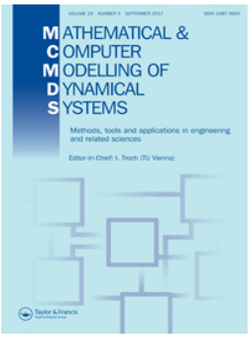

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Heat capacity and heat transfer coefficient estimation for a dynamic thermal model of rail vehicles

Raphael N. Hofstädter[a], Thomas Zero[b], Christian Dullinger[a], Gregor Richter[b] and Martin Kozek[a]

[a]Institute of Mechanics and Mechatronics, Vienna University of Technology, Vienna, Austria; [b]RTA – Rail Tec Arsenal Fahrzeugversuchsanlage GmbH, Vienna, Austria

ABSTRACT

This paper provides a method for estimating the parameters of a dynamic thermal rail vehicle model and reference values of these parameters. A linear dynamic discrete time system is used to model the thermal behaviour of the vehicle relevant for thermal comfort and air conditioning. The heat capacities and the heat transfer coefficients are stated for various vehicle classes. While dynamic thermal models are state of the art in buildings, cars and rail vehicles, no reference values can be found for these parameters. This paper shows how to estimate the heat capacity and the heat transfer coefficient from measured data for a given thermal model structure. Two different measurement data sources are used: special experiments and existing measurements. While specially designed experiments are only possible for new measurements, it is shown that satisfying results can be obtained with existing measurements. Measurement data from 13 vehicles are used to provide reference values for all passenger vehicles classes: tram, metro, regional and main-line. If all assumptions are satisfied, simulation results of the indoor air temperature agree well with measurements. Reference values for parameters of a dynamic thermal model are the basis for a wide application of such models in the rail vehicle industry.

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Thermal model; parameter estimation; heat capacity; heat transfer coefficient; rail vehicle

1. Introduction

Rail vehicles are the back bone of short-distance public transport (SDPT). In a large city like Vienna, the percentage of SDPT (including buses) is already at 35% [1]. As a result, the local operator serves, after own states, 2.5 million passengers per day [2]. Like every other industrial sector, the rail vehicle industry is subject to constant change. Since the 1950s, one of the key trends is the occurring urbanization which leads to a growth of cities and urban centres. By 2050, 84% of the European population will live in urban areas [3].

As a result, the requirements of the population for mobility will increase in number and complexity. In order to sustain this growth, transport should mainly be covered by SDPT. The increased energy costs and the effort to reduce CO_2 emissions support the use of rail vehicles. Thus, Vienna clearly prioritizes public transport, walking and cycling over car traffic [4, p. 25].

In his seminal work, Struckl [5] made a life cycle analysis of the metro Oslo to demonstrate energy saving potential for rail vehicles. About 30% of the total energy consumed is used for temperature control of the vehicle during driving cycles of the considered metro [5, see Fig. 4.53]. This magnitude is confirmed in [6]. In [7], it was measured that 11% of the total energy is consumed during stabling hours. The significant energy consumption of heating, ventilation and

CONTACT Raphael N. Hofstädter r.hofstaedter@gmail.com
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air condition (HVAC) systems calls for an efficient design of the related components. A fundamental element of this task is a dynamic thermal model of rail vehicles.

For the calculation of the annual energy consumption of the HVAC [8] or other optimization measures [9,10], a mathematical description of the considered system needs to be found and parameters of this system need to be identified.

1.1. *Literature*

Vehicles are usually air-conditioned by vapour compression refrigerators, although other methods exist [11] and are applied in practice [12]. According to [13], there are three possibilities to model HVAC systems: physics based, data driven or grey box. The very same principles can be applied to thermal models of (rail) vehicles.

Marcos et al. [14] developed and validated an analytical (physics-based) model of a car with two heat capacities. In [15], an analytical thermal model for an automotive vehicle is developed and validated. Parameters were estimated analytically (physics based), e.g. the heat capacity of the car was multiplied by the mass and the average specific heat capacity. Marachlian et al. [16] used an exergy-based numerical model to simulate the cars HVAC operations. Today, a thermal simulation software for automotive vehicles is already available [17] and used for the simulation of combined cooling loops [18]. The thermal behaviour of buildings can be simulated using a modular Modelica library [19]. In [20], dynamic cooling loads were studied using an analytical thermal model of a Chinese main-line train. Another dynamic thermal model of an urban rail vehicle is part of previous works of some of the authors and can be found in [21]. An analytical simulation model was also used by Li and Sun [22] to simulate and analyse the entire system of air conditioning unit and passenger room. All thermal vehicle simulation approaches are almost exclusively used for only one specific vehicle. The models that use an analytical approach are purposeful, but it is time consuming to determine every necessary parameter. For industrial practices, it would be advantageous if benchmarks or reference values for a dynamic thermal simulation model were available. Measurement data should be sufficiently available, because thermal tests of rail vehicles can look back on a long history.

Function tests have been conducted for rail vehicles in Vienna since 1958. Especially refrigerated wagons were examined back then and their heat transfer coefficient (k value) was measured. Over the years, testing was expanded to passenger trains and metros. Nowadays, function tests in a climatic wind tunnel (CWT) are part of standard commissioning. Since these tests are considered during construction of the vehicle, lower k values are intended. The k value of the vehicles is usually measured during these tests [23], according to European Standards [24,25]. These tests are done to keep operational costs low and availability high [26,27]. Although unpublished records about the identification of the heat capacity can be traced back until the 60s, no generally accepted procedures or regulations exist for the estimation.

In building technologies an obligatory holistic examination of buildings, in terms of energy efficiency, was introduced [28] by a new EU directive [29] and national law [30]. However, no standards exist for model structure and parameter choice of dynamic thermal models of rail vehicles' eigen behaviour. This paper is a step forward and provides a compact yet versatile model structure and reference values of the thermal behaviour of the vehicle for different analytical–thermal models and for various types of rail vehicles (tram, metro, regional and main-line).

1.2. *Contents*

Different models that are describing the vehicles' behaviour are derived from a general dynamic model in Section 2. Afterwards, the theoretical fundamentals and the practical requirements for the conducted and available measurements are discussed in Section 3. All assumptions are

summarized in Section 4, and the used simulation model and the estimation method are described in Section 5. In Section 6, the obtained results are shown and discussed.

2. Modelling

The modelling section summarizes the state of art for thermal modelling for rail vehicles and presents a low-order dynamic model structure which can be efficiently parametrized.

2.1. *Generic analytic–dynamic thermal model*

Relevant variables for the thermal comfort inside the a rail vehicle are T the temperature of the indoor air and Y the absolute humidity of the indoor air, according to the current standards [24,25]. The air velocity is just defined as a constraint that must be satisfied and is usually only considered during design of the air distribution system.

The entire rail vehicle consists of N thermal system. Every system i of the rail vehicle can be described individually. Equations for T and Y can be stated based on energy and mass balances for every system i.

$$C_i \frac{\mathrm{d}T_i}{\mathrm{d}t} = -\dot{Q}_{i,\mathrm{loss}} - \dot{Q}_{i,\,i+1} + \dot{Q}_{i,\,\mathrm{solar}} + \dot{Q}_{i,\,\mathrm{pas}} + \dot{Q}_{i,\,\mathrm{aux}} + \dot{E}_{i,\,\mathrm{sup}} - \dot{E}_{i,\,\mathrm{exh}} \tag{1}$$

$$m_i \cdot \frac{\mathrm{d}Y_i}{\mathrm{d}t} = \dot{E}^W_{i,\,\mathrm{sup}} - \dot{E}^W_{i,\,\mathrm{exh}} + \dot{E}^W_{i,\,\mathrm{pas}} + \dot{E}^W_{i,\,\mathrm{aux}} \tag{2}$$

In Equation (1), C_i is the heat capacity associated with temperature T_i. $\dot{Q}_{i,\mathrm{loss}}$ describes the dissipated heat from the component of the system with the temperature T_i to the environment. $\dot{Q}_{i,\,i+1}$ is the energy flow between the components with temperatures T_i and T_{i+1}, respectively. $\dot{Q}_{i,\,\mathrm{solar}}$ takes the solar radiation (direct and indirect) and $\dot{Q}_{i,\,\mathrm{pas}}$ the dissipated sensible heat by passengers into account. $\dot{Q}_{i,\,\mathrm{aux}}$ is the heat dissipated by auxiliaries, i.e. electrical lighting and passenger information system. $\dot{E}_{i,\,\mathrm{sup}}$ is the mass flow of supply air and $\dot{E}_{i,\,\mathrm{exh}}$ the mass flow of exhaust air. In Equation (2), m_i denotes the mass of the indoor air, $\dot{E}^W_{i,\,\mathrm{sup}}$ is the mass flow of water in the supply air and $\dot{E}^W_{i,\,\mathrm{exh}}$ in the exhaust air, $\dot{E}^W_{i,\,\mathrm{pas}}$ is the dissipated water due to sensible heat of passengers and $\dot{E}^W_{i,\,\mathrm{aux}}$ is any further mass flow of water in Equation (2).

Only parameters C_i, m_i and terms $\dot{Q}_{i,\mathrm{loss}}$ and $\dot{Q}_{i,\,i+1}$ are necessary to describe the vehicles' behaviour. Since the initial analytical guess of m_i, sufficed for the calculations of the absolute humidity Y in previous works of some of the authors [31], this paper will focus on C_i and the terms $\dot{Q}_{i,\mathrm{loss}}$ and $\dot{Q}_{i,\,i+1}$ for the calculations of the temperature(s) T_i. The air volume of system i was multiplied by the air density to obtain the mass of indoor air m_i.

Following subsections derive three vehicle models from the generic analytic–dynamic thermal model to describe the vehicles' behaviour.

2.2. *Second-order thermal vehicle model*

The vehicle is assumed to consist of two systems ($N = 2$) with two heat capacities and two temperatures, see Figure 1. The equation for system 1 ($i = 1$) follows from Equation (1) by keeping only terms relevant to the vehicles' behaviour.

$$C_1 \frac{\mathrm{d}T_1}{\mathrm{d}t} = -\dot{Q}_{1,\,\mathrm{loss}} - \dot{Q}_{1,2} + \dot{Q}_{1,\,\mathrm{solar}} + \dot{Q}_{1,\,\mathrm{pas}} + \dot{Q}_{1,\,\mathrm{aux}} + \underbrace{\dot{E}_{1,\,\mathrm{sup}} - \dot{E}_{1,\,\mathrm{exh}}}_{\dot{Q}_H}$$

In Figure 1, it is shown that HVAC ports are sealed. So, $\dot{E}_{1,\,\mathrm{sup}}$ and $\dot{E}_{1,\,\mathrm{exh}}$ need to be replaced by $\dot{Q}_H$ during measurements (see Section 3) which holds the sum of all introduced

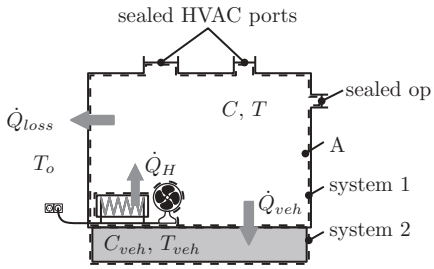


Figure 1. Schematic illustration of the second-order thermal vehicle model.

heat flows. Equation (3) is obtained by renaming $\dot{Q}_{1,2}$ to $\dot{Q}_{\text{veh}}$ and omitting index 1.

$$C\frac{\mathrm{d}T}{\mathrm{d}t} = \dot{Q}_H - \dot{Q}_{\text{loss}} - \dot{Q}_{\text{veh}}, \tag{3}$$

in which T is the indoor air temperature and C the heat capacity of the interior. $\dot{Q}_H$ is the sum of all introduced heat flows, $\dot{Q}_{\text{loss}}$ indicates the emitted heat flow to the environment and $\dot{Q}_{\text{veh}}$ is the heat flow to the car body (system 2).

For system 2, the described steps for system 1 are repeated. Additionally, it was assumed that $\dot{Q}_{2,\text{loss}}$ is zero for system 2. With this design choice the model stays compatible to the current standardized model, see Section 2.4, and all (analytical) knowledge for the k value is sustained. Then, C_2 is renamed to $\dot{Q}_{\text{veh}}$ and T_2 is renamed to T_{veh}. The temperature of the vehicle body T_{veh} is calculated using

$$C_{\text{veh}}\frac{\mathrm{d}T_{\text{veh}}}{\mathrm{d}t} = \dot{Q}_{\text{veh}}. \tag{4}$$

C_{veh} is the heat capacity of the vehicle body. Heat flow through surface A is assumed as heat flow through a flat vertical wall $\dot{Q}_{\text{loss}}$, in which

$$\dot{Q}_{\text{loss}} = kA(T - T_o) \tag{5}$$

applies. A is the overall uncoiled surface of the vehicle. k is the heat transfer coefficient and T_o is the outdoor air temperature.

To complete the model, the heat transfer between the interior room (system 1) and the capacity (system 2) is described as

$$\dot{Q}_{\text{veh}} = K_{\text{veh}}(T - T_{\text{veh}}). \tag{6}$$

K_{veh} is the heat transfer coefficient between the interior and the surface of the modelled heat capacity of the vehicle body C_{veh}. However, a split-up into two factors, as done in Equation (5), is not reasonable since neither the surface nor the heat transfer coefficient can be chosen distinctively. It is important to note that C_{veh}, K_{veh} and T_{veh} are purely fictitious quantities, and a strictly physical interpretation is not possible.

The two heat capacities (C and C_{veh}) can be interpreted in the following way: The heat capacity C not only consists of the heat capacity of the indoor air but also of the heat capacity of those parts of the passenger cabin which are in thermal equilibrium with the indoor air (e.g. seats, passenger handles etc.). The heat capacity of the air inside the interior alone is not large enough to describe the dynamic behaviour adequately. Consequently, the heat capacity C_{veh} consists of those parts of the vehicle that exchange heat with the heat capacity C.

The equations of the second-order model can be summarized to an equation for the indoor air temperature T and an equation for the vehicle temperature T_{veh}:

$$C \cdot \frac{\mathrm{d}T}{\mathrm{d}t} = \dot{Q}_H - kA(T - T_o) - K_{\mathrm{veh}}(T - T_{\mathrm{veh}}), \tag{7}$$

$$C_{\mathrm{veh}} \cdot \frac{\mathrm{d}T_{\mathrm{veh}}}{\mathrm{d}t} = K_{\mathrm{veh}}(T - T_{\mathrm{veh}}). \tag{8}$$

A schematic illustration of the second-order thermal vehicle model can be found in Figure 1.

2.3. *First-order thermal vehicle model*

In this model, the vehicles' behaviour is described by only one system. In addition to assumptions made in Section 2.2, $\dot{Q}_{\mathrm{veh}}$ is also assumed to be zero. Hence,

$$\bar{C}\frac{\mathrm{d}T}{\mathrm{d}t} = \dot{Q}_H - kA(T - T_o) \tag{9}$$

can be obtained, in which $\bar{C}$ is the heat capacity of the vehicle.

2.4. *Standardized static model*

The static model can be obtained by introducing the additional assumption that $(\mathrm{d}T/\mathrm{d}t) = 0$ to the already made assumptions in Section 2.3. As a result, the energy balance simplifies to

$$0 = \dot{Q}_H - k \cdot A \cdot (T - T_o), \tag{10}$$

resulting in the standardized model [24,25].

It is important to note that both proposed dynamic models are consistent with the standardized static model.

Equation (3) may be derived from the total energy balance (assuming that the temperature variations in the rail vehicle are small and that the specific heat capacity is constant). However, it is beyond the scope of this paper to show mathematically that the second law of thermodynamics is always guaranteed for the presented models. But since Equation (3) is frequently used, the standard model is applied in this study [32, cf. Example 11.4].

3. Measurements

Parameters of the proposed models are identified from measured data. First, general requirements for these measurements must be specified. In addition, two measurement approaches can be distinguished:

- Special experiments (step responses)
- Existing experiments (data from standard commissioning)

Requirements for measurement data of both approaches are described in this section.

3.1. *General requirements*

To estimate parameters C, k, C_{veh}, K_{veh} of the model from CWT measurement data, measurements of the model inputs (sum of all introduced heat flows $\dot{Q}_H$ and the temperature inside the CWT T_o) and model outputs (indoor air temperature T, vehicle temperature T_{veh}) are necessary. The indoor air temperature T is considered to be the (weighted) average measurement of all temperature measurements inside of the vehicle. The vehicle temperature is also calculated as a split-up coverage from several measurements (see Section 4, p. 8). The sum of introduced heat

flows $\dot{Q}_H$ is calculated both from the absorbed electrical power of the heater coils and the absorbed electrical power of the fans.

Measurements need to be recorded with an adequately high sampling rate. The typically used sampling rate of 10–1 min is sufficient. Since only the vehicles' behaviour should be measured, all other influences and disturbances, as shown in Equations (1) and (2), should be eliminated in the CWT as well as possible. The simulated wind speed should be kept constant, the simulated passenger load $\dot{Q}_{\mathrm{pas}}$, the solar radiation $\dot{Q}_{\mathrm{solar}}$ and additional auxiliaries $\dot{Q}_{\mathrm{aux}}$ must be turned off. All openings $\dot{E}_{\mathrm{exh}}$ and HVAC ports $\dot{E}_{\mathrm{sup}}$ are sealed, as shown in Figure 1.

3.2. *Special experiments*

Due to economical limitations, two step tests are conducted with different signs. Initial conditions should be well defined and known. Due to the fact that the measurement of the vehicle temperature is difficult, it is desirable that the vehicle temperature T_{veh} and the indoor air temperature T are constant at the beginning of the experiment.

Based on this state, one input is changed stepwise. At time $t = 0$ the supplied heat flow is switched to the value that follows from the expected k value. Usually, a rough estimate is known, because it is analytically calculated by the manufacturer or a maximum permissible value can be found in the standards for the vehicle class [24,25]. The experiment is conducted until a new steady state follows, i.e. the derivative of the indoor air temperature T and the deviations of the vehicle temperature T_{veh} are almost zero. To reduce the necessary experiment time the experiment can be stopped earlier, if the final value can be estimated from measurement data and 95% of the step response has already been achieved. The step experiment is then repeated with reversed sign. After the experiment ends the initial conditions should be reached again.

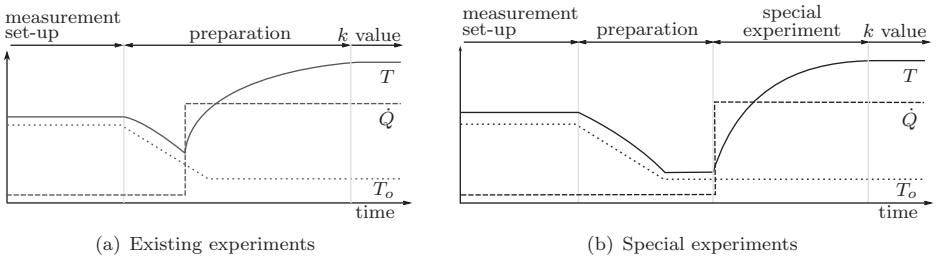
3.3. *Existing measurements*

The procedure described for special experiments cannot be applied to historic measurements and they cannot be repeated at justifiable cost. However, in the conducted measurements similar sections to the proposed special experiments can usually be found. These can also be used for parameter estimation, but not with the same accuracy. This includes the following experiment types:

- Pre-heating experiments of the vehicle using HVAC (pre-heating).
- Measurement of the heat transfer coefficient (k value).
- Cool down experiment (freezing test). The vehicle is allowed to cool down for 12 h.

The pre-heating and cool down experiment have the disadvantage that the introduced heat flow was not directly measured. Although it can be calculated from the measured air flow, the result is always subject to increased uncertainty. The measurement for estimating the heat transfer coefficient is almost always performed, though according to different standards.

This means that relevant parameters can typically be estimated with experiments for the measurement of the heat transfer coefficient, as well as the conducted preparation and post-processing experiments before and afterwards. Figure 2 compares the existing measurements with the special experiments. In the special experiments, only one input is changed at a time. First, the temperature inside the CWT is set, a steady state is awaited and then $\dot{Q}_H$ is changed.



(a) Existing experiments (b) Special experiments

Figure 2. Chronological sequence of x and u for special and existing experiments (schematic diagram).

Table 1. Overview of the available and evaluated experiments for the estimation of heat capacities and heat transfer coefficient.

	Tram	Metro	Regional	Main-line	Locomotive	Sum
k-Value measured	3	6	16	7	6	38
Experiment can be evaluated	2	5	4	2	0	13

4. Assumptions

The following assumptions have been made for the estimation of parameters:

- *Ideal mixing*: In the model, it is assumed that the air in the interior of the vehicle is ideally mixed. For the k-value experiments, this is ensured by temporary installed fans inside the vehicle.
- *No heat transfer between outdoor air and heat capacity*: The heat transfer between outdoor air and modelled heat capacity of the vehicle is neglected. For all considered vehicles below this is satisfied.
- *Measurement of the temperature of the vehicle's heat capacity*: As measurement value for the temperature of the vehicle's heat capacity, the mean surface temperature of different surfaces inside the vehicle is used. All other considered metering points were not accessible for measurement.
- *Identification*: An initial value must be given for identification. To estimate an accurate initial value, a steady state is advantageous; unfortunately, this state is not always available. Therefore, some experiments could not be used for identification (see Table 1).
- *Linear model*: The proposed model for identification is linear in its parameters. Although non-linear behaviour is observed in measurement data, the linear model fit is considered satisfying.

The simulation model and the estimated parameters from the measured data are only valid, if these assumptions are met.

5. Parameter estimation

The dynamic models, described in Section 2, are transformed to an explicit linear state space representation. To ensure compliance with the current standardized method, the k value is estimated accordingly. Afterwards, an assumption is made for the model structure by determining the noise model and the prediction error method (PEM) is used to estimate these parameters [33,34].

5.1. State–space representation

A linear state space system is given by

$$\dot{x} = \mathbf{A}x + \mathbf{B}u \text{ and} \tag{11}$$

$$y = \mathbf{C}x + \mathbf{D}u. \tag{12}$$

The input vector u is defined as $u^T = \begin{bmatrix} T_o & \dot{Q}_H \end{bmatrix}$. $\mathbf{C}$ is always assumed to be the identity matrix of appropriate size and $\mathbf{D} = 0$, so $y = x$.

For the first-order model $x = T$ is chosen, so

$$\mathbf{A} = \begin{bmatrix} -\frac{kA}{C} \end{bmatrix}; \quad \mathbf{B} = \begin{bmatrix} \frac{kA}{C} & \frac{1}{C} \end{bmatrix} \tag{13}$$

applies and for the second-order model, $x^T = \begin{bmatrix} T & T_{\text{veh}} \end{bmatrix}$ is chosen, so

$$\mathbf{A} = \begin{bmatrix} -\frac{kA+K_{\text{veh}}}{C} & \frac{K_{\text{veh}}}{C} \\ \frac{K_{\text{veh}}}{C_{\text{veh}}} & -\frac{K_{\text{veh}}}{C_{\text{veh}}} \end{bmatrix}; \quad \mathbf{B} = \begin{bmatrix} \frac{kA}{C} & \frac{1}{C} \\ 0 & 0 \end{bmatrix} \tag{14}$$

apply.

5.2. Two-stage estimation approach

To ensure compatibility with the current standardized static model, a two-stage approach is used for parameter estimation:

- First, the k value is estimated according to the standard method [25, p. 12]. Equations (11) and (12) are applied to appropriate measurement data.
- Second, missing parameters (first order: $\bar{C}$ and second order: C, K_{veh} and C_{veh}) are additionally estimated using the PEM.

5.3. Parameter estimation utilizing the PEM

Every system identification requires the assumption of a model structure, which is determined by the structure of the process and noise model. For linear systems, the general linear discrete time state–space representation of a process and noise model is given by

$$x(n+1) = \mathbf{A}(\theta)x(n) + \mathbf{B}(\theta)u(n) + \mathbf{K}(\theta)e(n) \tag{15}$$

$$y(n) = \mathbf{C}(\theta)x(n) + \mathbf{D}(\theta)u(n) + e(n) \tag{16}$$

with the initial state vector $x(0) = x_0(\theta)$, the parameter vector θ (cf. Equations (19) and (20)) and $e(n)$ being a stochastic zero mean noise input [35]. The $\mathbf{K}$ matrix is fixed to zero (i.e. $\mathbf{K} = 0$).

Using measurement data obtained by various experiments (see Section 3) in a CWT, parameters of the state–space system (cf. Equations (11) and (12)) can be identified by applying the PEM [33] according to the following criterion

$$J(\theta) = \mathbf{e}^T\mathbf{e} \rightarrow \min_{\theta}, \tag{17}$$

where

$$\mathbf{e} = \begin{bmatrix} \mathrm{e}(1|\theta) \\ \vdots \\ \mathrm{e}(N|\theta) \end{bmatrix} \quad \text{with} \quad \varepsilon(n|\theta) = \mathbf{y}(n) - \hat{\mathbf{y}}(n|\theta)\,. \tag{18}$$

Table 2. Heat transfer coefficients and heat capacities of existing vehicles.

Name	k (W/(m^2 K))	C (J/K)	K_{veh} (W/K)	C_{veh}(J/K)	R^2 (1)
Tram1	2.5	3.0×10^7	246	1.7×10^7	0.990
Tram2	3.2	1.8×10^7	974	1.0×10^7	0.995
Metro1	2.8	9.4×10^6	464	1.9×10^7	0.992
Metro2	3.1	9.2×10^6	199	9.6×10^6	0.949
Metro3	2.9	8.0×10^6	47,831	5.7×10^6	0.132
Metro4	2.4	4.6×10^6	230	1.3×10^7	0.628
Metro5	2.9	1.1×10^7	5479	2.3×10^7	0.969
Regio1	1.7	4.3×10^7	484	4.6×10^6	0.820
Regio2	1.3	6.4×10^6	1366	3.1×10^7	0.966
Regio3	2.0	3.6×10^6	217	1.1×10^7	0.126
Regio4	1.7	1.3×10^7	907	3.7×10^7	0.932
Main1	1.4	7.2×10^5	93,627	3.9×10^6	0.494
Main2	1.6	2.6×10^6	564	2.4×10^7	0.562

In Equation (18), $\varepsilon(n|\theta)$ is the prediction error (vector) (at time step n), which is the difference between the measured output (vector) $\mathbf{y}(n)$ and the predicted output (vector) of the model $\hat{\mathbf{y}}(n|\theta)$ and N is the number of training data samples. As k was already estimated during the first stage, the parameter vector is defined as

$$\theta = \bar{C} \tag{19}$$

for the first-order model and

$$\theta = [\, K_{\text{veh}} \quad C \quad C_{\text{veh}} \,]^T \tag{20}$$

for the second-order model. Other frequently used methods for estimation are the different least-square techniques [36]. The PEM has some advantages. It is applicable to a wide variety of model structures and it handles closed loop data in a direct fashion. A drawback is that it is labour intensive and requires good initial parameter values [34].

The implementation of the System Identification Toolbox of MATLAB was used. To begin with, the model with estimable parameters was defined using the function idgrey of MATLAB and afterwards, parameters of this model were estimated using the function PEM [37]. As initial values $C = 120,480\,J/K$, $C_{\text{veh}} = 500,000\,J/K$ and $K_{\text{veh}} = 20\,J/K$ were used. The calculation is performed on a contemporary Desktop PC (Intel Core i7 860 @ 2.80 GHz) in a few seconds.

Table 2 lists the results of the identification. These estimated parameters were used to produce comparable time series plots of measurements and simulation (see Section 6).

5.4. Significance of estimated models

Let $y(n)$ denote the measured and $\hat{y}(n)$ the simulated indoor air temperature at time step n (for $n = 1, \ldots, m$), respectively. Then the coefficient of determination R^2 of the model is given by

$$R^2 = 1 - \frac{SS_{\text{res}}}{SS_{\text{tot}}}, \tag{21}$$

where SS_{res} is the sum of squares of residuals (also called the residual sum of squares) computed by

$$SS_{\text{res}} = \sum_{n=1}^{m} \left(\underbrace{y(n) - \hat{y}(n)}_{e(n)} \right)^2 = \mathbf{e}^T \mathbf{e} \tag{22}$$

and SS_{tot} is the total sum of squares (proportional to the sample variance) obtained by

$$SS_{\text{tot}} = \sum_{n=1}^{m} (y(n) - \bar{y})^2, \tag{23}$$

where $\bar{y} = (1/m) \sum_{n=1}^{m} y(n)$ is the mean of the observed data [38].

The coefficient of determination R^2 is an indication that provides some information about the goodness of fit of a model. It describes how well measurements are reproduced by the thermal vehicle model. An R^2 of 1 indicates that the simulated indoor air temperature perfectly fits the measured indoor air temperature.

6. Results

The first-order and the second-order model are compared. Thereafter, results for the estimated parameters (C, k, C_{veh}, K_{veh}) are discussed and the estimated parameters for individual vehicles are generalized for different vehicle classes.

6.1. *Model order*

A first-order and a second-order grey box model are estimated for tram Tram2 using special experiments. Time series plots compare measurement data to simulation results in Figure 3. Measurement data can be satisfactorily reproduced with both models. Since second-order models are almost exclusively used in literature and provide a slightly better model fit they are used for all vehicles.

An even better fit to measurement data could be achieved by estimation of a black box model. In this case, the analytical structure of the model would be lost. A generalization of the model is no longer possible, and thereby no conclusion could be drawn for similar vehicles. Thus, the second-order model used for all vehicles is a grey box model.

6.2. *Estimated parameters*

Measurement data from the CWT were sighted, preprocessed and input into the developed software for the existing experiments. An overview about the conducted and evaluated experiments is shown in Table 1. Many experiments had to be discarded, because underlying assumptions were not met (see Section 4).

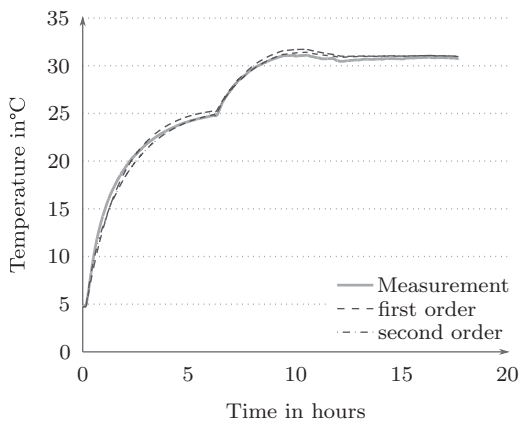


Figure 3. Tram2: Comparison between different models (simulation) and measurement utilizing data from step responses.

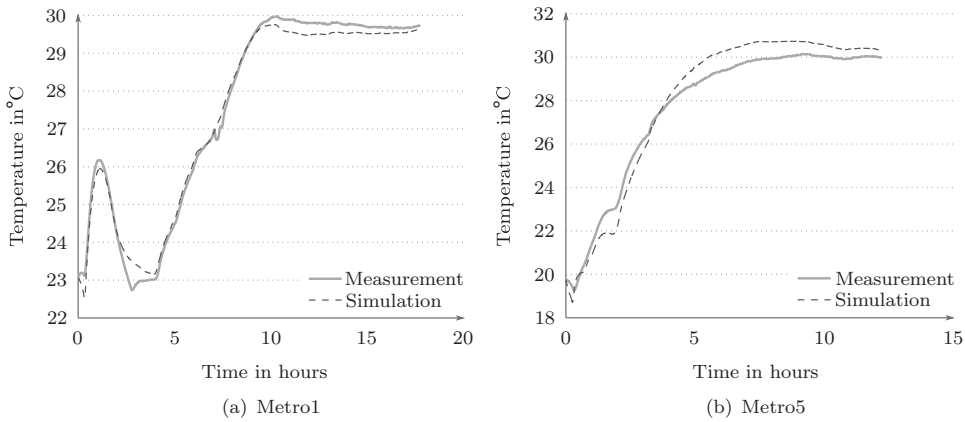


Figure 4. Comparison between estimated models (simulation) and measurements for indoor air temperature utilizing data from standard commissioning.

A summary of average values for all estimated parameters of all identified vehicles can be found in Table 2.

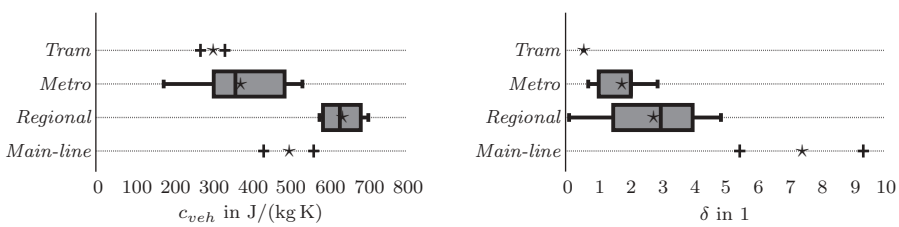
With the estimated parameters the simulation model was established. A comparison between simulation and measurement of the indoor air temperature is shown for two metros in Figure 4. Parameters for a model with small deviations could be estimated for all vehicles, as it can be seen in both examples. The deviation between measurement and simulation is similarly small as for Tram2, but the considered temperature range is smaller.

6.3. *Generalized parameters*

In addition to absolute results, the specific heat capacity c_{veh} of the vehicle body is calculated by

$$c_{\text{veh}} = \frac{C_{\text{veh}}}{m_{\text{veh}}}, \tag{24}$$

where m_{veh} is the mass of the vehicle. Results are grouped by vehicle type and plotted in Figure 5 (a). The vehicle type is used, because features of a vehicle correlate usually well with the vehicle type. Hence, it is assumed that various features of the vehicle, like number of seats, type of seats (with fabric cover or plastic only) and interior decoration can be mapped into the vehicle class. For example, metros and trams are mostly equipped with seats made of plastic, while main-line vehicles have more comfortable seats with fabric cover. For the two classes tram and main-line, no further conclusion is possible, due to the limited data set. In Figure 5(a), it can be seen that the



(a) Specific heat capacity of the vehicle body c_{veh} versus vehicle class

(b) Ratio of the two heat capacities δ versus vehicle class

Figure 5. Boxplots of generalized parameters for each vehicle class.

Table 3. Generalized parameters for existing vehicles.

Name	c_{veh} J/(kg K)	δ(1)
Tram1	270	0.56
Tram2	333	0.55
Metro1	533	2.05
Metro2	304	1.04
Metro3	175	0.71
Metro4	487	2.89
Metro5	360	2.05
Regio1	664	0.11
Regio2	577	4.88
Regio3	595	3.1
Regio4	703	2.88
Main1	562	5.47
Main2	433	9.35

two classes of metros and regional trains differ considerably from each other. The mean value of the specific heat capacity for metros is 372 J/(kg K) and for regional trains, it is 603 J/(kg K). Due to the small numbers of measurements and the high variance inside the vehicle classes, it cannot be statistically proven that the difference is significant.

Another generalized result is the ratio δ of the two heat capacities and can be calculated by

$$\delta = \frac{C_{\text{veh}}}{C}. \tag{25}$$

Figure 5(b) shows the ratio for different vehicle classes. The corresponding numbers are listed in Table 3. It can be clearly seen that the ratio increases from tram through metro and regional to main-line. Just as it would be expected, since main-line vehicles are a lot heavier than trams and metros. Hence, their vehicle body has a larger heat capacity.

6.4. *Plausibility check*

Due to the fact that only a small amount of data are available, a cross validation of models is not possible. Instead a plausibility check of results is done. There is a maximum of one usable experiment for each vehicle and this experiment is used for the parameter estimation. In Table 2 and Figure 5(a), it can be observed that the values for the specific heat capacity for the vehicle c_{veh} are in the range from 175 J/(kg K) to 703 J/(kg K). Values are exactly in the expected range.

During the construction of the vehicle especially steel ($c \approx 477\,\text{J}/(\text{kg}\,\text{K})$) and aluminium ($c \approx 896\,\text{J}/(\text{kg}\,\text{K})$) are used in larger quantities.

7. Conclusion

This paper presents the estimation of heat capacities and heat transfer coefficients for two dynamic thermal rail vehicle models. Different sources of measurement data are used. While special experiments are designed for the estimation, some existing measurements can sometimes be used additionally and comparable results are obtained. Simulation results are in good agreement with measurement data, if underlying model assumptions are met. Parameters for all relevant passenger rail vehicles classes are given: Tram, Metro, Regional and Main-line. Also, it is indicated that grouping into these vehicle classes is justified. The plausibility check shows that obtained results are generally in the expected range and correlate with the vehicle construction. The estimation results and the generalized parameters provide a first step towards a basis for future thermal vehicle models for all relevant rail vehicle classes.

This provides a basis for a wide application in the industry: The rail vehicle manufacturer can fall back on the proposed parameters for the dynamic energy consumption calculation (which is already done in some cases), until those parameters have been measured in the CWT. Calculations are easier to understand for the customers and operators of rail vehicles, if consistent parameters are used as standard for the thermal vehicle model. By the use of the proposed parameters, numerical values for the dynamic thermal vehicle models are available during the design phase of the HVAC to the manufacturer. In addition, the proposed dynamic thermal vehicle models are the basis for further optimization of all thermal vehicle components. Thus, a modern controller (i.e. a model-based predictive controller) can be designed that uses the proposed models for energy consumption optimization. The designer is supported by the use of the proposed parameters, because a laborious analytical calculation is not required.

Measurement of heat capacity and heat transfer on all future vehicles would be greatly beneficial.

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