Physical Modelling of a Light Rail HVAC System Using Long-Term Measurements

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Abstract

A method to develop a physical HVAC model of a light rail using only operation data from long-term measurements is presented. Physical HVAC modelling is often based on costly wind tunnel tests or time and computationally intensive CFD calculations. This method is a new approach using only data from everyday operation of the light rail, reducing modelling cost and improving the model accuracy since real life conditions are analysed. Data from two years of passenger operation of a suburban light rail in Karlsruhe, Germany, is used. A standard physical model for a HVAC system and a train compartment is developed. This model is parametrised using data driven modelling and model training. For data driven modelling, the conducted data is analysed and suitable models are derived. For example, the cooling system is modelled using a look-up table based approach developed with the data. For model training, the data is first separated into test and training data. The training data is then separated into different batches (heating up, winter-night, winter-day and summer), to parameterise different physical quantities of the model. Using a systematic grid search, parameters that fit the training data in an optimal manner are found. Finally, the overall model is validated using the test data. Over a large temperature range from -5 °C to 35 °C the model shows good consistency with the test data. The mean absolute percentage error over all test data is 13 %. Within the batches, the summer data was modelled best with an error of about 8 %. The described method allows a fast and reliable method to develop an accurate physical HVAC model.

Keywords: HVAC Modelling; Physical Model; Long-Term Measurements; Light Rail

1. Introduction

The energy consumption of the auxiliary consumers can amount to about 40 - 50 % of the overall energy consumption of a light rail [1]. In order to develop energy efficient trains, the energy consumption of auxiliary consumers is getting more and more attention. The heating ventilation and air conditioning system (HVAC), as one of the biggest auxiliary consumers, is in the centre of this discussion. In order to understand, develop and improve future HVAC systems, accurate physical models of the HVAC system and the corresponding train compartment are necessary. These models are used, for example, to develop smarter operation strategies than the set point-based operation modes often used today. In addition, they can be used to show that the Total Cost of Ownership (TCO) of a more energy efficient solution, such as a heat pump instead of heating fins, compensates for the higher purchase price of this solution. A detailed look into HVAC modelling shows that the development of a physical HVAC model and the corresponding train compartment model is complex, time-consuming and costly. When a model is built, it has many degrees of freedom and simulation takes time. New train projects often include data mining. This data can be used to develop models, for example black-box models based on neural networks [2]. Black-box models have the disadvantage that it is not possible to change physical parameters within the model. Furthermore, it is difficult to split a black-box model into submodels. During HVAC development it is often necessary to change physical parameters or to substitute only a submodel, for example the heating system. Therefore, the presented method focuses on using physical models as a basis. Physical models are often not as accurate and they are computational time intensive. The idea is therefore to combine techniques known from black-box development with physical modelling towards a data driven physical model that gives accurate results with an acceptable computational effort. The presented method works without time and cost intensive testing of the HVAC system or the training set. Furthermore, the model accuracy can be increased since it is based on real live data.

2. Literature Overview

Two fields of research are important for this work: projects doing long term measurements including the auxiliary consumers, and physical HVAC modelling for rail cars. Depending on the investigated trainsets, HVAC or only heating and ventilating (HV) is analysed. For 13 months from 2011 to 2013, long-term measurements were done in a light rail in Gent, Belgium [3]. The project analysed different energy saving strategies by improving the HV management. From 2012 to 2013, a Metro Car of the Tyne and Wear Metro system in the UK was equipped with energy meters doing long term measurements, investigating that heating is one of the major energy consumers [4]. In [5], the energy consumption of a regional train in Switzerland is discussed, based on long-term measurements between 2012 and 2013. Since 2019, a light rail vehicle in Karlsruhe, Germany, is equipped with various measurement devices to track traction as well as auxiliary metrics [1]. The data collected in Karlsruhe is used for this work.

HVAC modelling often uses limited real live data: For example, in [6], a physical model of a subway car compartment as well as a HV model are developed without using real live data. Energy savings due to CO_2-controlled ventilation is discussed. In [7], an extensive HVAC model is developed using test data from the manufacturer. [8] develops a HVAC model and a corresponding tram compartment model using look-up tables from manufacturers as well as wind tunnel test data. Data from cooling tests in a depot were used for developing a HVAC and a compartment model in [9]. Since real world data is often missing, [10] is developing representative operating conditions for a train HVAC system, highlighting the need for real world data.

Overall it can be stated that the potential of long-term measurement data for HVAC modelling has not been exploited yet. Using two years of data to develop a physical model, this work shows the potential of this idea.

3. Method

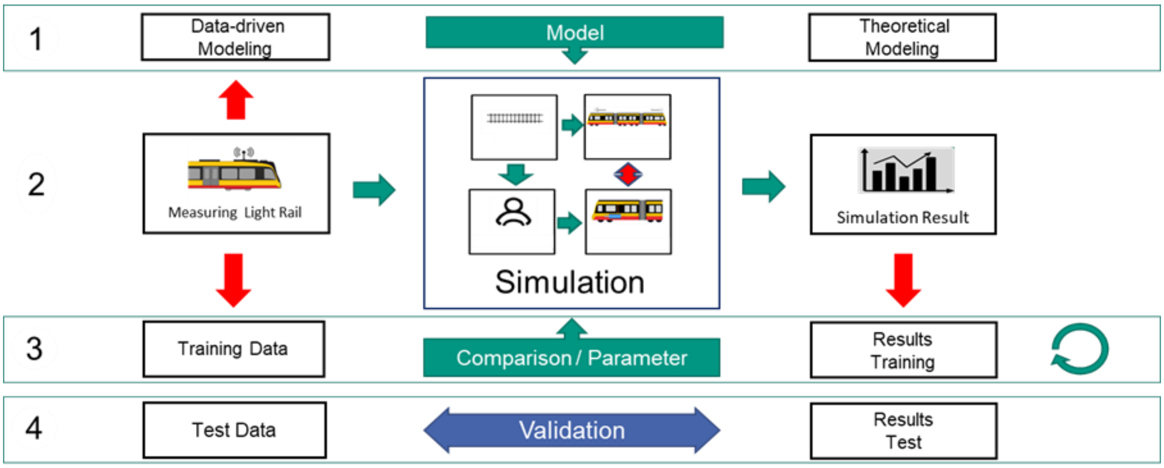

Figure 1: Method to derive the physical model from real train data

The methodology is presented in Figure 1 containing four steps. The basis of the methodology is real train data collected during normal operation of a light rail train running in the area of Karlsruhe, Germany. The data is split into two parts, a training and a test set, in order to ensure that data for later validation wasn't used to build or train the model. The data used in this paper was collected over a period of two years during an ongoing project that collects data until 2023. This project was presented on WCCR 2019 [11].

3.1 Step 1: Modelling

First, the train compartment and the HVAC model are developed using models from literature, mainly from [8]. For simplification, the train compartment is only modelled using one heat capacity and the train isn't separated into sections for each wagon. The overall system shown in Figure 2 can be divided into two subsystems, the HVAC system (black dotted line) and the train compartment system. To model the effects two approaches are considered: Theoretical modelling and data-driven modelling. If a physical effect is well known and easy to describe, then theoretical modelling is used. If data is present and the physical effect is difficult to describe, data-driven modelling is used.

Inside the HVAC system, outside fresh air $\dot{V}_{Air_{fresh}}$ as well as inside air $\dot{V}_{Air_{inside}}$ are mixed. This supply air $\dot{V}_{Air}$ is then pumped into the vehicle. If the HVAC is in heating mode, the supply air is heated. If the HVAC is in cooling mode, the supply air is cooled.

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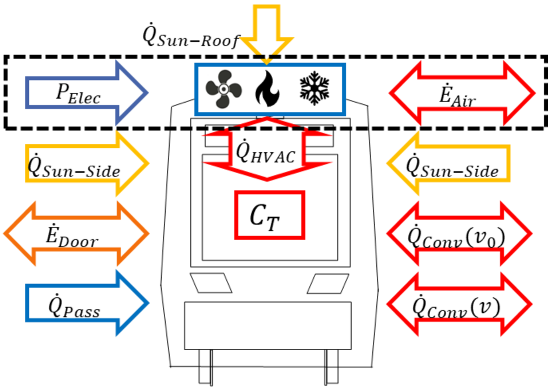

P_{Elec}	Electric power driving the HVAC
$\dot{E}_{Air}$	Enthalpy flow, ventilation and leakage
$\dot{Q}_{Sun-Roof}$	Heat flow due to radiation onto the roof
$\dot{Q}_{Sun-Side}$	Heat flow due to radiation onto the side
$\dot{E}_{Door}$	Enthalpy flow through open doors
$\dot{Q}_{Pass}$	Heat flow from passengers in the vehicle
$\dot{Q}_{HVAC}$	Heat flow from the HVAC system
C_T	Heat capacity of the vehicle
$\dot{Q}_{Conv}(v_o)$	Convection heat flow at standstill
$\dot{Q}_{Conv}(v)$	Convection heat flow

Figure 2: HVAC and train compartment model

The amount of intake fresh air as well as the amount of supply air is calculated according to data from the manufacturer. Data shows that to a good approximation the amount of fresh air intake within the operation mode is constant. It changes between the operation modes heating, ventilation and cooling. The temperature of the supply air T'_{Air} before heating or cooling is

$$T'_{Air} = T_{out} * \left(\frac{\dot{V}_{Air_{fresh}}}{\dot{V}_{Air}}\right) + T_{in} * \left(\frac{\dot{V}_{Air_{inside}}}{\dot{V}_{Air}}\right). \tag{1}$$

Besides the inside temperature the inside absolute humidity is relevant. The conducted data show that as a simplification the absolute humidity inside and outside the light rail can be considered as equal. The overall error due to this assumption is small. The absolute humidity of the supply air x_{Air} is therefore

$$x_{Air} = x_{Air_{inside}} = x_{Air_{outside}}. \tag{2}$$

Because of this assumption, the density ρ_{hAIR} and the heat capacity cp_{hAIR} of the humid air are calculated during the simulation according to outside temperature and outside dew point temperature serving as an input to the simulation.

With the assumption that the mass flow of air going into the tram is equal to the mass flow going out of the tram, the heat flow $\dot{Q}_{HVAC}$ going from the HVAC system into the tram can be calculated as

$$\dot{Q}_{HVAC} = \dot{m}_{Air} \cdot (h_{Air} - h_{in}) \tag{3}$$

with h_{Air} being the enthalpy of the supply air after heating or cooling and h_{in} the enthalpy of the air inside the train compartment. Because of Equation 2 for heating and ventilation, Equation 3 simplifies to

$$\dot{Q}_{HVAC} = \dot{V}_{Air} \cdot \rho_{hAIR} \cdot cp_{hAIR} \cdot (T_{Air} - T_{in}) \tag{4}$$

considering the temperature of the supply air after the HVAC system T_{Air}. During heating, P_{Elec} heats up a heat capacity modelling the heating fins. Using equations from [12], the cooling effect of the supply air to the heating fins is calculated. This cooling results in a temperature rise within the supply air, being the heating effect of the HVAC. Cooling is modelled using a data driven approach. Analysing the measured real live data, the temperature as well as the absolute humidity and the mass flow of the supply air after cooling is modelled using look-up tables and switch-on respectively switch-off time constants. The absolute humidity and the temperature of the supply air before cooling are look-up table inputs. P_{Elec} is then calculated according to the operation mode (switch-on, cooling, switch-off, idle) of the HVAC system.

With the temperature inside the tram as T_{in}, the governing equation for the train compartment system is

$$C_T \dot{T} = \sum \dot{Q}_i + \sum \dot{E}_i. \tag{5}$$

$\dot{Q}_{Sun-Roof}$ and $\dot{Q}_{Sun-Side}$, the heat flow due to radiation onto the tram, are modelled using the equations given in DIN 5034-2 [13]. Since the tram is equipped with a pyranometer, solar radiation is an input into the simulation. For simulating without knowing the solar radiation, a coherence analysis is done using the measured data to study the impact of light and shades onto the tram. A data driven model for the impact of shadows is built. The enthalpy flow $\dot{E}_{Door}$ results from a mass flow of air (dry air and vapor) through the open doors. The mass flow going into the tram is assumed to be equal to the mass flow going out of the tram. The resulting equation is

$$\dot{E}_{Door} = \dot{V}_{Door} \cdot \rho_{hAIR} \cdot cp_{hAIR} \cdot (T_{out} - T_{in}). \tag{6}$$

$\dot{V}_{Door}$ is calculated using literature values [14].

With n_{Pass} being the number of passengers inside the tram, $\dot{Q}_{Pass}$ is calculated according to DIN EN 14750 [15], considering sensible and latent heat from the passengers:

$$\dot{Q}_{Pass} = 118 \cdot n_{Pass}. \tag{7}$$

The heat flow due to convection is split into two parts: The effect at standstill and the effect that applies when the vehicle is moving. The effect at standstill is calculated using the heat transfer coefficient k_{v_0} from manufacturing data. The effect due to moving the vehicle is estimated using the effects present at a flat plate. A speed dependent factor $k_v(v)$ is calculated. The equation considering the tram outside shell area A_{shell} is

$$\dot{Q}_{Conv}(v_o) + \dot{Q}_{Conv}(v) = (k_{v_0} + k_v(v)) \cdot A_{shell} \cdot (T_{out} - T_{in}). \tag{8}$$

3.2 Step 2: Implementing

The model is modelled using the software tool Dymola with the object-based modelling language Modelica. Inputs to the simulation measured on the light rail are: location relative to the sun, speed, stop time, door opening time and global radiation. Inputs measured at a local weather station are: diffuse radiation, outside temperature and dew point temperature. A statistical input to the simulation is the number of passengers.

3.3 Step 3: Model Training

During model training the model is parameterized using separate batches of input data. With each batch only a few physical properties of the model are parameterized. The first batch is a highly separated batch containing only data that influences a few physical properties. From batch to batch the data can become more general since a previous parameterized parameter is not changed again. Each batch is used to parameterize two to three parameters. For the overall model shown in Figure 2, four batches are chosen:

1. Data from the heating up of the light rail are used to parameterize the heat capacity and the cooling coefficient of the heating fins and the heat capacity of the train compartment C_T.
2. Data from the tram operation during the night in winter are used to parameterize the amount of intake fresh air $\dot{V}_{Air_{fresh}}$, the air flow through the door $\dot{V}_{Door}$ and the speed dependent factor of the heat transfer coefficient $k_v(v)$. The advantage of using operation during the night is that no radiation due to sunlight impacts the train.
3. Data from the tram operation during the day in winter are used to parameterize the heat flow due to radiation $\dot{Q}_{Sun-Roof}$ and $\dot{Q}_{Sun-Side}$ onto the tram.
4. Data from the tram operation in summer are used to parameterize the switch-on respectively switch-off time constants used for AC modelling.

The parametrization is performed using a systematic grid search on the training data. This technique known from machine learning finds a set of parameters that fits in an optimal manner to the training data. This process enhances the model accuracy significantly in contrast to a normal physical model.

3.4 Step 4: Validation

In the fourth step, the derived model is validated using the predefined test data. The validation is performed separately for all batches and finally for the overall model.

4. Results

For the first training step, data from the heating up of the light rail is used. Since the measuring device also measures during idle time, this data can be used for parametrization. Only data is chosen where the light rail was stationed outside. For heating up, the inside temperature is compared between simulation $T_{Sim.}$ and measurement $T_{Meas.}$.

For all other training steps, normal operation trips from start to terminus of the light rail are simulated. Each trip contains up to 70 stops within a 2 hour ride. The measured auxiliary energy during the trip $E_{Meas.}$ is compared with the simulated auxiliary energy $E_{Sim.}$. Because the power consumption of the HVAC system isn't measured directly, the overall auxiliary power of the light rail is used. Since all other auxiliary consumers are known, this is a reasonable approach.

For each step during training the mean absolute error (MAE) and the mean absolute percentage error (MAPE) are calculated being the chosen quality criterion for the model. All results are presented in Table 1.

Batch	Training Data	Test Data	MAE	MAPE
Heating up	5 heating processes	5 heating processes	0.22 °C	1.43 %
Winter night	10 trips	10 trips	3.7 kWh/trip	10.3 %
Winter day	19 trips	24 trips	4.2 kWh/trip	9.2 %
Summer	20 trips	20 trips	1.4 kWh/trip	8.7 %.

Table 1: Results of the model training

5. Validation

For overall validation, 197 trips with different outside conditions from different days in 2019 and 2020 are simulated. The results are then compared to the measured data. A wide operation area of the HVAC is analysed, the results are presented using the mean outside temperature present during the simulated trip. In Figure 11, the simulated average auxiliary power during simulation and during measurement are compared. Figure 12 shows all validation data in an $E_{Sim.}/E_{Meas.}$ comparison. The mean absolute error of all validation data is 2.38 kWh/trip, the mean absolute percentage error is 12.92 %.

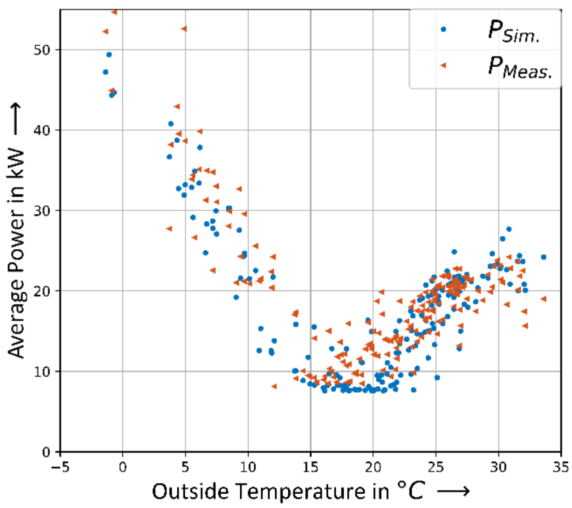

Figure 11 Simulated average auxiliary power during simulation and measurement

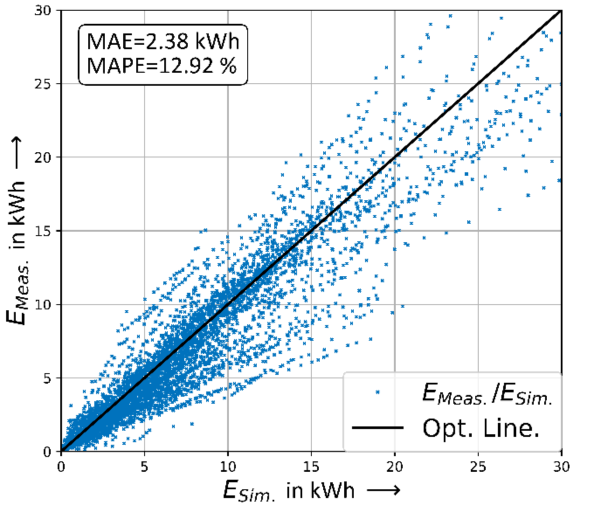

Figure 12 Energy demand comparison for all validation data

6. Conclusion

The presented physical model parametrized with the described method leads to a model with good accuracy of about 13 %. Figure 11 shows that the biggest relative error between simulation and measurements occurs between 15 °C and 22 °C. Within this temperature range, the simulated HVAC control sometimes switches to ventilation although the measured data shows that the HVAC was in cooling mode. Because of these different modes the relative error can become large, although the absolute error stays small since the overall energy demand of the HVAC system is small within this temperature range. The incoherent HVAC control is due to the simplifications made previously such as simulating just one heat capacity rather than one for each wagon.

Because of this simplification, the model assumes an even distribution of all passengers within the train. The uneven distribution of passengers which is normally present can lead to a small temperature difference within the wagons, allowing the HVAC control to switch on cooling.

Overall, a method is presented that leads to an accurate physical model of a HVAC system without the cost inefficient testing of the train in a wind tunnel or in the depot. Furthermore, complex computer simulations such as 3D CFD simulations are not necessary. Only real operation data is used, enhancing the model's accuracy and reducing the overall project cost.

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