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A Review on Challenges concerning Thermal Management System design for Medium Duty Electric Vehicles

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ABSTRACT

In the last decade, Battery Electric Vehicles (BEV) have been detected as a way to decrease greenhouse gases emission related to road transportation. Still, this technology faces several problems to break through the current automotive market because of the poor autonomy compared to ICE (Internal Combustion Engine) vehicles and of the average cost. These two issues are highly influenced by the design and the operation of the vehicle thermal management system. Auxiliary loads, heating and cooling demand can drastically decrease the BEV autonomy but also electric components lifetime because of inefficient cooling/heating resulting in improper operating temperature. Extensive scientific work has been performed to optimise the Vehicle Thermal Management System (VTMS) for electric/hybrid cars. However, the application of the found results or developed methodologies to Medium Duty Electric Vehicles (MDEV) has only been scarcely discussed so far. Hence, this paper proposes an insight on the scientific issues to be addressed to achieve an optimal design of MDEV thermal management system.

Keywords: *Medium duty electric vehicles, thermal management, design optimisation, control optimisation*

Abbreviations

GHG	Green House Gas
EV	Electric Vehicle
MDV	Medium Duty Vehicle
MDEV	Medium Duty Electric Vehicle
ICE	Internal Combustion Engine
BEV	Battery Electric Vehicle
VTMS	Vehicle Thermal Management System
COP	Coefficient of Performances
PCM	Phase Change Materials
HVAC	Heating Ventilation and Air Conditioning
MPC	Model Predictive Control
TCO	Total Cost of Ownership

1. INTRODUCTION

Light commercial trucks and passenger cars account for around 16% of total greenhouse gases emissions in Europe [1] so that in EU long term strategies for climate neutrality, the transport sector has to achieve a 30% reduction of its greenhouse gases (GHG) emissions by 2030 and 60% by 2050. In addition,

constraints on vehicles dedicated to urban applications (delivery services, refuse collections, etc.) are becoming increasingly severe resulting in two major issues for Medium Duty Vehicles¹ (MDV) manufacturers:

1. Access to urban centres in order to perform the services: in the medium term, current diesel vehicles will no longer be authorized to drive in city centres.
2. The economic profitability of the solutions: the alternative solutions offered must have a user cost and a purchase cost ensuring the viability of transport companies.

Electrification of the MDV powertrain could tackle the first issue but still strive to kick in the automotive market because of the second one. Indeed, a European report produced in the frame of the FP7-funded research project INTRASME (Innovative Transport Small Medium Enterprises Support Action), shows that price, vehicle autonomy and competition from conventional vehicles are the most important reasons for non-adoption of Medium Duty Electric Vehicles (MDEV) [2]. However, some advantages also emerge from the report: sustainability, reduced maintenance costs, fuel cost savings and economic incentives. A more recent study from Rout et al. [3], which compares Total Cost of Ownership (TCO) for various types of ICE, electric and Fuel Cell trucks, highlight that MDEVs are today close to competitiveness compared to their Internal Combustion Engine (ICE) counterparts. However, their study also stresses out that the competitiveness achievement depends heavily on the mission fulfilled by the truck. For example, while MDEV school bus achieve a lower TCO than the ICE version, for refuse truck the gap remains important with an increase of the TCO by 25% (about 2.0 £/km for MDEV vs. 1.5 £/km for ICE).

To tackle this issue, a possible contribution is to optimise the sizing of the Vehicle Thermal Management System (VTMS) to decrease both CAPEX and OPEX, while preserving the vehicle's ability to fulfil its mission (e.g. refuse collection) for given constraints (e.g. given shift time).

In an ICE vehicle, the thermal management system consists mainly in a heat rejection loop operating at a temperature range between 80 °C and 110 °C for the engine and HVAC pack for cabin heating and cooling. For the engine, the components can sustain high temperatures (around 125 °C) without dramatic degradation of their performance and/or lifespan, so that the precise control of operating temperatures is not an issue [4], the primary role of the VTMS being to avoid engine materials to reach their point of failure. Nevertheless, to go further, some authors have assessed the opportunity to optimise the VTMS use/design, with for example, Shu et al. [5] or Thomaz et al. [6] optimising the coolant flow rates to improve the fuel efficiency. Hence, for ICE trucks, the energy resource is barely an issue so that a common sizing approach consists in using extreme weather conditions to design the VTMS as no significant impact on the vehicle range is foreseen. The chosen extreme weather conditions resulting in a so called "worst case scenario" of course depend on the vehicle duty, manufacturer selling strategy, etc.

For MDEV the challenges are quite different. Indeed, batteries are very sensitive to temperature, and present specific thermal needs in order to ensure a good level of performance and lifetime. Secondly, power electronics and electrical machines also have specific cooling needs and contribute to the available amount of heat to be managed by the VTMS. However, the amount of available heat could be

¹ MDV refers to *Category N as defined by UNECE standards*, <https://alternative-fuels-observatory.ec.europa.eu/general-information/vehicle-types>

too low so that the heating requirement of the batteries and of the cabin is met thanks to active systems (e.g. electric heaters) resulting in vehicle's range rapid decrease. Hence, for MDEV, an approach based on "worst-case scenarios" raises new issues because of the constraint on energy resource (i.e. battery capacity). Indeed, in this case, there could be a benefit to not comply with the setpoint (e.g. battery optimal operating temperature) in case of extreme weather conditions to avoid an over consumption of electricity and in consequence a significant decrease in vehicle range. However, such a strategy leads to a degradation of the battery that results in a decrease of its lifetime and hence to a potential early costly replacement. Therefore, for MDEV it could be of great interest to optimise the sizing of the vehicle thermal management system to identify the best techno-economic trade-off [7].

To highlight the design differences between the VTMS ICE and electric MDV, some references given by the MDV manufacturer VOLVO (to which Renault Trucks SAS belongs) are reported in table 1 for a truck of 240 kW wheel power. The heat rejected by an electric powertrain is five times smaller than that of an ICE with also lower temperature requirements as the cooling duty is for electric components (inverters, motors, battery, etc.). Assuming an ambient temperature of 30 °C, the specific cooling power to be achieved by the VTMS of the MDEV is three times higher than that of the diesel counterpart. At fixed vehicle architecture, or space claim for the cooling system, this can lead to either packaging infeasibility, or to unreasonable power needs for the fan system. This has to be managed either by technology installation (active cooling systems, multi temperature cooling architectures), or by questioning the customer needs, hence the sizing methods, or both, which calls for implementing optimisation approach in the decision-making procedure.

Table 1 Vehicle Thermal Management Gap Analysis for a 240 kW wheel power truck (Source: Volvo group)

MDV	Diesel	Battery
Heat rejection of the VTMS [kW]	150	30
Cooling target temperature [°C]	~100	~25 - 50
Specific cooling power at $T_{amb} = 30^{\circ}\text{C}$ [kW/K]	2.1	6.0 (for target at 35°C)
Thermal reactivity	Fast (<10min)	Slow (<1h)
Heating power [kW]	-	2.5

The optimisation of the sizing of EVs' VTMS represents in general great challenges as reported in many studies (e.g. [8] for an approach based on weight, [9] for one based on cost and energy efficiency) compared to the work to be performed for an ICE.

A first challenge is to deal with the impact of weather conditions on vehicle autonomy as reported in many studies on battery electric vehicles, which trends also stay true for MDEV. Iora et al. [10] find that the auxiliary power required for cabin and battery heating during winter reduces the vehicle range by as high as 44%. Hao et al. [11] propose a deep analysis on real-world available data of nearly 200 electric vehicles circulating in the city of Beijing. Results show that when the ambient temperature is higher than 28 °C and lower than 10 °C, the electric consumption of the battery increases by 2.3 kWh/100 km for every 5 K change in ambient temperature. Reyes et al. [12] explore the effect of winter over electric vehicle autonomy. Below -15 °C, vehicle performances are highly affected by heating system operation

as expected, whilst for temperatures between the latter and 20 °C, travel range has a linear dependence with ambient temperature. On their side, Wang et al. [13] find a U-shape relationship which is confirmed by the extensive study on the topic performed by Haber et al. [14] based on numerous infield study available in the literature and covering various regions and vehicle types. These authors report the effect to be higher at lower temperature because of loss of performance of the battery pack which effect adds to the demand in heating for the cabin and battery pack itself. In their review, Ma et al. [15] point out that the battery optimal temperature range is 15 - 35 °C. When the battery is operated out of this temperature range, it results in the loss of capacity and power and its lifetime drops dramatically. This is due to the reduction in ionic conductivity at low temperature, as also pointed out by [16]. Furthermore, while internal resistance usually decreases with increase in operating temperature, the opposite occurs at high temperature (above 60°C), affecting the available power [17]. In addition, the degradation of active material at these high temperatures results in capacity loss. Hence, the battery operating temperature is usually limited below 60 °C to prevent any occurrence of chain reaction. Xia et al. [18] point out that the factors affecting the thermal behaviour of electric vehicles are extremely complicated to model and analyse. Different areas of study are affected simultaneously such as temperature, state of charge and state of health of the battery and cabin comfort. Thus, the choice of the modelling approach could also have an impact on the obtained final results. These areas are interdependent and connected to electrochemistry, heat transfer and electricity transfer as reported in [19].

The Table 2 resumes the ambient temperature impact studies conducted on different types of electric vehicles and the type of modelling used. The range loss is extracted from the studies as the difference between the maximum range registered during summer driving compared to winter driving. Depending on the temperature range analysed, the type of vehicle and the modelling used, range loss is estimated to be between 20% and 40% for the worst cases.

Table 2 Studies conducted on the impact of ambient temperature on electric vehicles autonomy.

Study	Temperature range analysed	Type of vehicle and N°	Modelling of the VTMS	Highest Range Loss observed compared to a base case
Iora et al. [10]	-15 °C to 20 °C	Nissan Leaf, 1	Quasi-steady backward-looking model	40%
Hao et al. [11]	-10 °C to 35 °C	Personal e-vehicles, 58	Data analysis approach	22%
Reyes et al. [12]	-15 °C to 20 °C	Nissan Leaf, Mitsubishi I-Miev, 2	Data analysis approach	40%
Tian et al. [20]	-7 °C to 43 °C	Nissan Leaf, 1	Experimental modelling	32%
Al-Wreikat et al. [21]	0 °C to 30 °C	Nissan Leaf, 1	Data analysis approach	28%
Rastani et al. [22]	-30 °C to 40 °C	Nissan Leaf, E-Ducato Fiat, 1	Data analysis approach	up to 20%
Yuksel et al. [23]	-26 °C to 43 °C	Nissan Leaf, 1	Data analysis approach	up to 28 %

The wide variation in range loss presented in Table 2 is explained by the different driving cycles that have been used to conduct the different studies, as the temperature conditions and the used vehicle configuration remain almost the same for every study. From this table, it is also highlighted that only very few studies are found concerning the impact of ambient temperature on medium duty electric vehicles' performance. The most relevant one performed by Rastani et al. [14] deals with the impact of ambient temperature on route planning for electric freight vehicles. From onboard measurements, correlations of energy consumption as a function of ambient temperature are identified and used to feed different models of optimal route planning at different ambient temperatures. Results show that the energy consumption of the vehicle can be increased as high as 54% compared to a mild temperature use case in case of extreme weather. However, a major limitation of this study lies in the use of data from electric cars applied to an electric freight study, which usage could differ in terms of energy demand. To tackle the loss of battery performance due to extreme weather conditions, battery pre-heating during vehicle charging is an identified solution. For example, Lei et al. [24] were able to achieve 80% of the performance at room temperature thanks to 15 min of pre-heating of their battery pack for initial temperature as low as -40 °C. However, a rapid heat up phase can result in total drainage of the battery autonomy [25].

A second challenge lies in the thermal management of the passenger compartment that can also impact the vehicle performance [26]. According to Zhang et al. [27] the usage of electric heaters to achieve thermal comfort in the cabin, can lead up to 60 % of exergy loss over the whole system. As mentioned in the XERIC project [28], current heating, ventilation and air conditioning technologies (incl. electric heaters for the heating phase) reduce the potential driving range of EVs up to 25 %. This range reduction is directly the consequence of the lower amount of generated heat by EV motors and batteries compared to that available in ICE vehicles. Hence, several studies aim at decreasing the required amount of energy to achieve cabin comfort. Schaut et al. [29] introduce a thermal management strategy for the passenger compartment of a battery electric vehicle that uses optimal control. They show that implementing a model predictive control helps to reduce the energy consumption of the thermal system by 20% compared to the standard configuration.

From these two challenges, it appears clearly the ambient temperature chosen as reference for the design step plays a major role. Furthermore, it has to be stressed out that for a manufacturer, it is more interesting from economic point of view to have a design that can apply to several locations and truck duty whenever possible. Hence, Figure 1 shows the temperature occurrence in three selected towns where VOLVO electric trucks are deployed. For the three locations, the largest occurrences are between 0 and 35 °C. Extreme high and low temperatures present a low cumulative percentage, which means that sizing a thermal management system on these extreme conditions could be questioned considering the effective vehicle working hours at these conditions.

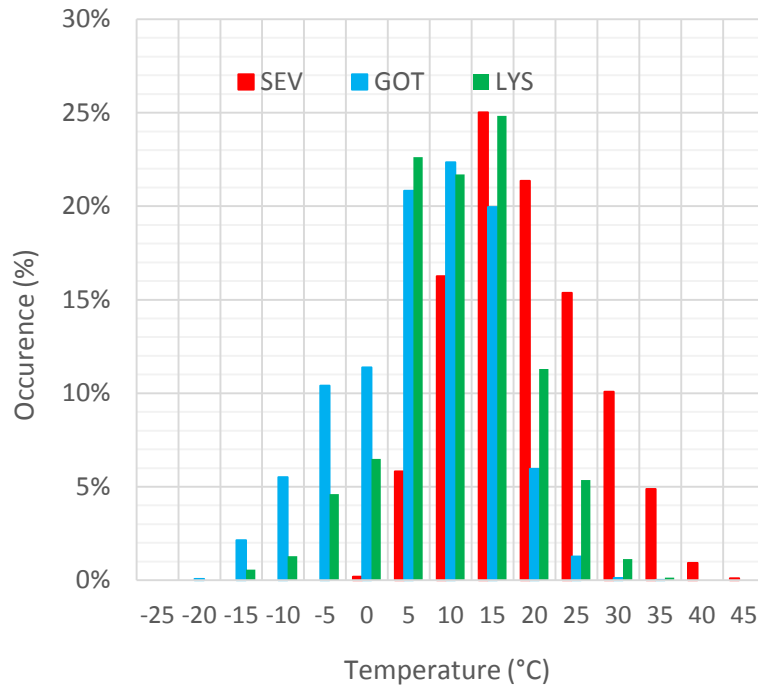


Figure 1. Occurrence of ambient temperature in Sevilla (SEV), Goteborg (GOT) and Lyon (LYS) reference cities for MDEV deployment (source Volvo Group)

This introduction highlights the difference in challenges between ICE and electric MDVs for the design of their VTMS. In addition, it is also stressed out that the vast majority of the available literature on EV VTMS is focused on electric cars which have clearly distinctive use to that of MDEVs. The optimisation of the design of the VTMS is then clearly identified as a possible tool to gain in TCO and then strengthen the competitiveness of MDEV whatever the usage. This statement is supported by the recent work performed by Corbet et al. [30] on electric city buses which are facing similar constraints as MDEV. From data recorded on buses in operation in various cities, they conclude that compared to a testing conducted at an ambient temperature of about 24 °C, an average temperature of 35 °C resulted in a 4% decrease of driving range while the decrease is of 12% for a temperature of about -7 °C. These authors also stress out the need of mitigation strategies to lower the resulting risk in order to foster the electrification of vehicle fleet by developing design and control approaches that better take into account the influence of weather conditions.

Hence, this review proposes to walk through the solutions that have been adapted to these problematics so far, highlighting different methodologies used on electric cars and how they could be reused. In particular, the attention will be focused on the following topics that are inherent to an optimisation work:

- **VTMS architecture.** A thermal management system can be based on passive or active architecture, depending for example on the presence of a component that could be controlled in order to produce cold water (e.g., a heat pump).

- **Design optimisation problem formulation and solving.** Although many works in the literature discuss the best approach to optimise the design of electric cars VTMS they cannot be directly transposed to MDEV because of the specific constraints and usage that are significantly different from that of electric cars. For example, concerning route scenario definition, no standardized cycle does exist for trucks because of the wide range of possible missions (urban freight, long haul, refrigerator, refuse collection). Methodology to create such scenarios needs to be discussed as they are mandatory inputs to perform an optimisation of the design.
- **Control phase.** As discussed in the introduction, MDEV VTMS design trade-off could result in not fulfilling components temperature setpoints to some extent. An efficient control strategy can help in reducing the impact of these periods and hence prevent components performance degradation.

2. THERMAL MANAGEMENT SYSTEM ARCHITECTURE

2.1. GENERAL OVERVIEW

Figure 2 shows which sub systems are concerned and the general boundaries of temperatures that must be respected to keep components working in the optimal range. The overall thermal management system of medium duty electric vehicle can be split in two sub-thermal management system:

- The *cooling architecture*, which defines the loops arrangement in the vehicle to either cool down or heat up components when needed.
 - The architecture can then be considered as an “active” or “passive” system. This terminology displays the solution adopted by the manufacturer to handle the cooling architecture through technologies that can either allow to go below ambient temperature or not (e.g., by introducing a heat pump).
 - The cooling architecture then connects the powertrain components (which contribute to part of the heat rejected) and the cabin (which acts on the overall system as a consumer of heating/cooling energy).
- The *battery pack thermal management*, which needs particular attention in terms of temperature levels as the range of the vehicle depends on it.

This sub-division is a concept that can be applied on any electric vehicle thermal management system. However, for medium duty vehicles, the challenge is slightly different from a common electric car since not only cabin comfort and optimal component temperature must be achieved but also respect the specific mission the truck has to achieve each day which influence the choice of the architecture.

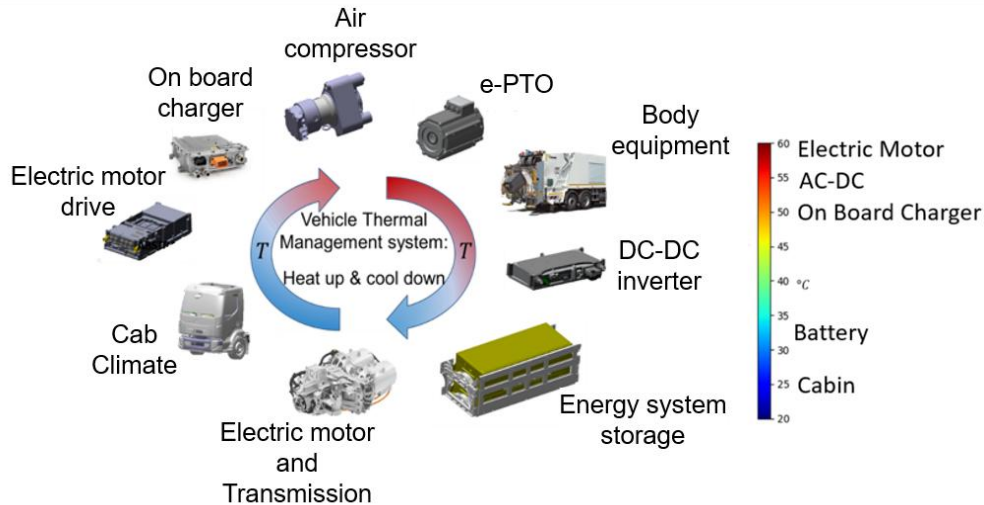


Figure 2. Medium electric duty vehicle thermal management system with temperatures boundaries.

Medium duty electric vehicles have to endure different tasks that require precise design features so that thermal management system should be designed to endure and perform well at different ambient temperatures, considering one model can be delivered in different cities around the globe. As developing electric trucks thermal management system is quite new, the state of the art relies mainly on technologies that have been developed for electric cars.

In 2010 the National Renewable Energy Laboratory (NREL) suggested that thermal management should be viewed at vehicle scale not just as a partial subsystem. The integrated system will provide an approach to evaluate combined heat loads and support an opportunity to develop analysis methods to quantify the transient and continuous heat loads of individual components and system under a wide range of operating conditions. This is confirmed by Bennion et al. [31] work on synergistic benefits of combining cooling loops in vehicles for all the components. They suggest that thermal management should be viewed at large vehicle system not just as a partial subsystem. According to these authors, to achieve a relevant strategy, it is necessary to develop analysis and methods to quantify the transient and continuous heat loads of individual components and system under a wide range of operating conditions. Their idea is to consider the vehicle thermal management of a single component as a degree of freedom for an integral system constantly put under thermal charges. Several studies have conveyed that looking at the whole vehicle and not just the partial subsystem shows more interesting results. Even if this approach makes the modelling approach more complex, the accuracy of the results is higher compared to partial subsystem modelling [32], [33], [34] and a potential cost reduction and performance improvements for thermal management system is observed.

2.2. BATTERY THERMAL MANAGEMENT

Keeping the battery at optimal ranges of temperature is essential for an electric vehicle in order to avoid runaways or premature degradation. Moreover, during the charge and discharge phase uneven temperature distributions could lead to specific cells degradation. Nowadays, the capital cost of a lithium-ion battery for electric vehicle usage is still over 150 €/kWh [35], thus it represents almost a half of the selling price of the electric vehicle itself when installing 69 kWh as in a medium duty electric truck. Battery thermal management (BTMS) is thus fundamental in order to operate in the good range of

allowed temperatures and use the cells at their fullest potential. Following the current state of art, the battery thermal management approaches can be summarized as follows: air cooling/heating, liquid cooling/heating, and Phase Change Material (PCM) cooling.

- Air cooling is a widely used solution as it guarantees a good temperature mitigation compared to the other technologies and it is the cheapest. Zhao et al. [36] deeply treat air cooling as a strategy for battery thermal management, pointing out that lightweight and high compactness makes it a preferable choice over the other thermal management solutions. However, as Rao et al. [37] show that air cooling cannot guarantee a temperature uniformity over the battery, leading to premature degradation of battery cells over the long run.
- A liquid based system presents higher heat transfer coefficients compared to air-based systems and requires also less power to circulate the coolant (pump vs. fan). Wu et al. [38] assess the performance of a battery thermal management with a direct contact between the liquid coolant and the surface of the battery, allowing the system to be compact. As it can handle bigger heat capacities, this methodology is the most adopted for duty electric vehicles. Various possibilities of improvements are found in the literature mostly focused on the optimisation of the thermal resistance between the coolant and the battery cell (e.g. Chalise et al. [39] work on coolant fluid velocity).
- PCM can be employed as a passive thermal management system, buffering high operative temperatures and represent an innovative way of cooling the battery back using liquid-solid state phases [40]. Bai et al. [41] propose to overcome temperature uniformity issues with a composite PCM/cooling water plate thanks to which they manage to limit battery maximum temperature during the charge/discharge steps. Jagemont et al. [42] illustrate an example of combining PCM cooling with the aforementioned systems showing that the benefits of both could lead to a better control of the uniformity of the temperature over the battery pack. PCMs are easier to use, more efficient, and more compact than active cooling systems. However, an additional active cooling system might be required to charge the PCM.

As they generate much larger power output when driving or when demanding charge, medium duty electric vehicles generally generate more heat and consequently the need for air or liquid cooling is bigger. This led to new challenges in terms of system sizing and technology choice. Thermal runaways could occur more often due to high rises of temperature over peak usage, which could be repetitive due to the type of usage of the vehicle (freight missions will be discussed in the next section). Excessive heat cumulation and over usage out of peak-performance boundaries could lead the battery pack to undesirable degradation and, consequently, to shorten battery pack lifetime. Battery aging is a recognised phenomenon in the automotive world, causing fast capacity fading. It has been demonstrated that aging is a factor highly dependent on the temperature of the battery cell. Redondo - Iglesias et al. [43] present two formulations that correlate both mechanisms of degradation (cycling and calendar) to temperature, state of charge and depth of discharge. The results presented are re-usable to study the effect of degradation over the usage of battery in a medium duty electric vehicle. According to Afzal et al. [44], a realistic heat transfer model could help understanding better the degradation mechanism of a lithium ion battery by correlating its aspect ratio and the volumetric heat generation. Over charging and over discharging the battery leads to critical behaviour that reflects negatively on to the performances of the battery itself.

Considering the impact that aging could have on the cost losses over the capital price of the battery, Andrew Thompson [45] introduce different ways of associating an economic assessment to the mechanism of degradation. The battery degradation cost is assumed to vary in time since it is associated to a phenomenon (calendar aging) that varies the total capacity available on the battery during its usage. However, so far, cost calculation has only been focused on the number cycles the battery could do during its lifetime. Considering these cost factors, they conclude a good battery thermal management system should minimize the time spent at high SOC and the general temperature rise. Hao et al. [46] illustrate an economic analysis over the Beijing market to analyse battery costs installation for electric vehicles. By analysing the battery lifetime of the battery and their actual cost on the market, they conclude that electric vehicles are more cost competitive than ICE. This competitiveness can be further enhanced by the cost savings expected from the development of batteries. Coupling methodologies such as the one proposed by [47] for driving cycles and [48] for battery degradation, could lead to better results compared to reality. As mentioned by Birkl et al. [49], these methodologies must be compared to data coming from real users driving in cities to validate results. Thus, Multiphysics simulations are also requested to recreate the physical system of the vehicle when data is not accessible.

2.3. IMPACT OF THE DESIGN OF COOLING/HEATING CIRCUIT AND HEAT-PUMP USE

In EVs, to heat-up the components and the cabin of the vehicle, one of the most applied and viable solution is to use electric resistors, which have the advantage of being easily controlled with a low thermal inertia. The Positive Temperature Coefficient (PTC) heaters are the most commercially used and they are presented in this study for both passive and active thermal management architecture. As for ICE, active air conditioning system can be used for cooling duty, both systems being part of the HVAC. However, as shown on Figure 3, HVAC represents a significant share in the overall EV energy consumption contrarily to the ICE case.

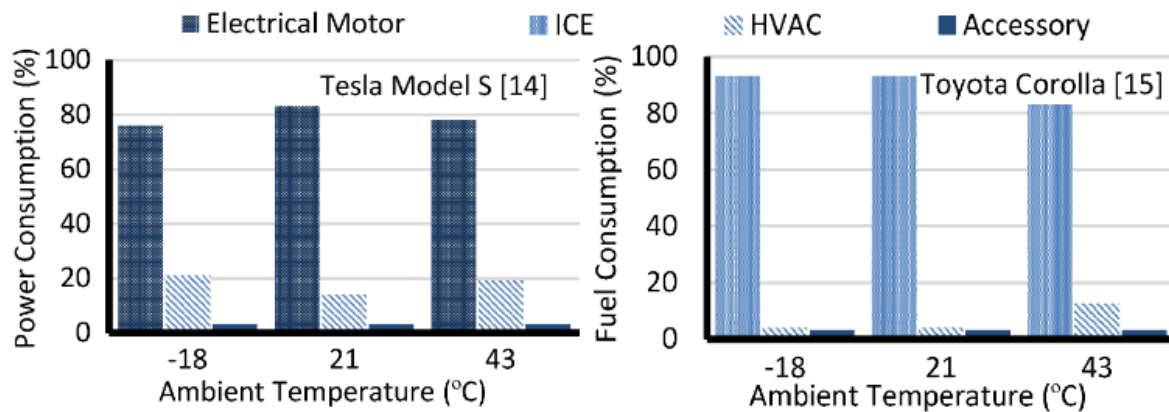


Figure 3 Comparison between different sources of power consumption in EV and ICE vehicle [50].

To decrease HVAC electricity consumption, heat pump solutions have been explored with several works concerning electric cars discussing various approaches to install such component. For example, S. Chowdhury *et al.* [51] have presented a new concept of thermal management architecture that satisfies diverse thermal and design needs of the auxiliary loads in the electric vehicle. The approach concerns an evaluation of the thermal charge on each component by considering the presence of a heat pump as well. Benefits can be observed in terms of range improvements, compared to a system which does not

have the same technology. De Nunzio *et al.* [52] present an optimized thermal management system that includes an active cooling system operated by a heat pump for the cabin heating/cooling. A reduction of 11% for energy consumption is observed compared to a reference system without heat pump. Increasing driving range and ensure a thermal comfort in the cabin are proven to be feasible by relying only on the heat pump cooling system. Zhang *et al.* [53] also show further studies that have been conducted on VTMS. Thermal losses from batteries and motor are used to heat up a coolant liquid along with the installation of a heat pump in the system in order to avoid drops in efficiency during cold weather for the heat pump.

Replacing common electric heaters with heat pump is a valuable solution for electric trucks in terms of energy savings since the higher demand of heat requested by the vehicle compared to electric cars. However, one of the most common issues of heat pump is the loss of efficiency at low ambient temperatures. Jeffs *et al.* [54] analyses the behaviour of a heat pump installed on an electric vehicle at low temperatures, providing a viable solution to avoid COP losses on the heat pump installed using heat rejection of power train components. Several low temperature scenarios have been analysed, leading to an average energy saving of 14.8% compared to a system with an electric heater installed.

The introduction of VTMS architecture involving a heat-pump has made it all the more important to consider the number of cooling/heating circuits. Indeed separated loops increase the flexibility in terms of temperature ranges control but at the cost of increased complexity. However, single cooling loops seemed inappropriate to handle problems related to electric machine and electronics integration, especially for optimum working points connected to oil and charged air cooling. The same thermal management solutions have been applied on electric vehicles, pointing out the differences in terms of components to be installed for the thermal management [55]. The different temperature levels lead to unwise design choice for heat exchangers and fan size. Thus, the installation of multiple-loop circuits to satisfy all the thermal requirements introduced by the electronics has been addressed as a viable solution. However, this could increase the complexity of the system and the weight of the overall system, impacting negatively the range of the vehicle and its performances [56]. Table 3 resumes the proposed architecture in various studies involving heat-pumps.

Table 3 Studies conducted on the VTMS implementation with a holistic view over the system.

Author	Number of loops	Type of vehicle	Components considered
Tian <i>et al.</i> [20]	2	(BEV)	Powertrain, Battery
Bennion <i>et al.</i> [31]	3	Toyota Prius (PHEV)	Powertrain (EV + ICE), Battery, Cabin and Architecture
Chowdhury <i>et al.</i> [51]	3	Fiat 500e (BEV)	Powertrain, Battery, Cabin and Architecture
De Nunzio <i>et al.</i> [52]	3	Fiat 500e (BEV)	Battery, Cabin and Architecture
Scholl <i>et al.</i> [57]	2	Renault Twizy	Powertrain, Battery, and Architecture
Leighton <i>et al.</i> [58]	3	Mid-sized electric vehicle	Powertrain, Battery, Cabin and Architecture

Rana et al. [59]	4	Personal vehicle	Powertrain, Battery, Cabin and Architecture
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Tian et al. [20] investigate a new thermal management system to look at thermal comfort, battery and motor cooling as a whole interactive system. They state that very limited examples can be found in the literature for VTMS design and performance analysis for EV.

Rana et al. [59] pointing out that most studies are conducted for either cooling mode or heating mode, propose a novel 4-loop thermal management system that handles cooling and heating introducing a heat pump in the system. The simulations are conducted over two stages. The first stage simulation operates to improve the battery thermal management system and the second one aims to have a look onto the impact on overall system coefficient of performance (COP) under typical thermal load conditions. The base case used for validation of the model is a set up in an in-house calorimeter laboratory. Results show that during peak loads, the architecture simulated has a COP 50% higher than the base case. Reheating using waste heat recovery from the water condenser is the key feature of their system.

Scholl et al. [57] propose an innovative thermal management architecture considering the influence of cutting-edge technologies such as thermoelectric materials and phase changing storage units. The goal is to specify an optimized strategy proving that the energy demand of the system can be reduced by choosing the strategy that fits well the integrated system. Solutions such as phase change materials and heat pump implementation allow the user to have a flexible and efficient thermal management system that can work under different climate conditions and usages.

3. VEHICLE THERMAL MANAGEMENT SYSTEM OPTIMISATION

Two objectives can be addressed when optimising an energy system. A first one, also called “optimal control” consists in using optimisation approaches to control a given configuration to minimise again a cost. In this case the characteristics of the components have been already determined with a sizing method, the only decision variables being on/off and load factor of each component. The second one, called “design optimisation” consists in defining the “best” combination of components (incl. consideration on presence of the component or not and its sizing) to deliver a service at the lowest “cost”. The cost could of course be a techno-economic cost like the TCO but also an environmental cost.

3.1. VTMS CONTROL OPTIMISATION

Control of energy VTMS represent a fundamental step for an optimal usage of the vehicle during its lifetime. Zhang et al. [53] and Huang et al. [60] in their review, present a way to categorize the type of control introduced in literature for hybrid cars energy management, dividing them into rule-based and optimisation-based. Furthermore, on-line and off-line approaches need to be defined. For off-line optimal control, the algorithm optimizes the system knowing beforehand the whole driving cycle of the electric vehicle. On-line optimal control algorithm adapts its parameter step by step without any determinist information on the cycle being performed at the cost of increased computing work.

According to [61] who discuss the different types of control for Hybrid Electric Vehicle, rule based energy management has been widely used because of its simplicity but suffer from various drawbacks, for example the dependence on expert knowledge for the deterministic configuration. This can be

partially solved by adding fuzzy rules. This is also underlined by Wei et al. [62] who state that rule based energy management relies on the driving cycle on which they have been calibrated. In consequence, during real-time assessment these rules are not continuously adapted to real driving conditions potentially limiting the achieved performance. These authors also underline that the thermal domain is often not considered in optimisation problem for electric vehicles, leaving room for improvement.

To go beyond the well-established rule-based approach, Model Predictive Control (MPC) and learning-based management can result in significant gain despite the specific challenges to be tackled. For example, Fu et al. [63] introduce an energy management strategy for a light duty hybrid commercial truck. Their methodology is based on a two-point boundary optimisation problem in order to consider the evolution of the state of charge of the battery and the power sources coming from the internal combustion engine. The optimal control has been compared to a normal rule-based control already implemented on the vehicle. Results show that the energy consumption of the vehicle over a predefined cycle has been reduced by 6.1% compared to the ruled based strategy.

3.1.1. MODEL PREDICTIVE CONTROL (PHYSICS DRIVEN APPROACH)

Model Predictive Control is based on a dynamic model of the system to be controlled that will be used to estimate the system behaviour over a given time horizon (a few time steps in general) and hence identify a reference trajectory that minimize a cost function considering several inputs (e.g. temperature, speed evolutions in the next time steps). Once this trajectory identified, the system configuration for the very next time-step is fixed and the time horizon window will shift forward of one time step. Hence, MPC requires the development of ad hoc models that simulate the physical behaviour of the thermal system: dynamic responses, components physics and all the phenomena involved during vehicle usage (heat transfers, electrochemistry, electricity, mechanics, components aging [48], etc.). Those models result mainly in a MINLP (Mixed Integer Non Linear Programming) formulation [64]. For example, in the case of VTMS a non-linearity occurs because of the energy balance of the fluid which involves the multiplication of two decision variables: the mass flow-rate and the fluid temperature. MINLP optimisation problem are hard to solve potentially resulting in a bottleneck to apply MPC [65].

He et al. [66] demonstrate the gain that can be achieved with an MPC in the case of city buses. They achieve energy savings of about 6% compared to rule-based control. They conclude also on the necessity to have an MPC that reflects appropriately the load variation (in their case passengers getting on and off the bus) as it impacts significantly the controller ability to achieve the expected gain. Three stochastic forecast approaches are assessed: RBF-NN (radial basis function neural network), Markov chain and Monte Carlo, the first one performing slightly better. Vatanparvar et al. [50] report as well the importance of cabin climate control and propose solutions to manage the HVAC power in order to increase the battery lifetime and the electric vehicle range. To tackle the issue of MINLP formulation, Ferrara et al. [67] choose to use a linear approximation close to the current operating point (e.g. for variation of the battery state of charge) to speed up problem convergence in the case of optimal control of an heavy duty fuel cell vehicle. With their approach, they manage to get close to the minimum reference consumption determined off-line (only 1.5% above). They also point out the limitations of their work by highlighting that it would be of great interest to include stochastic speed prediction (assumed perfectly known in their presented work). Lopez-Sanz et al. [68] underline how powerful model predictive control could be for cooling circuits control inputs. A reduction of 30 % in costs associated to thermal management application is shown by using a model predictive approach over a

standardized control strategy. This application has been developed for plug-in electric vehicles, however its flexibility allows it to be applied for other cooling circuits (e.g., full electric vehicles). Puma-Benavides et al. [69] report several optimisation and control methods currently under development for range extensions of electric vehicles. They point out the importance of developing new methodologies in order to obtain satisfactory topologies of the energy and thermal management system of the vehicle, considering different objective functions (environmental, costs, energy performances, weight, etc.). Given an optimal trajectory, real time controller can be derived and energy minimization as well as component lifetime can be drastically improved. According to them, multi-level optimisation frameworks can be envisaged to address all the problems conceiving an energy system: sizing, design and controlling. Li et al. [70] show how sizing and control can be coupled through optimisation methods and how the sizing phase is a key for optimal control which can result in significative improvements compared to separated solving. Several authors (e.g. [71], [72]) explore the possibility to use Dynamic Graph Model for MPC of complex system coupling electric circuit and thermal loop. They conclude positively on the relevance of this approach but also stress out again that the non-linearities have to be carefully handled.

From this rapid survey on MPC, no major issue on its application to MDEV does arise and the approaches developed for electric cars (or hybrid vehicle) or can be seen as a solid starting point. Nevertheless, the extreme sensitivity of MPC to prediction quality (future vehicle speed, load, etc.) support the necessity to have specific research work to better model these inputs for MDEV cases.

3.1.2. DATA DRIVEN APPROACH

As discussed in the MPC section above, a highly performant thermal management control requires detailed models and the supervision of several parameters which can result in tool with inadequate computation time for decision making. As an alternative to physical model simplification, artificial neural networks and machine learning in general are often used nowadays to model the characteristics of the thermal management system operation by using available data on driving cycles. These methods are becoming more and more popular thanks to the generation of important dataset with on-board sensors.

Park and Kim [73] illustrate an improved control methodology for electric vehicles that rely only on artificial neural network (ANN) model, without using any specific physical model to describe the thermal architectures. The dataset used to train the ANN comes from repeated drive cycle sampled with a time step of 5 sec, retrieving essential information of the VTMS while driving such as power inputs of the EWP (electric water pump), fan, and compressor, coolant flow rate, coolant temperature, battery temperature, vehicle speed, battery current, and AC switch operating status. The optimal VTMS scheduling is achieved by using two objective functions reflecting the usage of cooling/heating power as well as the optimal range of temperatures for components. Results show that ANN could estimate the same physical variables as the corresponding physical model with less calculation power, attaining positive results in terms of energy efficiency. Afzal et al. [74] use deep neural networks to predict the ability of a battery thermal management system to dissipate the heat based on a set of six operational parameters. These methodologies could be replicated to improve the capability of battery thermal management system, coupling with an online optimized control. In order to face the consumption coming from the air conditioning of the electric vehicle, Engel et al. [75] propose to use machine learning to predict external disturbances that could affect negatively the performance of the air conditioning system, impacting then the overall consumption. Results show that these methods perform

better than normal PI control currently implemented on vehicles. Tang et al. [76] show how to implement a machine learning model in order to performance on liquid-cooled battery thermal management for electric vehicles. A lot of experiments are required to present a full analysis of liquid cooled based battery thermal management system. The model presented based on particle swarm optimisation is shown as a valid alternative in order to predict performances by considering a set of operating conditions and drastically reduce the number of experiments to be conducted.

3.2. MDEVs VTMS DESIGN OPTIMISATION

At the difference of control optimisation, design optimisation implies to decide whether a technology will be installed or not from a given portfolio and to size it. This decision is achieved by minimising a cost function over a given period of use. In the case of MDEVs, considering the impact of weather on the system performance, the estimation of the performance over a year seems to be the minimum appropriate period. As for control, the minimisation of the cost function implies to develop an appropriate model to represent the physical behaviour of the system. However, because the time window during which the model has to be solved to make a decision is significantly longer than for control, the model has to be kept as simple as possible to avoid too long computing time while preserving enough complexity to simulate appropriately the dynamic constraints of the system for example (e.g. ramping up and down).

Different methods for sizing have been introduced for new generation vehicles due to the higher complexity of a hybrid/full electric system compared to a normal internal combustion engine vehicle. Most of them are mainly related to the drivetrain, as it is the primary source of propulsion for the vehicle and thermal management had not been recognized yet as an essential element for energy efficiency improvements [70]. Table 4 resumes some references focused on optimal design for thermal management and drivetrain, considering data pre-treatment for the mission carried out.

Table 4. Strategies presented for component sizing optimisation

Reference	Data Pre-Treatment – Mission definition	Application	Type of objective function	Strategy Used
[62], [77]	No	Hybrid Vehicle	Economic	Drivetrain optimisation, Thermal Management optimisation
[78], [79]	Yes	Hybrid Vehicle	Economic, Environmental	Drivetrain optimisation
[9], [80], [81]	No	Full Electric/ Hybrid Vehicle	Economic, Environmental	Thermal Management optimisation
[52], [82]	Yes	Full Electric/ Hybrid Vehicle	Fuel consumption	Single Component optimisation
[83], [84]	Yes	Hybrid Vehicle	Fuel consumption	Drivetrain optimisation
[85]	No	Hybrid Vehicle	Fuel consumption	Drivetrain optimisation
[86]	No	Hybrid Vehicle	Temperature range	Thermal Management optimisation
[57]	No	Full Electric Vehicle	Fuel consumption	Thermal Management optimisation

All these works are featured with the complexity introduced on working conditions of electric vehicles. Models are becoming more complex and synergies between components behaviour are being considered as an important part for electric vehicles manufacturing. Sizing components considering these aspects is fundamental in order to achieve a global optimal design solution. For example, Kulikov *et al.* [87] have proposed a sizing method that would find the best trade-off between engine and electric battery sizes for hybrid vehicles. A set of maps indicates fuel consumption and electric energy consumption, giving the possibility to the user to choose the best combination of components to install on the vehicle following their specifications. Given such a graphical instrument make it easy to size vehicle components. However, no solid optimisation approach is involved, the decisions relying only on worst case scenarios. Saha *et al.* [88] highlight the importance of new thermal management system architecture design by reviewing the typical approaches (worst case scenarios mainly) that have been used so far for vehicles component sizing. Their conclusions look into the development of more sophisticated models as it is fundamental to embrace challenges introduced by future thermal management systems. Instead of designing the thermal management system for extreme hot conditions with steady state, the new approach is to design it for transient drive cycles to capture time-based warm up and cooling behaviours. Huang *et al.* [60] list various methods for component sizing, categorizing them in three branches: experience-based design, equivalent calculation based sizing and optimisation based sizing. As multiple aspects of physics must be considered when working with complex apparatus such as thermal management of an electric or hybrid vehicle, the former methodology has been reckoned to be the more functional as it can handle easily every possible solution that could be found through one single formulation of the problem.

As the number of technologies installed on a vehicle increases (hybrid, fuel cells, heat pump, thermoelectric materials, etc.), the solution space tends to be wider and wider with multiple complex solutions being able to fulfil the design requirements. For this reason, the application of optimisation methods to find the best design of a thermal management system has to be regarded as necessary to avoid any preconception bias. Hence, operational research and multi-optimisation methodologies could give a huge hand solving these problems. Following those methodologies, a basic linear optimisation problem for system sizing is defined as follows:

$$f(x) = c^t \cdot x \quad (1)$$

$$\text{with } A \cdot x = b ; A' \cdot x \leq b' ; lb \leq x \leq ub \quad (2)$$

Where $f(x) = c^t \cdot x$ is the objective function. The optimal VTMS installation is obtained by the resolution of this optimisation problem. A, A', b, b' are the sets of constraint matrices given by the problem, x is the vector of the decision variables possibly composed by a mix of continuous and integer variables. In problems dealing with energy, the constraints are generally represented by the temperature ranges of components, the operational points of components, the maximal heating/cooling power that could be delivered or the maximal heat that can be dissipated by the system. The vector of decision variable is represented by the cooling/heating power to be installed, which defines the geometrical size of heating/cooling components following manufacturers' requirements.

As a thermal management system presents different components, not only the size of the system can be optimised, but also the arrangement of the components in order to find the best architecture among the possible existent combinations.

To deal with this issue, Silvas et al. [77] choose a “nested approach”, introducing a multi-level optimisation problem to be solved sequentially, first working on the size and the topology of the energy system and then on its control (Figure 4). Their review shows that works concerning size optimisation problem on electric vehicles have grown a lot, mostly due to legislative restrictions which have become increasingly tight during the last two decades. For the architecture choice and control design problem, these two-coordination methods could be resumed as follows: alternating methodology refers to architecture choice and its control. First the architecture of the thermal management system is optimally designed, then the outcome is used for the controller to be optimally designed. The cycle closes with a new optimisation of the architecture following the results of the new controller applied. For the nested approach, the solver alternates between optimizing the thermal management architecture and optimizing the control until the coupled variables have converged.

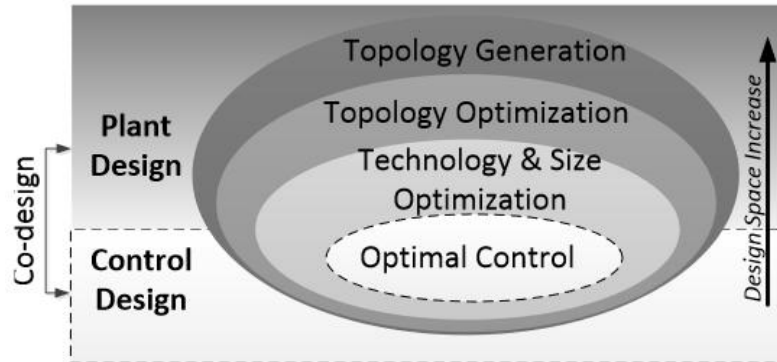


Figure 4. Nested optimisation methodology for system design of an electric vehicle [77]

Wei et al. [62] illustrate a methodology that combines multiple optimisation layers to achieve the best trade off in terms of complexity and optimality for the energy management system of a hybrid electric vehicle. The topology generation problem selects a suitable architecture among the possible solutions proposed to the optimisation problem in order to eventually improve the energy efficiency of the system itself during following steps of the nested approach. Once vehicle and drivetrain specifications are set, the sizing optimisation problem returns the type of drivetrain expressed in vehicle energy fluxes. A relevant fuel consumption decrease is observed overall compared to the non-optimized base case.

Zhao *et al.* [85] and Sinoquet *et al.* [83] propose an optimisation technique to design the powertrain of a hybrid electric vehicle based on a bi-level optimisation, for design and control. The powertrain issued of [85] optimisation presents an overall 6.5% fuel economy less than the baseline parallel hybrid electric vehicle, whilst for [83] it has been of 16.6%. The bilevel optimisation is then compared to the methodology used by [84], showing an improvement of computational efficiency (about 10 times faster).

Because of the complexity of the system, the reduction of the optimisation problem to minimising a unique objective function might result in partial results.

To avoid this bias, multi-objective optimisation has been thoroughly used for battery thermal management e.g. recently [89], [90], [91] but to a less extent for optimisation of the whole VTMS. Hamut *et al.* [9] propose an exergo-economic approach in order to assess the magnitude of inefficiencies in the hybrid electric vehicle thermal management system. Through a multi-objective optimisation (economic and environmental objective defined by a life cycle assessment), they have been able to enlarge the spectrum of solutions for design choice according to different objective functions, either related to energy efficiency or investment costs. Results have been compared to a normal single objective approach, showing great potential for trade off choices for the solutions sets. At the expense of costs, the exergy efficiency and the environmental impact could be improved respectively by 13% and 5%. Introducing multiple objectives turns to be very useful for a wider analysis, however, could be computationally demanding. Javani *et al.* [80] propose a similar approach to [9] based on exergo-economic analysis of a thermal management system implementing phase change materials. Again, multi-objective optimisation represents a valid methodology to assess different key parameters influencing energetic and economic performances of the system. As highlighted by Yu *et al.* [92] for battery thermal management optimisation, the complexity of multi objective optimisation has to be carefully considered when applying such methods. For example, Da Silva *et al.* [93] use three criteria, battery state of health, driving range and overall mass as objective functions to design the best configuration of hybrid energy storage system for EV application. As in the work by Liu *et al.* [94], they stress out the necessity to discuss the approach for final ranking of the multiple optimal solutions obtained because of the inherent difficulty to define a unique optimum.

3.3. DRIVING MISSIONS – ENTRY DATA FOR MODELLING

To design properly the VTMS, representative driving cycles of MDEV are needed. Reference driving cycles, e.g. Federal Test Procedure 72/75, New European Driving Cycle (NEDC), Japanese Cycle 08 (JC 08), etc. are extensively used to characterise ICE car performance, with a main focus on the fuel consumption [95]. However, according to the same authors, this approach can hardly be extended to electric vehicles, the vehicle's autonomy becoming the major point of concern with furthermore a more prominent dependence on weather conditions. Furthermore, many works stress out the high probability of generating large error when applying ICE cycles to EV (e.g. [96], [97]) and Wang *et al.* [47] show that existing drive cycles are constructed based on vehicles, and these standardized cycles are not suitable for electric vehicles as the driving characteristics are different. In consequence, research work has been performed to define specific driving cycle to better take into account the effective use of the electric vehicle because of the location [95], [98], or because of the use of the vehicle (e.g. Taxi for [47]). These authors do also stress out some major limitations in their model that need to be taken into account to gain in precision, e.g. ambient temperature evolution, road grade and change in load [95]. The impact of load variation is then a direct concern to design MDEV driving cycles. Indeed, MDEVs' missions are by nature strongly different depending on "the body equipment" which could be for instance a refuse truck or a refrigerated lorry so that driving cycles have to be created "on demand". On their side, Rupp *et al.* [99] focus their work on the optimisation of the charging phase of electric buses in order to reduce CO2 emission, taking into account the variability of electricity costs. For the purpose of this analysis, they use real world available data of electric buses currently driving on the road, differentiating 3 scenarios. Each scenario is at least composed by a charging phase where the speed of the electric bus is 0. For example, a scenario where the bus operates its daily mission after having been charged overnight is shown in

Figure 5. The charging scenarios have been analysed to evaluate the carbon impact of the bus taking into account the peak energy generation hours coming from renewable sources.

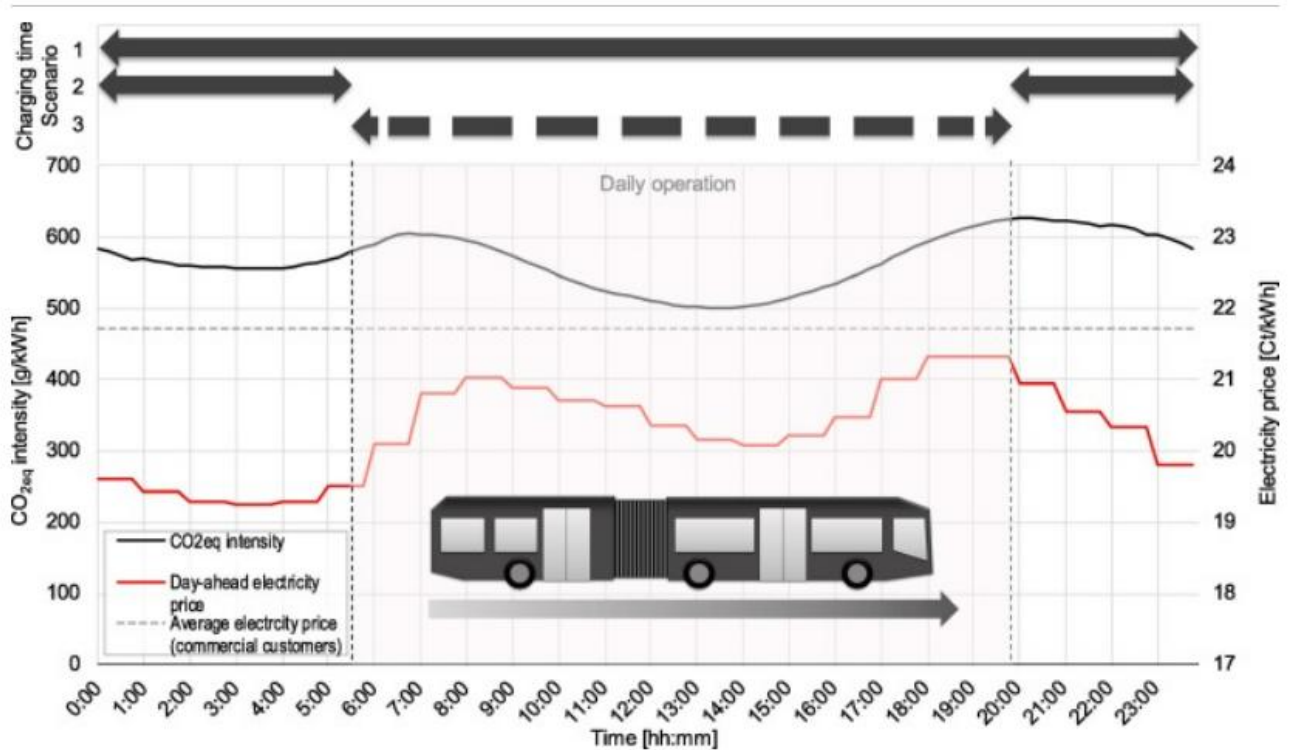


Figure 5. Example of a driving scenario for an electric bus [99]

Finesso et al. [100] present a study focused on the optimisation of the powertrain of a hybrid electric vehicle from a cost and layout point of view. The performance has been evaluated over a two-month driving cycle of a heavy-duty vehicle, and the representative values of the mission (road freight transportation) are respectively the duration, the average velocity, the max vehicle power and the total energy demand. This mission allows the user to perform a sensibility analysis over different varying parameters of the vehicle itself. A typical driving cycle can be easily evaluated and replicated to work out thermal or electric model of the system, since these values are not directly correlated to any thermal management system or powertrain. Ferrara *et al.* [101] point out how literature lacks energy analysis of electric vehicle that takes into account several driving cycles for the design optimisation, making these strategies less robust for post analysis or even application on real vehicles. Their work is based on an optimisation strategy applied on over 1750 h of real-world driving data including altitude, speed, vehicle mass and duration. However, such amount of data, when used for simulation and physical analysis, could lead to inefficient time usage for simulation as the diversity and the interdependence between type of data are inevitable (e.g., vehicle driving conditions influence the thermal losses of electric components). Furthermore, for design purposes, vehicle performances should be evaluated over a year of driving, and in some cases, over its lifetime so that the dataset size is clearly an issue to solve the optimisation problem.

To tackle the problem of tailored driving cycles for MDEV and the resulting possible high computing time, a possible solution consists in creating typical representative periods that would represent specific missions according to the type of MDEV under study. According to Hoffman *et al.* [102], time series clustering is one of the most used approach in the energy domain, which is confirmed by several works, e.g. [103], [104]. When processing a time series aggregation for vehicle route definition, the computed representative periods have to reflect the changes in weather conditions but also the changes in vehicle's route. The quality of the aggregation heavily depends on the quality of the data more particularly concerning their representativeness of real operating conditions. Data is more and more recorded through sensors which are directly installed on the vehicle and operates during their driving cycle, a first phase of data cleaning and filtering is essential as it permits to spikes out noises and peaks that could later result into nonphysical effects for the driver input data and the analysis of the thermal management system [105]. Once the input data is cleaned, the general time series aggregation aims to merge a set of data periods into groups, and each period have to be as similar as possible to the data group assigned. The group then is represented as a single period. The single period is the so called "typical period", which could be a day or a week following the user decision to represent a certain time span. Several algorithms are proposed and studied in literature. Teichgraber *et al.* [106] present a study where different time series aggregation algorithms are presented, highlighting the fact that in the last decade feature-based merging methodologies are used more and more by researchers for data input reduction of energy models.

Amongst them, the most used algorithms are k-means, hierarchical and k-medoids. The choice of the algorithm mostly depends on the difference in magnitude of the dataset treated and the repeated patterns that can be observed. Kotzur *et al.* [78] analyse k-means, k-medoids, and hierarchical clustering with medoid representation on an energy system optimization problem and show that the selection of aggregation algorithm has a little impact on the best system design. However, they stress out that the optimization error brought on by time series aggregation largely depended on the system being optimized. They contend that it is crucial to assess clustering techniques separately for the type of energy model analysed. To the authors' best knowledge, the application of such methodologies for MDEV's VTMS optimisation remains limited as today. For example, Smith *et al.* [107] provide an example of these applications to generate a relevant dataset that correlate the urban cycles operated by electric trucks and the degradation of the battery. They explore the possibility of reusing available data of electric vehicle fleets circulating in cities in order to retrieve daily driving cycles to be used for energy-based simulations and optimize the size of the battery installed on the vehicle. Driving data are clustered into three specific patterns to represent the overnight and day charging: isolated commuting, work-related driving, and social or recreational driving. Then, a battery size optimisation problem is run and results compared to a case with only overnight charging scenarios. The results show that reusing real available data to build overnight and day charging scenarios could lead to much better results, as the battery size storage has been decreased by up to 40 % without loss of functionality.

The generation of appropriate scenarios to reduce the size of the problem to optimally design MDEVs' VTMS is identified as one of the major challenges to be addressed in the future. The research work to be performed is twofold: 1) to generate the needed data with an adequate diversity to represent the various climates, missions etc. of MDEVs and 2) identify the proper classification methodologies to generate the representative period and characterise the generated error.

4. CONCLUSIONS

The recent developments for vehicle thermal management are discussed in this review with a focus on their application to medium duty electric vehicles. While the thermal management at component scale is of course of importance, the authors prefer to highlight the challenges in mutual interaction and operations, having a holistic view of the system being the core of this review. Future developments are moving toward lighter and sophisticated thermal management systems that could work in synergy respecting optimisation paths. Thermal management architecture conception could be divided in three main creation parts: sizing, designing and controlling. As it has been shown through the substantial literature in this review, several approaches have been proposed for normal electric vehicles, leading to interesting results that could improve the efficiency of the whole system.

However, medium duty electric vehicles work under different conditions and current methodologies of thermal management conceiving still reflect old solutions applied on ICE vehicles. A possible way to solve this issue, would be to transfer approaches developed for electric cars to electric trucks. However, the strong differences in missions/driving scenarios must be carefully considered as they will drastically change the way of conceiving thermal management architectures for medium duty vehicles.

As for electric cars, sizing the thermal management system of medium duty electric vehicle thanks to an optimisation approach seems mandatory to achieve robust and efficient design, considering the complexity of the system and of the constraints to be taken into account (e.g. battery ageing, autonomy, available space, weight, etc.). The review highlighted the importance of the objective function definition and thermo-economic approaches can be seen as the minimum standard as today. The inclusion of other criteria, more specifically to quantify the environmental impacts, has also been explored but requires extended optimisation methods and the development of specific methodologies to score the various optimal configurations obtained with a multi-objective optimisation. Once an option of sizing has been picked up, the design phase through multi-physics simulation will help see as a first approach if the results in terms of autonomy and performances are better than an established base case. Furthermore, once the sizing block has been worked through, an optimized real-time control over the topology could be applied. This methodology is usable for any case-scenario related to medium duty electric vehicles (refuse truck, urban cycle, transportation, refrigeration, etc.). This approach could be referred, as Wei et al. [62] and Silvas et al. [77] to an alternated optimisation approach or a nested optimisation approach.

Few nonetheless important conclusions can be pointed out for the research community working actively on these topics:

- **Heat pump.** This technology is a clear opportunity to efficiently manage heat and cold generation in medium duty electric vehicles, offering large flexibility in terms of installation and topology choices for thermal management architectures. They are all the more interesting in cold climate to contain the electricity demand replacing advantageously direct electric heater for battery heating and cabin comfort while taking advantage from waste heat released by power electronic components. However, research work is still needed to determine optimal integration strategy and control by using for example advanced thermo-economic approach (e.g. exergo-economic analysis) while taking into account MDEV constraints.
- **New approach for MDEV VTMS design.** An approach based on an optimisation problem formulation can bring significant gain and insights on the VTMS design compared to the usual “worst case scenario” one. However, several challenges are identified and need to be addressed

with appropriate research work based on the available literature work on electric VTMS optimisation. Indeed, because of the great variety of mission that can be fulfilled by a MDEV (refuse collection, delivery, etc.) new specific formulation of the optimisation problem need to be developed and efficiently solved while taking into account the corresponding MDEV techno-economic constraints (needed minimal autonomy to fulfil the mission, economic model through the obtained TCO, etc.). This implies to find the appropriate trade-off between model complexity and computation time. Time series clustering could help in reducing the problem size as for other energy problems but specific challenges arise and are identified in the present article, the most important being to efficiently embrace the specificity of the MDEV mission and the weather conditions efficiently in the obtained clusters.

- **New approach for MDEV VTMS control.** Because of the new sizing strategy, optimal control becomes even more a challenge. For example, it can help in reducing the negative impact of operation beyond or below the recommended temperature for the battery pack. Both MPC and data driven approaches are identified as promising as for other energy systems, but will also need specific research activities to transpose them to MDEV case. For example, an appropriate data driven approach implies to generate a relevant dataset which has to be built from experiment and/or simulation covering the various configurations and operating conditions that can occur.

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