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Adaptive Control of Thermal System in Electrified Heavy Vehicles

Investigation in how adaptive parameters used in predictive control can minimize model prediction errors

Master's thesis in system, control and mechatronics(MPSYS)

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Abstract

The development of battery electrical heavy vehicles is an important factor in reaching climate change goals and increasing the standard of living by reducing emissions and noise pollution. The cooling system serves as a crucial component for keeping parts in their ideal operating window which reduces wear, as well as increases performance. Applying predictive control to these vehicles is another step in improving performance with reduced power consumption and increased life expectancy of components. This work investigates the possibility of applying adaptive parameters to be used in predictive controllers to improve predictive estimates and thus also the control. We use estimation techniques, such as recursive least squares (RLS) and extended Kalman filtering (EKF) to estimate the adaptive parameters that can be fed back to a supervising controller, such as a model predictive controller (MPC). Results show that using adaptive parameters improves predictions with reduced prediction errors. The results indicate the possibility of accuracy improvements that combined with improved control structure could lead to better performance.

Keywords: Adaptive control, Predictive control, Thermal management, EKF, RLS.

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And perhaps the biggest acknowledgment of all to my longtime partner Linda and our two daughters Leia and Alma, who have kept me going through all my studies.

Mats Andersson, Gothenburg, July 2024

List of Acronyms

Below is the list of acronyms that have been used throughout this thesis listed in alphabetical order:

BEV	Battery Electrical Vehicle
DP	Dynamic Programming
EKF	Extended Kalman Filter
EMA	Exponential Moving Average
ESS	Electrical Storage System
EV	Electric Vehicle
HAEKF	Hybrid Adaptive Extended Kalman Filter
KF	Kalman Filter
MDS	Motor Drive System
MPC	Model Predictive Control
NTU	Number of Transferred Units
PE	Power Electronics
RLS	Recursive Least Squares
RT	Real-Time controller

Nomenclature

Below is the nomenclature of indices, sets, parameters, and variables that have been used throughout this thesis.

Indices

c	Index for variables and parameters concerning the coolant fluid
r	Index for variables and parameters concerning the radiator
env	Index for variables and parameters concerning the environment

Sets

x	State vector
u	Input vector

Parameters

ρ_c	Density of coolant fluid
ρ_a	Density of air
$C_{p,i}$	Specific heat capacity of i
Re	Reynolds number
Pr	Prandtl number
Nu	Nusselt number
μ	Viscosity of coolant liquid
k	Thermal conductivity of coolant liquid
D	Pipe diameter of cooling system
v_{max}	Maximum vehicle speed

Variables

T_i	Temperature of i
Q_{MDS}, Q_r	Heat generated over the MDS and radiator
ω_f	Fan speed
f_i	Volumetric flow rates of i
η	Valve opening rate (0 to 1)
α	Adaptive scaling factor
Q_{aux}	Auxiliary heat
v_v	Vehicle speed
v_{air}	Air speed

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1
Introduction

Predictive control is a widely used method in thermal management both in electrical vehicles(EV) [7] and other applications, such as aircrafts [9]. One important part of the predictive control is to have access to accurate predictions, and a key for the inaccuracy of these predictions are their models. Since models are inherently inaccurate, how they can be improved without increasing their complexity?
The difficulty arrives with the model errors that exists, since some components can be very complex within the cooling system, and the behaviour of certain components vary substantially with changes in their operating points. Thus a structure is needed to more accurately model these components and their effect on the cooling system and in turn, improve the control by the model predictive controller.
In this study the solution to this is online estimation of some of the models' parameters. The implementation of these estimation policies aims to increase the model and prediction accuracy of the current cooling system in hope of improving performance and longevity of the truck components.

1.1 Background

The advancement in heavy battery electrical vehicles(BEV) is crucial in reaching the climate change goals set by both the European union [1], and parts of the United Nations Sustainability Development Goals [2].
One of the key components of the electrical drive line is the cooling system. It is responsible for keeping components in their ideal operating windows to reduce wear of the components. This increases the range and operational life time of the components, which in turn reduces the need for replacement parts and with the combined effort of clean energy, can reduce emissions by 40 % by switching from a diesel truck to an electrical truck [4]. Additionally, the reduced noise pollution by driving electrical instead of a traditional combustion engine will increase the quality of life in urban areas.
Volvo Trucks is committed to reaching the climate goals set by the Paris agreement, and their development of battery electrical vehicles is another step in the decarbonization of the transport sector. In order to provide reliable products there exists a tremendous amount of modeled parts to vehicles constructed by Volvo. Usually, these can be quite computationally expensive, and investigating the possibility to use adaptive parameters in models in order to increase accuracy without significantly increasing computational complexity compared to the complexity that would be introduced by including more advanced models. This could be crucial to

increase prediction accuracy without extending simulation times and provide good performance.

1.2 Motivation

The goals of the thesis work is to provide insight in real time parameter estimation to be used in a predictive controller in order to increase performance. The work aims to be insightful and helpful in future works in related areas.

1.3 Aim

The aim of the thesis work has been to develop an estimation strategy that more accurately captures the system dynamics, in order to use this in a model predictive control of the temperatures of the batteries.
The suggested solution aims to applicable in a real time embedded application so investigations of the computational time are important in order to understand if the suggested solution is feasible or not.
The implementation of adaptive control parameters does not specifically aim to improve the efficiency of the cooling system but it aims to improve the accuracy of it, which in turn could aid in relaxing restrictions or limits of the controller and therefore lead to improvements in performance.
There are many benefits to this approach. Using adaptive control allows for simplified models, which can reduce model complexity. Additionally it allows the model to adapt to changes in environment and operating points, as well as changes between vehicles used and perhaps even as the components age and wear.
A clear final goal has been to provide an implemented solution in the current Simulink model that produces estimates of the desired parameters.
The final solution is compared to the current solution as well as compared to using the model without adaptation, to provide a good understanding of the performance effects of adaptation.

1.4 Problem statement

Initially, the work aimed to establish a general method of adaptation in order to optimize the control outputs used by the currently implemented controller. An investigation in suitable parameters to use for adaptation is first completed and then used as a base for the adaptation algorithms. Suitable adaptation usually requires a tuning processes and therefor we try to find well performing, tuned parameters as well as investigating the use of self tuning parameters. The main research questions are formulated as follows:

- What parts of the cooling systems are suitable for adaptation in order to improve performance?
- Is adaptive parameter estimation suitable for adaptation for the control of the cooling system?

- What effects does adaptive control have on the performance of the cooling system?

1.5 Ethical aspects

One of the main concerns with electrical vehicles is the production of batteries, especially the extraction of the raw materials, such as lithium and cobalt. Most of the lithium is extracted in salt flats in Argentina and Chile, where a large quantity of water is used, in an area that is otherwise very dry, and 90 % of the world's cobalt production is extracted in the Democratic Republic of Congo (DRC), where working conditions are extremely poor [3]. This further increases the demand of improved cooling strategies to reduce the wear and increase the lifetime of both the battery and other electrical components.

Another important aspect is the access to clean electricity, where currently around 30 % of the worlds electricity is generated by clean energies [6]. It is, however, a positive trend, since most of the newly installed power generation is clean energy, such as solar and wind power. The increase in EVs are also assisting this transition since the batteries of these vehicles are used as storage for excess power generated by these renewable resources, which can be reintroduced to the power grid if necessary.
Some concerns have been raised regarding the risk of accidents. Battery electrical vehicles in general are more risky than their diesel counterpart, since electrical fires are more troublesome than regular ones. Considering the size that batteries in heavy electrical vehicles have, there could be catastrophic effects in accidents with these vehicles.
Additionally the improvement to noise and air pollution that electrical vehicles can provide helps in reaching other sustainability goals. This improved air quality and reduced noise pollution increases the standard of living and public health specifically in cities where these vehicles would be most likely to operate. Concerns can be raised regarding an increased likelihood of accidents due to the reduced noise which can render pedestrians, cyclists or other motorists unaware of the presence of large electrical vehicles.

2

Theory

2.1 Predictive Control

The following section is a paraphrased chapter from [5]. A key feature of models is the possibility to predict future values of the outputs of said model. This provides a natural use of models in control design where expected values can be calculated as a function of possible future control actions. With this approach it is possible to optimize control actions based on some criterion.
Generally, the process is as follows:

1. At some time t, compute or predict a number of future outputs $\hat{y}(t+k|t), k = 1, \ldots, M$, which usually depends on some inputs $u(t+j), j = 0, 1, \ldots, N$ where $N < M$, and on measurements known at time t.

2. Choose a criterion based on these variables and optimize it with respect to $u(t+j), j = 0, 1, \ldots, N$.

3. Apply the optimized $u(t)$ to the plant

4. Wait for the next sampling instant $t+1$ and repeat from 1.

This is a very general and flexible method. It is also simple to include constraints on control actions and their derivatives, which makes it a powerful tool when working with control. This method is generally refereed to as Model Predictive Control (MPC).

2.2 Thermal modelling

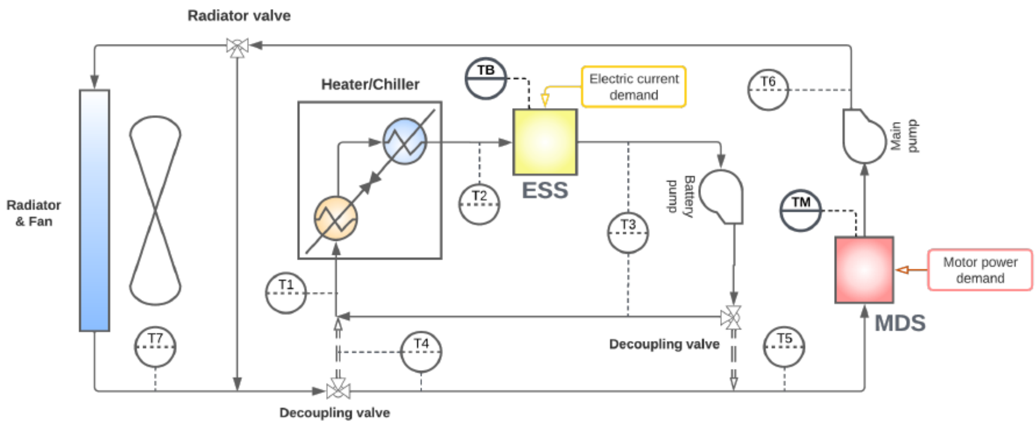


Figure 2.1: The assumed configuration of the cooling system [10]

For thermal modelling, the current system can be regarded as two cooling loops that can be coupled by changing the parameter η_d, where 0 corresponds to fully decoupled and 1 to fully coupled mode. In fully decoupled mode, the two cooling loops function as individual closed loop systems. The inner loop consists of a heater/chiller, an Electric Storage System (ESS), a battery pump while the outer loop consists of a Motor Drive System (MDS), an MDS pump, a radiator and a fan and a radiator valve. See Fig 3.1

2.2.1 Thermodynamics

One of the key concepts that affects this work is the thermodynamics of the system, more specifically, the heat transfer theory used for calculations. Three principles are discussed: Convection, Conduction and Radiation. One important law is the first law of thermodynamics, which is the conservation of energy [8] that can be expressed as

$$\Delta U = Q - W, \tag{2.1}$$

where ΔU is the change in internal energy, Q is heat added to the system and W is work done by the system. Assuming steady state, and no significant drop in pressure, the equation for heat added to the system, Q, simplifies to

$$Q = \dot{m}\Delta h, \tag{2.2}$$

where $\dot{m}$ is the mass flow rate, and Δh is the change in enthalpy. The change in specific enthalpy can be defined as

$$\Delta h \approx c_p \Delta T, \tag{2.3}$$

where c_p is the specific heat at constant pressure, and ΔT is the change in temperature. Combining (2.2) and (2.3) we get an important connection between heat rate and temperature difference:

$$Q = \dot{m} c_p \Delta T. \tag{2.4}$$

2.2.1.1 Convection

Convection is the heat transfer involving movement of a fluid, such as a liquid or gas. There are two main forms of convection, natural and forced convection.
Natural convection occurs when a fluid moves without the aid of any external force, driven solely by the temperature differences within the fluid.
Forced convection occurs when external force acts on the fluid to move it, such as a pump or a fan. In our work, mostly forced convection occurs.

2.2.2 MDS

The MDS is modelled as a heat source, where the loss in the motors causes an increase in temperature. The electrical engine has a high efficiency and thus the loss that occurs is regarded as heat loss to the cooling system, expressed as

$$Q_{MDS} = \eta \cdot P_{MOTOR}, \tag{2.5}$$

where η is an efficiency term, and P_{MOTOR} is the power from the motor. For the complete heat balance, there is also an auxiliary term for additional heat generated in the system, and this is currently modelled as a fixed constant, but can be of interest to make an adaptive parameter, since this auxiliary term will vary with load, temperature and other parameters.

2.2.3 NTU method

The Number of Transferred Units (NTU) [8] method is used instead of using log mean temperature difference (LMTD) when there is insufficient information about temperatures before and after a medium, since the LMTD requires two temperatures at each end of the medium in order to calculate the heat generated over the medium, while NTU works by energy balance. The formulas used are given in the next section to avoid repetition.

2.2.4 Radiator

The radiator is modeled with two types of forced convection, one between the cooling liquid and the radiator, and one between the radiator and the air. Thus, we need to find two thermal coefficients and combine them to get an overall heat transfer between the cooling liquid and the air.

For the coolant and the radiator body the equations are [10]

$$\begin{aligned}
C_c =& \rho_c f_m C_{p,c} \\
v =& \frac{4 f_m}{\pi D^2} \\
Re =& \frac{\rho_c v D}{\mu_c} \\
Pr =& \frac{\mu_c C_{p,c}}{k_c} \\
Nu =& 0.023 Re^{0.8} Pr^{0.35} \\
h_i =& \frac{Nu \cdot k_c}{D}
\end{aligned} \tag{2.6}$$

where C_c is the heat capacity rate, ρ_c is the density of the coolant fluid, f_m is the flow, $C_{p,c}$ is the specific heat capacity of the coolant, v is the velocity, D is the pipe diameter of the cooling system, Re is Reynolds number, Pr is Prandtl number, μ_c is the viscosity of the cooling liquid, k_c is thermal conductivity of the cooling liquid, Nu is Nusselts number, and h_i is the inner thermal exchange coefficient.
For the exchange between the radiator and the air, the equations are instead

$$\begin{aligned}
v_{air} =& v_v + (1 - \frac{v_v}{v_{max}})\beta\omega \\
Re =& \frac{\rho_a v_a L_r}{\mu_a} \\
Pr =& \frac{\mu_a C_{p,a}}{k_a} \\
Nu =& 0.3 + \frac{0.62 \cdot Re^{\frac{1}{2}} Pr^{\frac{1}{3}}}{(1 + (\frac{0.4}{Pr})^{\frac{2}{3}})^{\frac{1}{4}}} \left[1 + \frac{Re}{282000}^{\frac{5}{8}} \right]^{\frac{4}{5}} \\
h_o =& \frac{Nu \cdot k_a}{L_r}
\end{aligned} \tag{2.7}$$

where v_{air} is the velocity of the air, v_v is the vehicle velocity, v_{max} is the maximum velocity of the vehicle, L_r is the length of the radiator, ρ_a is the density of the air, μ_a is the viscosity of air, $C_{p,a}$ is the specific heat capacity of air, k_a is the thermal conductivity of air, and h_o is the outer thermal exchange coefficient. Combining the two thermal exchange coefficients uses

$$\frac{1}{U} = \frac{1}{h_i} + \frac{1}{h_o}. \tag{2.8}$$

Solving this for U gives the overall heat exchange coefficient over the radiator. Then we apply the NTU method to find the heat exchange of the radiator in a single pass, cross flow configuration.
Finding the heat capacity rates through

$$\begin{aligned}
C_c =& \rho_c f_m C_{p,c} \\
C_a =& \rho_a A_a v_a c_{p,a}
\end{aligned} \tag{2.9}$$

where A_a is the area of the radiator facing the front of the vehicle, this is simply assumed to be the length by the width of the radiator.
The ratio between the capacity rates,

$$C_r = \frac{C_c}{C_a} \tag{2.10}$$

also termed the heat capacity ratio. The lesser of these capacity rates is assumed to be C_c, and is thus used in the calculation of the NTU, i.e,

$$NTU = \frac{U \cdot A_r}{C_c}, \tag{2.11}$$

where A_r is the area of the exchanged heat, this is extracted from more advanced simulation models used by Volvo, and is assumed to be correct.

The efficiency parameter for this setup is given by [10]

$$\epsilon_r = 1 - \exp\left(\frac{1}{C_r} NTU^{0.22} (\exp\left(-C_r NTU^{0.78}\right) - 1\right), \tag{2.12}$$

and the expression for the radiator heat transfer can be expressed as

$$Q_r = \epsilon_r \cdot C_c (T_{amb} - T_{radIn}) \tag{2.13}$$

2.3 Estimator design

2.3.1 Extended Kalman filtering

Extended kalman filters (EKF)[11] are used in non-linear problems in order to estimate states and parameters in the non-linear dynamic models from known measurements of input and outputs. The extended kalman filter extends the kalman filter by linearizing the system at each time instant around the current estimate. This allows the application to treat equations as locally linear.

A state transition model can be given by a function f

$$x_k = f(x_{k-1}, u_k) + w_{k-1}, \tag{2.14}$$

and the measurement model is given by a function h

$$z_k = h(x_k, u_k) + v_{k-1}, \tag{2.15}$$

where w and v are process noise and measurement noise, respectively, that are assumed to be normal distributed gaussian white noise with covariance matricies Q and R, respectively. Using these we can linearize them w.r.t the states at the current state and input (x_k, u_k):

$$
\begin{aligned}
F_{k+1} &= \left.\frac{\delta f_k(x,u_k)}{\delta x}\right|_{x=x_k,u=u_k} \\
H_k &= \left.\frac{\delta h_k(x)}{\delta x}\right|_{x=x_k}
\end{aligned} \tag{2.16}
$$

In the prediction step, we calculate the predicted value of our state, given previos value of our estimated state in our state transition model, $\hat{x}_{k|k-1}$, and then we predict the covariance P of this estimate, i.e

$$
\begin{aligned}
\hat{x}_{k|k-1} =& f(\hat{x}_{k-1|k-1}, u_k) \\
P_{k|k-1} =& F_{k-1}P_{k-1|k-1}F_{k-1}^T + Q_{k-1}
\end{aligned} \tag{2.17}
$$

where F_{k-1} is the Jacobian of our state transition function estimated at our previous estimate $\hat{x}_{k-1|k-1}$ and Q_{k-1} is some process noise covariance matrix for the uncertainties in our state model.
We can then update our estimates and covariance using the kalman gain.

$$
\begin{aligned}
K_k =& P_{k|k-1}H_k^T(H_kP_{k|k-1}H_k^T + R_k)^{-1} \\
\hat{x}_{k|k} =& \hat{x}_{k|k-1} + K_k(z_k - h(\hat{x}_{k|k-1})) \\
P_{k|k} =& (I - K_kH_k)P_{k|k-1}
\end{aligned} \tag{2.18}
$$

where H_k is the jacobian of h evaluated at $\hat{x}_{k|k-1}$ and R_k is some measurement noise covariance matrix for the uncertainties in our measurements.

2.3.2 Recursive least squares

In least squares, the idea is to adapt parameters to a set of measurements, in order to minimize the squared error between modelled outputs and measurements. In Recursive Least Squares (RLS) [12] one updates the estimated parameters when obtaining new measurements by using only the new measurements instead of using all historical measurements in order to save computational costs, and data storage. We describe the general idea here. Let us assume that

$$
\hat{y_k} = \theta_{k-1}x_k, \tag{2.19}
$$

where $\hat{y_k}$ is an estimated value, θ contains our adaptive parameters and x is our observed value.
If we then have a measured value of y, we can use the residual to update our adaptive parameter by

$$
\begin{aligned}
\varepsilon_k =& y_k - \hat{y_k} \\
K_k =& \frac{P_{k-1}x_k}{\lambda + x_k^T P_{k-1}x_k} \\
\theta_k =& \theta_{k-1} + K_k\varepsilon_k
\end{aligned} \tag{2.20}
$$

where P is the covariance matrix and its inital value is important for the initial dynamics of the estimates, and the recursion of it follows an algebraic Riccati equation according to:

$$P_k = \frac{1}{\lambda}(I - K_k x_k)P_{k-1}. \tag{2.21}$$

In (2.20) and (2.21), λ is a forgetting factor used in order to control the sensitivity of the updates. If λ is set close to 0 it will disregard most of the old measurements and adapt very quickly, and if it is set close to 1 it will retain almost all information from old measurements and consequently adapt slower.

3
Methods

3.1 Cooling system structure

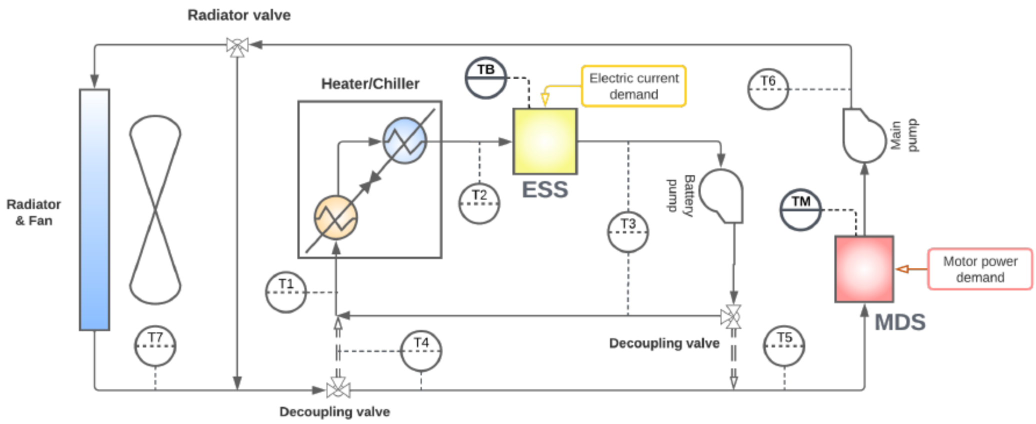


Figure 3.1: The assumed configuration of the cooling system [10]

An assumed configuration of the cooling system can be observed in Fig 3.1.
The cooling system used consists of two connected loops, one for the inner loop containing the heater/chiller, the ESS, and the ESS pump. The other is the outer loop which contains the MDS, the MDS pump, and the radiator. There are also three valves. The radiator valve controls the flow to the radiator, and the decoupling valves controls the connection between the two loops. Coolant temperature measurements are available at the locations marked T1,. . . ,T7, Battery temperature is available at TB and MDS temperature at TM. The temperatures of special interest are the coolant temperatures before and after the MDS and the radiator, since those are the sections of the cooling system that will be adapted.

3.2 Parameter identification

One of the research questions focused on finding suitable parameters for adaptation. Two main areas were chosen, the auxiliary heat in the MDS cooling circuit and the cooling effect of the radiator. These were chosen because there could be observed a difference between the estimates from the supervisor compared to measured values from simulations of a more advanced plant model. The conclusion from this observation was that if it is possible to adapt these by using adaptive parameters in their respective models, the difference between the predicted value and the measured value could be reduced.

In Fig 3.2 a clear discrepancy between the measured values of the heat gener-

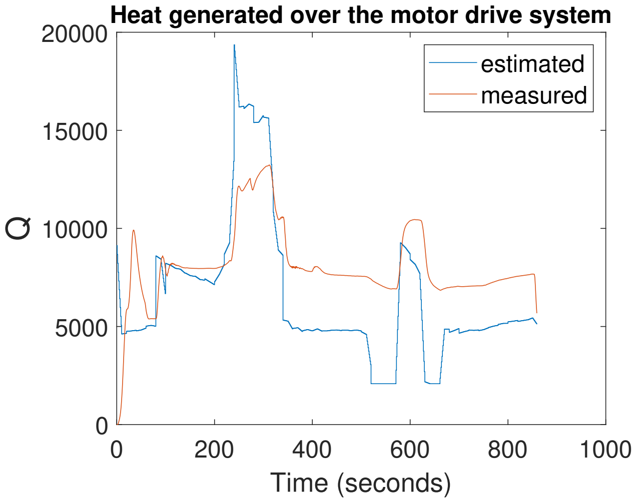


Figure 3.2: Heat generated over the MDS

ated over the MDS and the estimated (without adaptation) heat generated can be observed. The hypothesis is that the reason for this is some extra heat generated that is not modelled and if we can estimate the extra heat generated, we can add that term to the calculation of the heat generation and thus reduce the error. The thought is that this term is fairly constant, and letting it be an adaptive parameter, with a rather high forgetting factor this parameter can accurately estimate the difference in heat generation to give better estimates. In Fig 3.3 we can also see that

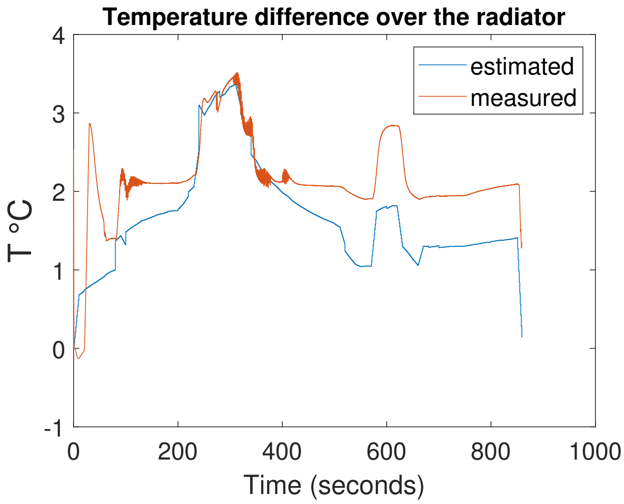


Figure 3.3: Temperature difference over the radiator

there is a difference between the estimated temperature and the measured one over the radiator, and it was therefore selected as a candidate for adaptation. The difficulty, however is what parts to adapt. The currently implemented radiator model is

different from the one described in 2.2.4, but in order to apply an adaptation over it, the simplified model described in this thesis work was implemented instead.
Because the state transition function is a function of our inputs we use an extended kalman filter for estimating the temperature after the radiator.
The idea of the adaptation was to provide a slower feedback to the supervisor, where the adaptive parameters could assist in making more correct predictions during the predictive control.

3.3 Adaptation concept

In order to adapt the parameters used by the supervisor, a slow feedback is used, where the adaptive parameters are updated slowly and fed back to the supervisor in order to provide better estimates and more accurate control inputs by the supervisor. An overview of the adaptation concept is provided in Fig 3.4. The outputs from the

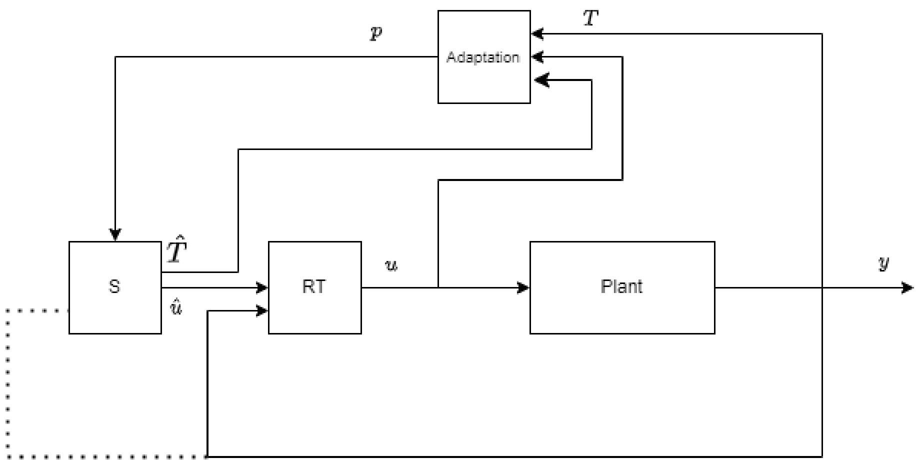


Figure 3.4: Idea of the adaptation structure. S is the supervisor predictive controller, RT is the real-time controller, the plant is our cooling system and adaptation is our adaptive algorithms.

supervisor (S) is used in a feed forward way to the real-time controller (RT). The RT is used for a faster feedback that is needed for some certain actuators, and it also outputs controller inputs based on the ones suggested by the supervisor. There are two main ways that the RT can operate, either by reference tracking of the states or the suggested actuator signals. The Adaptation then uses the control signals from the real-time controller with information about the system and the estimated states from the supervisor in order to update the adaptive parameters p for use in the future predictions from the supervisor.

3.4 Auxiliary power adaptation

The first adaptation was done over the MDS, where we could measure the temperature before and after the MDS and thus relate a difference between the expected auxiliary heat and the predicted one, then the assumption was that there was a linear connection between the two and a RLS algorithm was implemented in order to predict the auxiliary heat.
Using the knowledge about heat transfer describe in the Theroy chapter the temperature measurements before and after the MDS can be used to find the actually transferred heat by applying Equation (2.4),

$$Q = \dot{m}c_p(T_{inMDS} - T_{outMDS}). \tag{3.1}$$

Now the supervisor can calculate the difference over the MDS in heat as well and we can compare those with our actual measurements in order to find the auxiliary term that we are interested in. We have

$$Q_{est} = \dot{m}c_p(T_{inMDSest} - T_{outMDSest}). \tag{3.2}$$

If we add an adaptive term θ we can form the relationship between our actual and estimated values of the heat transfer in the MDS:

$$Q = Q_{est} + \theta \tag{3.3}$$

Now in order to use RLS we have an observed value of our adaptive parameter θ which is going to be the difference between the actual and the estimated heat transfer in the MDS,

$$y = Q - Q_{est}. \tag{3.4}$$

This means that the residual will be

$$\varepsilon = y_k - \theta_{k-1} \tag{3.5}$$

An observation is that since we are adapting an additative parameter our x is just a scalar value, set to 1. In order to find the kalman gain, we initially set P to a large value since we are not sure about the covariance. Since we are only adapting one parameter, P is also a scalar value, and we get

$$K = \frac{P}{\lambda + P}. \tag{3.6}$$

Since we are looking for a slow adaptation we set λ to be very close to 1, so that we trust our older measurements more. This assures that we do not send a highly oscillating value as the input into the supervisor to avoid large errors by the predictions made in the Supervisor.
The update of θ is then

$$\theta_k = \theta_{k-1} + K_k\varepsilon_k \tag{3.7}$$

which is then fed back into the supervisor as an adaptive parameter used in the MDS heat calculations.

3.5 Radiator effect adaptation

The next task is the adaptation of the radiator model, where observations of the actual power and the power by the model could be observed to be linearly offset and, thus, the idea of estimating a scaling parameter for the model efficiency was applied. Using an EKF, since the function describing the cooling power is highly non-linear, a scaling parameter were able to be estimated in order to adapt the model to more closely track the actually supplied cooling power.

$$\begin{bmatrix} x_1 \\ x_2 \end{bmatrix} = \begin{bmatrix} \alpha \\ \hat{T}_{radOut} \end{bmatrix}, and \qquad \begin{bmatrix} u_1 \\ u_2 \\ u_3 \\ u_4 \\ u_5 \\ u_6 \end{bmatrix} = \begin{bmatrix} \eta \\ f_m \\ T_{radIn} \\ T_{amb} \\ v_v \\ \omega_{fan} \end{bmatrix} \tag{3.8}$$

For the EKF states are the scaling factor α and the temperature after the radiator, $\hat{T}_7$. Our control inputs consists of radiator valve opening η, the mass flow f_m, the temperature before the radiator T_6, ambient temperature T_{amb}, vehicle speed v_v and radiator fan speed ω_{fan}. Our measured output is the measured output of the temperature after the radiator T_7.

In order to find the temperature change over the radiator we could derive the it from the calculated heat from our radiator model and the first law of thermodynamics, i.e

$$\begin{aligned} T_{radOut} =& T_{radIn} + \Delta T_{rad} \\ T_{radOut} =& T_{radIn} + \frac{Q_r}{\rho_c C_{c,cp} \eta f_m} \end{aligned} \tag{3.9}$$

For our state transition function

$$f(x,u) = \begin{bmatrix} x_1 \\ u_3 + x_1 \frac{Q_r(u)}{\rho_c C_{c,cp} u_1 u_2} \end{bmatrix} \tag{3.10}$$

Because of the dependency on a value of flow in the calculation of the temperature change over the radiator, this only works when the radiator valve is not 0. Therefore we can only run the adaptation when the radiator is used.

Because when the $\eta = 0$ in Equation (3.10) the model is no longer valid.

Another note is that the function for Q_r is quite large but it is derived in the Section 2.2.4. The measurement model is quite straightforward:

$$h(x,u) = \begin{bmatrix} x_1 \\ x_2 \end{bmatrix}. \tag{3.11}$$

Now looking at our observed values, and since we are looking for a scaling factor that affects the amount of heat that the radiator dissipates, we can compare the difference between our estimated temperature and the measured temperature.

That means that the our "measured" values of α and T_{radOut} are:

$$\begin{aligned} z_1 =& \frac{T_{radOut} - T_{radIn}}{x_2 - T_{radIn}} \\ z_2 =& T_{radOut} \end{aligned} \tag{3.12}$$

Additional restrictions were added to make sure that the adaptive parameters were not changing too quickly, to avoid errors with the prediction horizon of the supervisor. Problems would arise when the radiator valve is changing from on to off and vice versa. Because of this an exponential moving average was added to make the adaptive parameter change more slowly.

$$\alpha_k = \psi \alpha_k + (1 - \psi)\alpha_{k-1}, \tag{3.13}$$

where ψ is a scaling parameter that is set close to 0, which in turn makes us retain more of the information from old values of α in order to avoid highly oscillating values being fed back to the supervisor.

4

Results

Each section of this chapter represents a different drive cycle. There are 4 different drive cycles evaluated in this work, where one is synthetic and 3 of them are data from actual roads.

4.1 Synthetic Road

The synthetic road consists of a roughly 19 km long simulation where there is a hill in the middle with an altitude of roughly 40 m (see Fig 4.1). The speed reference is at 80 km per hour or 22 m per second.

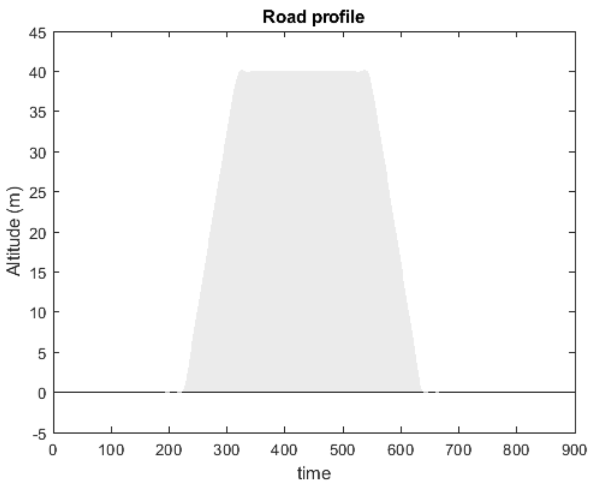
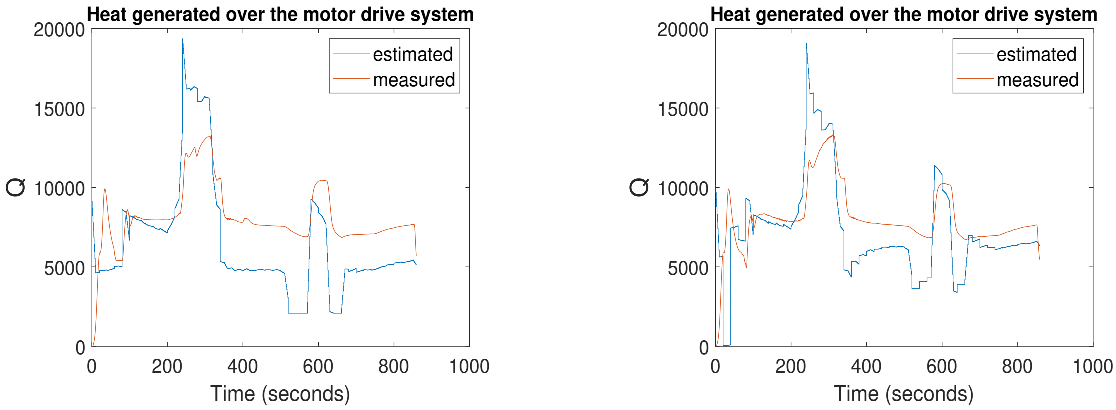


Figure 4.1: Synthetic road profile

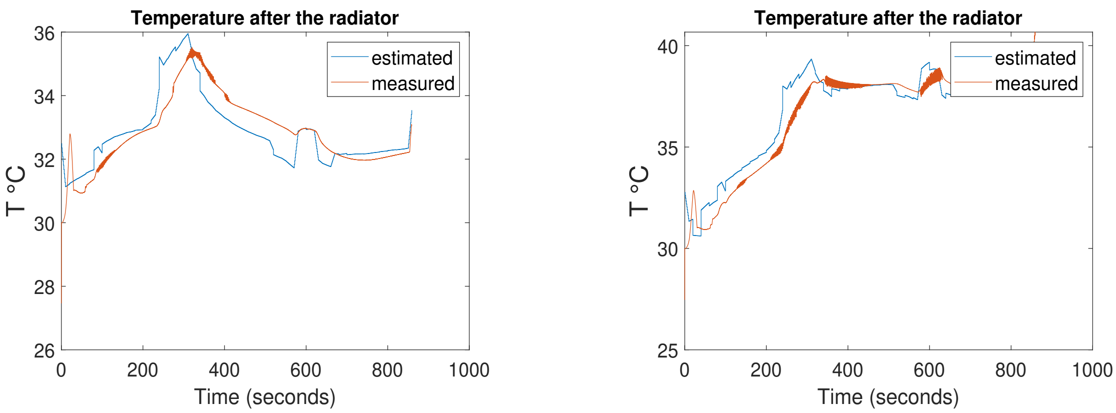


(a) Heat generated before adding the auxiliary term

(b) Heat generated after the adding the auxiliary term

Figure 4.2: Comparing the output of the supervisor before and after adding the adaptive MDS term

Looking at Fig 4.2 we can see that the auxiliary terms aid the estimation from the DP in minimizing the error between the estimated value and the real value. We can also observe that there is less oscillations, when using the adaptive auxiliary term.

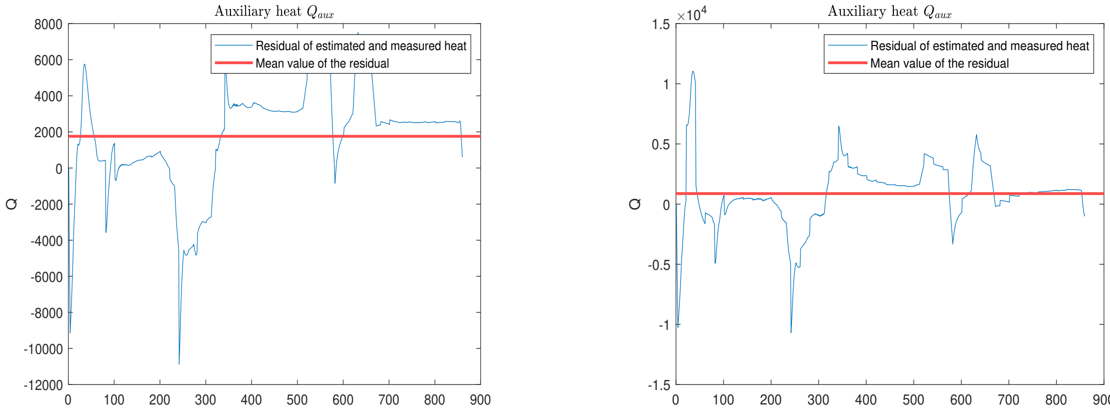


(a) Radiator before the adaptation

(b) Radiator after the adaption

Figure 4.3: Comparing the temperature change over the radiator before and after adapting the efficiency of the radiator.

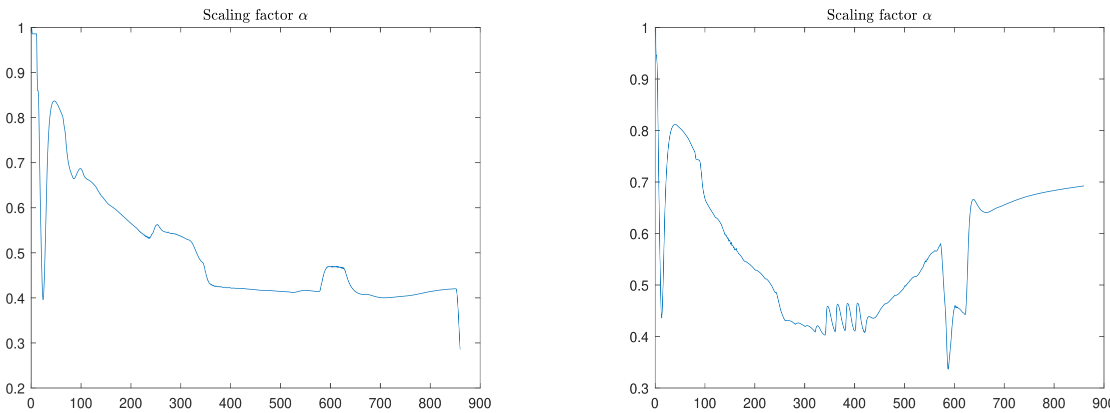
From Fig 4.3 we observe that the estimated values are closer to the measured values, though slightly higher, after introducing adaptation. The adaptation also reduces the steady state error when the system is in its non-transient phase.



(a) MDS residual before adaptation **(b)** MDS residual after adaptation

Figure 4.4: Residual of MDS heat at 30°C

Observing Fig 4.4 we can also see that the error shrinks after adding the adaptation.

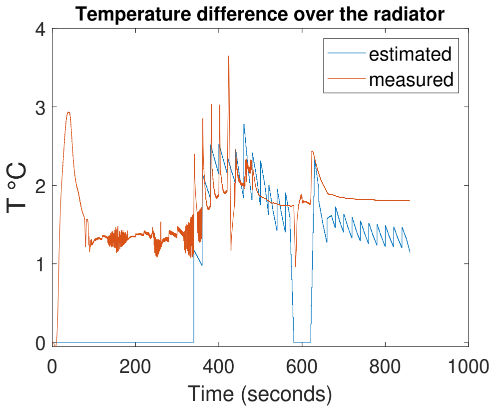


(a) Scaling factor at 30°C **(b)** Scaling factor at 0°C

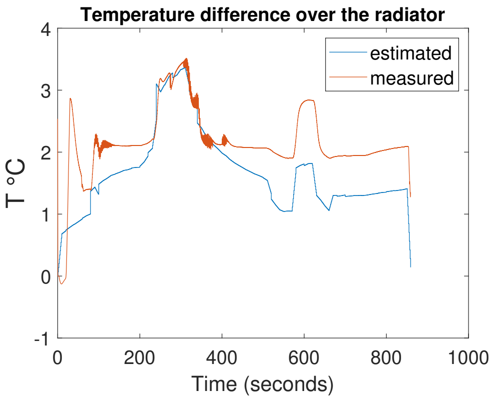
Figure 4.5: The adaptive parameter for scaling the radiator efficiency at different temperatures

Investigating the scaling parameter for the radiator it can be observed that the value differs for different ambient temperatures. In Fig 4.5 we see the case for two different ambient temperatures and how the value settles at around 0.4 in one case and at 0.7 in the other. This indicates that the efficiency depends more than anticipated on the temperature difference between the coolant and the ambient air.

Another interesting aspect is the dependency the radiator has to ambient temperature. This is not really a surprising results, since if the ambient temperature is high, the possible cooling effect it has reduces with the reduced difference in temperature.



(a) Temperature difference over the radiator at $0°C$

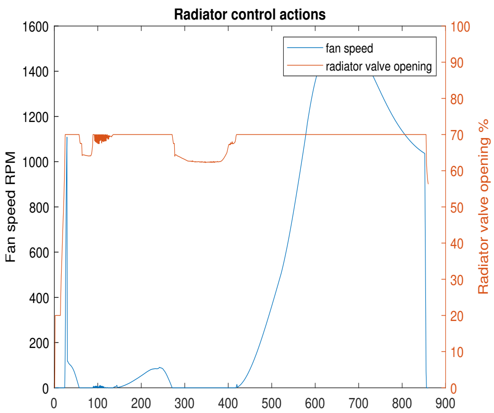


(b) Temperature difference over the radiator at $30°C$

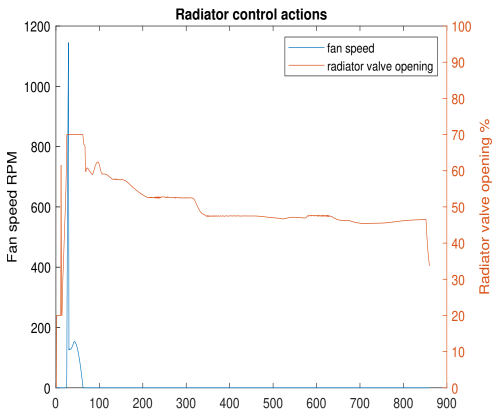
Figure 4.6: Temperature change at different ambient temperatures without adaptation.

Looking at Fig 4.6 we see that the difference varies quite a lot at different ambient temperatures, mostly because at lower ambient temperatures, the radiator is not used as much, which means we cannot run the estimator to calculate the correct scaling value.

Another result is the effect on control that the adaptation has. Looking at Fig 4.7 where, without the adaptation, we have bigger radiator valve opening, and a higher fan speed. After the adaptation, we reduce the radiator usage, which is good since running the fan requires a lot of power and is one of the main increases in power consumption for the trucks.



(a) Radiator valve opening and fan speed, no adaptation



(b) Radiator valve opening and fan speed, adapted

Figure 4.7: Control actuator values before and after adaptation at $30°C$

4.2 BLB

BLB is a road cycle that covers the distance between the two cities Borås and Landvetter, and back. It runs for a distance of around 85 km at a reference speed of 85 km per hour. The cycle has a mixed hilly terrain profile (see Fig 4.8).

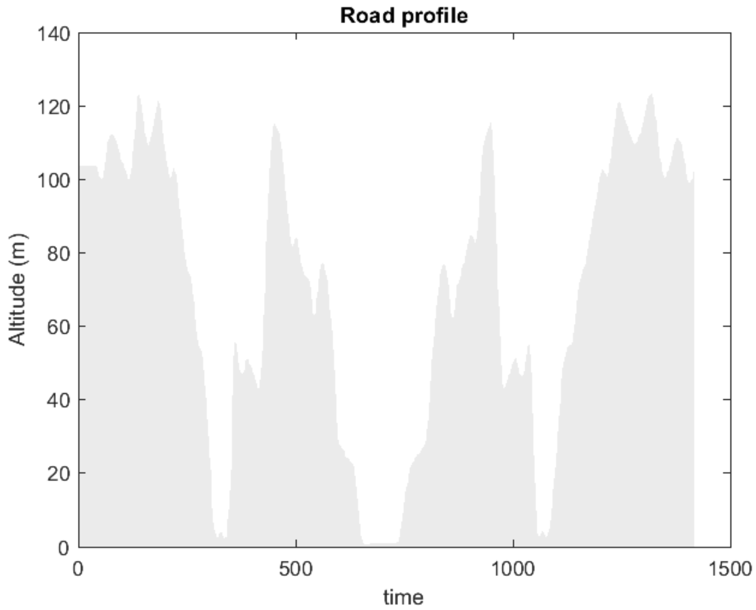
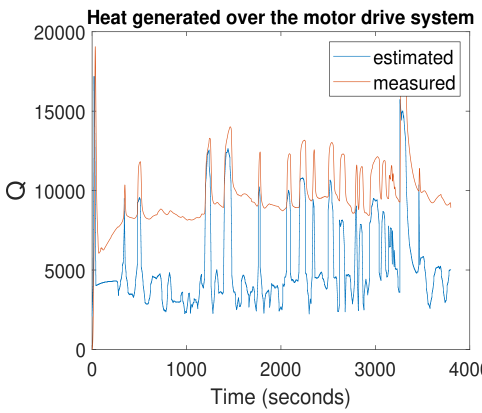
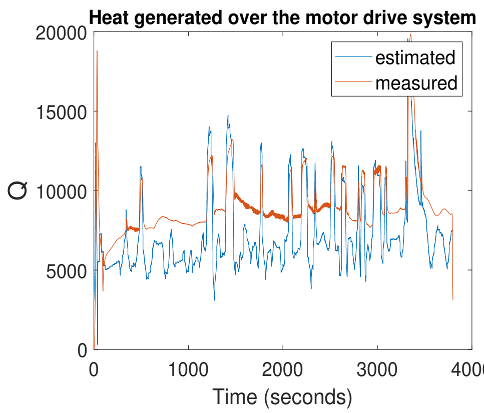


Figure 4.8: Road profile of the BLB cycle



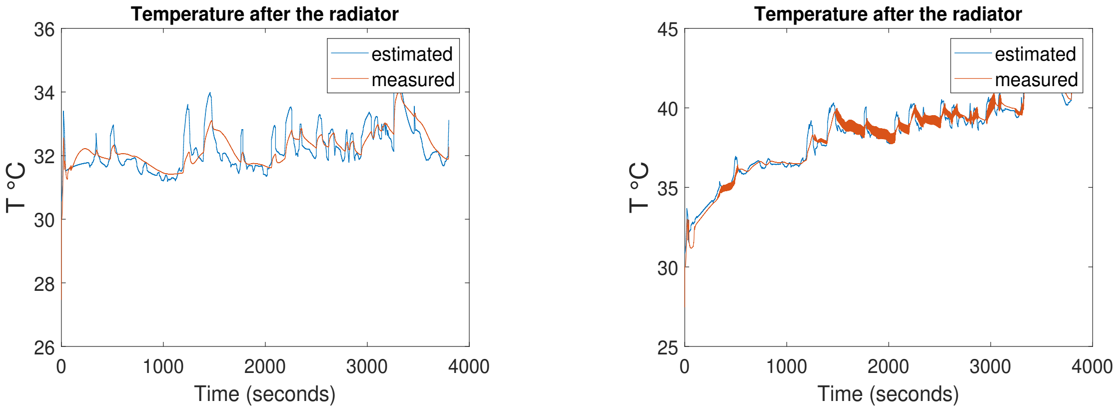
(a) Heat generated before adding the auxiliary term



(b) Heat generated after the adding the auxiliary term

Figure 4.9: Comparing the output of the supervisor before and after adding the adaptive MDS term

Looking at Fig 4.9, the results from simulations made with and without adaptation are presented. We can again observe the changes in heat seen for the synthetic profile, and again its reduced quite substantially.

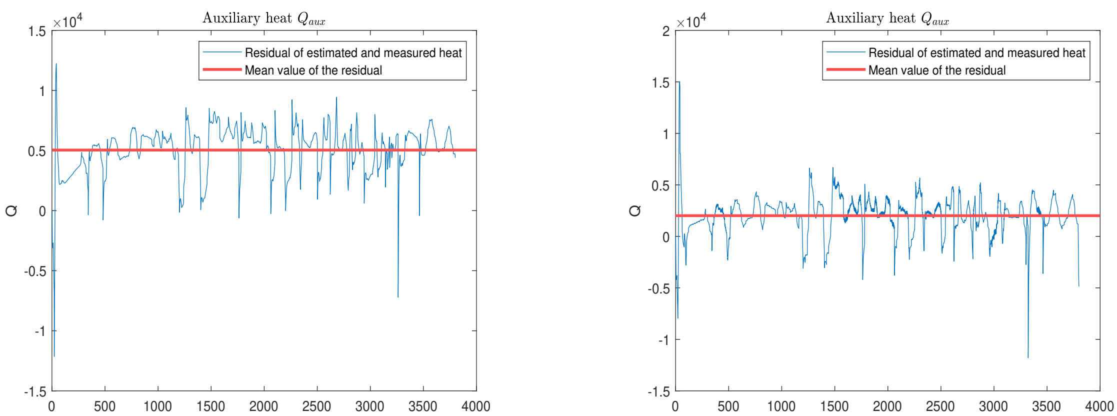


(a) Radiator before the adaptation

(b) Radiator after the adaption

Figure 4.10: Comparing the temperature change over the radiator before and after adapting the effect of the radiator.

Looking at the temperature difference over the radiator in Fig 4.10, we can again observe a reduction in the difference between estimated and measured values for the radiator coolant temperature.

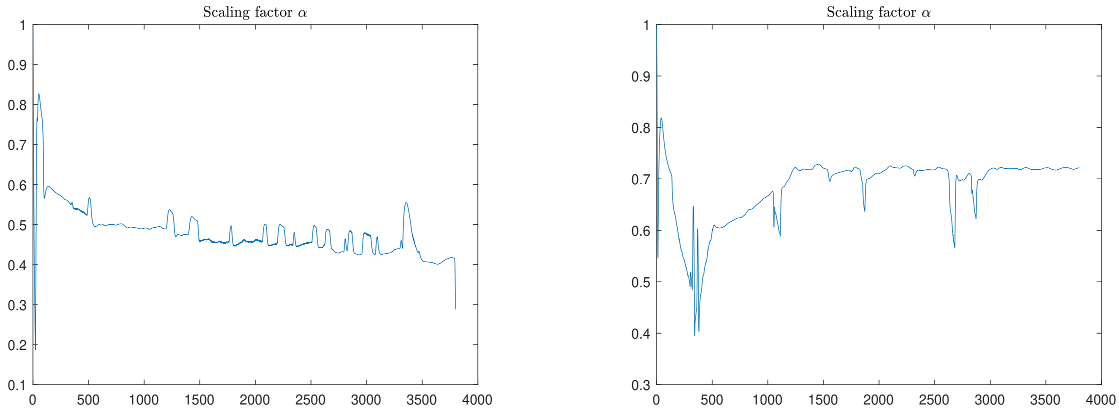


(a) MDS residual before adaptation

(b) MDS residual after adaptation

Figure 4.11: Residual of MDS heat at $30°C$

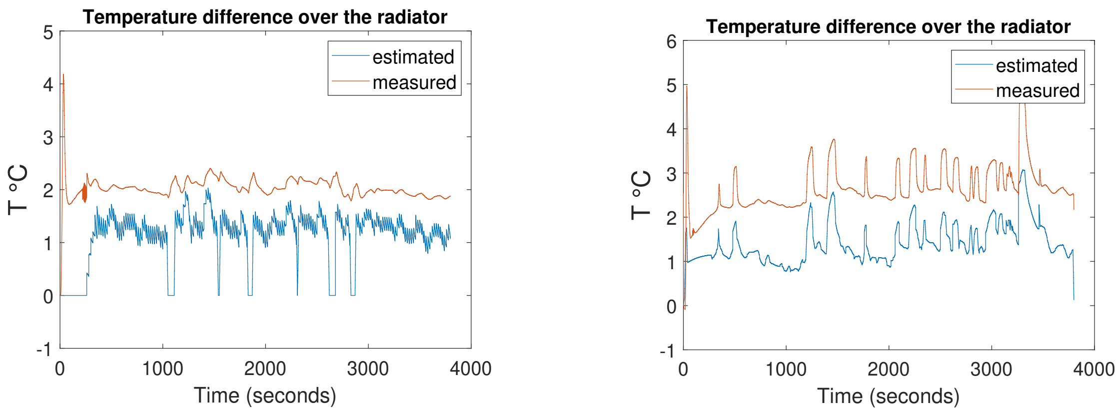
Observing the residual in Fig 4.11 we see they have been reduced by about half the value by the adaptation.



(a) Scaling factor at $30°C$ **(b)** Scaling factor at $0°C$

Figure 4.12: The adaptive parameter for scaling the radiator effect at different temperatures

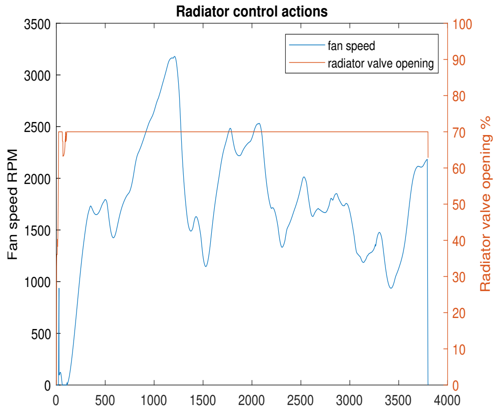
In Fig 4.12 similar patterns are shown for the scaling parameter α, that for higher temperatures it settles around 0.4 and for lower temperature it is around 0.7.



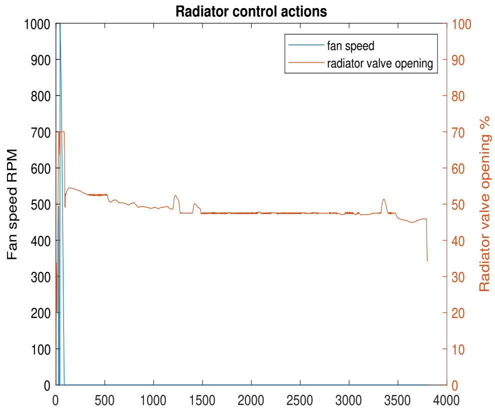
(a) Temperature over the radiator at $0°C$ **(b)** Temperature over the radiator at $30°C$

Figure 4.13: Temperature change at different ambient temperatures.

In Fig 4.13 comparisons between different ambient temperatures are displayed, where there is no adaptation. We see that the changes are consistent over different temperature changes, although at higher temperatures there seem to be a reduction in the error.



(a) Radiator valve opening and fan speed, no adaptation



(b) Radiator valve opening and fan speed, adapted

Figure 4.14: Control actuator values before and after adaptation at $30°C$

Observing Fig 4.14 we can again see that there seems to be a reduction in fan usage over the radiator, which is a good indication, since fan usage is very power consuming.

4.3 Marble hills

Marble hills is a cycle with a long uphill that covers a distance of around 80 km, with a reference speed of 85 km per hour. The road profile is depicted in Fig 4.15

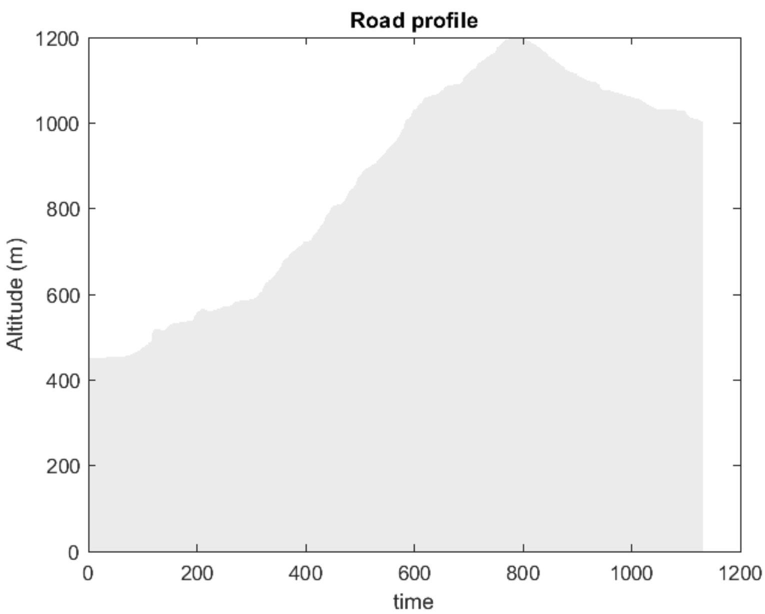
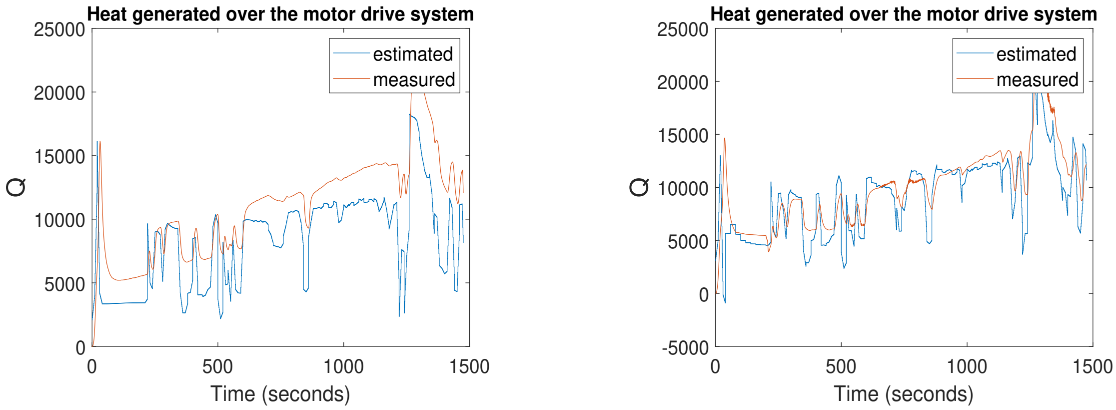


Figure 4.15: Road profile of the Marble hills cycle

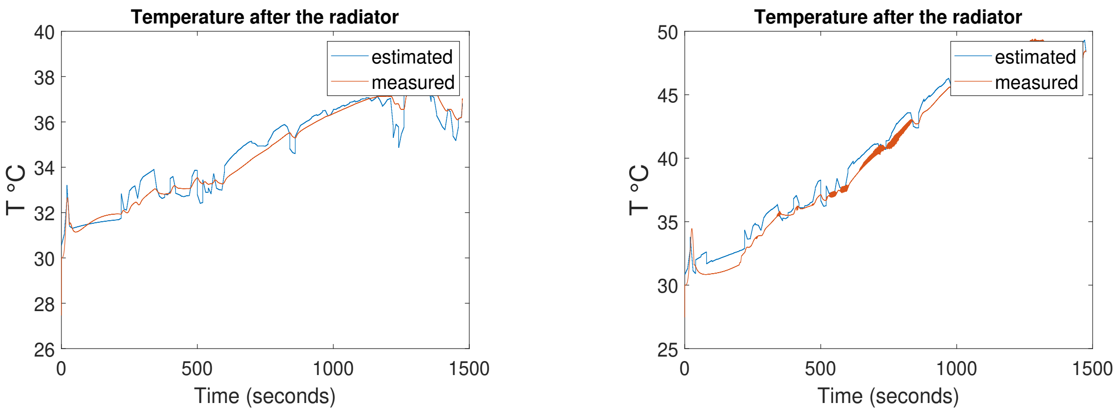


(a) Heat generated before adding the auxiliary term

(b) Heat generated after the adding the auxiliary term

Figure 4.16: Comparing the output of the DP after adding the adaptive MDS term

Observing Fig 4.16 we see that after the adaptations, the estimates are quite close for most of the simulations, which is probably because of the nearly constant power that is being supplied, since it is a long hill, which means that the behavior is not very transient and that aids in the estimation of the parameters.

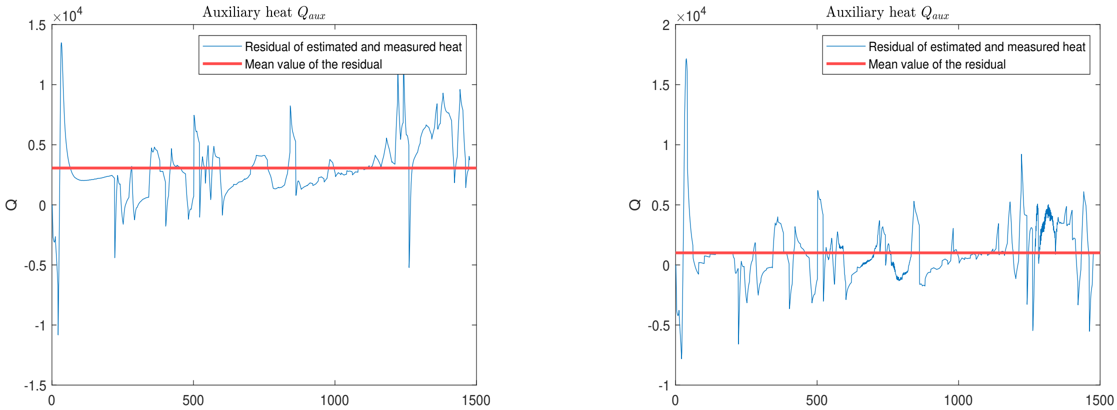


(a) Radiator before the adaptation

(b) Radiator after the adaption

Figure 4.17: Comparing the temperature change over the radiator before and after adapting the effect of the radiator.

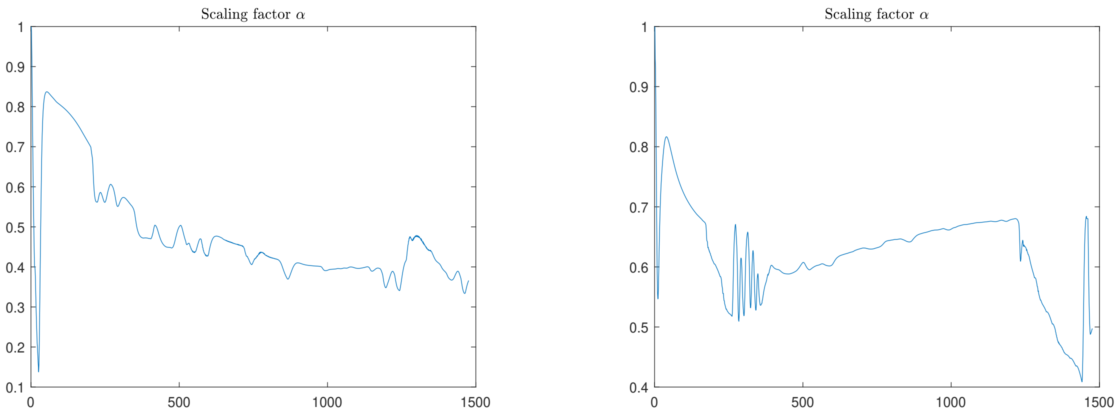
Observing Fig 4.17 we can see that the adaptation does not make much of a difference, but a key thing is that after the adaptation allows the temperature in the coolant to reach higher temperatures, while still staying within the bounds. This also becomes apparent when looking at the actuator signals.



(a) MDS residual before adaptation **(b)** MDS residual after adaptation

Figure 4.18: Residual of MDS heat at 30°C

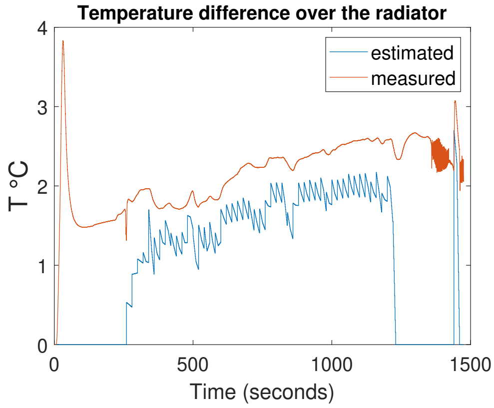
Again, Fig 4.18 shows a reduced residual between estimated and measured heat and after adaptation it is even lower.



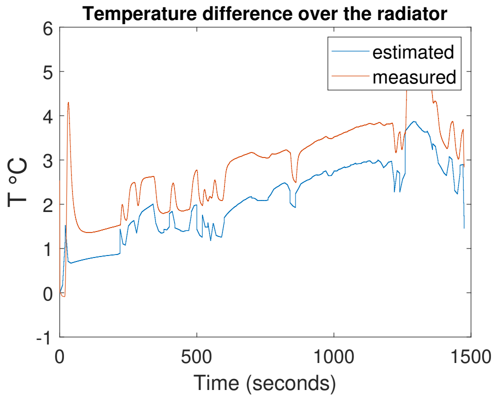
(a) Scaling factor at 30°C **(b)** Scaling factor at 0°C

Figure 4.19: The adaptive parameter for scaling the radiator efficiency at different temperatures

In Fig 4.19 the scaling parameters are again higher in the case where temperature is lower.



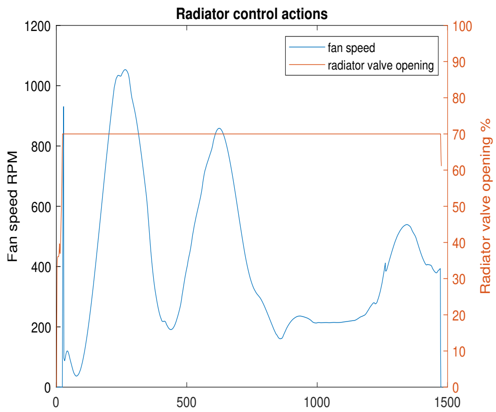
(a) Temperature over the radiator at $0°C$



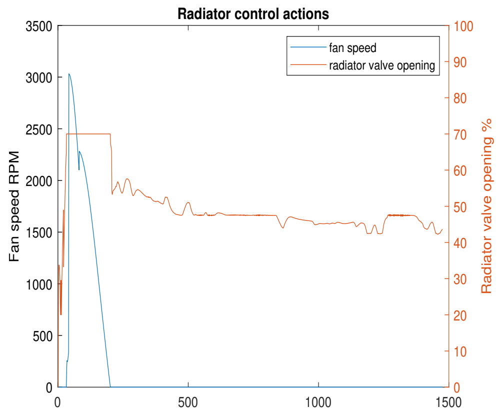
(b) Temperature over the radiator at $30°C$

Figure 4.20: Temperature change at different ambient temperatures.

Looking at Fig 4.20 we can see the difference between ambient temperatures, and the reason for their difference is because at lower temperatures, the radiator valve is not open as frequently, and thus we cannot update the adaptive parameter.



(a) Radiator valve opening and fan speed, no adaptation



(b) Radiator valve opening and fan speed, adapted

Figure 4.21: Control actuator values before and after adaptation at $30°C$

Similar to previous results, in Ref 4.21 we see again that the actuator signal after adaptation reduce fan usage.

4.4 A75

A75 is a longer cycle with more varying terrain. (See Fig 4.22) This makes it a good test for endurance.

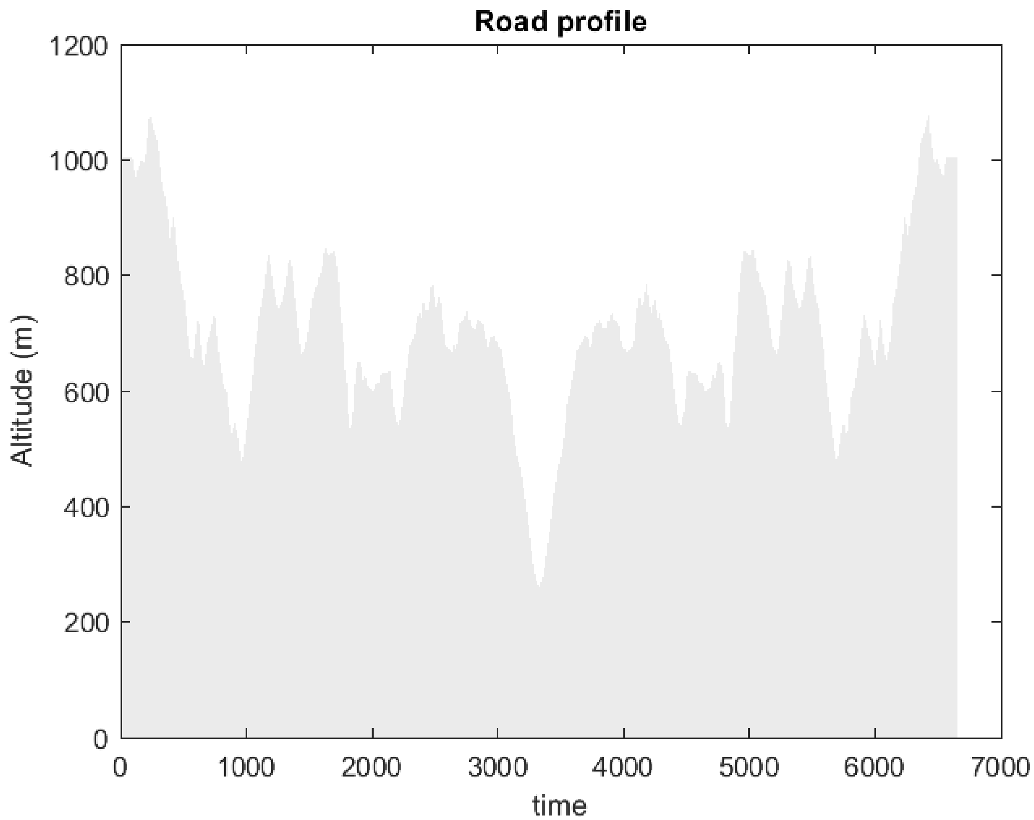
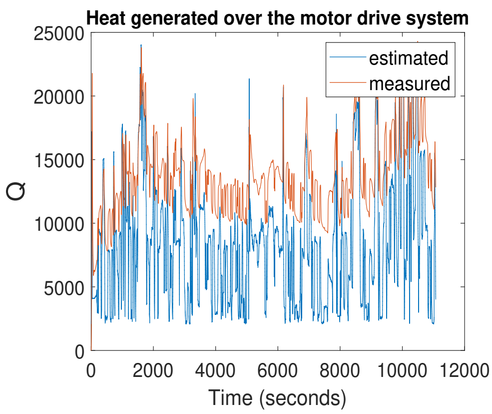
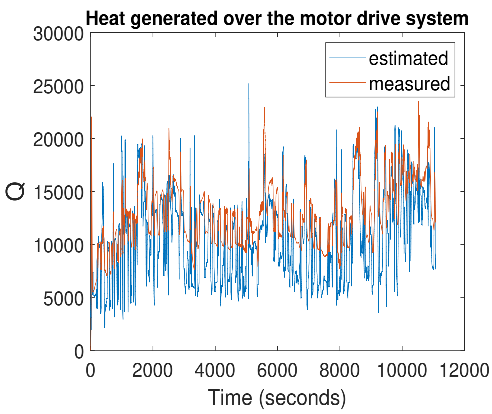


Figure 4.22: Road profile of the A75 cycle



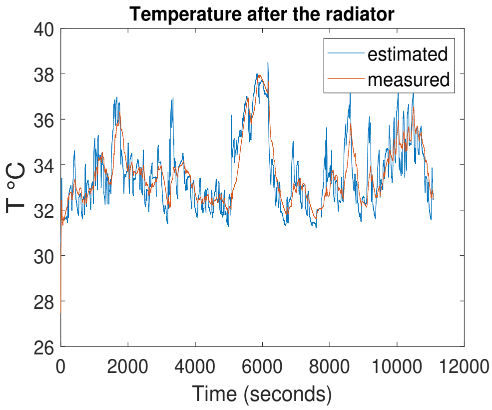
(a) Heat generated before adding the auxiliary term



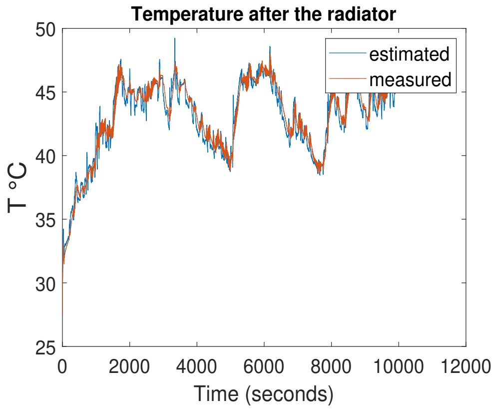
(b) Heat generated after the adding the auxiliary term

Figure 4.23: Comparing the output of the DP after adding the adaptive MDS term

Looking at the heat over the MDS, we can observe from Fig 4.23 the improvement by the adaptation over the MDS.



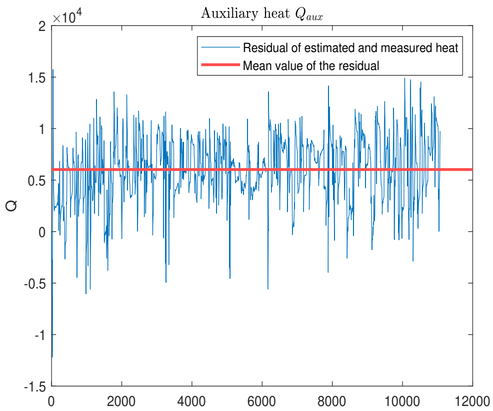
(a) Radiator before the adaptation parameter



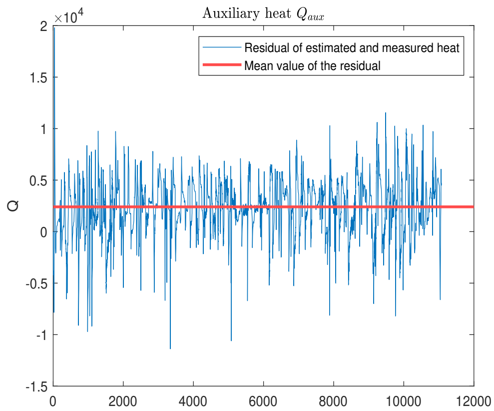
(b) Radiator after the adaption parameter

Figure 4.24: Comparing the temperature change over the radiator before and after adapting the efficiency of the radiator.

Seeing similar results as previous test, over the radiator Fig 4.24, there are also improvement, specifically reducing the peaks of errors.



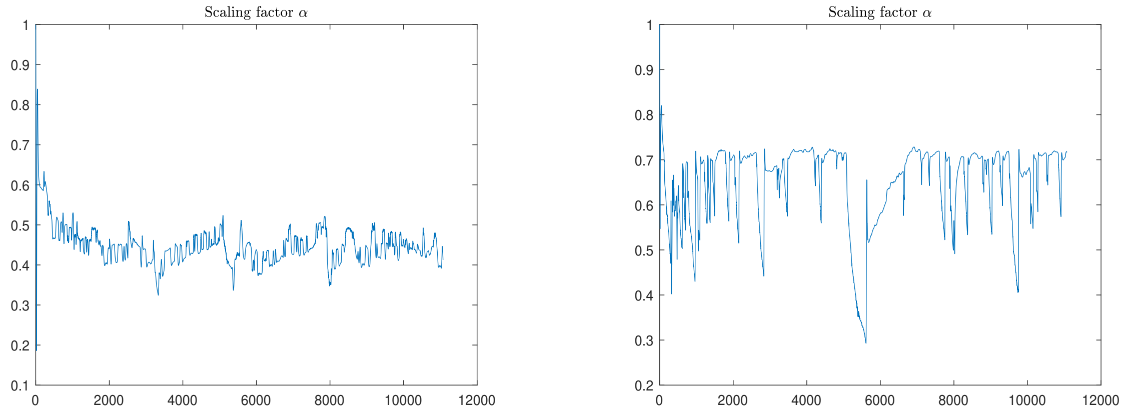
(a) MDS residual before adaptation



(b) MDS residual after adaptation

Figure 4.25: Residual of MDS heat at $30°C$

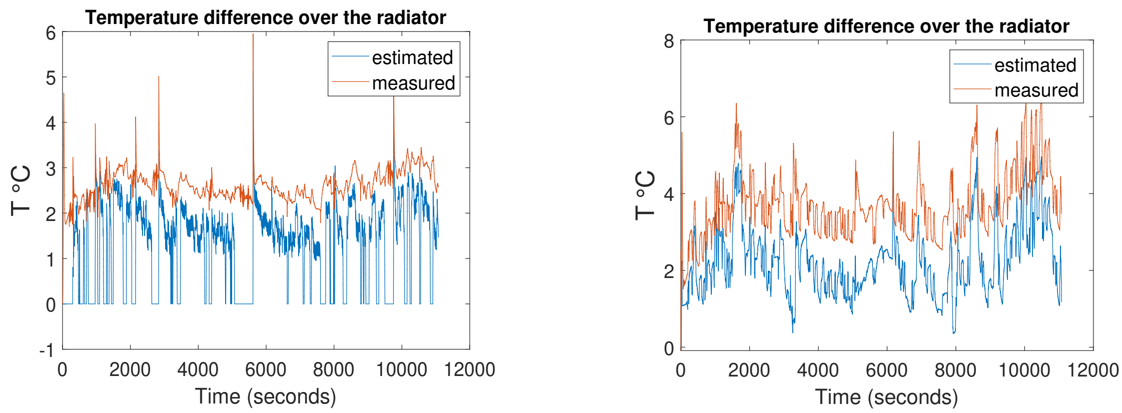
The residual heat, is again reduced as can be observed in Fig 4.25.



(a) Scaling factor at 30°C **(b)** Scaling factor at 0°C

Figure 4.26: The adaptive parameter for scaling the radiator effect at different temperatures

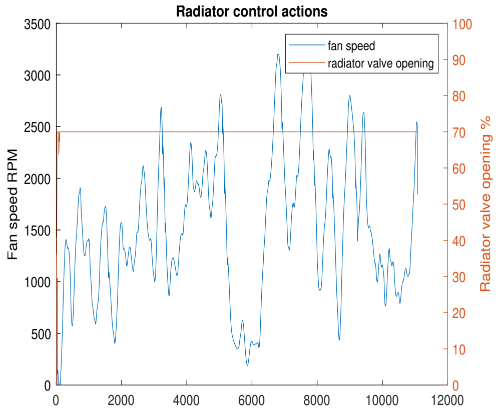
Looking at the difference of the scaling factor for the heat changes in Fig 4.26, we can confirm the results from the other profiles. 30°C it converges to around 0.4 and for simulations at 0°C it converges to approximately 0.7.



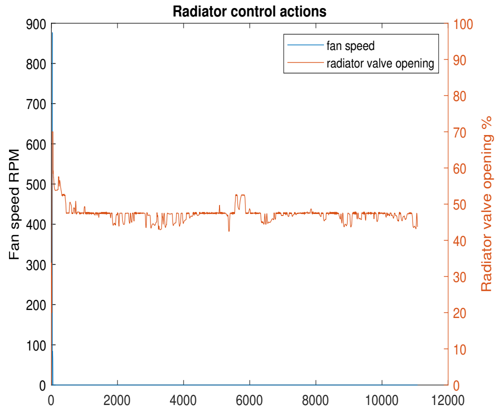
(a) Temperature over the radiator at 0°C **(b)** Temperature over the radiator at 30°C

Figure 4.27: Temperature change at different ambient temperatures.

For the temperature difference, (see Fig 4.27) at different ambient temperatures, the errors seems to be close. Thus for this kind of highly varying drive cycles, it might not be as beneficial as in the other simulations.



(a) Radiator valve opening and fan speed, no adaptation



(b) Radiator valve opening and fan speed, adapted

Figure 4.28: Control actuator values before and after adaptation at $30°C$

However, the control actions seem to improve with adaptation (see Fig 4.28).

5
Conclusion

5.1 Reflections about the work

Looking at the initial research questions, we can see that the two areas chosen for adaptation appears to be good choices. The adaptive parameter for differences in the coolant temperature after the MDS resulted in a simple implementation of a straightforward algorithm. Yet it proved useful in reducing the gap in prediction errors from the supervisor.

The radiator, also serving as an important part of the cooling system, is a good choice for adaptation. Improving the radiator is challenging since most models of radiator power are highly non-linear, but there are still model errors with these high-level models. Therefore, using an adaptive parameter to scale the efficiency of the models to improve predictions is a motivated approach.

As for the suitability of adaptation, that is a difficult question to answer. In simulations, there seem to be very good results from using adaptation to reduce model errors, but, as with all things, there are trade-offs. Since the adaptation algorithm runs at a faster rate than the predictive controller, we need to ensure that the changes to our parameters are robust. This is why we included limitations such as a high forgetting factor and an exponential moving average to avoid over-sensitive changes in our parameters and to prevent sending oscillating values of the parameters to the supervisor.

One benefit of the adaptation was the reduced use of fans in many cases. The more accurate estimates appear to help the supervisor manage fan usage more flexibly, allowing for a balance that is less conservative than before the adaptation, while still staying within set boundaries.

Regarding the performance benefits that adaptation has on the control of the cooling system, there seems to be an indication that the predictions reach a steady state faster with adaptive parameters, suggesting a performance enhancement. If we can conclude that the adaptive parameters significantly improve model predictions, there is the possibility of loosening the constraints implemented in the supervisor and thus potentially improved system performance. There also seems to be a general gain from improving the predictions. This is likely due to the choice of tracking by the controller. If we chose reference tracking of the predicted states instead of the predicted reference from the supervisor, with more accurate temperatures due to reduced prediction errors, the control actions are also improved. The RT controller does not have to adjust the radiator control functions as much since we are not deviating from the predicted state as much.

Therefore, there is a clear indication that the reduction of model error leads to an improvement in control actions as well.

5.2 Future work

The solutions for adapting the cooling models are quite simple and work under certain assumptions. A more advanced approach would involve examining specific parameters within the radiator model to see if they change with changes in the states. By doing this, we could derive some dynamics around them, moving from a static scaling parameter to a variable changing parameter that could change during the horizon of the supervisor. This is in contrast to the current approach, where the scaling parameter remains the same over the entire horizon.

Regarding the motor adaptation, a suggestion was given by the examiner, for a possible approach where the losses over the MDS can be approximated as a first-order system to more accurately capture the behavior of the losses based on initial investigations of the results.

Furthermore, there are more sections of the cooling system that could be implemented with adaptive parameters. However, including too many sections might result in an over-reliance on adaptation. Running numerous adaptations will increase computational time and may not be feasible in real-world application. It might also introduce more inaccuracies than it solves.

Finally, I will give a remark about a change in strategy. There is the possibility of using data-driven models instead of mathematically derived models. I believe that for sections with unknown dynamics, with enough data generated from simulations, it is possible to derive data-driven models that would be interesting to compare to current solutions. The issue, obviously, is that without properly annotated data or enough good data, it might be difficult to find models that perform as desired.

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