OPTIMAL CONTROL OF THE COOLING SYSTEM IN HEAVY VEHICLES[1]

Niklas Pettersson[a,b], Karl Henrik Johansson[b]

[a]*Scania CV AB, Södertälje, Sweden*
[b]*Department of Signals, Sensors & System, Royal Institute of Technology, Stockholm, Sweden*
niklas.pettersson@scania.se, kallej@s3.kth.se

Abstract: Control of the cooling system in heavy vehicles, with the objective to minimise energy consumption, is studied. Control actuators are electrically driven cooling fan and water pump, and the electrical generator. The problem is posed as a constrained optimal control problem with feedforward from measurable external variables. The design is based on a simplified model derived from physical principles. It is evaluated through simulations with external variables collected from measurements. The results show that significant energy savings can be obtained.

Keywords: Automotive Control, Energy Management Systems, Optimal Control, Predictive Control.

1. INTRODUCTION

Improving fuel efficiency is central when developing heavy vehicles. Increasing the controllability of the auxiliaries may be one method to save fuel. Today, the auxiliary systems are mostly mechanically driven by the engine, and are thus constrained to revolute with a fixed ratio to the engine speed. Since they have to work properly in all possible situations, they often have surplus capacity for the most frequent driving cases. This results in energy losses. With electrically driven auxiliaries, the output can at every time instant be controlled to match the actual need. The performance of power electronics, electrical machines and energy storage devices for automotive use are rapidly improving, making electrical alternatives worth considering. The price to pay is that the peak efficiency will be lower, since the electrical drive includes energy conversion in several steps. Therefore, it is of great importance to evaluate the performance of the regarded alternatives during dynamic conditions. Control strategies with the objective to minimise input energy could significantly benefits from knowing something about the future external quantities that affect system. For vehicle applications, a possibility to accurately predict the future could be realised with an onboard GPS receiver together with digitalized maps including information of the altitude and speed limits on the travelled road. With a vehicle model, the future influences can be simulated from the slope of the road and the presumed velocity.

This paper presents a study on cooling system control in heavy vehicles. An electrically driven cooling fan and an electrically driven water pump, together with predicted external variables are utilised to reduce the fuel consumption. The problem is posed as a constrained optimal control problem in continuous time. Optimal control theory allows for a wide range of cost criteria and system descriptions. A disadvantage is that solutions are often complicated to find even if the complexity of the system is low. Here a simple, but yet relevant, model is used to describe the physics. The numerical computations for finding the solution of the optimal control problem are reasonable. Our problem formulation fits into the framework of model predictive control, e.g., (Maciejowski, 2002), but the existing schemes seem not to be directly applicable. The solution here is instead based on the particular structures of the dynamics and the cost criterion. The derived optimal control gives a measure of the achievable performance. This is not intended for direct implementation but can be used to evaluate different physical layouts.

The outline of the paper is as follows: In section 2 the cooling system is described. The model used for the control design is defined in section 3. In section 4 the optimal control is derived. Simulation results are presented in section 5. Finally in section 6, conclusions from the study are drawn.

2. THE COOLING SYSTEM

The principal layout of the cooling system in a truck is illustrated in fig 1.

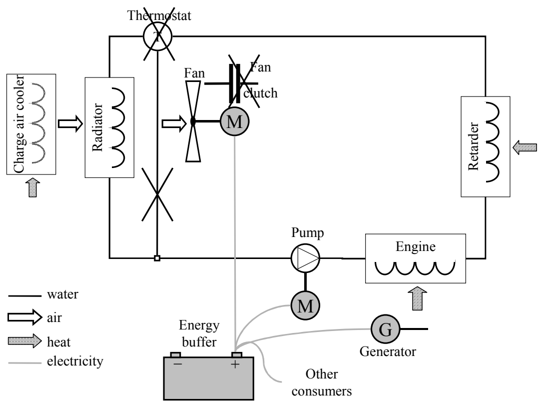

Fig 1. Cooling system layout. Components in a traditional truck, but excluded in this study, are x-marked. Novel components added to enable the improved control are grey.

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There are two adjoining flows of mass and energy: the flow of coolant fluid and the airflow. The pump drives the flow of coolant fluid through the engine and the retarder. The combustion process in the engine generates heat, which is transmitted to the coolant. The retarder is a hydraulic brake mounted on the secondary side of the gearbox. When used, it releases heat into the cooling system. The heat transferred to the coolant is emitted in the air-cooled radiator. The air enters at the air intake at the front of the truck cab and exits at the air outlet at the rear. The airflow is partly driven by the fan and partly by the pressure build up caused by the wind speed at the intake and outlet. The air is used to cool both the radiator, and the turbo charged intake air to the engine. The charge air cooler and the radiator are connected in series so that the air first passes the charge air cooler and then the radiator. Both the charge air cooler and the radiator are cross directional heat exchangers, i.e., the hot and the cool media streams are perpendicular.

In the current design of a Scania truck, the water pump is directly driven from the crankshaft while the fan is connected to the shaft via a viscous clutch, enabling a passive speed control. The temperature of the coolant is controlled with the thermostat and the fan clutch. However, the pump is restricted to run with a fixed ratio to the engine speed and the fan can only be controlled in a span limited by the lowest achievable torque in the clutch and the speed of the engine. This result in energy losses: both in the coolant flow in the by-pass pipe (not contributing to the cooling) and in the fan clutch (from the presence of non-zero torque and slip speed).

In this study, the mechanical drives of the pump and the fan are replaced with speed controllable electrical motors, enabling continuous control of the coolant flow and the airflow. The electricity is produced with a generator driven by the engine. The generator is assumed to be controlled with a power electronic converter. Its overall efficiency is supposed to be substantially higher than in the type of generators used in cars and trucks today. Electric energy can be stored in a buffer, which could be an electro-chemical battery that endures frequent cycling of the charge level and high de-charge and charge peaks. Alternatively, it colud be a module of double-layer capacitors (so called super caps or ultra caps), which are inherently well suited for this kind of use. Besides the energy consumption in the pump and the fan, auxiliary electrical consumption is regarded. This represents use of electricity for lights, comfort equipment, etc. The thermostat and the by-pass pipe are removed. It is assumed that it is possible to find a minimal coolant flow, which is sufficiently large to prevent the engine from running too hot at the worst spot, while small enough so that the entry temperature to the engine does not fall below the lowest acceptable level. In practice, this might not be true for the whole range of operating conditions. However, the studied concept can with small modification be changed to include a on/off valve acting as a thermostat at low ambient temperatures.

3. MODEL

In order to apply the optimal control theory a mathematical model of the physical system is needed. In (Pettersson and Johansson, 2003), a simulation model that can be used to study the cooling system is developed. This model, which is built in Modelica (Modelica, 2002), contains a fairly detailed description of the main components in the cooling system. It is too complex to be used for control design. However, it is a valuable starting point for finding a simplified model. Here the separate volumes and heated masses in the simulation model are aggregated into one single body representing the total heat capacitance of the cooling system. Further, a low-order rational function approximates the nonlinear behaviour of the radiator. This gives the following first order model for the cooling system

$$\begin{aligned}\dot{x}_1 &= -c_2\left(x_1 - \frac{c_6 v_2}{u_2 + c_3 v_3}\right) \\ &\quad \frac{u_1(u_2 + c_3 v_3)}{c_4 u_1 + u_1(u_2 + c_3 v_3) + c_5(u_2 + c_3 v_3)} + c_1 v_1 \\ &:= f_1(x_1, u_1, u_2, v_1, v_2, v_3) \qquad (1)\end{aligned}$$

Here, the state x_1 represents the temperature in the cooling system minus the ambient temperature. The control variables u_1 and u_2 are the speed of the water pump and the fan, respectively. The time varying external variables v_1, v_2, v_3 cannot be manipulated. The main external influence v_1 represents the sum of the heat transferred to the coolant from the engine and from the retarder. The heat emission in the charge air cooler and the vehicle speed are denoted v_2 and v_3, respectively.

A comparison with measurements indicates that this model is able to capture the main dynamics of the cooling system. Data were recorded during a dynamic drive cycle performed on a dynamometer in a wind tunnel, where the load and the speed were programmed to follow trajectories corresponding to a specified road. In figure 2 the model in equation (1) is compared with the more detailed Modelica model and with the measurement.

The energy in the electrical storage is modelled as an integration of the net power in and out of the buffer

$$\begin{aligned}\dot{x}_2 &= c_7 u_3 - c_{10} u_1^3 - c_{11} u_2^3 - c_8 v_4 \\ &\quad - c_9 (c_7 u_3 - c_{10} u_1^3 - c_{11} u_2^3 - c_8 v_4)^2 \\ &:= f_2(u_1, u_2, u_3, v_4) \qquad (2)\end{aligned}$$

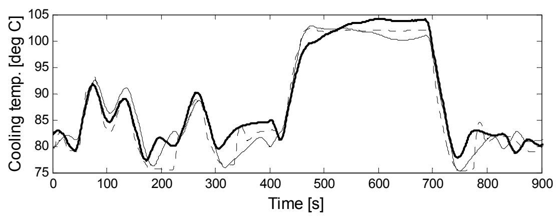

Fig. 2. Coolant temperature obtained with the model used for control design (thick solid) compared with temperature obtained with the Modelica model (thin solid) and with measurements (dotted).

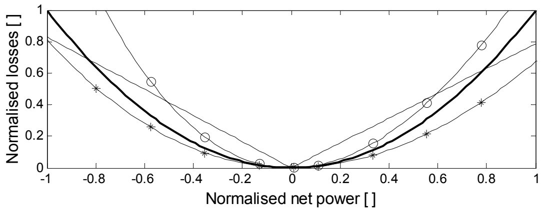

Fig. 3. Power losses obtained with different models of the energy buffer. The model used for the control design (thick solid) is compared with a constant efficiency model (thin solid), and a circuit model at minimum (solid-circles) and maximum (solid-stars) state of charge.

Here the state x_2 represents the state of charge above the lowest allowed level. The power produced in the generator is denoted with u_3 and the power consumption of the pump and the fan are described as a cubic function of the speeds u_1 and u_2:

$$l_c(u_1,u_2) = c_{10}u_1^3 + c_{11}u_2^3 \quad (3)$$

Other electrical consumption in the truck is represented by v_4. The last term of (2), represents the power loss in the buffer, which thus is assumed to be proportional to the square of the difference between the generated and the consumed power. In general, the power loss will be a function of the power flow and the state of charge. When studying the energy level in the storage, a simple model suffices. Related models can be derived from either assuming an efficiency factor of the storage or to model it as an equivalent electrical circuit. In figure 3 these different models are compared. The circuit model includes a dependency of the state of charge while the others do not. At low state of charge and a large negative net power, the simpler models tend to underestimate the losses compared to the circuit model. For this study, the loss model in equation (2) still seams to be sufficient.

4. OPTIMAL CONTROL

The control objective is to minimise fuel used to drive the generator, while keeping the temperature in the cooling system and the charge level in the energy buffer within specified limits. It is assumed that the time trajectories of v_1, v_2, v_3 and v_4 are known or can be predicted for some time ahead. In practice this prediction horizon is limited by the ability to accurately estimate the external variables from input data. Based on the model defined in the previous section, and knowledge of the future external variables, the optimal input trajectory is calculated.

4.1 Problem formulation

The control objective of minimising the fuel consumption is comparable to minimising the power produced in the generator integrated over times when fuel is injected in the engine, based on the assumption that the both the combustion engine and the generator have a nearly constant efficiency. This is reasonable since the efficiency of the diesel engine in heavy vehicles varies with a few percentage points in the rpm range utilised in highway driving. The generator could be designed with fairly constant efficiency in the corresponding speed interval. The regarded prediction horizon spans from the present, t_i, up to a fixed time $t_f = t_i + t_p$, where t_p is the prediction horizon. Let $\delta=\delta(t)$ be a binary weighting factor that equals one when fuel is needed to drive the vehicle forward, while it is zero when no fuel is injected in the engine. Then, the objective can be formulated as

$$\min_{u_1,u_2,u_3 \in U} \quad J = \int_{t_i}^{t_f} \delta(t)u_3(t)dt \quad (4)$$

subject to the dynamics (1) and (2), and the state constraints

$$0 \le x_{i\min} \le x_i \le x_{i\max} = 1, \quad i = 1,2 \quad (5)$$

The set of admissible controls is equal to

$$U = \{u : 0 \le u_{i\min} \le u_i \le 1, \quad i = 1,2,3\} \quad (6)$$

The optimisation is performed in a receding horizon scheme where only an initial part of the calculated input is applied. The length of the input trajectory that is applied in each control update is called the control horizon and spans from t_i to t_i+t_c, with $t_c < t_p$. When time t_i+t_c is reached, the initial and final time is set to $t_i := t_i+t_c$ and $t_f := t_f+t_c$, and a new optimal control is derived. In order to force the control not to utilize the buffers in the end of the optimisation interval, constraints on the final states are introduced:

$$x_i(t_f) = (x_{i\min} + x_{i\max})/2, \quad i = 1,2 \quad (7)$$

The optimal control for the case when state constraints are inactive, is derived from the Hamiltonian (Bryson and Ho, 1975)

$$H = \delta u_3 + \lambda_1 f_1(x_1,u_1,u_2,v) + \lambda_2 f_2(u,v) \quad (8)$$

where u and v denote the vectors of control and external variables, respectively. The adjoint variables should satisfy the differential equation

$$\dot{\lambda}_1 = -\frac{\partial H}{\partial x_1} = -\lambda_1 \frac{\partial f_1}{\partial x_1}$$
$$\dot{\lambda}_2 = -\frac{\partial H}{\partial x_2} = 0 \quad (9)$$

Hence λ_2 is constant. In the above setting, the initial and final states are known, while the boundary conditions for the adjoint variables are not. Due to the constraints on the final states, the final values of the adjoint variable, $\lambda(t_f)$, is arbitrary.

4.2 Sequential solution

Suppose first that the sate constraints are inactive. The problem above can be numerically solved with a shooting method (Bryson 1999). However, although the model involves only two dynamic states, the solution is hard to obtain. The complexity of the problem can be reduced by solving for the control of one state at a time, as discussed next.

Let us first minimise (4) with respect to u_3. For intervals when $\delta(t) = 0$, the optimal u_3, is dependent only on the sign of λ_2. It is straightforward to see that λ_2 should be negative. This gives the control

$$u_3 = \begin{cases} \text{sat}^+(\text{sgn}(-\lambda_2)) = 1, & \delta = 0 \\ \text{sat}^+\left(\dfrac{1+c_7\lambda_2}{2c_9c_7^2\lambda_2} + \dfrac{l_c(u_1,u_2)+c_8v_4}{c_7}\right), & \delta = 1 \end{cases} \quad (10)$$

where $\text{sat}^+(\alpha) = 1$, if $\alpha > 1$, 0 if $\alpha < 0$, and α otherwise. Note that when $\delta = 1$, not only the sign of λ_2 is of importance. Here λ_2 should be chosen such that the constraints on x_2 are satisfied. If u_3 does not saturate when $\delta = 1$, the Hamiltonian becomes

$$H = \begin{cases} \lambda_1 f_1(x_1,u_1,u_2,v) + \lambda_2[c_7 - l_c(u_1,u_2) - c_8v_4 \\ \quad - c_9(c_7 - l_c(u_1,u_2) - c_8v_4)^2], & \delta = 0 \\ l_c(u_1,u_2)/c_7 + \lambda_1 f_1(x_1,u_1,u_2,v) + h(\lambda_2,v_4), & \delta = 1 \end{cases} \quad (11)$$

where $h(\lambda_2, v_4)$ is a known function. If $\delta(t) = 1$, $t_i \le t \le t_f$, the controls u_1 and u_2 that minimise H are obviously independent of u_3, λ_2, and x_2. When $\delta(t) = 0$, $t_i \le t \le t_f$, the minimising controls u_1 and u_2 are independent of u_3, and x_2, but depends on the sign of λ_2 (which is known to be negative). This suggests separation of the control of x_1 from the control of x_2: first u_1, u_2 is derived from (11), then $l_c(u_1,u_2)$ is plugged into equation (10), giving u_3. However, if δ change in the prediction interval, λ_2 must be known when deriving the control of x_1. The optimal control problem for the cooling system corresponding to the Hamiltonian in (11) can thus be formulated as

$$\min_{u_1,u_2 \in U} \quad J_c = \int_{t_i}^{t_f} \{\delta l_c(u_1,u_2) - (1-\delta)\lambda_2 c_7[l_c(u_1,u_2) + c_9(c_7 - l_c(u_1,u_2) - c_8v_8)^2]\}dt \quad (12)$$

subject to state equation (1) and constraints in equation (5) and (7). Hence, the control of cannot be separated from each other. However, here the approach is to solve for the control of x_1 and x_2 in sequence, and iteratively update the parameters linking the controls together. The simplification this yields is considerable since only one-dimensional problems are solved at each step. The iteration scheme and convergence properties of the iteration are discussed in the next section.

4.3 Iteration of the sequential solution

The cooling optimisation problem in (12) is solved with an initial guess of the constant λ_2. If this value coincides with the solution to (10), or if $\delta(t)\, u_3(t) = 0$, $t_i \le t \le t_f$, an optima of the original optimal control problem (4) is found. If this does not hold, the sequential solution can be iterated until the optimality condition is satisfied. This gives the following algorithm:

0. Set λ_2 to an initial guess (e.g., $-1/c_7$).
1. Solve the cooling optimisation problem in (12) with the current value of λ_2 to obtain u_1 and u_2.
2. Find a new λ_2 such that the constraints on x_2 are satisfied and apply (10) to obtain u_3.
3. Terminate if the current λ_2 is close enough to λ_2 used in 1 or if $\delta(t)\, u_3(t) = 0$, $t_i \le t \le t_f$, otherwise jump to 1.

There are two interesting special values of λ_2 that should be considered when selecting an initial guess. These correspond to a zero cost policy (u_3=0 whenever δ=1) and a constant charge policy ($\lambda_2 = -1/c_7$ giving f_2=0). With the zero cost policy, the buffer is charged when δ=0, and the stored energy is utilised when δ=1. If it is possible to satisfy the constraints with this policy it will indeed be optimal. With the constant charge policy, the produced power exactly compensate for the consumption. This policy will be optimal whenever $\delta(t) = 1$, $t_i \le t \le t_f$.

Solving for the control of a single state implies finding the initial value of the corresponding adjoint variable while the control of the other state is given from the previous iteration. As a measure of the deviation from the correct initial values, one residual is defined for the control of x_1 and one for the control x_2. The residuals are evaluated in the end of the time interval where the shooting method is applied and should equal zero when proper initial values are found. The residuals are derived from the conditions at the final time t_f, or at times when the states entering or leaving the constraints. The optimal control is a function of x, λ and t. Further, for a given time interval the initial condition of x is fixed. Therefore, the residuals will be functions of the initial condition of λ and the end point of the considered time interval. If t_s and t_e denote start and end point of the time interval, respectively, and the notation $\lambda_{is} := \lambda_i(t_s)$, i=1,2 is introduced, the residuals can be expressed as $r_i(t_e, \lambda_{1s}, \lambda_{2s})$, i=1,2. Let r_1 represent condition on the control of x_1, while r_2 represent condition on the control of x_2. In each iteration, k, the initial values of λ_1 and λ_2 are updated so that λ_{1s}^{k+1} is the solution of $r_1(t_e, \lambda_{1s}, \lambda_{2s}^k) = 0$, while λ_{2s}^{k+1} is the solution of $r_2(t_e, \lambda_{1s}^{k+1}, \lambda_{2s}) = 0$. Local convergence of the scheme is obtained if

$$\mu := \left| \frac{\partial r_1}{\partial \lambda_{2s}} \frac{\partial r_2}{\partial \lambda_{1s}} \Big/ \left(\frac{\partial r_1}{\partial \lambda_{1s}} \frac{\partial r_2}{\partial \lambda_{2s}} \right) \right| < 1 \quad (13)$$

holds in a neighbourhood of the optimum. Thus, local convergence is obtained if λ_{1s} mostly influences the control of x_1, and λ_{2s} mostly influences the control of x_2. An analytic proof has not been obtained for that (13) holds when the control does not saturate. Nevertheless, numerical analysis indicates that this is the case. To illustrate this, μ is evaluated as a function of the mean of $\delta(t)$.

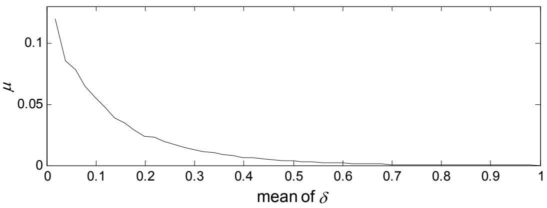

Fig 4. Relation (13) as a function of the mean of δ(t).

The result is shown in figure 4. Here the external variables are held constant and constraints are not considered. It exists cases when (13) does not holds, for instance when the control inputs saturate over large parts of the prediction horizon. These situations are detected and handled in a special manner.

4.4 Handling of state constraints

The solution to the cooling optimal control problem described in equation (12) is straightforward if the state constraints are not encountered (as described above). However, if the state constraints are active the solution is somewhat more complicated, as discussed next. The adjoint variable can be discontinuous at time instances where the state constraints go from being active to non-active, or vice versa. Therefore the optimal trajectory x_1^* must be divided into constrained and unconstrained arcs. Consider the case when $\delta = 1$, and assume that the optimal trajectory consist of the three parts: an unconstrained arc, $x_1^*(t)$, $t_i \le t \le t_1$ ending on a constraint, say x_{1max}, a constrained arc, $x_1^*(t) = x_{1max}$, $t_1 \le t \le t_2$, ending at t_2 when the state leaves the constraint, and an unconstrained arc, $x_1^*(t)$, $t_2 \le t \le t_f$ ending at the final state value $x_1^*(t_f) = (x_{1min} + x_{1max})/2$.

The optimal control that keeps $x_1^*(t) = x_{1max}$ is

$$[u_1 \quad u_2]^T = g(x_{1\max}, v) = \arg\min\{l_c(u_1,u_2) \ : u \in U, \ f_1(x_{1\max}, u_1, u_2, v) = 0\} \tag{14}$$

In this case the cost function can be re-written as

$$\begin{aligned} J_c = & \int_{t_i}^{t_f} l_c(u_1,u_2)dt = \int_{t_i}^{t_1} l_c(u_1,u_2)dt + \int_{t_1}^{t_2} l_c(g(x_{1\max},v))dt \\ & + \int_{t_2}^{t_f} l_c((u_1,u_2)dt = \underbrace{\int_{t_i}^{t_1} l_c(u_1,u_2)dt - \int_{t_i}^{t_1} l_c(g(x_{1\max},v))dt}_{J_{c1}} \\ & \underbrace{+\int_{t_2}^{t_f} l_c(u_1,u_2)dt - \int_{t_2}^{t_f} l_c(g(x_{1\max},v))dt}_{J_{c2}} - \underbrace{\int_{t_i}^{t_f} l_c(g(x_{1\max},v))dt}_{J_{c0}} \end{aligned} \tag{15}$$

Since J_{c0} is independent of u, t_1 and t_2, the problem can be divided into two separate optimal control problems over unconstrained arcs. The times t_1 and t_2 are free parameters. Hence, the optimisation should be performed over open time intervals. The condition on the final state (7) is now replaced by the condition that the corresponding Hamiltonians should equal zero when the state is entering or leaving the constraint, (Bryson and Ho, 1975).

The discussion above can easily be extended to a general case when the state trajectory enters and leaves the constraint several times. The cost function then becomes

$$J_c = J_{c1}(t_1) + J_{c2}(t_2) + \sum_{k=3,5,7...,N} J_{ck}(t_k, t_{k+1}) - J_{c0} \tag{16}$$

Consequently, the optimisation can always be separated into independent problems over unconstrained arcs. In the numerical solution this is done iteratively, searching over the prediction horizon for trajectories that satisfy the condition that the Hamiltonian is equal to zero at the entry and exit to the constraints.

5. SIMULATION RESULTS

The optimal control strategy is simulated with input data collected from an experiment in a wind tunnel. The external variables v_1, v_2 and v_3 are measured on the truck when the load and speed of the dynamometer are programmed to follow trajectories corresponding to a specified road. Simulations are performed over two road sections with altitudes depicted in figure 5. The first simulation runs over part of the road between Koblenz and Trier in Germany. It contains rather steep downhill slopes where a lot of heat is emitted to the cooling system from the retarder. The second simulation runs over part of the road between Södertälje and Norrköping in Sweden. It contains long flat sections with some moderate uphill slopes where the engine produces heat that have to be cooled away.

The prediction horizon is set to t_p=600 seconds and the control horizon to t_c=100 seconds. It is assumed that the controller has exact knowledge of the external variables over the prediction horizon. The parameters of the electrical components are chosen to realistic values. In figures 6 and 7, the simulation results are shown. Simulations where optimal control is applied (thick lines) is compared with measurements on a traditional truck (thin lines). In the upper plot, the temperature obtained with optimal control (thick) and measured temperature (thin) is shown. The second plot shows optimal control of the pump (thick solid) and the fan (thick solid-stars) compared with the speed of the pump (thin solid) and

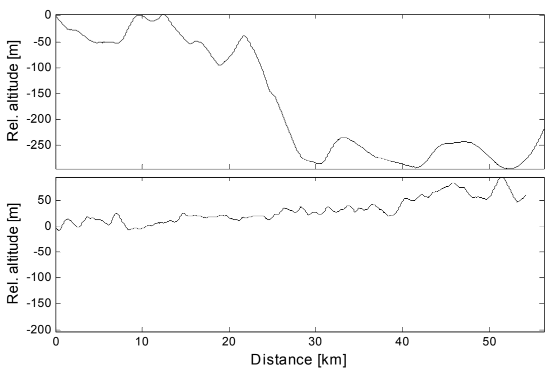

Fig. 5. Road altitudes used to collect external data. The used part of the Koblenz-Trier road is shown in the upper plot and the used part of the Södertälje-Norrköping road in the lower.

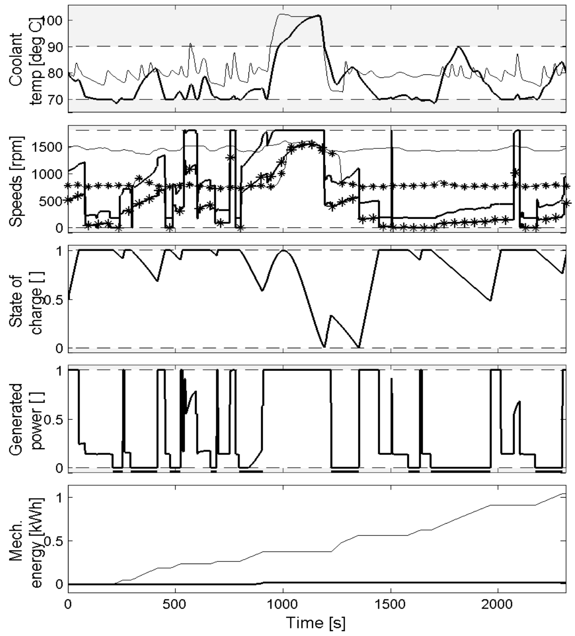

Fig. 6. Simulation results on the Koblenz-Trier road. The variables are explained in the text.

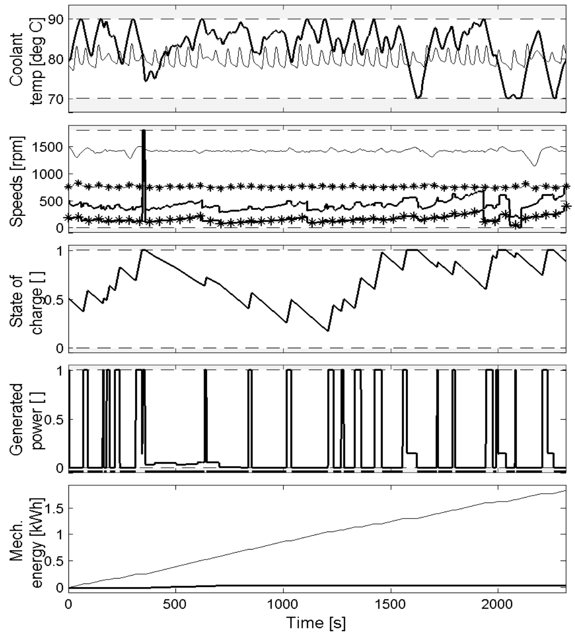

Fig. 7. Simulation results on the Södertälje-Norrköping road. The variables are explained in the text.

the fan (thin solid-stars) in the traditional truck. The third plot shows simulated state of charge in the energy buffer. The forth plot shows optimal control of the generator and indicates the intervals where $\delta(t)$=1 as a bar on the time axis. The lowest plot shows the energy taken from the engine (when δ=1), with optimal control (thick) and with traditional control (thin). Note that with the optimal control, the energy saving is significant in both figure 6 and 7.

The optimal control utilizes the admissible range of coolant temperature and state of charge. Therefore most of the electricity can be produced when $\delta(t)$ =0, i.e., at times t when no fuel is injected in the engine and auxiliary loads can be added without any cost. This can be seen in the forth plot of the figures where the bar on the time axis indicates when $\delta(t)$=1. The variables δ and u_3 are simultaneously non-zero only in the interval 800 to 900 s in figure 6 and in the interval 350 to 800 s in figure 6. As a result, the accumulated cost to drive the auxiliary systems, shown in the lowest plot of the figures, increases only in these intervals. All other times, the auxiliaries are run without cost.

Note that neither of the optimal or the traditional control is able to keep the temperature within the required limits in the first simulation (figure 6). With the optimal control, the electrical buffer is empty and the generator is saturated when that happens at about 1000 s, and thus, the temperature constraint cannot be satisfied. However it is notable that the optimal control solution prepares for this situation and lowers the temperature as much as possible before this occurs (the temperature is equal to x_{1min}=70º C at t=900 s). This can be done since the controller know about future external influences.

It should be noticed that the fan clutch installed on the truck in the measurements is of an older type with relatively high idle speed (≈700 rpm). There exist other clutches on the market with lower idle speed (≈300 rpm instead of ≈700 rpm). In comparison with those, the potential energy saving will be lower but still considerable.

6. CONCLUSIONS

Optimal control of electrically driven auxiliaries in the cooling system of heavy vehicles is derived. The result shows that controllable components in conjunction with prediction of external influences offer a potential to save fuel in this type of application. The saving constitute a fraction of the total fuel consumption, but improvements of this order is certainly worth considering since fuel economy is one of the most important performance factors of long haulage trucks.

The assumptions on the electrical components are preliminary, in order to give more precise estimates of the achievable energy saving, refined models will be derived in future studies.

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