A Novel Model-Predictive Cruise Controller for Electric Vehicles and Energy-Efficient Driving

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Abstract— **This paper presents a novel energy-efficient model-predictive cruise control formulation for electric vehicles. A predictive eco-cruise controller involves the minimisation of a compromise between terms related to driving speed and energy consumption which are in general both described by nonlinear differential equations. In this work, a coordinate transformation is used which leads to a linear differential motion equation without loss of information. The energy consumption is modeled by the maximum of a set of linear functions which is determined implicitly by the optimisation problem and thus leads to a piecewise linear model. The reformulations finally result in a model-predictive control approach with quadratic cost function, linear prediction model and linear constraints that corresponds to a piecewise linear system behaviour and allows a fast real-time implementation with guaranteed convergence. The controller and the underlying dynamic model are designed to meet the properties of a series-production electric vehicle whose characteristics are identified by measurements. Simulation results of the MPC controller and the simulation model in closed-loop operation finally provide a proof of concept.**

I. Introduction

The cruising range is one of the most decisive drawbacks of electric vehicles and an important problem that needs to be solved in electric mobility. Since the on board (tank-to-wheel) efficiency of electric vehicles can hardly be improved, there are only two possibilities to increase the range. The first one is the improvement of the battery technology towards higher capacities and lower weights. However, soon enhancements here are questionable. The second opportunity is to address the driving style that has a huge influence on the energy consumption of a vehicle [1]. Due to possible savings of 10 to 20 % and the fact that efficiency improvements of this magnitude cannot be expected by improving the vehicle technology, it is a promising approach to improve the driving style in order to save energy.

A sophisticated way to address this problem is controlling the driving speed automatically by a driver-assistance system (eco-cruise control). Eco-cruise control can be described as an optimal control problem [2], [3]. The accelerator pedal position is the control input of the system while the driving speed and the energy consumption are given by an underlying dynamic vehicle model (based on the previous knowledge of the speed limits and the road slope). The control inputs are the optimisation variables that minimise a cost function containing terms related to driving speed and energy consumption. As the car is running under changing traffic and environment conditions, it is hardly possible to calculate the complete optimal driving strategy in advance. A suitable approach to overcome this problem is to apply model-predictive control (MPC) in a receding horizon fashion, where the optimisation is carried out for a finite prediction horizon and is repeated at every time step. This control strategy has been considered as the tool of choice for the eco-cruise control of fuel-powered cars in several works [4], [5], [6]. Recently, eco-cruise control for purely electric vehicles has been considered in [7], [8], [9]. The biggest challenge in the application of MPC is the requirement of a fast online-optimisation which is hampering a real-time implementation. Therefore, the formulation of the optimal control problem is decisively important in order to achieve a fast solution. The most desirable formulation comprises a quadratic cost function and linear constraints including a linear dynamic plant model, since efficient solvers with guaranteed convergence are available for the resulting discretised quadratic optimisation problem.

However, an overall linearisation of the vehicle dynamics around one operation point is not satisfactory since the prediction has to be carried out over a wide range of operating points whereas a linearisation only yields good results in the area close to the operating point. Previous works use analytical solutions of the nonlinear optimal control problem based on Pontryagin's Maximum Principle (indirect methods) [2], [3] or alternatively efficient discretisation techniques to solve the nonlinear optimisation problem directly [5], [10], [11]. Using analytical solutions however, the optimal controller cannot be designed in a flexible way since it is then difficult to consider constraints on the states, dynamically changing weightings or measured disturbances. On the other hand, the numerical methods for nonlinear optimisation do not guarantee a (fast) convergence of the optimisation algorithm.

This paper contributes a model-predictive eco-cruise controller especially for an electric car using a quadratic cost function and linear constraints (Section III). The linear dynamical model is obtained by reformulations of the equations and an exploitation of the optimisation problem setup instead of an overall linearisation. Thus, the nonlinearities are considered implicitly by the control system while the results are equivalent to a nonlinear approach. The proposed controller is simulated in closed-loop operation with a simulation model of a series electric vehicle - a *Smart Electric Drive (ED)* to investigate the closed-loop performance (Section IV). This is followed by the conclusions in Section V.

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II. Overall System Setup

The proposed MPC controller is part of an experimental cruise-control system that will be tested in a real electric vehicle (*Smart ED*). The system is planned to work as a driver-assistance system that controls the speed automatically depending on predictive information about the road curvature, the road slope angle, the speed limits (from the digital maps of a navigation system) and the distance to the preceding vehicle (measured by an automotive radar).

A reference generator (not considered in this work) generates a safe speed set-point trajectory based on this information. Given the speed reference, the model-predictive cruise controller aims at finding a traction force trajectory leading to an optimal compromise between speed reference tracking and minimisation of the energy consumption. Since the traction force cannot serve directly as control input to the vehicle, a subsidiary controller regulates the traction force by actuating the accelerator pedal. The brake pedal is not planned to be actuated in this setup. This paper focuses on the design of the MPC controller. The subsidiary traction force controller is assumed to work ideally, here.

III. Controller Design

The synthesis of the energy-efficient model-predictive cruise controller comprises the underlying dynamical model as well as the constraints and the cost function.

A. Underlying Dynamic Model for the Controller Design

A suitable model needs to meet the dynamic behaviour of the *Smart ED* whose centre-piece is a permanent-magnet synchronous machine. This three-phase AC machine is able to work as motor or generator allowing energy recovery when decelerating. A lithium-ion battery serves as accumulator and supplies the synchronous machine via a DC/AC converter. The rear wheels are driven by the motor through a gear box with one fixed transmission ratio.

The model is subdivided into a model of the driving speed v (Section III-A.1) and a model of the energy consumption E_{el} of the vehicle (Section III-A.2). The model input (and control input) is the traction force at the wheels F_{trac}.

1) Model of the Longitudinal Motion Dynamics: The common approach to model the longitudinal dynamics of a vehicle is to consider the car as a point mass and describe a one-dimensional motion based on Newton's second law $\sum F = m \cdot \frac{dv}{dt}$. The main forces acting on the vehicle in longitudinal direction are the traction force F_{trac} as well as the driving resistance forces [12].

The rolling resistance force F_r is a function of the road slope angle α_{sl}. The parameters are the vehicle kerb weight m_v, the payload m_l, the gravitational constant g and the rolling resistance coefficient of the tyres c_r [12]. In curves, c_r increases slightly but this effect is neglected here.

$$F_r = (m_v + m_l) \cdot g \cdot c_r \cdot cos\big(\alpha_{sl}(t)\big) \tag{1}$$

The grade resistance force F_{gr} depends on road slope angle as well [12].

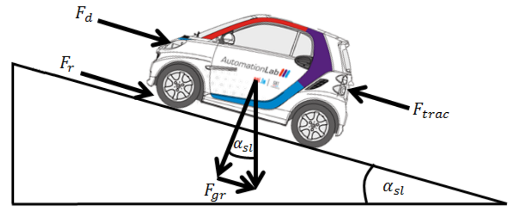

Fig. 1. Forces acting on the vehicle in longitudinal direction.

$$F_{gr} = (m_v + m_l) \cdot g \cdot sin\big(\alpha_{sl}(t)\big) \tag{2}$$

The air drag resistance force F_d is a function of the square of the driving speed v. The coefficients are related to the shape of the vehicle (projected front surface area A_v, air drag coefficient c_d) and the air density ρ_a [12].

$$F_d = \frac{1}{2} \cdot \rho_a \cdot c_d \cdot A_v \cdot v(t)^2 \tag{3}$$

A diagram of the forces acting in longitudinal direction is given in Fig. 1.

Given these forces, the acceleration of the vehicle in longitudinal direction can be computed from the difference between the traction force and the driving resistance forces divided by the equivalent mass of the vehicle m_{eq}.

$$\begin{aligned} \frac{dv(t)}{dt} = \big(&F_{trac}(t) - F_r(\alpha_{sl}(t)) \\ &-F_{gr}(\alpha_{sl}(t)) - F_d\big(v(t)\big)\big)/m_{eq} \end{aligned} \tag{4}$$

The equivalent mass m_{eq} is given by the relation $m_{eq} = (m_v + m_l) \cdot e_i$ which takes the rotational inertia of the drive train components into account by augmenting the vehicle mass $(m_v + m_l)$ by a constant factor that is assumed to be $e_i = 1.01$.

The vehicle specific parameters in (1) to (4) are accessible from data sheets [13]. The rolling resistance coefficient c_r is assumed to be 0.013. The gravitational acceleration is assumed to be $g = 9.81 \frac{m}{s^2}$ and the density of surrounding air to be $\rho_a = 1.2 \frac{kg}{m^3}$. All parameters are summarised in Tab. I.

For the application of a predictive cruise controller however, it is useful to describe the model (4) as a function of the position instead of time, since the inputs related to the road ahead (slope angle and speed limits) are also given as functions of the position. The model can be reformulated by applying the following transformation:

$$\frac{d}{ds} = \frac{d}{dt} \cdot \frac{dt}{ds} = \frac{d}{dt} \cdot \frac{1}{v} \tag{5}$$

The reformulation (5) consequently leads to a motion equation depending on the inverse of a state variable (the velocity v). This is disadvantageous for a fast solution of the optimisation problem. Following the idea in related works ([11], [14]), a coordinate transformation is applied to calculate the kinetic energy

$$e_{kin} = \frac{1}{2} \cdot m_{eq} \cdot v(t)^2 \tag{6}$$

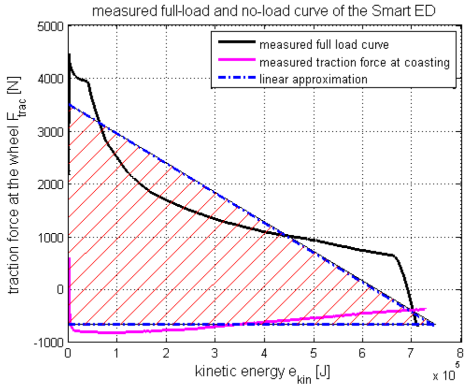

Fig. 2. Measured traction force of the Smart ED at full-load (100 % accelerator position, black line) and coasting (pedals released, pink line). The linear approximation is given in blue. The hatched area is the feasible region of the traction force F_{trac}.

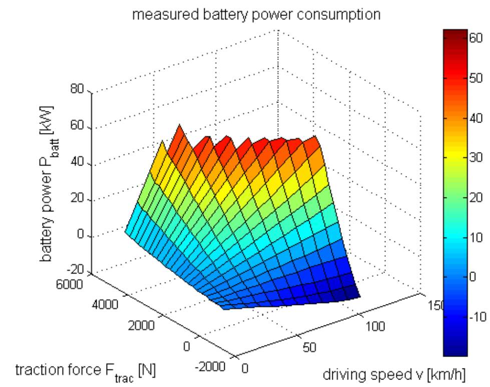

Fig. 3. Electrical battery power consumption of the electric vehicle as a function of the driving speed v and the traction force F_{trac}

of the moving vehicle instead of the driving speed. Since only positive speed values are considered, the speed can be calculated from the kinetic energy values at a given vehicle mass after the optimisation. Derivation of (6) with respect to the position s yields

$$\frac{de_{kin}}{ds} = m_{eq} \cdot \frac{dv}{dt} \tag{7}$$

By applying the coordinate transformation (7) to the motion equation (4), the following linear differential equation is obtained. The values of the sine and cosine functions of the slope angle $\alpha_{sl}(s)$ are considered as a measurable disturbance and assumed to be known predictively.

$$\frac{de_{kin}}{ds} = F_{trac}(s) - F_r\big(\alpha_{sl}(s)\big) - F_{gr}\big(\alpha_{sl}(s)\big) - F_d\big(e_{kin}(s)\big) \tag{8}$$

Herein, F_d is rewritten in terms of kinetic energy:

$$F_d(e_{kin}) = \frac{1}{m_{eq}} \cdot \rho_a \cdot c_d \cdot A_v \cdot e_{kin}(s)$$

Since (8) is only valid for positive kinetic energy values, the inequality constraint

$$e_{kin} \geq 0 \tag{9}$$

must be imposed on the optimisation problem.

To stay within the limitations of the vehicle, the traction force needs to be limited. The measured full-load curve as well as the traction force at coasting (giving the maximum and minimum possible traction force depending on the kinetic energy of the moving vehicle) of the Smart Electric Drive are given in Fig. 2. The full-load curve has been measured at fully pushing the accelerator pedal but without pressing the ”boost” switch below the accelerator pedal of the *Smart ED*. The traction force at coasting has been measured with released pedals (slight energy recovery).

However, since only linear constraints should be considered here, the measured curves are linearised using a least-squares approximation, resulting in the hatched polygon in Fig. 2 and represented by the following linear inequality:

$$F_{trac,min} \leq F_{trac} \leq c_1 \cdot e_{kin} + c_2; \quad e_{kin} \geq 0 \tag{10}$$

For coasting (driving with accelerator and brake pedal released), a constant minimum brake force $F_{trac,min}$ is considered.

2) Dynamic Model of the Energy Consumption: In order to relate the electrical input of the drive train with the mechanical power output, the drive train and motor characteristics must be modeled. A detailed model of all physical processes in these components is not suitable here due to its complexity.

Here, measurements of the overall drive train characteristics are available in the form of a characteristic map. The battery power P_{batt} is considered as a function of the traction force at the wheels F_{trac} and the driving speed v. The data to set up this relation has been extracted from measurements in static operating points on a dynamometer test bench. Since the battery power is measured, all drive train and ancillary losses are included. The resulting characteristics are depicted in Fig. 3. It is assumed that these characteristics measured in quasi-static operation also hold in dynamic operation since the electrical time constants are much faster than the ones related to the mechanics. Quasi-static drive train models are widely used in applications with accurate results [12].

Since the vehicle motion model (8) is formulated with respect to the position s, the energy consumption must also be derived in terms of position. Here, it is advantageous that every operating point in the power consumption map (Fig. 3) is related to a certain driving speed due to the fixed transmission ratio. Hence, each point of the power consumption map (Fig. 3) is divided by its related driving speed v according to reformulation (5) to obtain the energy consumption per meter. In addition to this, the x-axis is rescaled in terms of the kinetic energy of the moving vehicle in order to fully comply with the reformulated motion equation (8). The resulting map of the energy consumption per meter as a function of the kinetic energy and the traction force is given in Fig. 4a. The objective is to implement an approximation of these characteristics in the underlying dynamic model of the controller.

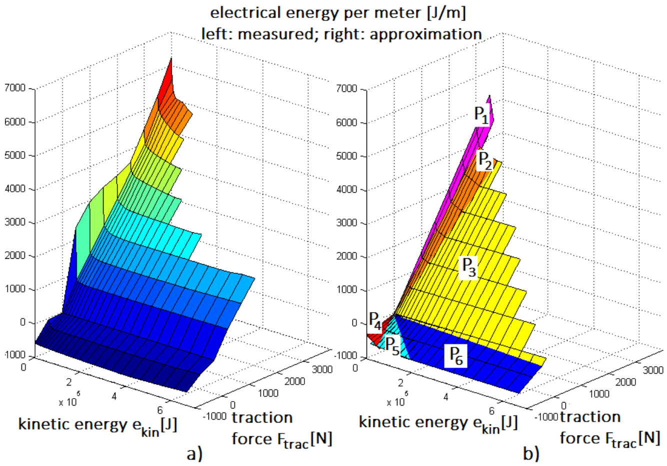

Fig. 4. The figure shows the vehicle energy consumption per meter. The x-axis has been rescaled in terms of the kinetic energy of the moving vehicle. a) gives the measured characteristics; b) gives the approximation by six linear inequalities.

One possible method for the approximation of energy consumption maps is the use of fitted polynomials [3], [15]. Nevertheless, a closer look at Fig. 4a shows that the given characteristics are more suitable for a piecewise linear approximation since they can hardly be captured by one single lower order polynomial. The use a piecewise linear problem formulation would be appropriate but in general requires the use of different dynamic models in different regions of the state space (i.e. operating points) which makes the problem more time-consuming to solve and less suitable for a real-time implementation. In the following, a problem formulation is presented that avoids the use of different dynamic models but still represents a piecewise linear energy consumption behaviour.

First of all, six linear functions (P_1 to P_6) that form the lower boundary of a convex set are introduced. They are fitted to the different regions of the map in Fig. 4a by a least-squares regression, see Fig. 4b. The different regions are chosen manually with respect to the gradient of the map. The approximations have the form

$$P_i(e_{kin}, F_{trac}) = a_i \cdot e_{kin} + b_i \cdot F_{trac}, \quad i = 1...6 \tag{11}$$

Secondly, P_1 to P_6 are transformed into inequality constraints on a decision variable u_{cons} that represents the energy consumption of the vehicle per meter.

$$P_i : \quad u_{cons} \geq a_i \cdot e_{kin} + b_i \cdot F_{trac}, \quad i = 1...6 \tag{12}$$

This step will lead to an approximation of the energy consumption map by the maximum of the set of linear functions (11) because the minimisation of the energy consumption will be part of the objective function.

$$u_{cons}(e_{kin}, F_{trac}) = max\Big(P_i(e_{kin}, F_{trac})\Big), \quad i = 1...6 \tag{13}$$

The optimisation problem (as discussed later in Section III-B) is then set up in a way that this maximum is determined implicitly in the optimisation and the decision variable u_{cons} always lies on the boundary of the feasible region and hence represents the energy consumption per meter of the vehicle according to the following piecewise linear model:

$$\begin{aligned} u_{cons} &= a_i \cdot e_{kin} + b_i \cdot F_{trac} \quad \text{if } P_i \text{ is active} \\ u_{cons} &\geq a_j \cdot e_{kin} + b_j \cdot F_{trac} \quad \text{for } j \neq i \end{aligned} \tag{14}$$

In other words, it can be stated that one of the inequality constraints (12) is always active. Which one is active depends on the actual operating point (specified by the kinetic energy e_{kin} and the traction force F_{trac}). Hence, the variable u_{cons} represents a piecewise linear approximation of the power consumption per meter without the necessity of defining a piece-wise changing dynamic model explicitly and using a solver for piece-wise linear problems.

Given this information, the energy consumption of the vehicle E_{el} can simply be modeled by integrating the decision variable u_{cons} (representing the energy consumption per meter) with respect to the position.

$$\frac{dE_{el}}{ds} = u_{cons} \tag{15}$$

Approximating nonlinear maps by (the maximum of) linear functions is a known technique in nonlinear optimisation and called *separable programming* [16]. However, to the best of the authors' knowledge, this method has so far not been used to model piecewise linear dynamics in MPC formulations.

B. Overall Problem Formulation

Based on the results of the previous sections, the complete model-predictive eco-cruise control problem is formulated as a dynamic optimisation problem with quadratic cost and linear constraints. The cost function consists of the weighted sum of the squared kinetic energy tracking error at the end of the prediction horizon

$$M_1(s_{end}) = Q_1 \cdot \big(e_{kin}(s_{end}) - e_{kin,ref}(s_{end})\big)^2 \tag{16}$$

and the squared energy consumption at the end of the prediction horizon

$$M_2(s_{end}) = Q_2 \cdot E_{el}(s_{end})^2 \tag{17}$$

as well as the accumulated kinetic energy tracking error throughout the horizon.

$$L(s) = Q_3 \cdot \big(e_{kin}(s) - e_{kin,ref}(s)\big)^2 \tag{18}$$

Including the terminal energy consumption $E_{el}(s_{end})$ (instead of the accumulated) leads to an "intelligent" predictive controller behaviour with the freedom to increase the consumption at any position if there is the benefit to save more energy later as a result of this anticipatory action. The squared terminal kinetic energy tracking error $(e_{kin}(s_{end}) - e_{kin,ref}(s_{end})^2$ is included in the cost function in order to prevent the controller from planning an undesirable standstill of the vehicle at each optimisation instant. The accumulated kinetic energy tracking error finally is a measure for the deviation from the speed reference trajectory. The initial value of the energy consumption $E_{el}(s_0)$ is constant (not updated) throughout the simulation and ensures that E_{el} can never be negative throughout the prediction horizon. The distance to the preceding car is considered in the speed reference generation to keep the optimisation simple.

The complete optimisation problem is given as follows:

$$\min_{F_{trac}(s),u_{cons}(s)} M_1(s_{end}) + M_2(s_{end}) + \int_{s_0}^{s_{end}} L(s) \cdot ds \tag{19a}$$

subject to the model of the system dynamics:

$$\begin{aligned} \frac{de_{kin}}{ds} &= F_{trac} - F_r - F_{gr} - F_d(e_{kin}) \\ \frac{dE_{el}}{ds} &= u_{cons} \end{aligned} \tag{19b}$$

subject to the initial conditions:

$$E_{el}(s_0) = E_{el,0}; \quad e_{kin}(s_0) = e_{kin,0} \tag{19c}$$

subject to the limits on states and inputs:

$$0 \le e_{kin}; \quad F_{trac,min} \le F_{trac} \le c_1 \cdot e_{kin} + c_2 \tag{19d}$$

subject to the approximations of the power consumption map:

$$u_{cons} \ge a_i \cdot e_{kin} + b_i \cdot F_{trac}, \quad i = 1...6 \tag{19e}$$

As already mentioned in Section III-A.2, this problem formulation includes the linear inequality constraints (19e) on the decision variable u_{cons}. In the cost function, u_{cons} only affects the energy consumption E_{el} (see (15), (17)), i.e. the cost function is *separable* with regard to this variable. Since the initial value $E_{el}(s_0)$ (see (19c)) ensures that E_{el} can never be negative throughout the prediction horizon, the optimiser will make the value of $E_{el}(s_{end})$ as small as possible. This can only be achieved by making the decision variable u_{cons} as small as possible at each position step. Hence, u_{cons} will always lie on the boundary of the feasible region defined by the inequality constraints (19e). Since different constraints become active in different operating points, this leads to a problem formulation that is equivalent to the use of a piecewise linear model of the energy consumption per meter u_{cons}.

IV. Simulation of the Closed-Loop Control

For the simulation of the control system, the proposed MPC controller is simulated in closed loop with the dynamic motion model formulated in terms of time (4) and the vehicle energy consumption model using the lookup table according to Fig. 3. A scenario including down-hill and up-hill driving is chosen. The speed reference and road slope profile is given in Fig. 5a+b.

The scenario is simulated twice with the proposed MPC controller but once with a zero weight on the energy consumption leading to pure kinetic energy reference tracking

TABLE I

Parameters of the controller setup

symbol	value	symbol	value
A_v	1.95 m^2	m_{eq}	1200 kg
c_d	0.38 $-$	m_l	170 kg
c_r	0.013 $-$	m_v	975 kg
g	9.81 m/s^2	ρ_a	1.2 kg/m^3
a_1	-0.0423 $1/m$	b_4	0.2876
a_2	-0.0034 $1/m$	b_5	0.5048
a_3	1.266E-4 $1/m$	b_6	0.62
a_4	-0.0054 $1/m$	c_1	-0.0056
a_5	-5.91E-4 $1/m$	c_2	3505
a_6	5.64E-6 $1/m$	$F_{trac,min}$	-658 N
b_1	1.5274	Q_1	5
b_2	1.3390	Q_2	0.75
b_3	1.2307	Q_3	0.5

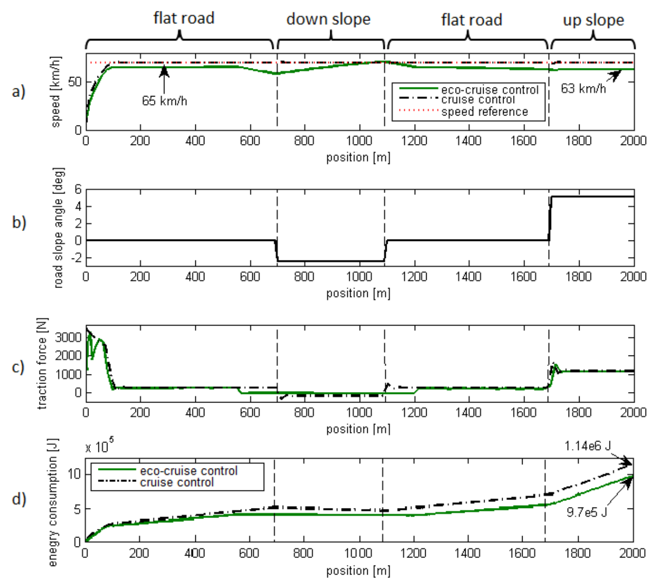

Fig. 5. Simulations results of the vehicle motion and energy consumption in closed-loop control.

for comparison. The optimisation problem (19) is discretised and solved consecutively by the *MATLAB Model-Predictive Control Toolbox* and the simulation is run within *SIMULINK*. The prediction horizon of the MPC controller comprises 40 steps of 10 m. The results are depicted in Fig. 5.

It should be noted that the simulation model is run with respect to time while the controller computes its predictions as a function of the position. This is equivalent to the situation in practical implementation, where the controller sampling time is constant while the travelled distance between two time instants depends on the driving speed. However, if the sampling time is sufficiently small, this will not result in an error.

The pure kinetic energy reference tracking controller starts accelerating the car as fast as possible and then keeps the speed constant despite of the disturbances (road gradient angle).

The eco-cruise controller accelerates at first with a pulsative traction force pattern and keeps the car then at a constant steady driving speed of 64.9 km/h on the even

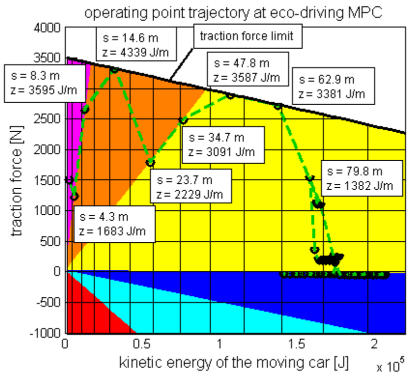

Fig. 6. Operating point trajectory (dashed green line) of the system controlled by the proposed eco-cruise controller.

road segment. Before the down-slope is reached, the vehicle decelerates. This shows the predictive behaviour of the MPC controller and serves to save energy since the speed loss can be recovered with no traction force effort during the upcoming down-slope. At down-hill driving, the vehicle accelerates up to a small overshoot over the desired speed of 70 km/h. This kinetic energy reserve allows to save energy on the following even road segment. In front of the following up-slope, the driving speed is decreased again down to 62.8 km/h.

To understand the acceleration pattern of the eco-cruise controller at the beginning of the simulation, a closer look at the simulated operating point trajectory is taken. Fig. 6 shows the projected top view onto the piecewise-linear approximation of the power consumption map that has been presented in Fig. 4.

The system trajectory leaves the magenta coloured plane (valid for operating points at very low speed) already in the second position step by reducing the traction force at a now higher driving speed to avoid driving at this state of high energy consumption. The simulated vehicle accelerates then along the borderline of the magenta and orange plane. After one position step at the maximum traction force limit, the operating point then moves to the intersection between the orange and yellow plane. This provides a good compromise of accelerating at a higher traction force without spending the progressive energy cost at the orange plane. The system trajectory shows the desired behaviour of avoiding driving at low efficiencies and the acceleration from standstill is still performed reasonably fast.

Since problem (19) only consists of quadratic cost function terms and linear constraints, the discretised problem can be written in the standard form of quadratic programming and turns out to be convex. The proof is omitted here for brevity. Convex quadratic programs can be solved in polynomial time which is a good basis for a real-time capable algorithm. In practical tests, the optimisation shall be solved every 0.1 seconds. The time to solve the optimisation problem within *MATLAB* on a desktop PC (Intel Core i7) varies between 0.3 and 0.6 seconds during the presented simulation. Solving the same problem with a C-code based quadratic programming solver, a significantly faster real-time capable computation can be expected.

V. Conclusion

The eco-cruise control problem is converted into the form of a quadratic optimisation with linear constraints without applying an overall linearisation. The major nonlinearities are considered by using reformulations of the original problem. The motion equation is reformulated to obtain a linear differential equation. The energy consumption of the vehicle is modeled by the maximum of several linear functions that is determined implicitly by the optimisation which makes the formulation equivalent to the use of a piecewise linear model. This provides a better fit of the vehicle characteristics than lower order polynomials. The proposed formulation guarantees a fast solution of the optimisation problem with guaranteed convergence and is much more suitable for a real-time implementation than a nonlinear problem formulation. The next step will be the practical implementation of the controller in the real vehicle.

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