

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

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Abstract—Traditional Model Predictive Control (MPC) is known for its robust decision making and precision in control. However, for systems with high inertia requiring longer prediction horizons like temperature control in intelligent electric refrigerated vans, it suffers from heavy computational loads. To address this, a Hierarchical MPC (H-MPC) framework is proposed for the thermal management system of intelligent refrigerated vans. This approach combines a planning layer for long-term predictions and an operating layer for short-term adjustments, utilizing different sampling times and prediction horizons to improve the cooling performance and computational efficiency. Simulation results demonstrate that the proposed H-MPC reduces computational time by up to 90% compared to traditional MPC while maintaining similar energy consumption and achieving up to 10% energy savings in some scenarios. These results highlight the real-time applicability of H-MPC in the refrigerated transport industry.

Keywords—refrigerated transport, temperature control unit, thermal management, optimisation, model predictive control.

I. INTRODUCTION

Refrigerated transport is employed to deliver various goods, including food (prepared, frozen, or ready-to-eat products), plants, flowers, and medical products. In 2010, approximately 4 million refrigerated vans were in operation, with this number predicted to increase to 6.5 million by 2030 [1]. Studies indicate that refrigerated transport powered by internal combustion engines accounts for about 15% of global fossil fuel consumption and contributes to 40% of global greenhouse gas emissions [2]. Therefore, the electrification of refrigerated transport is crucial for addressing both the energy and environmental crises.

A typical refrigerated transport system is equipped with a temperature-controlled refrigeration unit (TRU), which interacts with the vehicle's cargo space to regulate the internal conditions and maintain the goods' temperature within allowable ranges to ensure their safety and property [3]. The most common temperature control approach for the Thermal Management System (TMS) in refrigerated transport is on-off feedback control. In this method, the compressor is activated based on the difference between the measured cargo space temperature and the setpoint [4]. However, this approach can lead to significant temperature fluctuations within an allowable range, potentially compromising the preservation of goods. Additionally, it tends to be less energy-efficient, as it often fails to account for various disturbances, such as ambient temperature, solar radiation, door openings, and the number of packages.

More efficient control strategies have been implemented to meet cooling demands and mitigate disturbances, with a focus on maximizing energy efficiency and thereby directly benefiting the environment. Model Predictive Control (MPC) has emerged as a promising method for the TMS of refrigerated

transport, where conflicting objectives and disturbance predictions must be managed. For example, [5] develops and implements an exergy-based MPC for a vapor compression system (VCS), aiming to improve operational efficiency by minimizing exergy destruction. This study employs a lumped parameter moving boundary model to simulate the VCS's heat exchangers and optimize control actions based on exergy efficiency. Simulation results demonstrate that the exergy-based MPC improves system efficiency by over 40% compared to a first-law MPC, offering deeper insights into the impact of variable-speed actuators on system performance. During loading and unloading, with the door open, the inflow of warm ambient air constitutes a significant portion of the total cooling load, with air infiltration through the door accounting for more than half of the cooling load in cold storage facilities [6]. In [7], MPC is used to optimize temperature control and energy consumption while managing the effects of door openings. The study reveals that controlling the temperature of the cargo, rather than the air temperature, can significantly reduce energy consumption. Additionally [8] explores the benefits of implementing MPC in a TMS for refrigerated transport. A comparative study between the developed MPC controller and a traditional PI controller, conducted using a physical thermal rig, shows that MPC can achieve up to 43% energy savings.

Given the large thermal inertia of the refrigerated transport system, its temperature response is slow, necessitating a longer prediction horizon for the MPC controller to achieve optimal performance. However, this extended horizon increases computational complexity and introduces additional uncertainties. To address these challenges, various MPC variants have been explored, such as adaptive MPC [9], explicit MPC [10], hierarchical MPC [11, 12]. There is also growing interest in integrating Machine Learning (ML) with MPC [13]. For instance, ML has been used to model the internal dynamics of MPC controllers [14], to emulate the MPC controllers [15], and to optimize MPC hyperparameters [16]. While these approaches have not yet been directly applied to the TMS of refrigerated transport systems, they offer valuable insights and potential strategies for future applications.

The objective of this paper is to develop a Hierarchical MPC (H-MPC) controller for the TMS of a refrigerated transport van. The modelling and control of the thermal system are organized using the Energetic Macroscopic Representation (EMR) [17]. A Nonlinear MPC (NLMPC) serves as the baseline. The proposed H-MPC [12, 18] is formulated with a planning layer and an operating layer using two NLMPC with different sampling times and prediction horizons in distinct layers. The simulation results show a significant reduction in computational time while maintaining comparable or improved energy efficiency.

The rest of the paper is organized as follows: Section II covers the modelling and control of the thermal system in a refrigerated transport system. Section III focuses on the development of the MPC controller. Section IV presents the simulation results, and Section V provides the conclusion.

II. MODELLING AND CONTROL OF THE REFRIGERATED CHAMBER OF A VAN

A. Configuration of the truck chamber

The van's chamber temperature is regulated by a TRU (Figure. 1), which consists of a condenser, evaporator, thermal expansion valve, and compressor. Further details about the TRU can be found in [19]. In this paper, it is assumed that the cooling pipe is embedded in the inner wall of the chamber. By controlling the compressor, the temperature of the inner wall is reduced, which in turn lowers the temperature of the chamber air and the packaged goods.

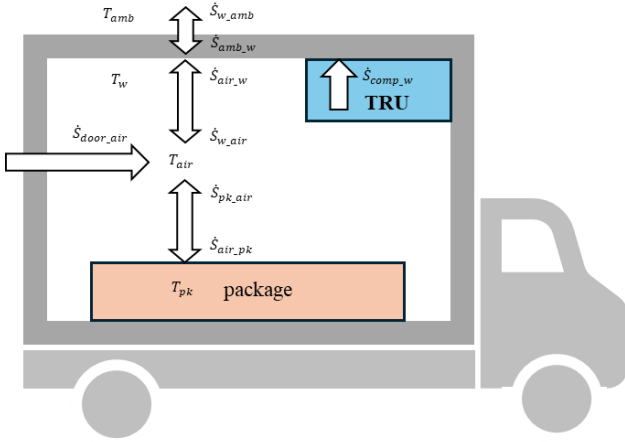


Figure. 1 Scheme of the chamber of the van

B. Modelling of the truck chamber

As shown in Figure. 1, the thermal dynamics of the chamber's inner wall are driven by the net entropy flow rate ($\dot{S}_{net,w}$). Consequently, the temperature of the inner wall (T_w) can be modeled as:

$$M_w C_w \frac{d}{dt} T_w = T_w \dot{S}_{net,w} \quad (1)$$

where M_w and C_w represent the mass and specific heat capacity of the wall, respectively.

The net entropy flow rate of the wall is influenced by contributions from the compressor ($\dot{S}_{comp,w}$), the chamber air ($\dot{S}_{air,w}$) and the ambient environment ($\dot{S}_{amb,w}$):

$$\dot{S}_{net,w} = \dot{S}_{amb,w} + \dot{S}_{air,w} + \dot{S}_{comp,w} \quad (2)$$

The heat exchange between the inner wall and the surrounding environment is represented as follows:

$$\begin{cases} \dot{S}_{amb,w} = k_{w,amb} \frac{T_{amb} - T_w}{T_w} \\ \dot{S}_{w,amb} = k_{w,amb} \frac{T_w - T_{amb}}{T_{amb}} \end{cases} \quad (3)$$

where $k_{w,amb} = A_w h_{w,amb}$ denotes the heat transfer coefficient. In this expression, A_w represents the wall area, $h_{w,amb}$ is the thermal conductivity, T_{amb} is the ambient temperature, $\dot{S}_{w,amb}$ is the entropy flow rate to the ambient.

For the compressor, the entropy flow rate to the wall ($\dot{S}_{comp,w}$) is described by an empirical equation derived from a reference compressor:

$$\dot{S}_{comp,w} = -\frac{P_{comp}}{T_w} \quad (4)$$

with

$$P_{comp} = \frac{P_{comp,e} - P_{comp,loss}}{1 + \eta_{loss}} \quad (5)$$

$$P_{comp,e} = P_{comp,e,ref} \frac{q}{q_{ref}} \left[\beta_1 + \beta_2 \left(\frac{\omega}{\omega_{ref}} \right) + \beta_3 \left(\frac{\omega}{\omega_{ref}} \right)^2 \right] \quad (6)$$

$$q = q_{ref} \left[\alpha_1 \left(\frac{\omega}{\omega_{ref}} \right) + \alpha_2 \left(\frac{\omega}{\omega_{ref}} \right)^2 + \alpha_3 \left(\frac{\omega}{\omega_{ref}} \right)^3 \right] \quad (7)$$

where P_{comp} is the polytropic compression power, $P_{comp,e}$ is the input electrical power, $P_{comp,loss}$ represents the constant loss due to electro-mechanical loss, η_{loss} is the ratio of electromechanical losses to P_{comp} . Additionally, q is the volumetric flow rate, ω is the rotational speed, α_i and β_i are the estimated coefficients. The subscript 'ref' refers values from the reference compressor. More detailed information on compressor modeling can be found in [20].

The thermal dynamics of the packages within the chamber are described by:

$$M_{pk} C_{pk} \frac{d}{dt} T_{pk} = T_{pk} \dot{S}_{air,pk} \quad (8)$$

with

$$M_{pk} = n_{pk} m_{pk} \quad (9)$$

where M_{pk} and C_{pk} are the total mass and the average specific heat capacity of the packages, m_{pk} is the mass of each individual package, n_{pk} is the number of packages, T_{pk} is the temperature of the packages, and $\dot{S}_{air,pk}$ is the entropy flow rate from the chamber air to the packages. It is assumed that all packages are of the same average specific heat capacity and that they are always in thermal equilibrium with each other. During a standard van operation, the number of packages is expected to change at door opening events. For sake of simplicity, it is assumed that the new packages are already at the same temperature as the ones kept in van.

The heat exchange between the chamber air and the packages is modeled as follows:

$$\begin{cases} \dot{S}_{pk,air} = k_{air,pk} \frac{T_{pk} - T_{air}}{T_{air}} \\ \dot{S}_{air,pk} = k_{air,pk} \frac{T_{air} - T_{pk}}{T_{pk}} \end{cases} \quad (10)$$

where $k_{air,pk} = A_{pk,total} h_{air,pk}$ represents the heat transfer coefficient. In this expression, $A_{pk,total}$ is the total surface area of the package, $h_{air,pk}$ is the thermal conductivity, T_{air} is the chamber air temperature, $\dot{S}_{pk,air}$ is the entropy flow rate from packages to the chamber air.

The thermal dynamics of the chamber air are described as follows:

$$M_{air} C_{air} \frac{d}{dt} T_{air} = T_{air} \dot{S}_{net,air} \quad (11)$$

with

$$M_{air} = \rho_{air} V_{air} \quad (12)$$

$$V_{air} = V_{space} - V_{pk} \alpha_{pk} \quad (13)$$

where M_{air} is the total mass of the air in the chamber, C_{air} is the specific thermal capacity of the air, $\dot{S}_{net_air}$ is the net entropy flow rate of the chamber air, ρ_{air} is the air density, V_{air} , V_{space} and V_{pk} represent the volumes of the chamber air, the chamber, and the total package, respectively, and, α_{pk} is a package filling coefficient.

The net entropy flow rate to chamber air ($\dot{S}_{net_air}$) is calculated as follows:

$$\dot{S}_{net_air} = \dot{S}_{w_air} + \dot{S}_{pk_air} + \dot{S}_{door_air} \quad (14)$$

where $\dot{S}_{w_air}$, $\dot{S}_{pk_air}$ and $\dot{S}_{door_air}$ are the entropy flow rates to the chamber air from the wall, the packages, and the ambient when the door is open, respectively.

The heat exchange between the inner wall and the chamber air is described by:

$$\begin{cases} \dot{S}_{w_air} = k_{w_air} \frac{T_w - T_{air}}{T_{air}} \\ \dot{S}_{air_w} = k_{w_air} \frac{T_{air} - T_w}{T_w} \end{cases} \quad (15)$$

where $k_{w_air} = A_w h_{w_air}$ represents the heat transfer coefficient. In this expression, A_w is the area of the wall, h_{w_air} is the thermal conductivity.

The entropy flow rate from the ambient environment to the chamber air when the door is opening is modeled as:

$$\dot{S}_{door_air} = \xi k_{air_door} \frac{T_{amb} - T_{air}}{T_{air}} \quad (16)$$

where $k_{air_door} = A_{door} h_{air_door}$ represents the heat transfer coefficient. In this expression, A_{door} is the area of the door, h_{air_door} is the thermal conductivity, ξ is a coefficient that describes the door opening effect, where $\xi = 0$ indicates the door is closed, and $\xi = 1$ signifies the door is fully opened.

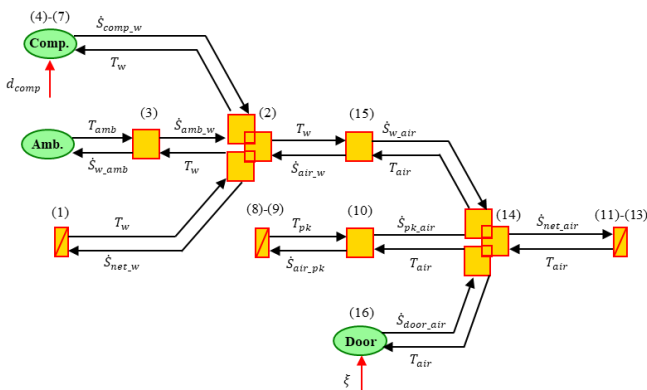


Figure. 2 EMR of chamber of the van

The model is organized using the Energetic Macroscopic Representation (EMR), as illustrated in Figure. 2, with the relevant relationships outlined in the brackets. EMR is a graphical description tool for structuring complex system models. By employing EMR, a system is divided into several subsystems that are linked through 'action' and 'reaction' dynamics. These interactions enable the transfer of power between the subsystems. For comprehensive information of EMR's, please see [17].

III. MODEL PREDICTIVE CONTROL

A. Formalization of the MPC controller

MPC relies on a plant model that takes as inputs the current state estimations, along with both measured and unmeasured disturbances, to predict the future behavior of the system. Using this information, MPC evaluates the impact of potential control sequences over a defined period, known as the prediction horizon. The prediction horizon is denoted by Np , a positive integer that represents the number of sample times considered in the future, making the total prediction time interval $Np \cdot Ts$, where Ts is the sampling time. The sequence of control inputs is optimized to meet predefined performance requirements, such as stability and reference tracking and in this case, temperature control. However, the control inputs are typically updated only within a control horizon, denoted by Nc , which is always less than or equal to Np . This means that after the control horizon Nc , the control inputs remain unchanged for the remainder of the prediction horizon. From the optimized control sequence, only the first control input is applied to the system as the control signal. This process is repeated at each sample time Ts , as the optimization is computationally intensive, necessitating regular intervals between updates to ensure real-time feasibility.

The goal of the temperature control system in the van is to control the temperature of the packages to the desired temperature. However, the packages are not connected to a thermocouple or temperature sensing device. It is only through the maintenance of the cabin air temperature T_{air} that the temperature control of the packages can be achieved.

For the benchmark traditional MPC, the states variables x , the control input u and the measured disturbances are defined as follows:

$$x = [T_{air}, T_w, T_{pk}]^T \quad (17)$$

$$u = \omega \quad (18)$$

$$w_D = [T_{amb}, \xi, n_{pk}]^T \quad (19)$$

The state functions are adopted from the relations of the TRU model as defined in the previous section.

$$\dot{x} = f(x, u, w_D) = [\dot{T}_{air}, \dot{T}_w, \dot{T}_{pk}]^T \quad (20)$$

where $\dot{T}_{air}$ is taken from (19), $\dot{T}_w$ from (1) and $\dot{T}_{pk}$ from (8). As evident from the system dynamics, the state function is non-linear and thus a nonlinear MPC is used for optimization.

Finally, the MPC is defined as an optimization problem with constraints as follows:

$$\begin{aligned} \min_{\omega} \sum_{k=1}^{Np} & \alpha_1 P_{comp_e}(k) + \alpha_2 \omega(k) + \alpha_3 \Delta \omega(k) \\ & + \alpha_4 (T_{air}(k) - T_{ref})^2 + \alpha_5 \sigma_1 \end{aligned} \quad (21)$$

s.t.

$$[T_{air}(k+1), T_w(k+1), T_{pk}(k+1)]^T = f(x(k), u, w_D) \cdot T_s \quad (22)$$

$$T_{air}^{LL} - \sigma_1(k) \leq T_{air}(k) \leq T_{air}^{UL} + \sigma_1(k) \quad (23)$$

$$\omega_{min} \leq \omega(k) \leq \omega_{max} \quad (24)$$

$$0 \leq \sigma_i(k) \quad (25)$$

where k represents the current time step in the discretized model. The MPC attempts to minimize the operating costs (20) by changing the manipulated variable ω in the control horizon N_c . α_1 - α_5 are the weights associated with different objectives of the cost function. ω_{min} and ω_{max} are the lower and upper limits of the compressor rotational speed $\omega(k)$, which is also the manipulated variable or the controller output. T_{air}^{LL} and T_{air}^{UL} are the lower and upper bounds for the air temperature respectively and $\sigma_1(k)$ is the slack variable imposing a soft constraint on $T_{air}(k)$. The cost function includes five objectives. The first component aims at minimizing the electrical power drawn by the compressor according to (6). The second and third component aims at reducing compressor speed and fluctuations respectively. The fourth component penalizes temperature deviation from the set point reference T_{ref} and the fifth component aims at reducing the slack variable to keep T_{ref} within bounds.

B. Hierarchical MPC (H-MPC)

To minimize the computational cost involved with MPC, a hierarchical MPC is proposed in this section. The objective function of the controller is divided into planning and tracking layers. The planning layer MPC has a long prediction horizon and generates the optimal temperature profile which is then tracked using a short horizon operating layer MPC. The planning layer is formalized as the following:

$$\min_{\omega} \sum_{k=1}^{N_{planning}} \alpha_1 P_{comp,e}(k) + \alpha_2 \omega(k) + \alpha_3 \Delta \omega(k) + \alpha_4 (T_{air}(k) - T_{ref})^2 + \alpha_5 \cdot \sigma_1 \quad (26)$$

s.t.

$$[T_{air}(k+1), T_w(k+1), T_{pk}(k+1)]^T = f(x(k), u, w_D) \cdot T_s \quad (27)$$

$$T_{air}^{LL} - \sigma_1(k) \leq T_{air}(k) \leq T_{air}^{UL} + \sigma_1(k) \quad (28)$$

$$\omega_{min} \leq \omega(k) \leq \omega_{max} \quad (29)$$

$$0 \leq \sigma_i(k) \quad (30)$$

where $N_{planning}$ denotes the prediction horizon of the planning layer. The operating layer is formalized as the following:

$$\min_{\omega} \sum_{k=1}^{N_{operating}} (T_{air}(k) - T_{air,ref}^*)^2 \quad (31)$$

s.t.

$$[T_{air}(k+1), T_w(k+1), T_{pk}(k+1)]^T = f(x(k), u, w_D) \cdot T_{s,oper} \quad (32)$$

$$\omega_{min} \leq \omega(k) \leq \omega_{max} \quad (33)$$

$$0 \leq \sigma_i(k) \quad (34)$$

where $N_{operating}$ represents the prediction horizon of the operating layer. This layer has a shorter prediction horizon and a smaller sampling time. $T_{air,ref}^*$ is the optimal trajectory of temperature determined by the planning layer of MPC using

interpolation. $T_{s,oper}$ is the sample time for operating layer MPC.

IV. SIMULATION RESULTS

A. Control comparisons

In this section, the performances of the controllers are evaluated with a standard refrigerated van cycle. A cycle length of 4hrs is used with varying ambient temperatures between 25°C and 35°C, varying number of packages and randomized door opening times. The simulation results are shown in Figure.3. In these simulations, the cabin air temperature and the package temperatures are assumed to be 10°C at the start of the simulations and the reference temperature for the van is set to $T_{ref} = 5^\circ\text{C}$. For MPC, the sample time is set to 5s, the prediction horizon is set to 20 steps and the control horizon to 5 steps. For H-MPC, in the planning layer, $N_{planning}$ is set to 4, sample time to 25s and control horizon to 1 step. This results in prediction horizons of equal time in both controllers (100s). For the operating layer MPC in H-MPC, the sample time is 5s, which is equal to MPC, the prediction horizon $N_{operating}$ is set to 2 and control horizon is set to 2 as well.

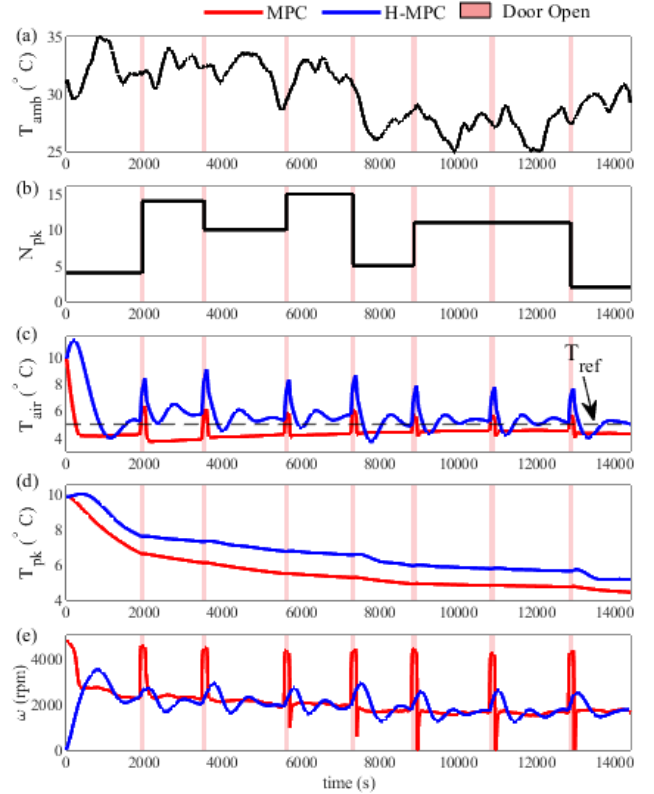


Figure. 3 Simulation results – comparison between MPC and H-MPC controllers. (a) shows the ambient temperatures at different times, (b) shows the number of packages in the van. (c) shows the resulting cabin temperatures in the van. (d) shows the package temperatures and (e) shows the speed of compressor. The door opening times have been shaded into the background of the plots.

The differences between the control input $\omega(k)$ between the two controllers are mainly due to differences in the cost functions considered. As a result, the cabin air temperature isn't as well tracked as in MPC, and the package temperature is always higher.

The key performance indicators for these two controllers are listed in Table I. It is seen that H-MPC has higher constraint

violation than MPC but has similar energy consumption and saves simulation time by 71%.

Table I. Performance of the controllers

Control- ler	Constraint Vi- olation (Ks)	Energy Con- sumption (kJ)	Simulation time (s)
MPC	1328.5	29725	127.21
HMPC	12607	28088	36.98

B. Sensitivity analysis

In the previous section, the prediction horizon lengths for both controllers are kept same. However, it is essential to analyze the impact of prediction horizon lengths and controller sample times on controller performances. In this section, a comparative study is performed using prediction horizons of five different lengths – (50s, 100s, 150s, 200s and 250s) and combinations of different sample times. For the H-MPC controller, the planning layer horizon is varied while the operating layer horizon remains fixed. The sample time for the planning layer is set to either 25s or 50s, while the sample time for the operating layer is chosen from 5s or 10s.

Figure.4 shows the energy use for different controllers with the standard van cycle as shown in Figure. 3. H-MPC results in a decrease in energy use compared to MPC. In the case with prediction horizon length of 250s, the H-MPC controller with planning sample time of 25s and operating sample time of 5s, consumes 10% less energy compared to the MPC controller. It is also seen that while larger prediction horizon lengths in MPC, results in higher energy consumption while the reverse is mostly true for the H-MPC controllers. In cases where planning sample time is set to 25s, the increasing the prediction horizon leads to reduced energy consumption. However, when the operating layer sample time is set to 50s, the energy use increases in few cases with controller with operating sample time of 10s using exceptionally high energy with prediction length of 250s.

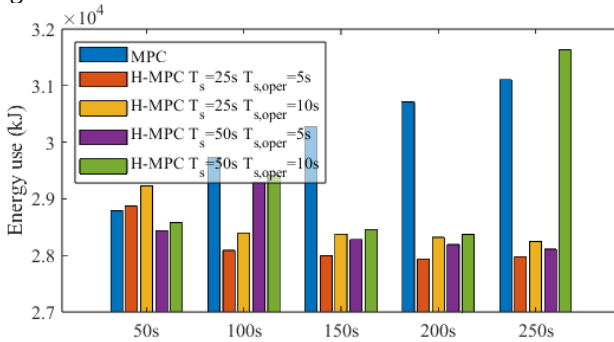


Figure. 4 Energy use comparisons for MPC and H-MPC

As the main reason for deployment of the H-MPC controller is the reduction of the computational costs associated with predictions, the simulation times for both types of controllers are compared with different prediction horizons in Figure.5. It is seen that the simulation time increases exponentially for the MPC controller but for the H-MPC controller it almost remains same irrespective of the prediction horizon length. The H-MPC controller reduces the computation time in all cases with

a computational time reduction of at least 90% where the prediction horizon is 250s. Also, it is seen that the computational costs associated with higher sample times for both planning and operating layers H-MPC controllers are lower in each case.

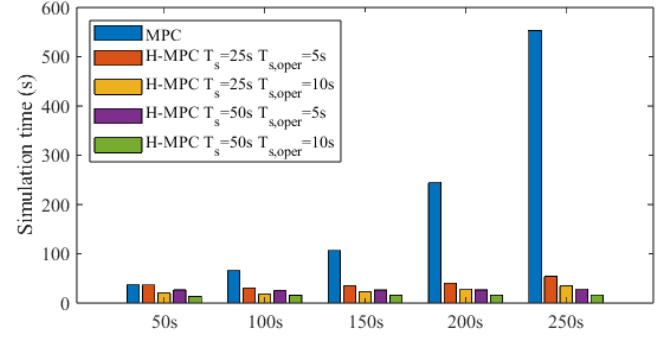


Figure. 5 Simulation times comparisons for MPC and H-MPC

The controller is tasked to maintain the van cabin temperature at $T_{ref} = 5^\circ\text{C}$. A temperature above it counts as a violation of the constraint. In Figure.6 MPC and HMPC controllers at different prediction horizons are compared for their ability to maintain cabin air temperature. It is seen that MPCs are better in controlling cabin temperature to the set point than all H-MPC controllers. Furthermore, larger horizons for MPC result in decreased constraint violations while the converse is observed in case of H-MPC. The constraint violation for H-MPC is observed to be consistently more than MPC. One of the possible reasons for this is the increase temperature references from the planning layer at door opening events.

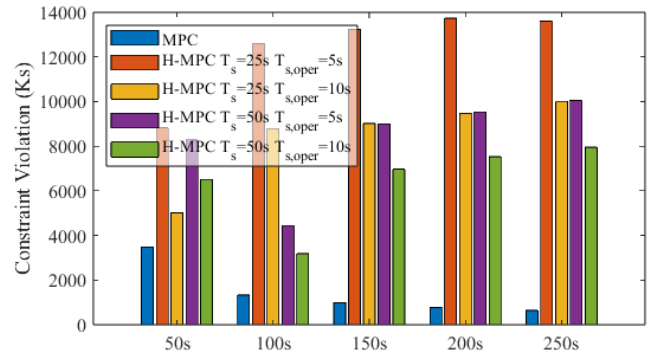


Figure. 6 Constraints violation comparisons for MPC and H-MPC4

V. CONCLUSION

Temperature-controlled Refrigeration Unit TRU in vans is an energy intensive system. It is therefore essential to have an intelligent energy efficient controller for electric vans. However, the traditional (Model Predictive Control) MPC controllers are complex, and vehicle on-board controllers are incapable of the processing power required for it. In this paper an alternative controller, Hierarchical MPC (H-MPC), is proposed to address the challenges posed by TRU system complexity and varying operational conditions such as ambient temperature fluctuations and door openings. The H-MPC involves separate MPCs for planning and operating with different sample times and prediction lengths. The operating layer MPC has a short prediction horizon, therefore reducing the computational load. Simulation results demonstrate that H-MPC achieves comparable energy efficiency to traditional MPC with energy savings up to 10% in some cases while significantly reducing computation time up to 90%, making it a more practical solution for

real-time applications in refrigerated transport systems. Future work could explore further optimization of H-MPC parameters and its potential integration with machine learning techniques to enhance predictive accuracy and adaptability and minimize constraint violations.

In the future, the prediction of door-opening events will be incorporated to enable pre-cooling of the air temperature, enhancing system efficiency.

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