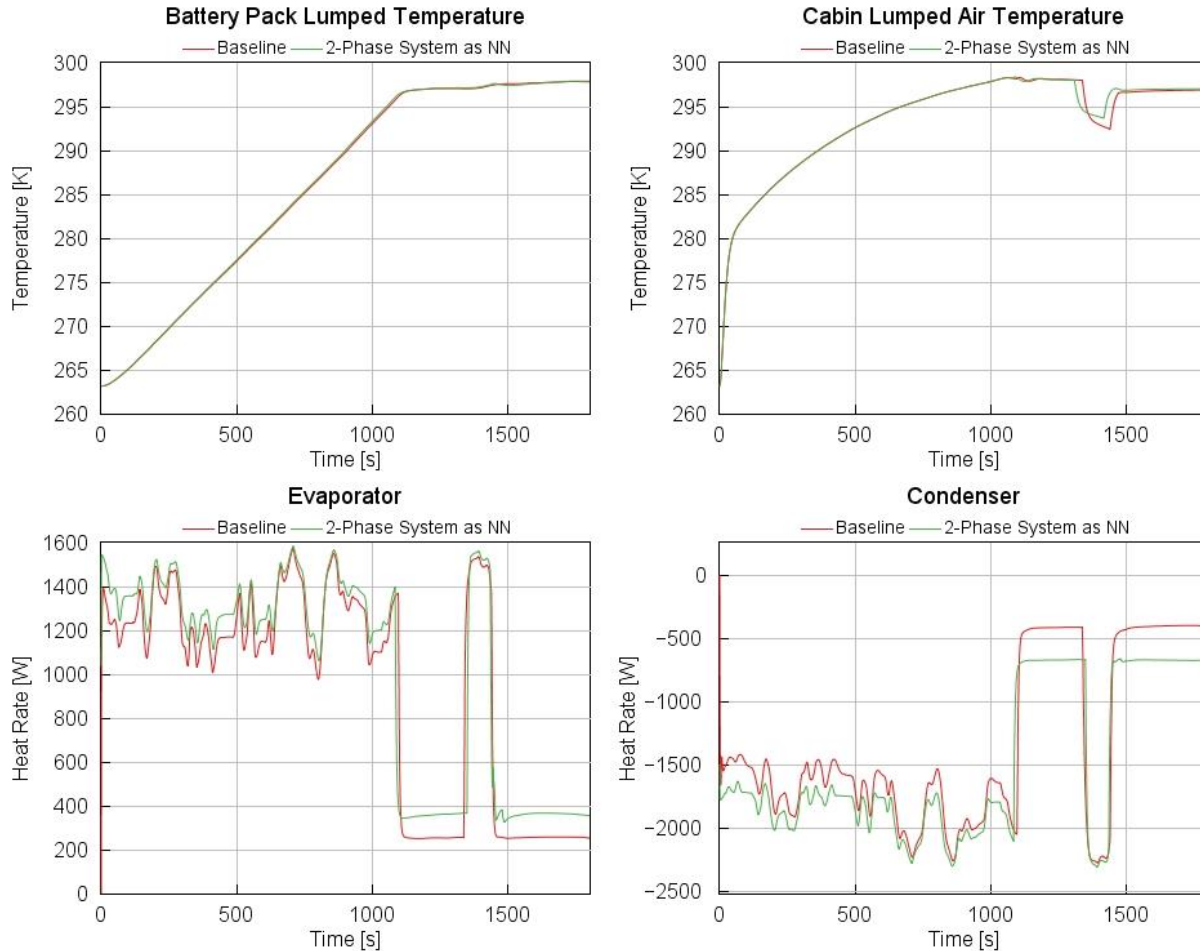
Battery Pack Lumped Temperature

Cabin Lumped Air Temperature

Evaporator

Condenser

Figure 7: Comparison of physics-based simulation results (red) with neural network-based results (green) for heat-up. The parameters shown are battery temperature (top left), cabin temperature (top right), evaporator heat transfer rate (bottom left), and the condenser energy rate (bottom right).

5. DISCUSSION

A key consideration while using reduced-order models (ANNs in this case) is the tradeoff between speed and accuracy. For our models, we measure the efficacy of the neural net by comparing the speed of simulation using the ANN vs the physics-based models. An important parameter, in this case, is the RT factor of the simulation. The RT factor is the ratio of the simulation time to real-time. When using the physics-based model in this simulation the RT factor calculated over the entire run is 0.27 whereas it is 0.17 in the case of the ANN model. This indicates that the neural net model is nearly 37% faster than the physics-based solution. While this is a substantial speedup, one can expect a much higher speedup if once only looks at the A/C circuit in isolation and not the full system model. However, there is an accuracy penalty associated with this speed increase. As can be seen in the heat-up case the heat exchanger energies are not well captured during the transient simulation. This may be further exacerbated if major thermal events are happening in a single drive cycle (for example, compressor on-off operation or heat-up and cool-down in the same drive cycle). To capture these behaviors, better neural net architectures can be used, such as feedback neural nets like NARX which are well known to reproduce transient behavior accurately. But NARX type deep learning models come with an increase in calculation time even with a good metamodel simply due to the number of layers. In such cases, one always needs to be aware of the increase in simulation time when substituting with non-physics models. Another thing to consider is the extrapolation of trained metamodels to situations outside the training set. If there are significant differences between conditions of the training set, then good accuracy is not guaranteed. With these factors in mind, one must always consider the appropriate situation in which such models are beneficial. With a well-trained dataset, such NN-based models can be used for controls development when the

thermal design is in a mature phase but might not prove to be useful when working on the initial design of thermal architectures like those present in practical devices like BEVs. Finally, one must think whether an ANN is required if your physics-based model is already faster than RT.

6. CONCLUSION

In this paper, we have successfully implemented a replacement feedforward neural network for the time-limiting portion of an integrated thermal management system simulation, namely the refrigerant circuit. We have shown that the NN is successfully able to reproduce important parameters such as the battery and cabin temperatures during both cool-downs and heat-ups over a transient drive cycle. However, it is not fully able to reproduce the transient behavior of the heat exchanger energy and heat transfer rates when significant thermal events in the heat-up occur. These results indicate that appropriate neural network architecture is required to produce accurate results and the time factor associated with these metamodels should also be considered when selecting for use in physical systems.

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