« Advanced Model Predictive Control for Energy-Efficient Thermal Management in Intelligent Electric Refrigerated Vans »

Kaibo Li[1], Sankhadeep Bhattacharyya[1]

Truong Quang Dinh[1], Jongil Yoon[2], Bom Yun[2]

[1]WMG, University of Warwick, UK

[2]KOCETI, South Korea

1. Background and Objective
2. Modelling of the Refrigerated Van
3. Model Predictive Control
4. Simulation Resutls
5. Conclusion

Background and Objective

Background and Objective

Background

- ❑ Refrigerated transport is essential for delivering food, plants, flowers, and medical products
- ❑ Global refrigerated vans are expected to increase from **4 million (2010) to 6.5 million (2030)**
- ❑ Refrigerated transport contributes **15%** of global fossil fuel consumption and **40%** of greenhouse gas emissions

Challenges

- ❑ Traditional on-off control causes temperature fluctuations and is energy-inefficient
- ❑ External disturbances (ambient temperature, solar radiation, door opening events) impact performance

Model Predictive Control (MPC)

- ❑ MPC improves energy efficiency and adapts to disturbances better than traditional methods
- ❑ Studies show up to **43% energy savings** with MPC over conventional PI controllers

Hierarchical MPC (HMPC)

- ❑ Proposed H-MPC structure with a **planning layer and an operating layer**
- ❑ Uses two Nonlinear MPCs (NLMPC) with different sampling times and prediction horizons
- ❑ **Reduced computational time** while maintaining or **improving energy efficiency**

Objective

To develop a computationally efficient predictive control for refrigerated van using hierarchical architecture

Modelling of the refrigerated van

Graphical description

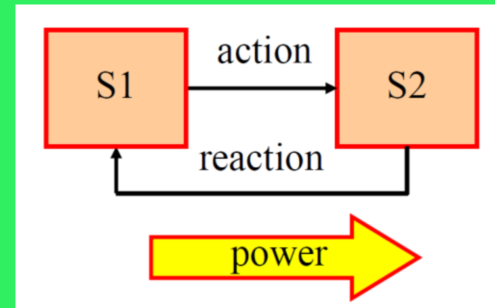
=

organization
of models of
complex systems

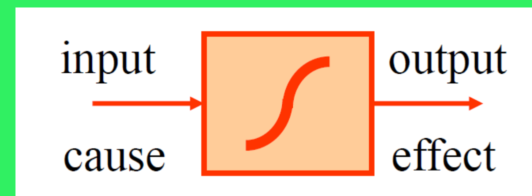
⇩

Systematic deduction
of organization of
control schemes

Principle of interaction
Each action induces a reaction

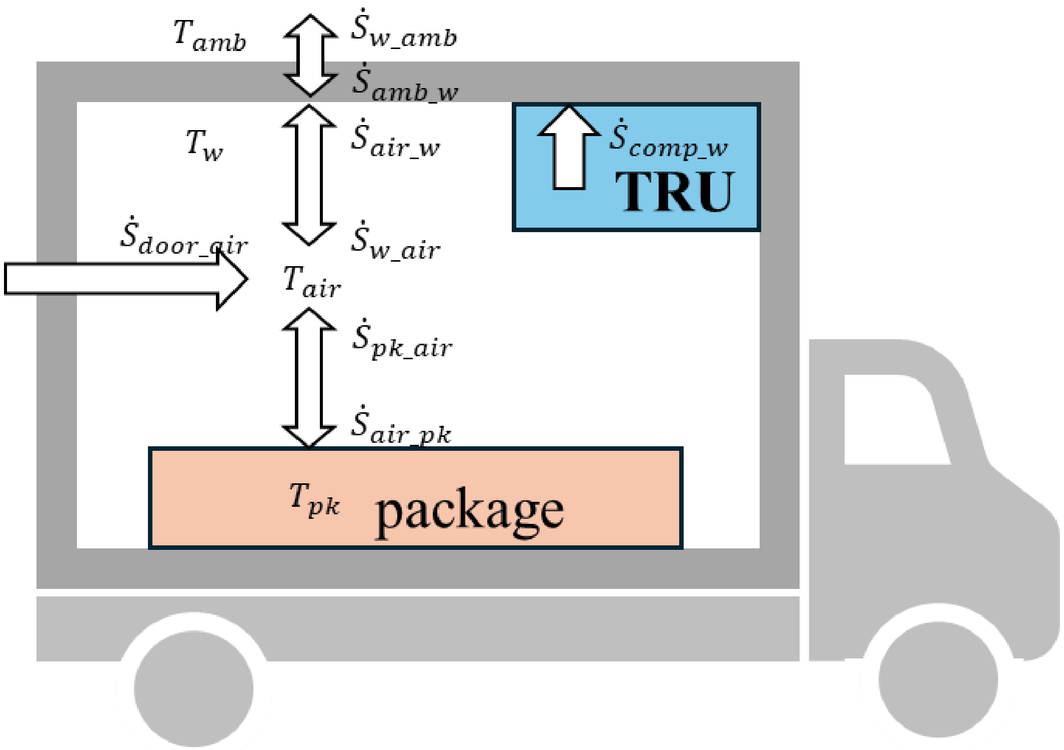


Principle of causality



Different meaning in different domains:

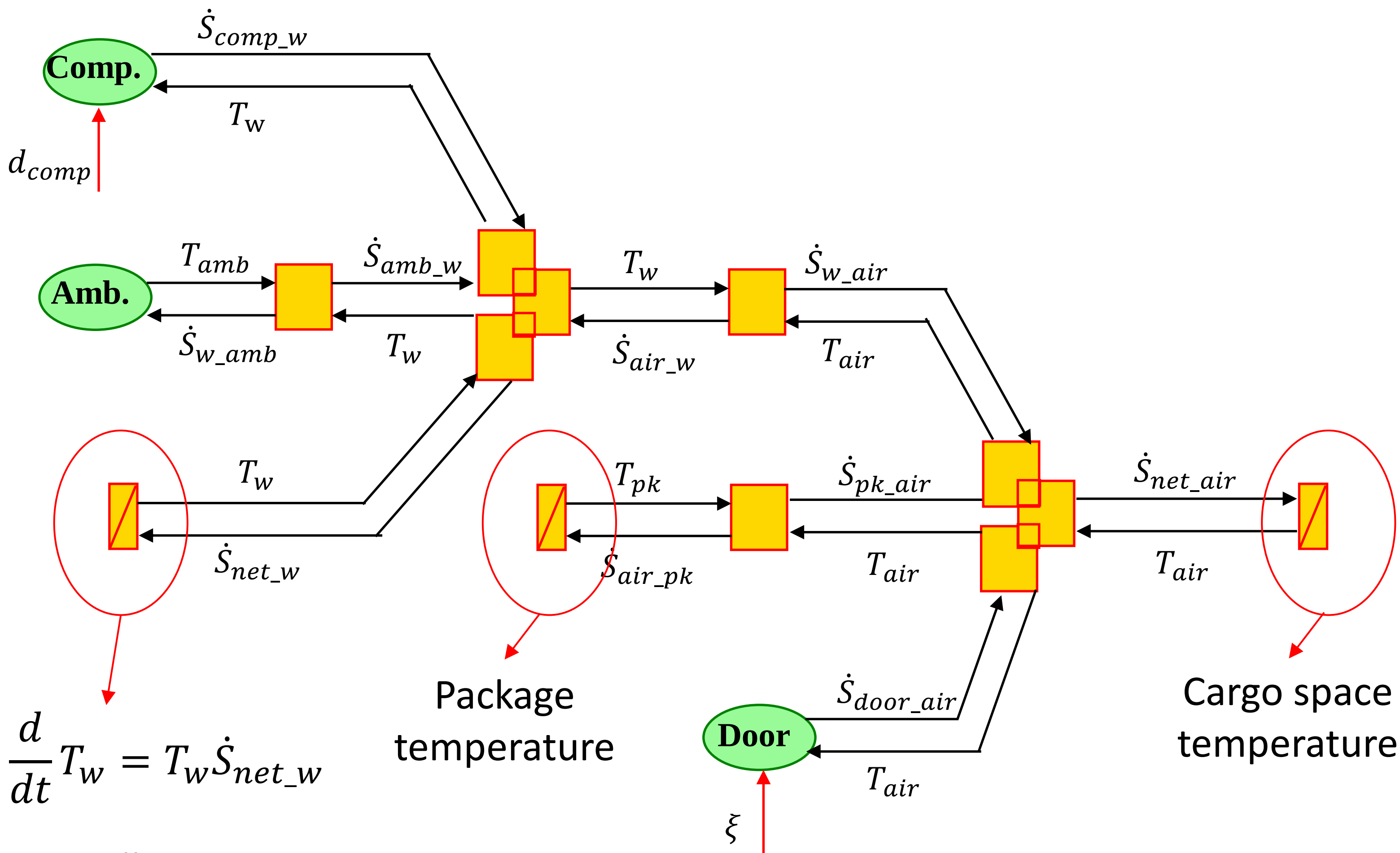
- Physics: output is obtained from input after a delay
- Mathematics: output is an integral function of input
- Automatic control: output is the state variable
- Energy: output is the energetic variable



Assumptions:

- Temperature-controlled Refrigeration Unit (TRU) consists of a condenser, evaporator, thermal expansion valve, and compressor
- The cooling pipe is embedded in the inner wall of the chamber
- The number of packages is expected to change at door opening events
- The new packages are already at the same tempera-ture as the ones kept in van

Model of the Refrigerated Van with EMR



$$M_w C_w \frac{d}{dt} T_w = T_w \dot{S}_{net\_w}$$

Inner wall temperature

Model Predictive Control

- State variables:

Inner wall temperature — Cargo space temperature — Package temperature

$$x = [T_w, T_{air}, T_{pk}]$$

- Control variable:

$$u = \omega$$

Compressor speed

- Measureable disturbances:

$$w = [T_{amb}, n_{pk}, \xi\ ]$$

Ambient temperature — Package number — Door opening event

NLMPC controller

Optimization algorithm

$$\min_{\omega} \sum_{k=1}^{N_{NLMPC}} \alpha_1 P_{comp\_e}(k) + \alpha_2 \omega(k) + \alpha_3 \Delta\omega(k) + \alpha_4 \left(T_{air}(k) - T_{air\_ref}\right)^2 + \alpha_5 \sigma_1(k)$$

s.t.

$$T_{air}^{LL} - \sigma_1(k) \leq T_{air}(k) \leq T_{air}^{UL} + \sigma_1(k)$$

$$\omega_{min} \leq \omega(k) \leq \omega_{max}$$

$$0 \leq \boldsymbol{\sigma_1}(k)$$

u

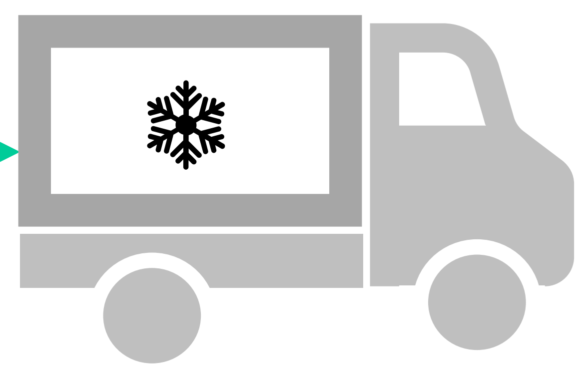
$[T_w, T_{air}, T_{pk}]$

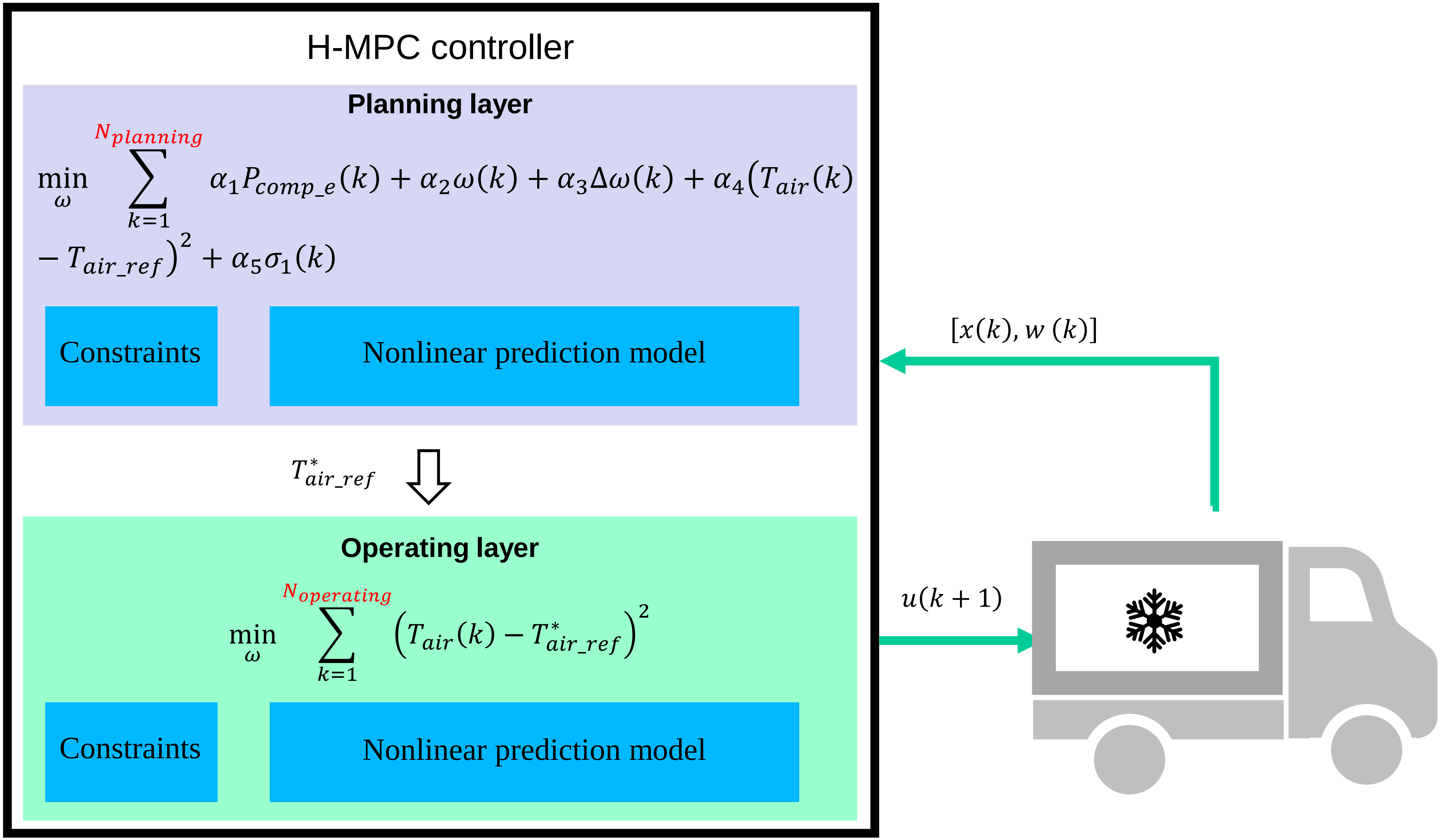
Nonlinear prediction model

$$[T_{air}(k+1), T_w(k+1), T_{pk}(k+1)] = f_{bat}\big(x(k), u(k+1), w(k+1)\big) T_s$$

$[x(k), w(k)]$

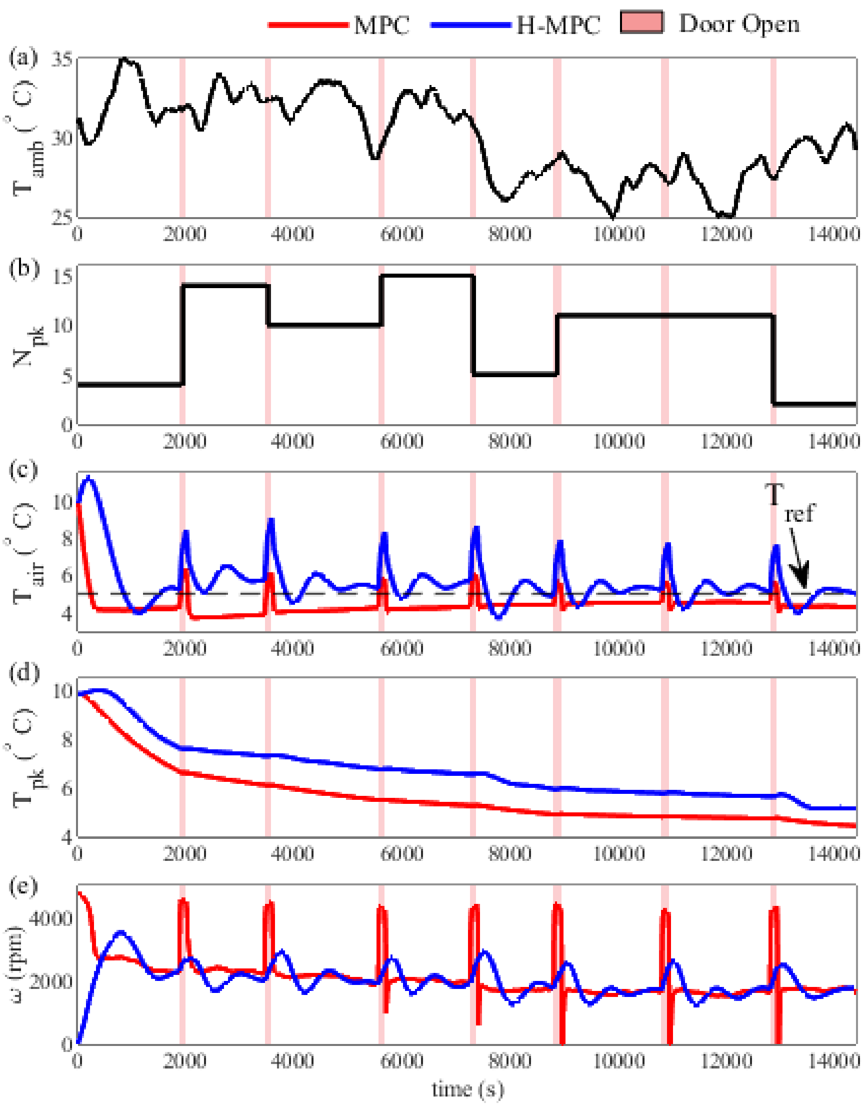
$u(k+1)$




H-MPC controller
Planning layer
$$\min_{\omega} \sum_{k=1}^{N_{planning}} \alpha_1 P_{comp\_e}(k) + \alpha_2 \omega(k) + \alpha_3 \Delta\omega(k) + \alpha_4 \left(T_{air}(k) - T_{air\_ref}\right)^2 + \alpha_5 \sigma_1(k)$$
Constraints
Nonlinear prediction model
$T^*_{air\_ref}$
Operating layer
$$\min_{\omega} \sum_{k=1}^{N_{operating}} \left(T_{air}(k) - T^*_{air\_ref}\right)^2$$
Constraints
Nonlinear prediction model
$[x(k), w\,(k)]$
$u(k+1)$

Simulation Results

Comparisons between NLMPC and HMPC



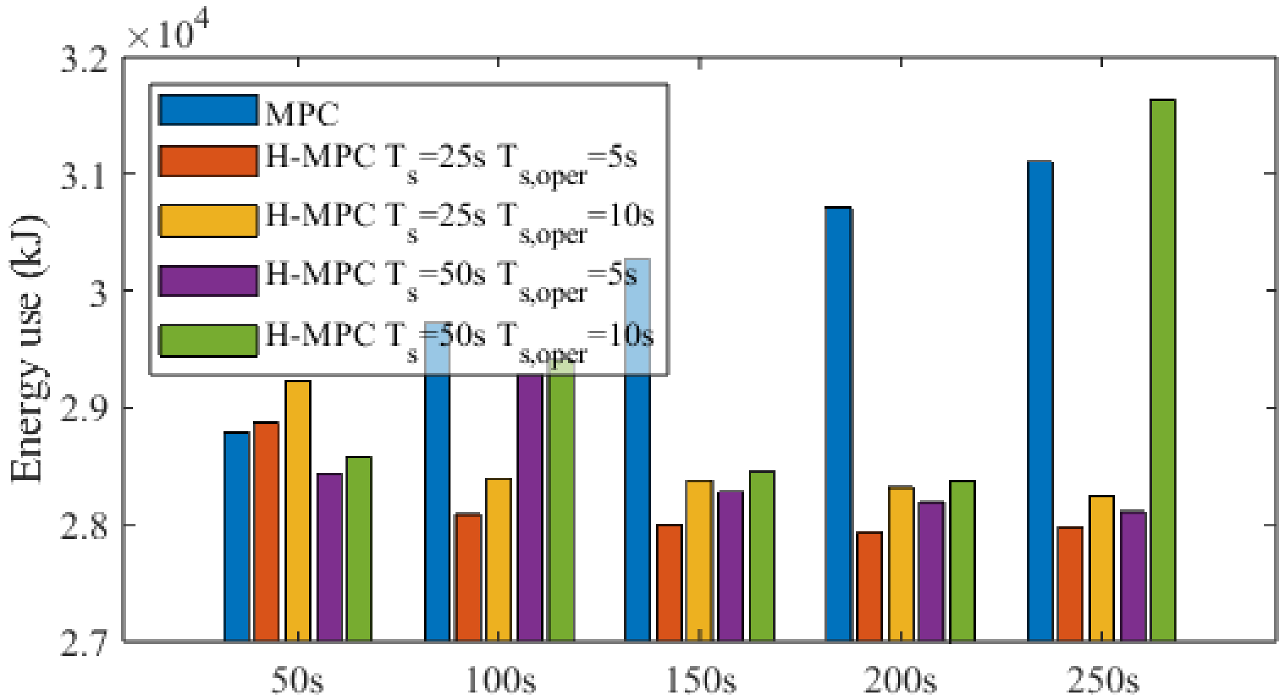
- Ambient temperature varies due to factors like solar radiation
- Number of packages changes only during door openings
- NLMPC maintains a lower air temperature compared to the reference
- H-MPC causes air temperature to fluctuate around the reference temperature
- Air temperature rises when the door is open due to warm air inflow
- Control performance differences stem from variations in cost functions

Comparisons between NLMPC and HMPC

	Constraint violation (Ks)	Energy Consumption (kJ)	Simulation time (s)
MPC (benchmark)	1329	29725	127.21
HMPC	12607	28088	36.98

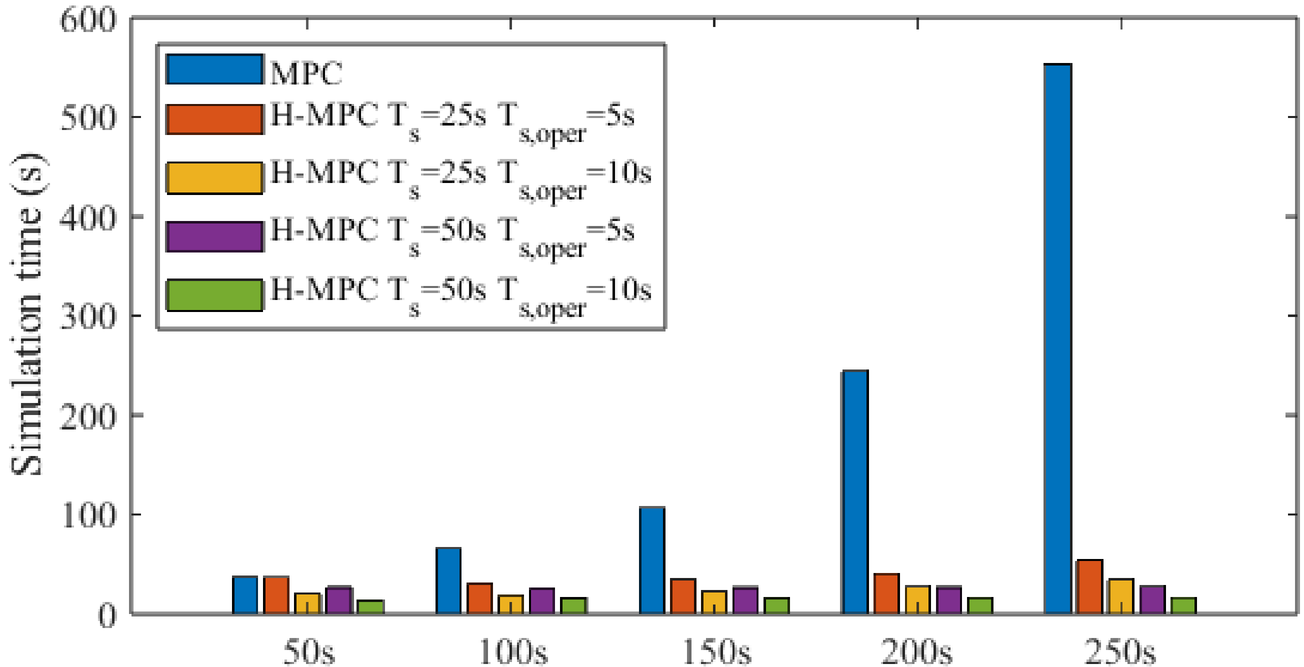
Note: The prediction horizon and sampling time for NLMPC are set to $N_{NLMPC} = 20$ and $T_s^{NLMPC} = 5s$, respectively. For H-MPC, the prediction horizon and sampling time of the planning layer are specified as $N_{planning} = 4$ and $T_s^{planning} = 25s$, while for the operating layer, they are set to $N_{operating} = 2$ and $T_s^{operating} = 5s$.

- ❑ H-MPC has higher constraint violation than MPC
- ❑ But has similar energy consumption and saves simulation time by 71%



Prediction length

- H-MPC reduces energy consumption compared to standard MPC. With a 250s prediction horizon, H-MPC (planning: 25s, operating: 5s) uses 10% less energy than MPC
- Longer prediction horizons in MPC increase energy use, while H-MPC generally benefits from longer horizons



Prediction length

- MPC simulation time increases exponentially with longer prediction horizons, while H-MPC remains nearly constant
- H-MPC reduces computation time across all cases, with at least 90% reduction for a 250s prediction horizon
- Higher sample times in both the planning and operating layers of H-MPC further lower computational costs

Conclusion

Conclusion

- TRU systems in vans are highly energy-intensive, requiring intelligent, energy-efficient controllers for electric vans
- Traditional MPC controllers are complex and on-board vehicle controllers lack the necessary processing power
- H-MPC is proposed as an alternative, using separate planning and operating MPCs with different sample times and prediction lengths
- H-MPC reduces computational load by using a shorter prediction horizon in the operating layer

Simulation results

- Up to 10% energy savings compared to MPC
- Up to 90% reduction in computation time, making it competitive for real-time use

Future work

- Further optimization of H-MPC parameters
- Integration with machine learning for improved predictive accuracy and adaptability
- Predicting door-opening events to enable pre-cooling and enhance system efficiency

Questions and discussions