35th International Electric Vehicle Symposium and Exhibition (EVS35)
Oslo, Norway, June 11-15, 2022

Thermal management analysis and range estimation for Electric Vehicles on EPA 5-Cycle procedure using system simulation

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Summary

A model-based development process is presented for an electric vehicle system simulation including the different vehicle subsystems and the thermal management system. The model development workflow consists in starting with simple functional model. After that, the model complexity is increased. Finally, the HVAC model is reduced using a surrogate approach to ensure the model real time compatibility. The system simulation results over the EPA 5-Cycles highlight the impact of driving cycle and climate on the energy consumption and driving range.

Keywords: simulation, range, thermal management, air conditioning, BEV

1 Introduction

Electromobility has expended in the last years and controlling the battery pack temperature is essential to improving the electric vehicle performance in terms of safety, battery life and driving range.

The key challenge in studying the battery thermal management and analyzing the different design choices is to handle the various parameters involved. For instance, climate conditions and dependency on the other vehicle subsystems under real driving conditions must be considered.

This work aims at answering this challenge. It presents an electric vehicle system modeling including: the vehicle powertrain, the electric circuits and the different subsystems cooling loops: the battery, the power electronics and e-motor thermal management systems, as well as HVAC and cabin systems are represented.

In this study, a model-based development process is proposed. It is based on different system simulation modelling approaches. First, a functional representation of the vehicle subsystems is presented. Second, the refrigeration loop system and the chiller are modelled with physics-based components. Finally, the detailed air conditioning system model is reduced using a machine learning approach based on neural networks to ensure the model compatibility with real-time controls.

The system simulation results over the EPA 5-Cycles procedure are presented. Above all, the impact of driving cycle and climate on the energy consumption and driving range are discussed.

2 Electric vehicle model development workflow

An integrated and continuous modeling strategy have been developed in Sicmenter Amesim. Concerning the electric powertrain model, its purpose is to compute the full energy balance of the battery under various driving profiles and various environmental conditions.

For a proper estimation of the energy consumption, the electric powertrain model has to represent first the sum of all losses from the battery to the wheels: internal resistance of the battery, the electric motor and inverter losses, the gearbox/reducer losses as well as the vehicle rolling and aerodynamic losses. Then, low voltage auxiliary electrical consumers are also considered. More details on this model are given in the next paragraph.

Second, thermal management circuits are impacting the electrical power consumption: motor to drive the HVAC compressor, motors to drive the pumps and the low temperature radiator fan, the blowers, as well as the electric heaters (PTC).

To account for the cooling/heating performance of the thermal management systems and its power consumption, various levels of model are used. In all cases, a physical model of the liquid cooling loops is used, at the opposite of the refrigerant loop:

- First, a functional representation with Coefficient of Performance (COP) is used. A parametric study is performed for different values of COP to estimate its impact on the vehicle range estimation
- Second, the refrigeration loop system and the chiller are modelled with physics-based components to accurately predict thermal results
- Finally, the detailed air conditioning system model is reduced using a machine learning approach based on neural networks to ensure the model compatibility with real-time controls.

3 The electric powertrain model

A lumped-parameter model of the electric powertrain and vehicle have been developed. This model includes:

- the motor and brake controller: it computes the requested motor torque to ensure the acceleration. It also gives the needed braking command of the vehicle to follow the driving cycle.
- the chassis and environment: the vehicle component is used to evaluate the operating car acceleration and velocity throughout the scenario. This velocity mainly depends on the electric machine torque, the resistive forces applied on the vehicle and the vehicle mass. Environmental temperature can be also set
- the traction motor: the motor model gives the requested torque computed in the Vehicle Control Unit (VCU) to the powertrain. The motor model computes realistic operating characteristics (torque vs speed for various battery voltage as well as loss maps) for a given motor considering its architecture and high-end performances (continuous base power, maximum continuous torque and maximum speed). Model details are presented in references [1] and [2]. A transmission ratio is applied between the electric motor and the wheels.
- a high-voltage electric bus with the high-voltage battery and inverter but also the compressor for the HVAC system and the electric heaters (one for the battery, one for the cabin). A dynamic equivalent circuit model

of battery cell is used to represent a high-power Nickel, Manganese, Cobalt -Graphite (NMC-C) Li-ion cell of 8 Ah. The model simulates both electrical and thermal behavior of the cell. The model has been calibrated and validated by experimental tests data from IFP Energies Nouvelles battery tests facilities [3]. The dynamic circuit model can consider the reversible and irreversible heat exchanges for a more accurate thermal energy balance representation.

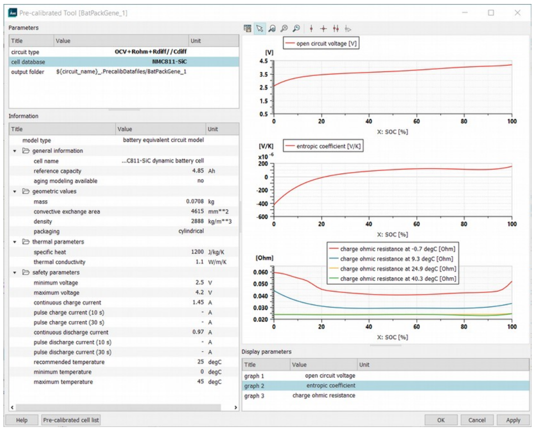


Figure 1: Parameters of the NMC-C battery cell model

- a low-voltage electric bus with the low-voltage battery and consumers such as electric pumps, low temperature cooling fan and blowers
- the driver component: it is used to predict the driver acceleration and braking commands to fulfill the driving scenario. The parameter window of the driver component makes it possible to define different driving cycles, with or without slope.

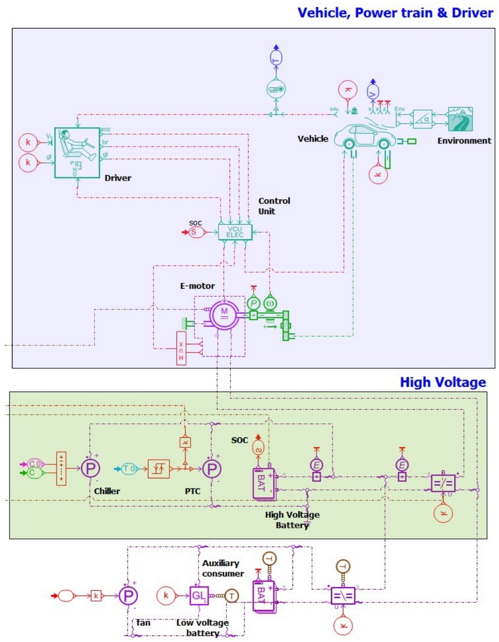


Figure 2: functional model of the electric vehicle

EPA 5-cycle procedure [4] has been developed for conventional as well as hybrid vehicles. For Electric Vehicles, different adjustments are done to Derive FE label Estimates. The EPA uses five drive cycles performed on a dynamometer under controlled conditions to determine the fuel economy: a city cycle (FTP-75), a gentle highway cycle (HWFET or HFEDS), an aggressive higher-speed cycle (US06), an air conditioning cycle (SC03) and a cold-start cycle (cold FTP-75). The two last cycles highlight the effect of temperature on energy consumption, especially in the case of EVs:

- Hot cycle: need to not only cool down the cabin but also the battery
- Cold cycle: no "free" heating coming from the ICE losses

The interest of quickly assessing the vehicle range for different cycles and different thermal management strategies is then growing.

Test	*Driving*	*Ambient temperature*	*Engine condition at start*	*Accessories*
FTP	Low speed	24°C (75°F)	Cold and hot	None
HWFET	Mid-speed	24°C (75°F)	Hot	None
US06	Aggressive; low and high speed	24°C (75°F)	Hot	None
SC03	Low speed	35°C (95°F)	Hot	A/C on
Cold FTP	Low speed	–6.7°C (20°F)	Cold and hot	None

Source: US EPA (2006, p.34)

Figure 3: EPA 5-Cycle procedure

4 The thermal management system model

4.1 Reference vehicle

The thermal management system of the Hyundai's new 2019 Kona Electric [5] has been selected to create the simulation model.

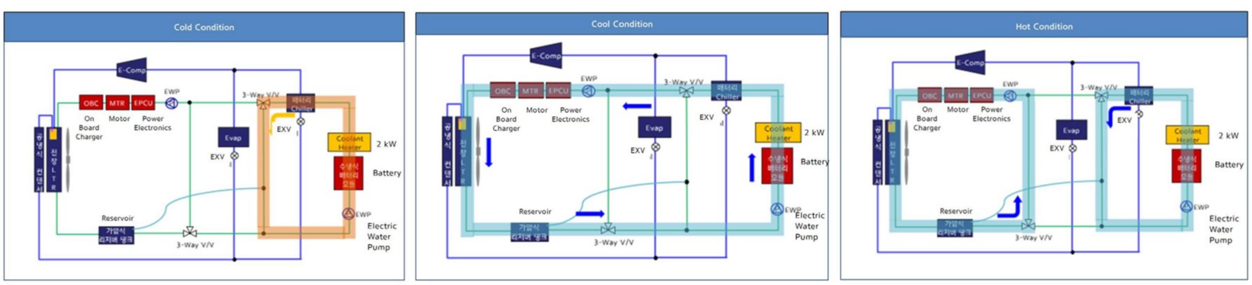


Figure 4: 2019 Kona Electric coolant loop modes

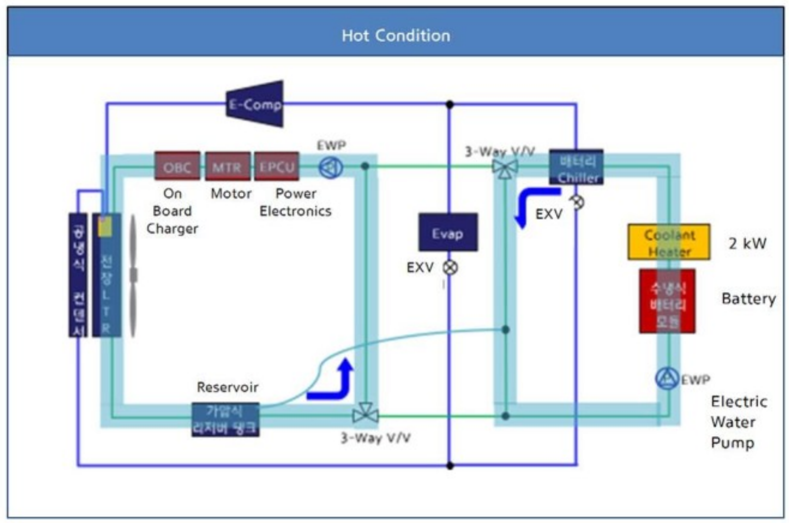
Three modes (Figure 3), function of the temperature conditions, correspond to the three different computer-controlled valve settings and coolant flow diagrams:

- Cold conditions (bellow 0°C): both cabin and battery have to be heated-up. An electric heater is used to warm-up the battery, a second one is used to heat up the cabin. An electric water pump circulates the fluid in the battery then in the coolant heater. On the e-motor and inverter loop, the pump starts and circulates the coolant in the low temperature radiator only when these electric devices reach a threshold temperature.

- Cool condition (between 0°C and 25°C): the heat produced by the e-powertrain (battery, inverter and motor) is released in the ambient through the low temperature radiator. Both circuits (battery loop and emotor loop) are connected, and the two electric pumps are operating.
- Hot conditions (higher than 25°C): again, the two cooling loops are split. The battery is cooled down using a chiller. The motor and inverter are cooled down using the low temperature radiator. The passenger cabin needs to be cooled down as well, using an evaporator connected in parallel of the chiller on the same refrigerant loop. The e-compressor is used to circulates the refrigerant in the 2-phase loop.

4.2 Initial results on the complete EPA 5-cycle procedure

A model representing the various components (pumps been developed and connected to the electric powertrai



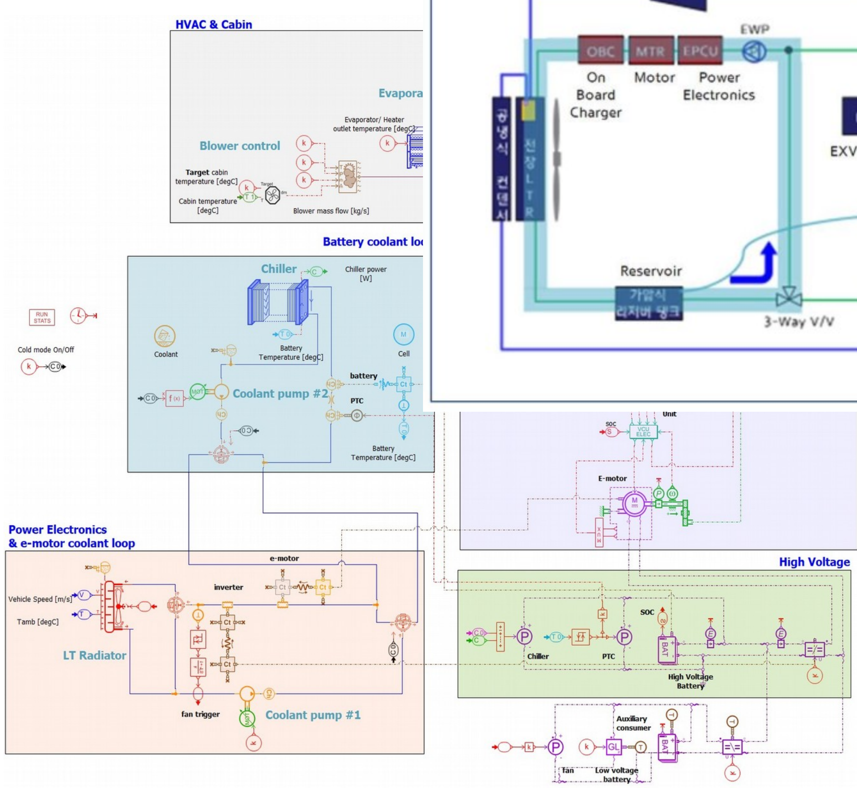


Figure 5: model of the electric powertrain thermal management system

Simulation results for the 5 cycles are depicted in Figure 5. The 3 first cycles at 24°C are not requiring the compressor of the refrigerant loop not the PTCs. Not surprisingly the range is lower on the SFTP-US06 cycle (466 km) due to a higher mean value speed compared with HWFET (625 km) and FTP-75 (695 km).

Figure 6: vehicle range and vehicle velocity for the 5 driving cycles

4.3 Functional model of the refrigerant loop and chiller

Let's now focus on the SFTP-SC03 cycle performed at 35 degC. The simulated range is 507 km for a COP of the refrigerant loop of 3. The energy consumption due to the refrigerant loop accounts for almost 30% of the total electrical energy consumption (Figure 7).

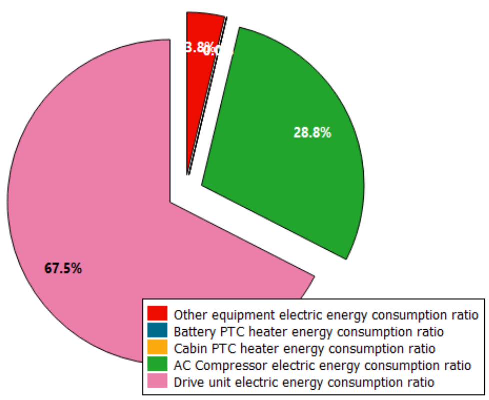


Figure 7: SFTP-SC03 cycle at 35 degC - energy consumption split

In a first approach, a functional representation with Coefficient of Performance (COP) is used for the chiller and the cabin evaporator.

Concerning the chiller (Figure 8), the battery temperature triggers its activation. When activated, the chiller removes 7kW of heat from the coolant flowing into the battery pack. At the same time, electric power consumption due to the compressor is computed using a constant COP.

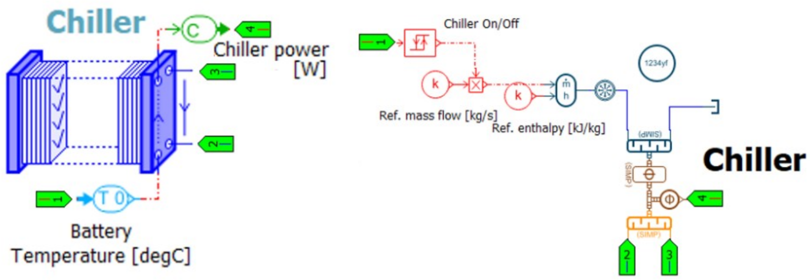


Figure 8: functional model of the chiller

Concerning the evaporator used to cool down the cabin, same approach has been used: the evaporator can generate up to 3kW of cooling power to produce fresh air at 5°C. The electric power consumption due to the compressor activation is also computed using a constant COP.

J. Steven Brown and al. [6] have determined that the values of the COP of automotive air conditioning systems operating with CO2 and R134a varies between 2 and 4, function of the compressor speed, ambient temperature and type of refrigerant used. As a consequence, a parametric study was performed for values of COP from 2 to 4, to estimate its impact on the vehicle range estimation. Results are presented in Figure 9 and shows that an optimal refrigerant loop is necessary to guaranty temperature control whilst minimizing the impact on the consumption. Indeed, the vehicle range can vary from 443 km (COP=2) to 546 km (COP=4), meaning a difference of 23%.

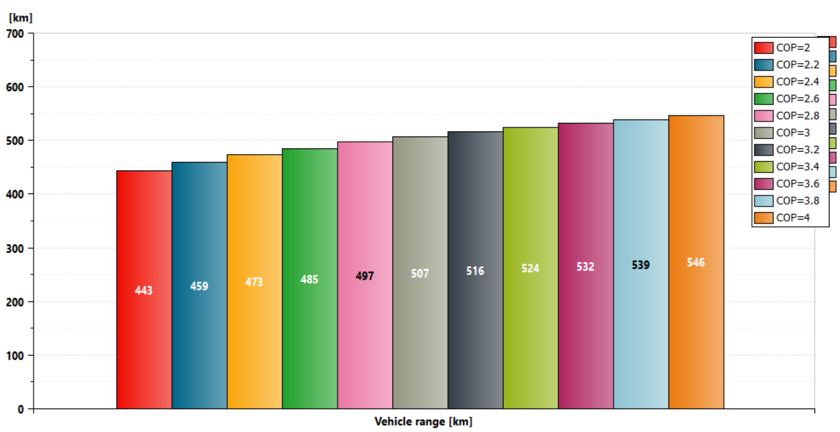


Figure 9: SFTP-SC03 cycle at 35 degC – vehicle range function of the refrigerant loop COP

4.4 Physics-based model of the refrigerant loop

The refrigeration loop system and the chiller are modelled now with a physics-based component approach, firstly presented by El Bakkali and al. [7] and used for many studies for hybrid and electric vehicles such as Natarajan [8], Lajunen [9], Rostagno and al. [10] and Linderoth [11]. This physics-based component approach is essentially dedicated to the sizing of air-conditioning components (especially heat exchangers), proceeding to transient and steady-state analysis of systems (modeling of thermal refrigerant and solid wall capacities), designing, and testing current and new system configuration (more particularly refrigerant mixture systems and heat pump systems) and studying the impact of the air-conditioning system on the whole vehicle energy management. It is composed of basic elements (boundary conditions, sensors, ducts, pressure losses…) as well as specific air-conditioning system global components such as evaporator, condenser, chiller and compressor.

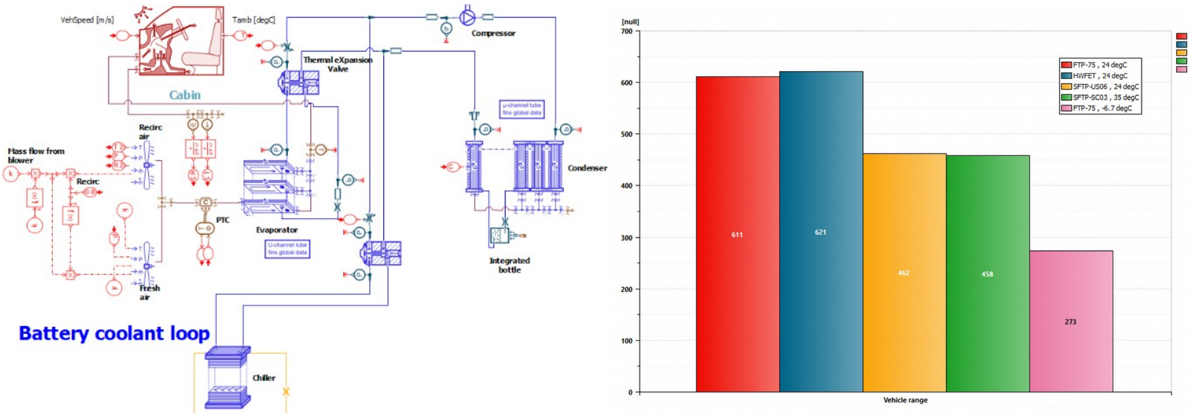


Figure 10: Physics-based model of the refrigerant loop and simulation results on EPA-5 cycle procedure

With this approach, the COP is no more imposed but is a consequence of the performance of the refrigerant loop imposed by the sizing of the various components of the two-phase system.

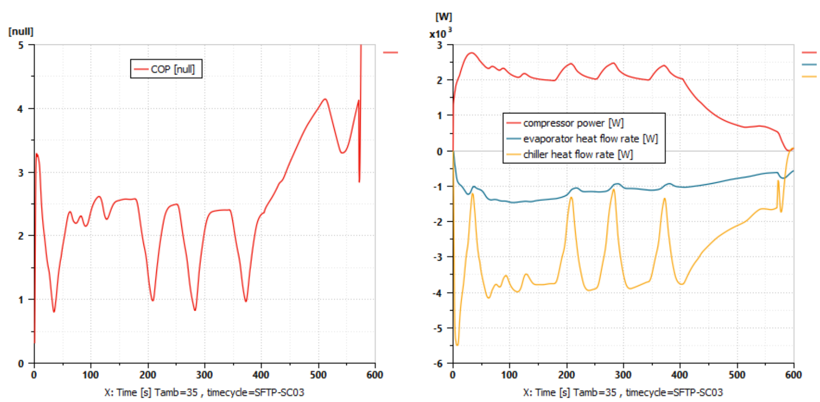


Figure 10: Physics-based model of the refrigerant loop and simulation results on EPA-5 cycle procedure

This predictive approach has a consequence in term of calculation time. CPU time using this physical approach is 430s for 600s simulated, which is still faster than real time but much slower than with the functional approach (30s, so roughly 14 time slower).

4.5 Surrogate model of the refrigerant loop

The surrogate model of the refrigeration loop system and the chiller is created for the purpose of running real-time simulations. Indeed, the physics-based modeling approach is not suitable for running with a fixed time step solver.

The HVAC surrogate model is represented by neural networks which are made up of several layers, and each layer consists of a fixed number of units or “neurons”. The first layer is the input layer, which has eight dimensions as represented in the figure below. The model inputs are the compressor speed, the chiller coolant flow rate in, the chiller coolant temperature in, the evaporator air flow rate in, the evaporator air temperature in, the condenser air flow rate in, the condenser air temperature in and the condenser air humidity in. The last layer is the output layer which has three dimensions as represented in the figure below. The HVAC surrogate model predicts the compressor torque, the evaporator total heat flow rate as well as the chiller total heat flow rate.

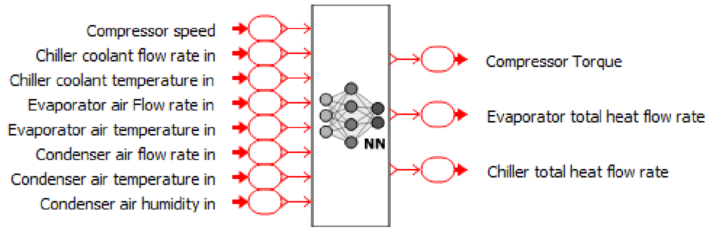


Figure 11: Neural network-based model inputs and outputs

4.5.1 Isolate the HVAC physics-based model and create reference datasets

The starting point is the vehicle model including the physics-based HVAC loop.

The refrigeration loop system and the chiller components are isolated from the other vehicle subsystems and controls. The objective is to create a virtual test bench to generate reference datasets using the physics-based modeling approach. Corresponding results will be used in a second step for training and validation of the surrogate HVAC model.

Figure 12 shows the isolated HVAC physics-based model where the eight input parameters representing the same surrogate model inputs are highlighted. Random values are assigned to these input parameters during a batch computation including 180 runs and corresponding values are stored in the watch variable section.

The results regarding the compressor torque, the evaporator total heat flow rate and the chiller total heat flow rate are stored in the watch variable section as well. These results represent the same surrogate model outputs.

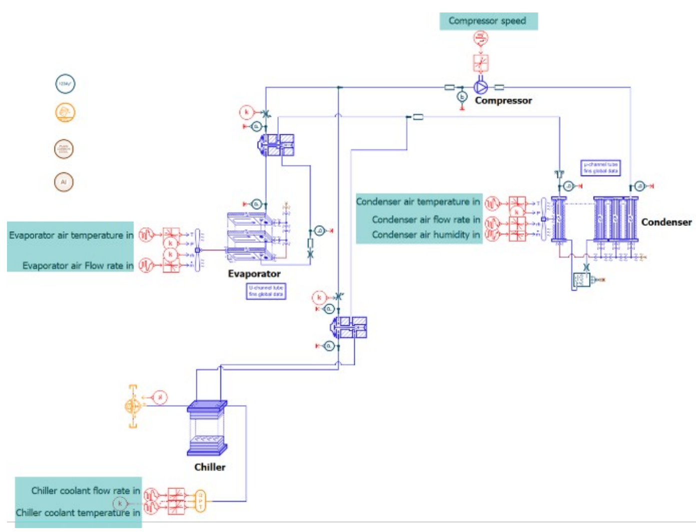


Figure 12: Isolated physics-based HVAC model

4.5.2 Surrogate model creation

The datasets generated from the model described in 4.5.1 section were used to create the HVAC surrogate model. Corresponding model was generated using the Simcenter ROM Builder which is a general-purpose model order reduction tool [12]. It enables creation and export of reduced-order models from various sources of data, including simulation results. A model sweep was performed to compute a set of predefined configurations on the training data and generate an automatic exploration of models and hyperparameters. The evaluated models with corresponding training and validation fidelity are shown in the figure below.

Model name	Training	Validation
rom_6	96.99	96.78
rom_4	93.68	94.42
rom_5	93.5	93.67
rom_1	92.9	90.78
rom_2	82.36	80.34
rom_3	78.99	65.67

Figure 13: Evaluated surrogate HVAC models

The rom-6 model showing the best fidelity was selected. The table below shows the model details and hyperparameter's values [13]. Corresponding model was then exported as a Simcenter Amesim submodel.

Table1: Details of selected training model

Type of model	Training fidelity [%]	Validation fidelity [%]	Layer types	Number of cells	Activation types	Training method
Dynamic Neural Network	96.99	96.77	['Dense', 'RNN', 'Dense']	[12, 8, 10]	['tanh', 'linear', 'tanh']	Levenberg-Marquardt

4.5.3 Surrogate model integration

The generated surrogate model was integrated into the vehicle model by replacing the physics-based refrigeration loop system and the chiller. The surrogate model inputs and outputs were connected to the other vehicle subsystems using sensors and sources.

Simulation results for the SFTP-SC03 driving cycle with the ambient temperature at 35°C shows good agreements with the physics-based model. The figure below compares the vehicle model with surrogate HVAC results with the physics-based one in terms of the surrogate model outputs as well as the battery temperature, the cabin temperature, and the vehicle range. The latter shows an error of 3%. In terms of computation time, the vehicle model with surrogate HVAC is 80 time faster than the real time.

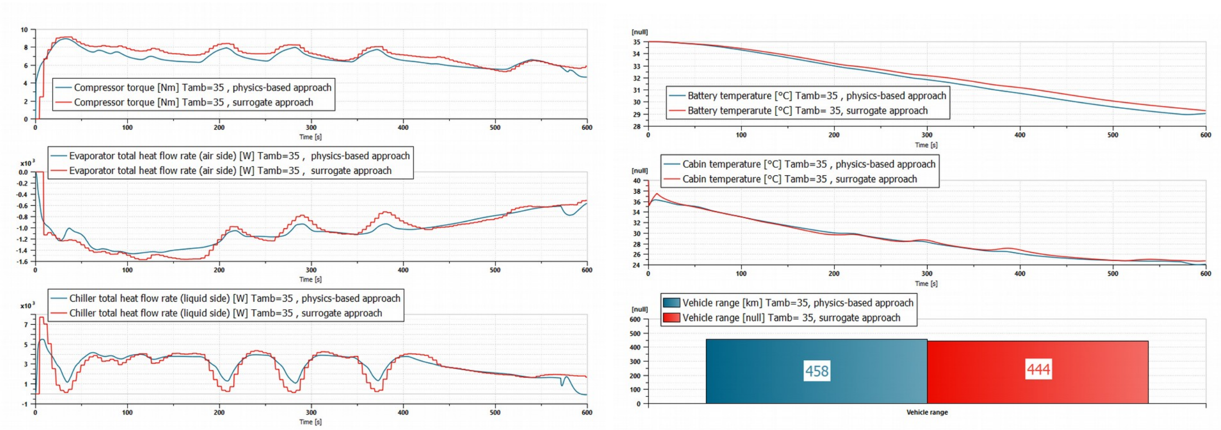


Figure 14: Comparison between physics-based and surrogate model's results

5 Model preparation for control validation

To use the model for the SiL and HiL tests, it must be run with fixed step solver and must be faster than real time at each integration step. Best practices to make a lumped parameter thermofluid model compatible with fixed step solver have been applied (reduce the number of state variables and remove short time constant by bundling volumes and pressure drops, replace detailed modelling approach by functional one…).

The adapted model was run with a Euler fixed step solver by setting the integration time step to 0.002 s. The simulation was carried out on a laptop with Intel i5 2.6 GHz CPU, 16 GB RAM. Figure 15 shows an analysis of the simulation time for the SFTP-SC03 driving cycle with the ambient temperature at 35°C: comparison of the main results (temperatures and range) as well as the cumulative CPU time for the simulation. Simulation time is 125 s at the end of the simulation, which is 1.8 times faster than the duration of the scenario (600 s): the real-time capability of the model is then validated.

Figure 14: Comparison between physics-based and fixed step solver model and CPU time of the fixed step model

6 Conclusion

This work aimed presenting a model-based development process, based on different system simulation modelling approaches, with a specific focus on an EV thermal management system. A functional representation of the refrigerant loop with Coefficient of Performance (COP) was used to estimate its impact on the vehicle range. The refrigeration loop system and the chiller were in a second step modelled with physics-based components to accurately predict thermal results. Finally, the detailed air conditioning system model was reduced using a machine learning approach based on neural networks to ensure the model compatibility with real-time controls. The system simulation results over the EPA 5-Cycles procedure were presented, the impact of driving cycle and climate on the energy consumption and driving range were discussed.

7 References

[1] A. Abdelli, Optimal Design of an Interior Permanent Magnet Synchronous Motor for Wide Constant-Power region Operation: Considering Thermal and Electromagnetic aspects SAE Int. J. Alt. Power. 3(1):2014.

[2] F. Le Berr, A. Abdelli, D.-M. Postariu and R. Benlamine, Design and Optimization of Future Hybrid and Electric Propulsion Systems, OGST Journal, Vol. 67, No. 4, pp. 539-645.

[3] E. Prada, J. Bernard, R. Mingant, V. Sauvant-Moynot, EVS-25 Shenzhen, China, Nov. 5-9, 2010 - The 25th World Battery, Hybrid and Fuel Cell Electric Vehicle Symposium & Exhibition

[4] D. Good, EPA Test Procedures for Electric Vehicles and Plug-in Hybrids, November 14, 2017, https://www.fueleconomy.gov/feg/pdfs/EPA%20test%20procedure%20for%20EVs-PHEVs-11-14-2017.pdf

[5] J. Nisewanger, Details on Hundai's new battery thermal management design, December 20, 2018, https://electricrevs.com/2018/12/20/exclusive-details-on-hyundais-new-battery-thermal-management-design/

[6] J. Steven Brown, Samuel F. Yana-Motta, Piotr A. Domanski, Comparitive analysis of an automotive air conditioning systems operating with CO2 and R134a, International Journal of Refrigeration, Volume 25, 2002

[7] Amin El Bakkali, Gérard Olivier, A Virtual Air Conditioning System Based on the Physical Simulation of AC Components, FISITA 2004 World Automotive Congress, Barcelona, Spain, May 2004

[8] Natarajan, S., S, S., Amaral, R., and Rahman, S., "1D Modeling of AC Refrigerant Loop and Vehicle Cabin to Simulate Soak and Cool Down," SAE Technical Paper 2013-01-1502, 2013

[9] Lajunen, A., Energy Efficiency and Performance of Cabin Thermal Management in Electric Vehicles, SAE Technical Paper 2017-01-0192, 2017

[10] Ferraris, W., Rostagno, M., and Bettoja, F., Thermal Management Architectures Virtual Evaluation for HEV/PHEV, SAE Technical Paper 2018-37-0025, 2018

[11] J. Linderoth, Thermal Management of a Battery Electric Vehicle: How thermal management strategies can improve the performance of a battery electric vehicle for various driving cycles and conditions, Master Thesis, 2021, https://odr.chalmers.se/handle/20.500.12380/303772

[12] Siemens. Help Document of ROM builder; Simcenter Amesim V2022.1; Siemens: Munich, Germany, 2022.

[13] Medsker, L.R., and L.C. Jain, Recurrent neural networks: design and applications, Boca Raton, FL: CRC Press, 2000

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