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Mobility, Advanced™

Thermal Management Systems Symposium

Co-located with SAE Energy & Propulsion Conference & Exhibition

October 14-15, 2025 | Ypsilanti, Michigan

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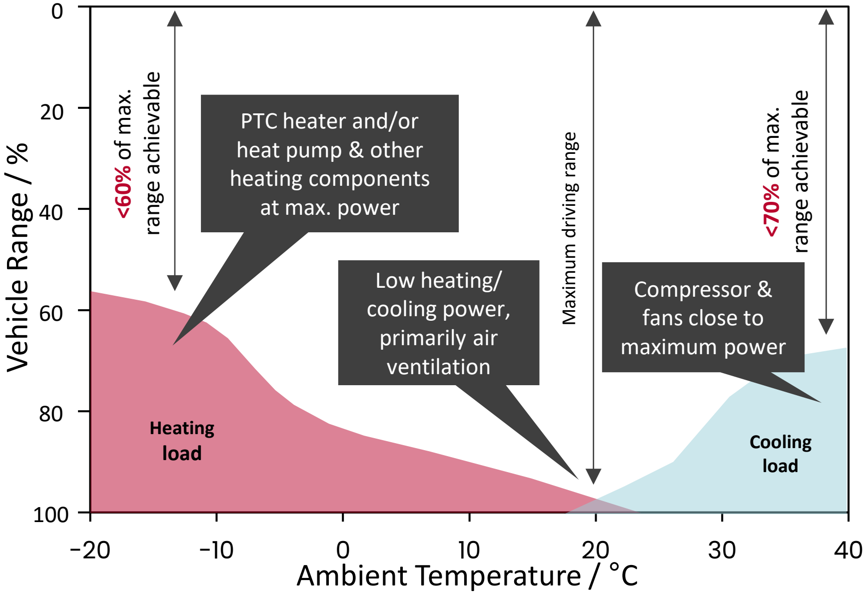
Predictive Control Models and Machine Learning for EV Thermal Management

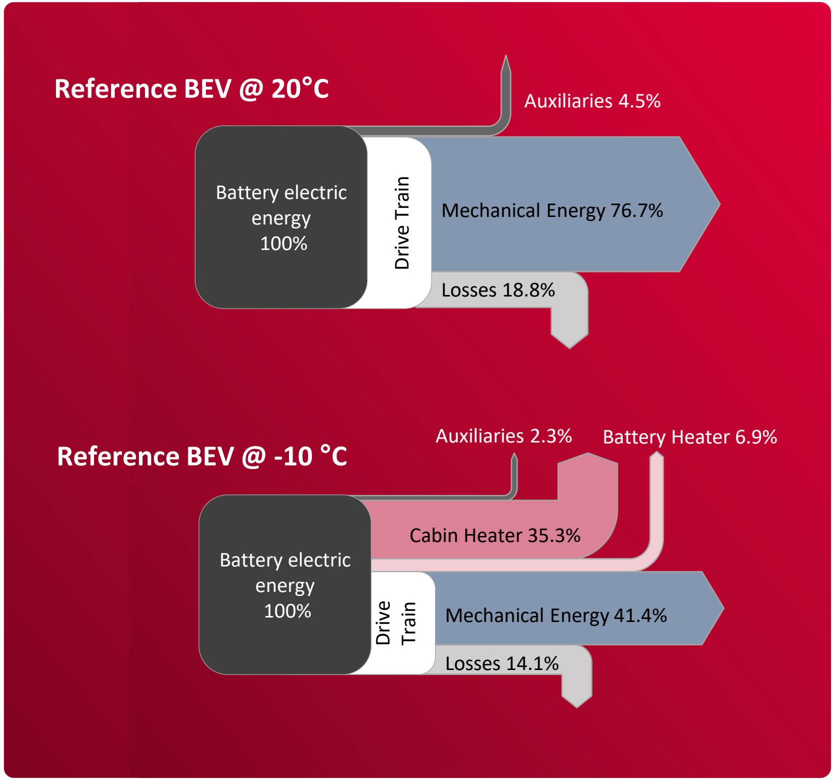
Manpreet Chadha

Patrick Schutzeich

BEV's driving range can be reduced up to 40% due to thermal management requirements

Illustrative





Source/Note: 1) Losses can also be significantly higher, "normal" conditions & typical drive cycle assumed
Note: Indicative for state-of-the-art BEV, but heating and cooling loads strongly depending on vehicle and operating conditions; Source: FEV

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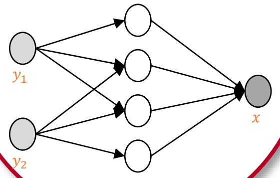
The methods of machine learning (ML) can be used to drive forward the simulation models or controls of thermal management systems

ML-Based



System Identification

Black-Box Identification
Identifying system behavior and dynamics without detailed knowledge of parameters or internal.

Precision Enhancement
Improving the accuracy of models by refining them with machine learning techniques.

Model Acceleration
Creating accelerated models that capture the essential behavior of complex systems enabling real-time applications.

Reinforcement Learning

Adaptive
Adjusting control strategies dynamically in response to changing conditions and system states.

Self-Optimization
Enabling systems to autonomously improve performance over time by learning from interactions with the

Complex Systems
Optimizing systems with interconnected components that are difficult to model using traditional approaches with machine

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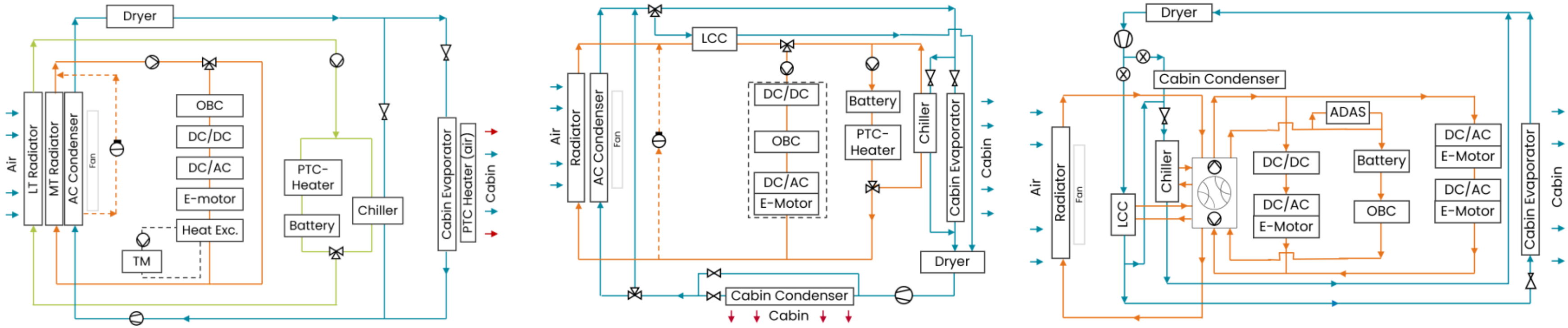
The complexity and versatility of thermal systems is increasing and is having a growing impact on the scope of simulation models

Illustrative

The development of modern control strategies requires fast Running models



Basic Systems | Advanced Systems | Highly Integrated Systems

Challenges for the simulation of thermal management systems

- Increasing number of interconnectable circuits
- More complex refrigerant circuits with heat pump functionalities

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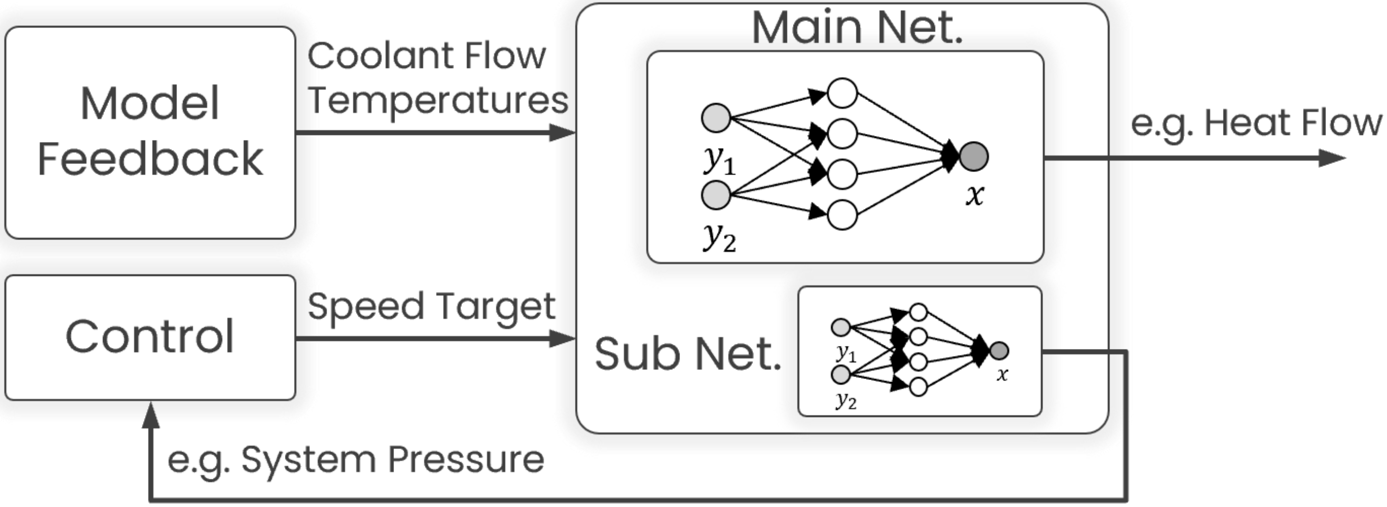
The use of system identification can help to significantly accelerate complex thermal system models

Illustrative

An increase in model performance sustainably increases their usability



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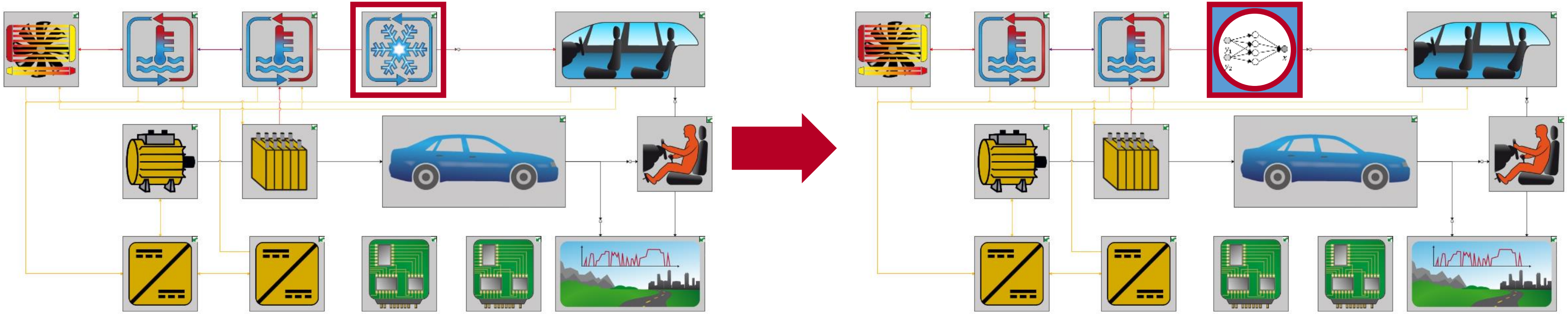

Refrigerant Circuit

Black-box

Preparation for the system identification:

- Identify physical system boundaries and related signal ranges for adjustment of the system identification process
- Define relevant control signals and limitations
- Definition of targets for model accuracy, use cases and desired run-time

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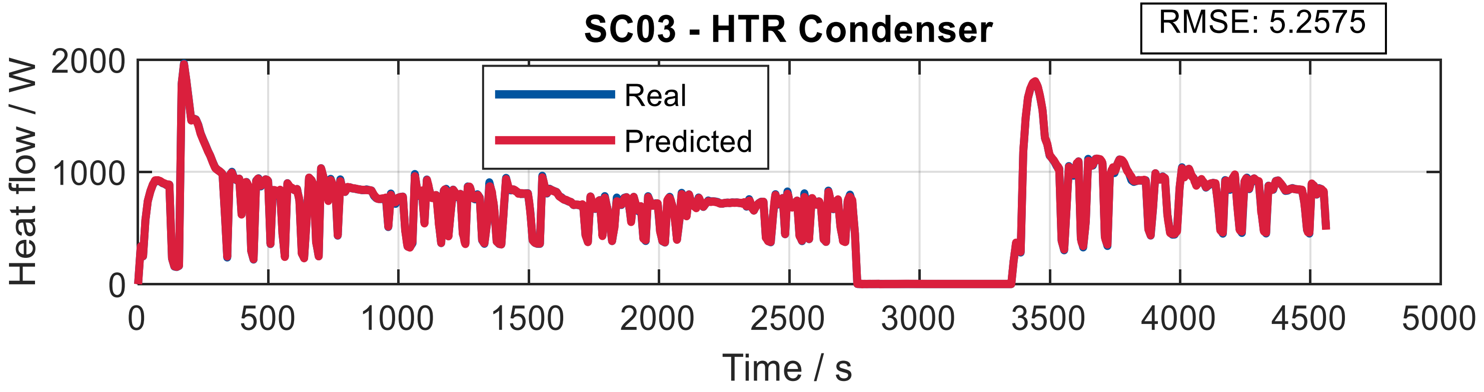
The use of system identification can help to significantly accelerate complex thermal system models

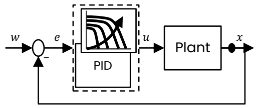
An increase in model performance sustainably increases their usability



- Comparison of heat flow between phys. model and neural network. Example of a heat exchanger in the AC circuit (HTR condenser) - Exemplary results for a SC03 at hot conditions (35 °C)
- Model was accelerated to be used for control strategy development
- Overall run-time improvement of up to 44 %

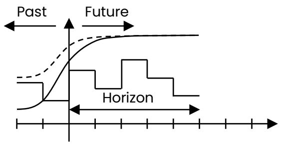
The development of thermal systems for future vehicle concepts will require a combination of different control approaches

Conventional Rule-Based Control



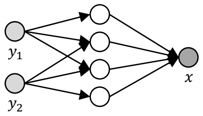
Conventional Rule-based Control uses predefined if-then logic to manage thermal conditions based on sensor data. It’s straightforward and easy to implement but lacks adaptability to dynamic environments, as it doesn’t consider multiple interacting factors.

Model Predictive Control



Model Predictive Control (MPC) employs mathematical models to predict future states and optimize control actions over a defined horizon. It minimizes a cost function like energy use or temperature deviation, making it more effective in complex environments, though it requires accurate modeling and higher computational power.

Machine Learning-Based Control



Machine Learning-based Control utilizes data-driven models to learn and predict optimal thermal management strategies from past data and real-time inputs. It adapts to nonlinear systems and improves over time, making it ideal for variable environments, though it demands large datasets and more complex implementation.

Focus: The right approach for the system to be controlled

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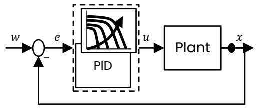
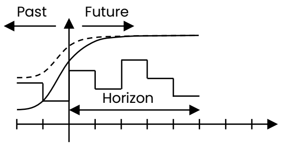
Conventional Rule-Based Control



Pros
- Simplicity
- Predictability
- Low Cost

Cons
- Limited Adaptability
- Complex calibration
- Sub-optimal Performance

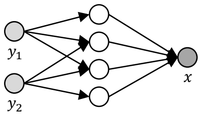
Model Predictive Control



Pros
- Optimization
- Flexibility
- Improved Performance

Cons
- Complexity
- Implementation Complexity
- Model Dependency

Machine Learning-Based Control



Pros
- Adaptability
- Optimization
- Scalability

Cons
- Data Dependency
- Interpretability
- Implementation Complexity

Focus: The right approach for the system to be controlled

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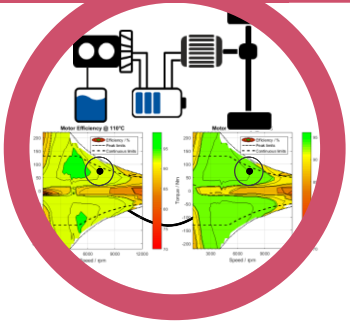
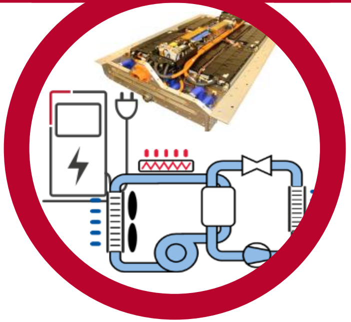
Model predictive control (MPC) approaches can be variably adapted to optimize system behavior in applications of thermal management

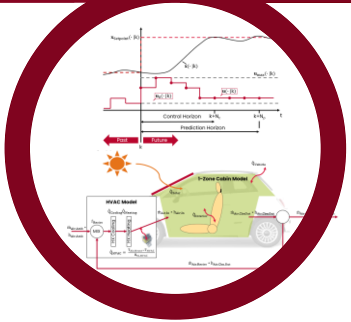
Powertrain Conditioning



Battery Conditioning



Cabin Conditioning



Drivetrain Efficiency

- Exploitation of **temperature dependent efficiencies** of powertrain components
- Monitoring of powertrain temperature while driving (sensors & digital twin)
- **Demand-oriented cooling** of the components to reduce auxiliary energy demand
- Consideration for **preceding driving profile** & **ensuring performance reserves**

Charging Time & SoH

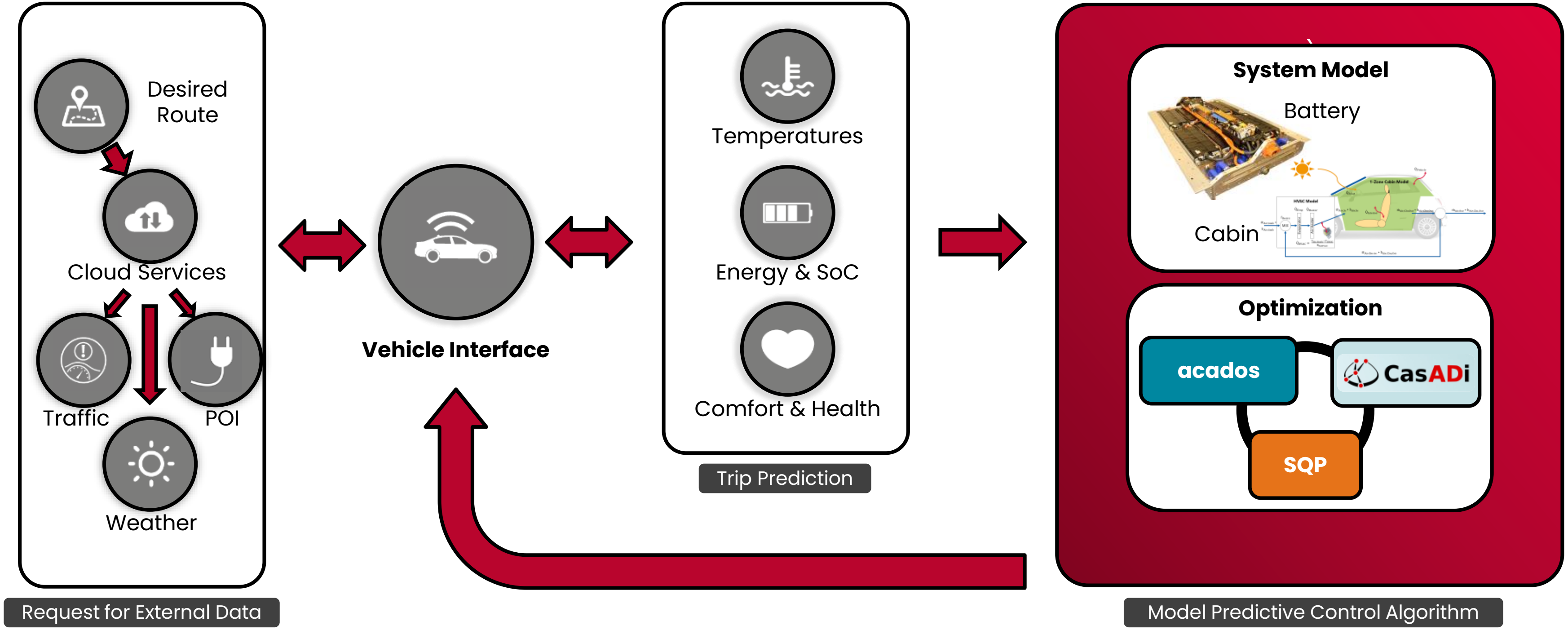
- Charging and discharging limitations are highly **temperature dependent**
- Cell temperatures have an impact on **battery ageing effects**
- **Predictive preconditioning** of the battery can help to reduce charging times
- Additional criteria **like State of Health (SoH)** can be considered in the cooling strategy

Thermal Comfort & Energy

- Cabin conditioning has a significant **impact on driving range** at extreme ambient conditions
- MPC contributes to identify the best **compromise between thermal comfort and energy demand**
- Active handling of air humidity as part of interior **comfort and safety (window fogging)**
- **Air Quality Management**

The modular functional architecture of the model predictive controls allows a wide range of customization options

Exemplary Functional Architecture for a Cabin and Battery MPC



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In a model-predictive control strategy, a wide variety of targets can be combined and taken into account for optimization

Predictive Cabin Conditioning

- Model Predictive Control Algorithm
  - **Tailored to target vehicle**
  - Adapted to the configuration of air conditioning system
  - **Flexibility in the configuration** of the interfaces
- Optimization of Energy Consumption
  - Consideration of LV and HV consumers
  - Maximum usage **of air recirculation & optimized control**
- Maintaining Comfort and Air Quality
  - **Comfort evaluations** can be implemented
  - Limiting CO_2 concentration & other **air quality criteria**
  - Active **humidity control**

UP TO:

55 % **Energy Savings for Cabin Conditioning**

Predictive Battery Conditioning

- Prediction of the battery load & boundary conditions
  - According to planned route
  - **Traffic information via external data sources**
  - Ambient temperature & Weather conditions
- Optimization Target of MPC Control Approach
  - Minimize **energy consumption**
  - Minimize **charging stop duration**
- Consideration of the operating conditions for battery
  - Maximum charging and discharging powers
  - Maximum cell temperatures & temperature differences
  - Consideration of **ageing effects**

UP TO:

3 % **Driving Range Increase**

10 % **Charging Time Reduction**

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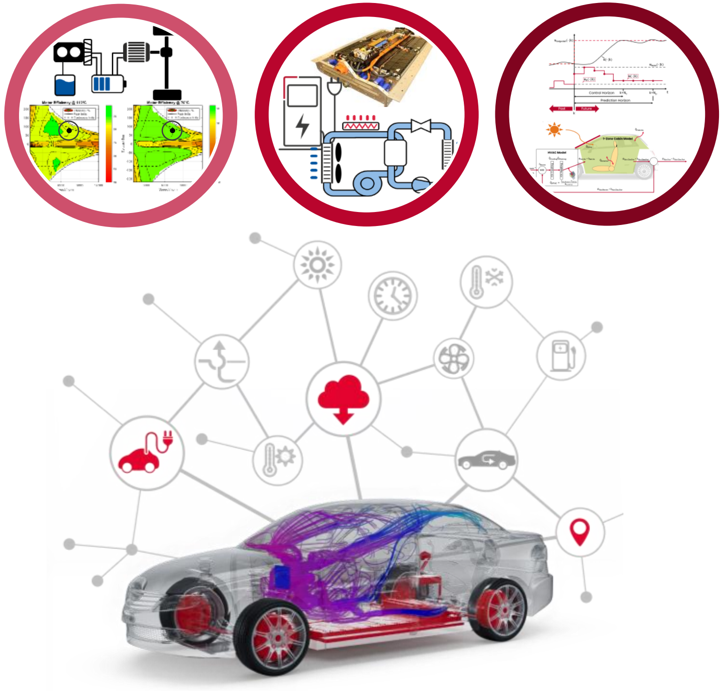
Future applications require a holistic approach to predictive thermal management, which can flexibly fulfill requirements

Integrated systems benefit from a holistic evaluation of energy consumption

- Development of an optimization-based control strategies for thermal systems
- **Complete vehicle thermal management** controlled by MPC
- Connection of different sub-systems via **highly integrated cooling circuits** or **sophisticated heat pump systems**
- Can be adapted to various vehicle and thermal system topologies
- Enhanced performance **by machine learning** extensions

Powertrain Conditioning | Battery Conditioning | Cabin Conditioning



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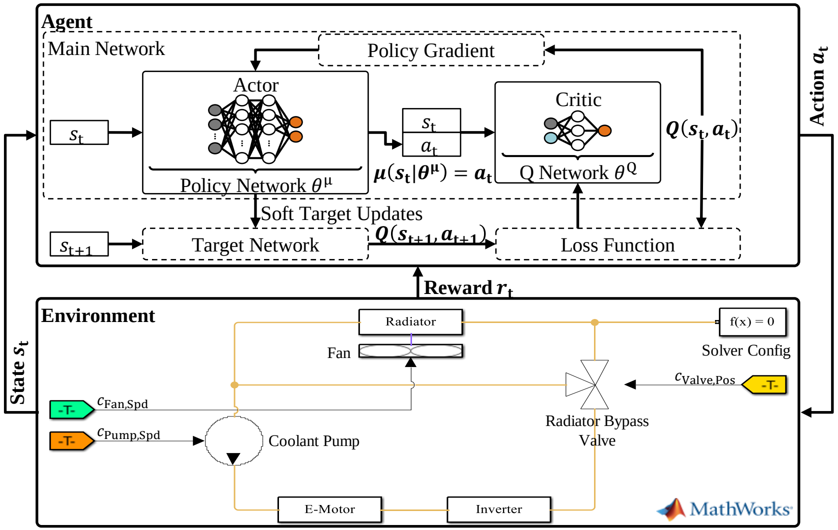
Reinforcement learning (RL) for the optimization-based control of a thermal management systems



Introduction & Overview

- Development of an optimization-based control strategies for thermal systems
- Investigation on different RL options
- Fan, pump and valve control for a basic thermal system of a BEV
- Single vs. Multi RL-agent approaches
- Different optimization targets for the investigation:
  - Target temperatures or temperature limits
  - Minimization of the energy demand
  - Considerati

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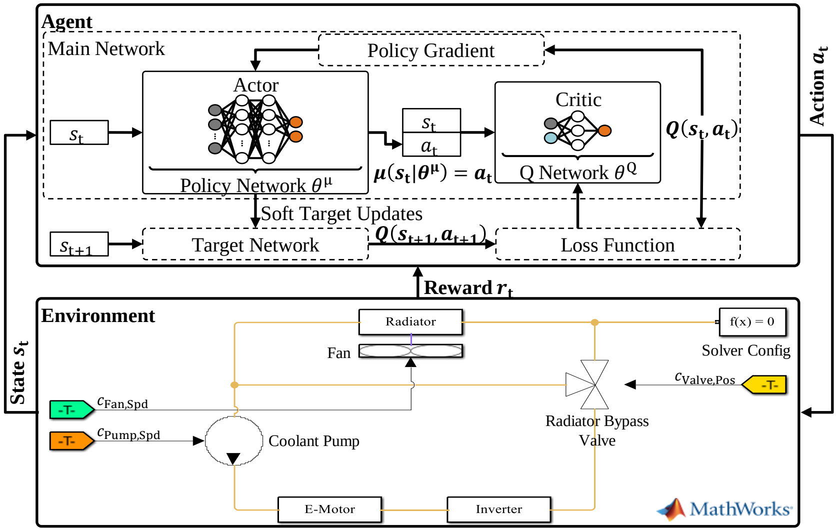

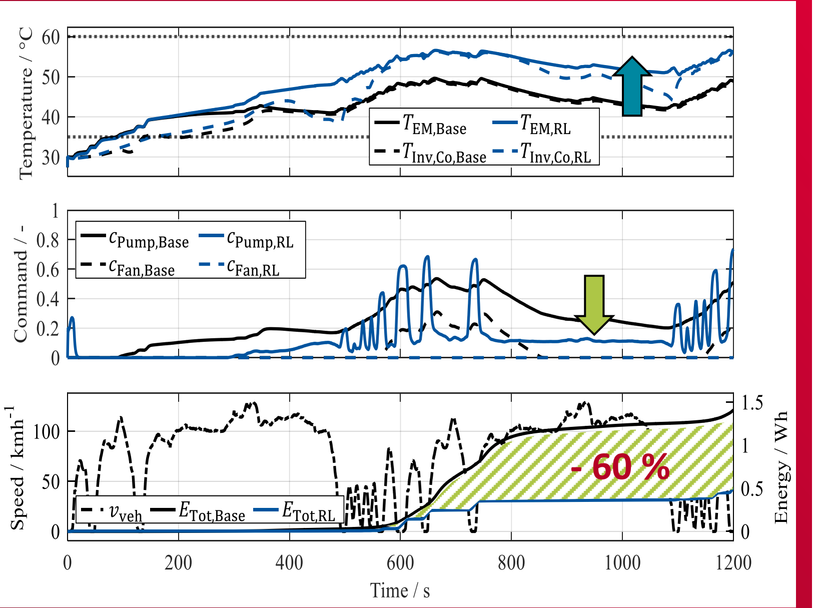

Simulation for Artemis Motorway 130 @ 30 °C

$T_{EM, Base}$ – Motor Temperature (rule based), $T_{EM, RL}$ – Motor Temperature (RL based),
$T_{Inv, Co, Base}$ – Motor Temperature (rule based), $T_{Inv, Co, RL}$ – Motor Temperature (RL based),
$c_{Pump, Base}$ – Pump Duty Cycle (rule based), $c_{Pump, RL}$ – Pump Duty Cycle (RL based),
$c_{Fan, Base}$ – Fan Duty Cycle (rule based), $c_{Fan, RL}$ – Fan Duty Cycle (RL based),
$E_{Tot, Base}$ – Total Energy (rule based), $E_{Tot, Base}$ – Total Energy (RL based),
v_{veh} – Vehicle Speed

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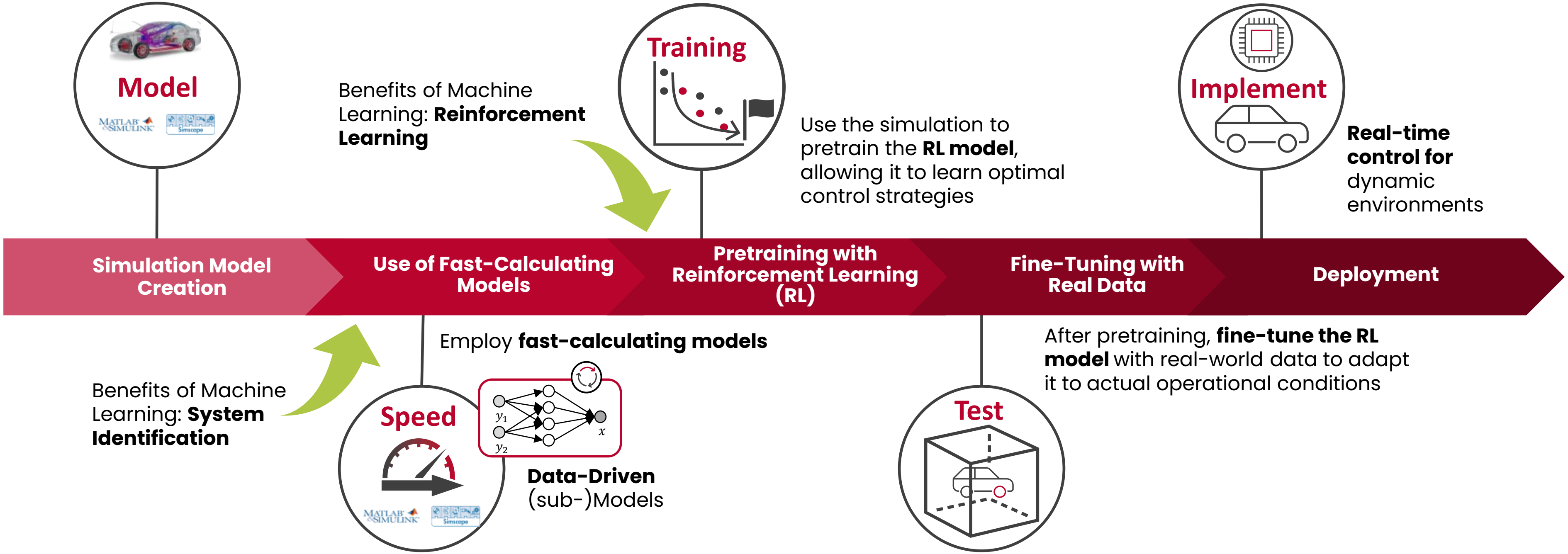
The use of machine learning approaches requires a rethink of the development process

The targeted use of machine learning can generate significant advantages



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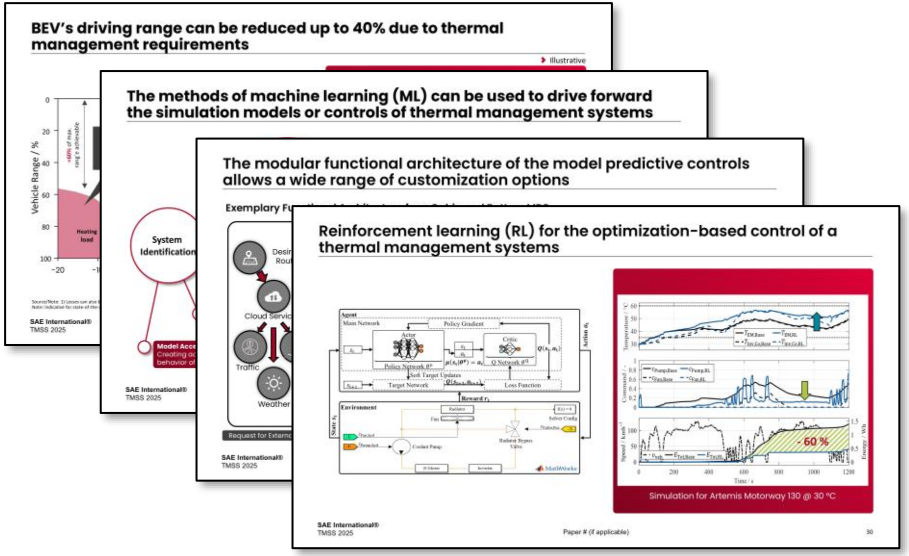
MPC and machine learning (ML) will make a significant contribution to improving the thermal management of vehicles



Next Steps

- Development of holistic MPC for thermal system with complex heat pump systems
- Improvement of Machine Learning Approaches for the use in thermal system development and control definition
- Combination of MPC Controls and prediction models generated by ML

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