Model Predictive Control for Mobile Refrigeration Systems: Challenges and Approaches

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ABSTRACT: This work outlines a comprehensive model and a sophisticated predictive control strategy for compressor-powered cooling units mounted in mobile, small-scale cooling chambers. The investigated system comprises several cooling units to improve failsafe performance and utilizes an extended refrigeration architecture extending control options. Due to door openings and the possibility of turning the compressor and the fan on and off, the mathematical model contains continuous and binary variables. A completely distributed model predictive approach is suggested to overcome computational bottlenecks and increase the failsafe performance of the overall concept. This paper provides a rough understanding of the topics mentioned above for a broad audience. References guide the interested reader to more detailed considerations.

1. INTRODUCTION

In the last decades, air conditioning has become an ever-greater energy consumer. Growing world population combined with increasing demand for pleasant room climate and almost global cold chains for food transportation yield high carbon dioxide emissions. Although cooling units consume enormous amounts of energy during their lifetime, widely-used control algorithms for these applications are usually simple, most often only rely on room temperature measurements, and are designed and operated without appropriate models of the surroundings.

While linear model predictive approaches are well studied (Rawlings & Mayne 2009; Wang 2009), including binary decision variables (e.g., turning the cooling unit on/off) requires appropriate extensions and represents a highly topical challenge (Bemporad & Morari 1999; Borrelli et al. 2017). Since state-of-the-art refrigerated trucks are often equipped with several cooling units to improve reliability and because such optimizations determining continuous and binary inputs require enormous computing capacities, distributed control has gained interest in recent years (Jia & Krogh 2001; Camponogara et al. 2002; Nebenborn et al. 2006; Moroşan et al. 2010).

In the following, a model predictive control algorithm in a distributed formulation is outlined. It considers given temperature limits while minimizing overall energy consumption. A comprehensive model of a refrigerated truck, including door openings, serves as a basis for control design.

2. CHALLENGES

While refrigerated transportation of goods entails various challenges from a control engineer's point of view, customers' needs form the origin – see Fig. 1. Firstly, cargo temperature should remain within a specific range to inhibit waste of perishable goods and extend its shelf life (Fig. 1a). Secondly, customers constantly want to improve the overall system's efficiency to reduce costs on the one hand and to lower their environmental footprint on the other hand. As most classic control approaches merely take the temperature into account, they lack appropriate strategies to consider energy consumption (Fig. 1b).

However, control design requires extending these two overarching goals depending on the given system architecture. In order to serve application in a broad field by a single truck concept, a sophis-

ticated control scheme should be able to handle a varying number of mounted cooling units (Fig. 1c). Thus, it is possible to cover trucks that, e.g., operate in the north of Europe and may need two refrigeration units and vehicles used in a region close to the equator and therefore may need four. Fulfilling this requirement is also vital for the failsafe performance of the overall system. In this sense, the algorithm should still perform adequately, although one or more cooling units exhibit a fault (Fig. 1d).

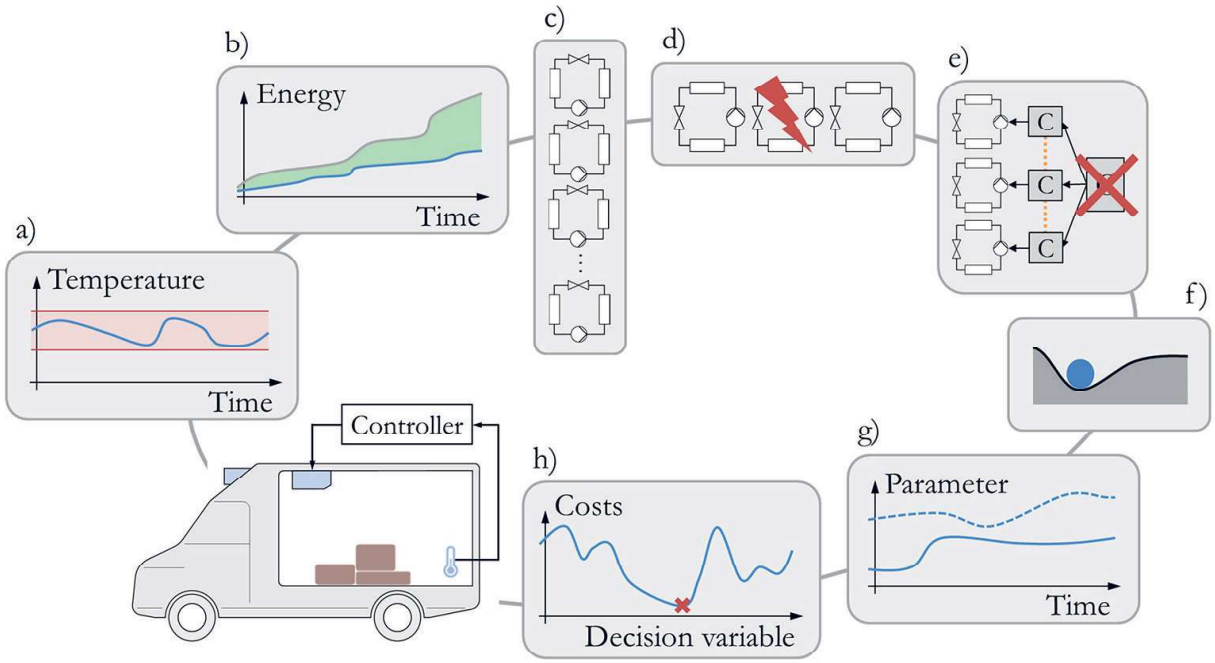

Fig. 1: Requirements to a sophisticated control scheme for mobile refrigeration systems: (a) keeping cargo temperature within a specific range, (b) increasing efficiency compared with state-of-the-art operating strategies, (c) handling a varying number of cooling units, (d) managing faulty refrigeration units, (e) offering fail-safety by applying distributed controllers, (f) exhibiting asymptotic stability of the closed-loop, (g) providing robustness in the face of parameter changes, and (h) ensuring global optimality despite applying a distributed approach.

To further improve reliability in such a multi-unit setup, separate controllers should manage each cooling unit independently. While some state-of-the-art approaches use an additional global controller or several identical globally acting agents to ensure an optimal workload distribution (Luchini et al. 2019; Poks 2021), information exchange between local agents allows an entirely distributed setup if designed appropriately (Fig. 1e). Especially if considering such communication among controllers, it is of particular importance to keep track of and ensure the closed-loop system‘s asymptotic stability (Fig. 1f).

Furthermore, the algorithm should be robust in the face of slight parameter changes (Fig. 1g). For example, a very likely source of it in mobile cooling applications is degradation or damage of the insulation (Luchini et al. 2018).

Finally, although the proposed concept is acting on a purely local level, communication among controllers should yield a solution at or at least sufficiently close to a global optimum (Fig. 1h).

3. SYSTEM DESCRIPTION

In order to apply appropriate methods, fulfilling the challenges mentioned above, detailed system insight is inevitable. Fig. 2 depicts the investigated system. The air temperature inside the cooling chamber ϑ_{cc} experiences various disturbances, see Fig. 2a. Since real insulations still conduct heat, ambient

temperature ϑamb is one of those. Although weather conditions and the initial cargo temperature $\vartheta c,init$ at the loading time also influence temperature evolution inside the chamber, the control model neglects explicit incorporation of these effects due to their large number of unknown and time-variant parameters. However, door openings (*sdoor*) have the most significant impact on the inner air temperature compared with the other disturbances. Despite that, most current approaches only cover them heuristically or by a pre-defined heat flow (Luchini et al. 2020). By contrast, the proposed modeling approach explicitly incorporates door openings and models them as an actual connection between the cooling chamber and the ambient air (Lafaye de Micheaux et al. 2015).

In contrast to widely-used cooling units, the investigated one exhibits an extended architecture (Fig. 2b). In addition to the fundamentally needed refrigeration circuit, the second loop uses a mixture of water and glycol as its coolant. This extension increases the system's flexibility as the water-glycol mixture may serve as a cold reservoir. Nonetheless, complexity remains on a reasonable level because the fluid in there is in its liquid state at all times. In contrast to typical applications, not the evaporator but only the air chiller is mounted inside the cooling chamber. At this very point, the heat flow $\dot{Q}_0$ causes cooling of the air inside the chamber. This system structure comes along with superior advantages: on the one hand, the refrigerant cannot contaminate any goods within the storage room as it is isolated by the water-glycol cycle in between. On the other hand, the storage effect of the glycol-water mixture offers the opportunity

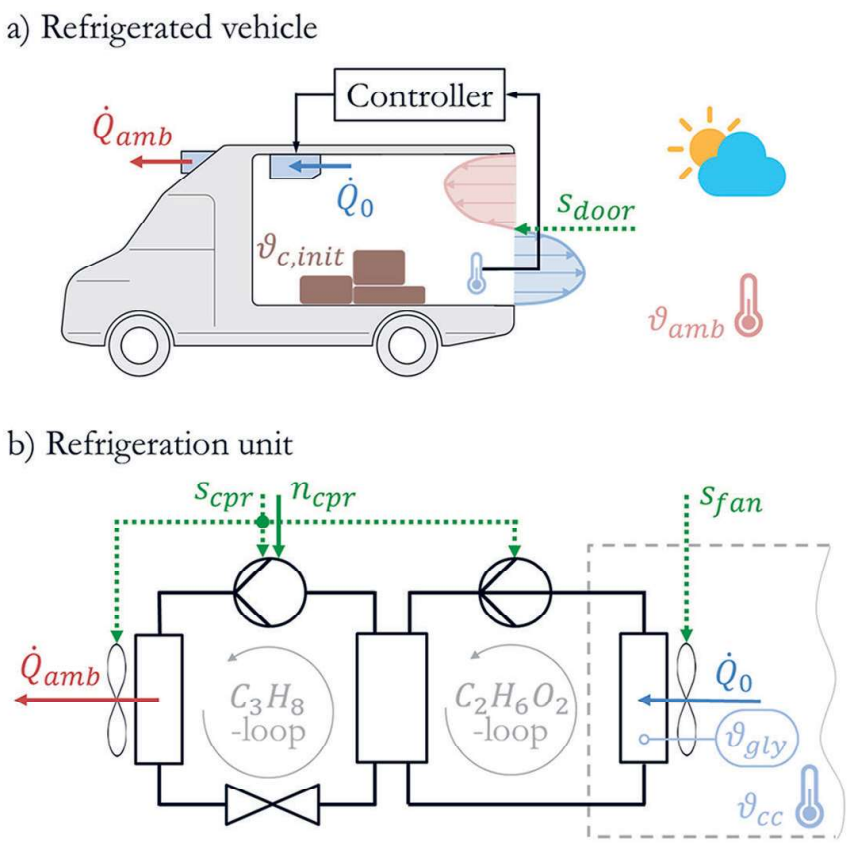

Fig. 2: Schematic illustration of (a) a refrigerated vehicle with disturbances acting upon it and (b) the structure of the investigated cooling unit. The cooling device comprises a classic refrigeration loop using propane (C_3H_8) as its coolant and a storage loop driven by a mixture of water and glycol ($C_2H_6O_2$). Quantities important for understanding and modeling are labeled appropriately according to the following listing. Temperatures: air inside the cooling chamber ϑ_{cc}, ambient air ϑ_{amb}, cargo at the time of loading $\vartheta_{c,init}$, glycol inside air chiller ϑ_{gly}. Heat flows: into the atmosphere $\dot{Q}_{amb}$, cooling capacity $\dot{Q}_0$. Binary inputs: door opening s_{door}, compressor switch s_{cpr}, fan switch s_{fan}. Continuous input: compressor speed n_{cpr}.

towards a more flexible operating strategy with a strong focus on both temperature limits and overall efficiency. Therefore, to fully utilize the system's functional scope, a suitable control concept defines the compressor speed n_{cpr}, the compressor switch s_{cpr}, and the fan switch s_{fan} at every time step.

As the system incorporates binary and continuous variables, associated models are denoted as *hybrid* (Bemporad & Morari 1999; Borrelli et al. 2017). The given system architecture allows formulating a set of affine models. Every combination of the three binary inputs (s_{cpr}, s_{fan}, and s_{door}) presents a certain mode *i(t)* with its continuous-time state-space representation according to:

$$\begin{aligned} \dot{\boldsymbol{x}}(t) &= \boldsymbol{A}^{i(t)}\boldsymbol{x}(t) + \boldsymbol{B}^{i(t)}\begin{bmatrix} n_{cpr}(t) \\ \vartheta_{amb}(t) \end{bmatrix} + \boldsymbol{f}^{i(t)}, \\ \boldsymbol{y}(t) &= \boldsymbol{C}^{i(t)}\boldsymbol{x}(t) + \boldsymbol{D}^{i(t)}\begin{bmatrix} n_{cpr}(t) \\ \vartheta_{amb}(t) \end{bmatrix} + \boldsymbol{g}^{i(t)}, \end{aligned} \tag{1}$$

where

$$\boldsymbol{x}(t) = \begin{bmatrix} \vartheta_{gly}(t) \\ \vartheta_{cc}(t) \\ \vartheta_{w1}(t) \\ \vartheta_{w2}(t) \end{bmatrix}, \qquad \boldsymbol{y}(t) = \begin{bmatrix} \vartheta_{cc}(t) \\ P_{el}(t) \end{bmatrix}, \tag{2}$$

with the state vector x, the output vector y, the temperatures of the insulation ϑ_{w1} and ϑ_{w2}, and the electrical power consumption of the refrigeration unit P_{el}. Other quantities are matrices (A,B,C,D) or vectors (f,g) of appropriate size, resulting from physical modeling and parameter identification. Please note that f and g render the otherwise linear model affine.

As the control concept determines binary and continuous variables (manipulated variables: n_{cpr}, s_{cpr}, and s_{fan}), a mixed-integer solver, e.g., Gurobi (Gurobi Optimization 2021), is necessary. To incorporate the switched-affine model dynamics **(1)** into an optimization problem, they have to be translated into a set of inequalities. A common and helpful tool for such a translation is HYSDEL (Torrisi & Bemporad 2004).

4. DISTRIBUTED HYBRID MODEL PREDICTIVE CONTROL SCHEME

Distributed control schemes that aim towards a solution sufficiently close to a global optimum require appropriately designed communication among controllers, see Fig. 3 and for a comprehensive overview (Camponogara et al. 2002). Each control agent solves a local optimization problem to define:

$$\boldsymbol{\Phi} = \begin{bmatrix} \boldsymbol{U}_c \\ \boldsymbol{U}_l \end{bmatrix} \tag{3}$$

with the sequence of continuous manipulated variables U_c and logical ones U_l within the horizon. While actual formulation depends on users' preferences, the objective function J_{total} can be written in the form:

$$J_{total}(\boldsymbol{\Phi}) = \boldsymbol{\Phi}^T \boldsymbol{P}_1 \boldsymbol{\Phi} + \boldsymbol{P}_2\, \boldsymbol{\Phi} + P_3 \tag{4}$$

with the matrix P_1, vector P_2, and the scalar value P_3. Please note that these matrices and the scalar value embody actually chosen temperature and energy objectives and are therefore application-dependent. Besides model dynamics, various constraints can be considered as well. The overall problem incorporates them by inequalities, stated as:

$$\boldsymbol{G}_1\boldsymbol{\Phi} \leq \boldsymbol{G}_2(\boldsymbol{x}(0), \boldsymbol{V}_c, \boldsymbol{V}_l) \tag{5}$$

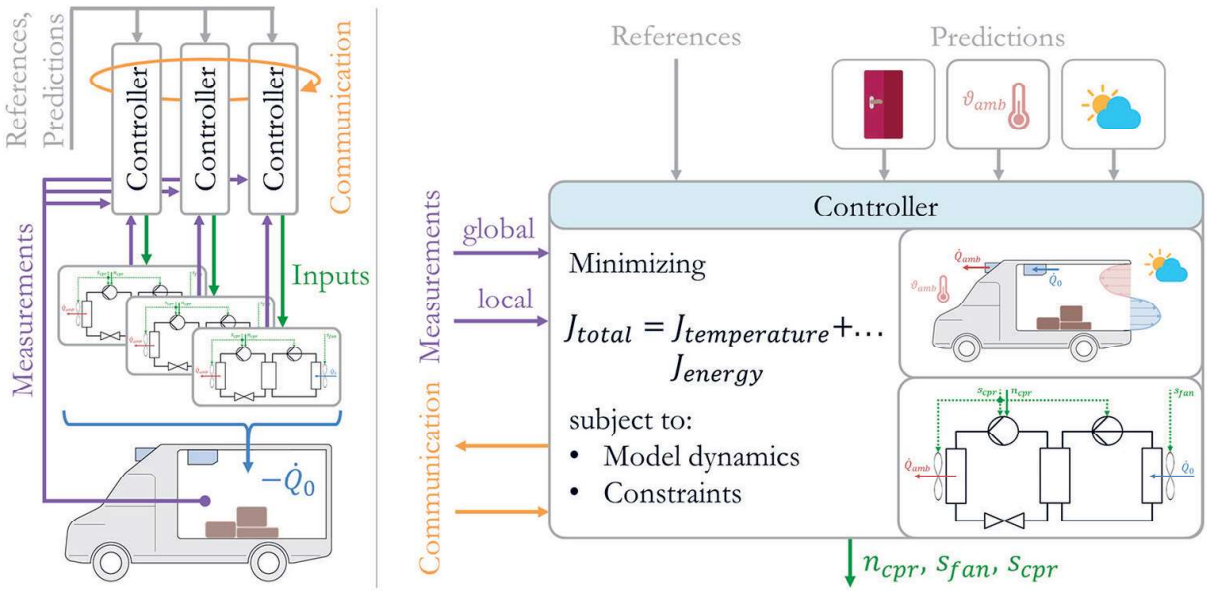

Fig. 3: Schematic of the distributed control concept (left) in its general view and (right) focusing on a single controller's workload. Each controller determines manipulated variables by minimizing an objective function J_{total} based on given references, predictions (door opening, ambient temperature, and weather conditions), global and local measurements, and communication with other agents.

where G_1 and G_2 result from the chosen restrictions and the system model and V_c and V_l denote sequences of continuous and binary predictions, respectively. These prediction vectors also contain communicated values between agents. Solving this problem yields the optimal solution:

$$\boldsymbol{\Phi}^* = \arg\min_{\boldsymbol{\Phi}} J_{total} \tag{6}$$

Extracting and applying the first values of the optimal input sequences U^*_c and U^*_l complete the workload during a single time step.

Design of the communication among controllers is vital to ensure robustness and stability of the overall concept. Actual dynamics highly influence possible communication options. A promising and straightforward possibility communicates each cooling unit's planned cooling capacity at the beginning of every time step (Jia & Krogh 2001; Groß 2013). After that, each agent runs its local optimization based on knowledge about the other agents' plans. However, as the plans may vary from step to step, only suboptimal results are achievable. Furthermore, rapid plan changing from at least one agent can yield unstable behavior. To overcome this issue, plan-changing penalties provide stability but also minimize performance (Dunbar 2007).

Another possibility is to run several optimizations in every time step and communicate intermediate results to all other agents. Although the computational advantage of the distributed approach is shortened in such a framework, optimal results sufficiently close to the global optimum are achievable (Negenborn et al. 2006).

This setup promises to meet temperature restrictions better and decrease overall energy consumption compared with standard control approaches for refrigerated trucks. A detailed comparison of various aspects is subject to current investigations.

5. CONCLUSIONS

Transporting perishable goods by refrigerated trucks entails numerous challenges for controlling cargo temperature. Obeying temperature restrictions while simultaneously offering high efficiency requires sophisticated control schemes. Providing redundancy by applying several cooling units within a single truck renders the control problem even more complex. A modeling approach explicitly incorporating door openings offers a more comprehensive insight into system dynamics and allows a more flexible control strategy compared with standard approaches. The presented outline of a distributed model predictive control scheme shows operators' significant advantages in keeping better track of temperature restrictions and increasing overall efficiency. Both are associated with economic favors.

Besides its usage in mobile cooling applications, apparent system similarities to stationary systems, e.g., air conditioning of wall-coupled rooms (Moroşan et al. 2010), promise advantages of the proposed scheme in a broad field.

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