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# Consumption minimisation for an academic vehicle

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## Abstract

The present article is a study of an optimal control problem having a non-differentiable, but Lipschitz, cost function. It is inspired by the minimisation of the energy consumption of a car-like vehicle or robot along a road which profile is known. This problem is stated by means of a simple model of the longitudinal dynamics and a running cost that comprises both an absolute value function and a function that accounts for the efficiency of the energy conversion process. A regularity result that excludes chattering phenomena from the set of solutions is proven. It is valid for the class of control affine systems, which includes the considered problem. Three case studies are detailed and analysed. The optimal trajectories are shown to be made of bang-bang, inactivated, singular and backward arcs.

## Introduction

This article presents a study of an optimal control problem having a non-differentiable cost for certain values of the control or of the state. One of the most notable class of such problems is known as  $L^1$ -minimisation and consists in the minimisation the  $L^1$ -norm of the control:

$$\int_0^{T_f} |u(t)| dt \rightarrow \min$$

As it is well-known, cf. [2, 5, 8, 9, 16, 18, 20], such a cost structure implies *inactivations*, that is, non-trivial intervals of time where the control vanishes. As mentioned in [9, 20], this behaviour seems relevant when considering energy consumption minimisation in the sense that inactivations act as a selection process that singles out moments when the control variable is the most efficient.

The problem addressed in this paper is an “academic” model of the optimal energy consumption of a car-like vehicle or robot along a road which profile is known. It follows the ideas of [4] regarding the minimisation of the absolute work of an actuated mechanical system. For instance, if  $x(t)$  is a displacement and  $u(t)$  a (external) force, the absolute work of  $u$  is just

$$\int_0^{T_f} |\dot{x}(t)u(t)| dt$$

In the paper, the running cost is derived from this latter expression with the help of a yield function that translates the efficiency of the energy conversion process. As it is discussed and highlighted in the rest of the article, optimal strategies are made of classic bang-bang controls and inactivations, but may also include singular arcs that cannot be obtained from the successive time derivatives of the switching function (e.g. [3, 11]).

In Section 1, the problem under consideration is stated through the derivation of both the model of the vehicle dynamics and the running cost. Section 2 is dedicated to two regularity issues, namely, a theorem that allows us to exclude chattering phenomena and a lemma that allows us to restrict the set of candidate trajectories for optimality. Finally, three case studies are detailed in Section 3.

The first case, for a flat road and without friction, is treated in Section 3.1. It is very simple since optimal trajectories are always obtained from bang-bang controls and inactivations only. Although counterintuitive, in this case, the optimal strategy doesn't depend on the yield function used. In the second case study, where frictions are now considered, optimal trajectories having singular arcs are observed. The presence of such arcs depends more on the value of the final time than on the yield function itself. Still, this function has a noticeable influence on the result, as it is highlighted in Section 3.2. The third case study is addressed in Section 3.3, where a non-flat road profile and no friction coefficient are considered. On top of all the previous phenomena, we display optimal trajectories that require the vehicle to travel backward for some time.

## 1 Problem statement

In the following, in order to simplify the notations, the time dependency of time varying functions is omitted as soon as there is no ambiguity. The sign function is denoted by  $\text{sgn}$ , and  $X^t$  is the transpose of vector  $X$ .

### 1.1 Vehicle dynamics

The vehicle travels on a road represented in a position-height plane as it is sketched in Figure 1 (see [19, 12] for a model that takes into account both the longitudinal and the lateral dynamics). Its coordinates are denoted by  $(\xi, h)$ , and  $\theta$  is the orientation. We assume that only the four following forces act on the vehicle and that the tyre slip is negligible:

- the gravity  $\mathbf{G}$ , which norm is equal to the gravitational constant  $g$  times the mass of the car  $m$ ;
- the reaction of the road  $\mathbf{R}$ , which norm equals  $mg \cos(\theta)$ ;
- the propulsion force  $\mathbf{F}$ , which norm is the control variable  $u(t)$ ;
- the drag force  $\mathbf{f}$  opposes motion and, in this work, we consider fluid friction only with a norm proportional to speed:  $\|\mathbf{f}\| = \alpha \sqrt{\dot{\xi}^2 + \dot{h}^2}$  where  $\alpha \geq 0$  is the drag coefficient.

The dynamics is given by Newton's second law of motion:

$$m \begin{pmatrix} \ddot{\xi} \\ \ddot{h} \end{pmatrix} = \begin{pmatrix} u \cos(\theta) \\ u \sin(\theta) \end{pmatrix} - \begin{pmatrix} 0 \\ mg \end{pmatrix} - \begin{pmatrix} \alpha \text{sgn}(\dot{\xi}) \sqrt{\dot{\xi}^2 + \dot{h}^2} \cos(\theta) \\ \alpha \text{sgn}(\dot{\xi}) \sqrt{\dot{\xi}^2 + \dot{h}^2} \sin(\theta) \end{pmatrix} + \begin{pmatrix} -mg \cos(\theta) \sin(\theta) \\ mg \cos^2(\theta) \end{pmatrix} \quad (1)$$

We assume that the road profile is given by a  $\mathcal{C}^1$  function  $h = \varphi(\xi)$ . Since the angle  $\theta$  belongs to the interval  $]-\frac{\pi}{2}, \frac{\pi}{2}[$ , it is uniquely determined by  $\theta(\xi) = \arctan(\varphi'(\xi))$  where  $\varphi'$  denotes the derivative with respect to  $\xi$ . Thus, system (1) has in fact only one degree of freedom having the following dynamics:

$$\begin{cases} m\ddot{\xi} = u \cos(\theta(\xi)) - \alpha \dot{\xi} \sqrt{1 + (\varphi'(\xi))^2} \cos(\theta(\xi)) - mg \cos(\theta(\xi)) \sin(\theta(\xi)) \\ \theta(\xi) = \arctan(\varphi'(\xi)) \end{cases} \quad (2)$$

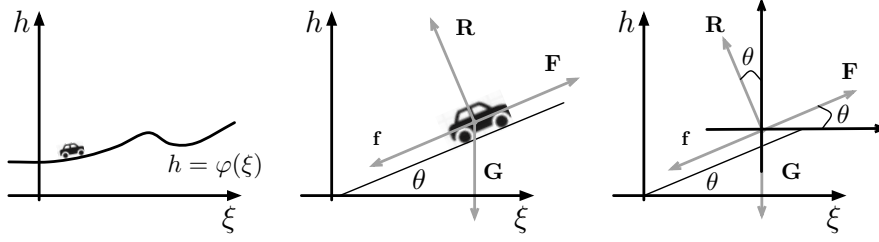


Figure 1: Modelling and notations.

Now, let  $x$  be the curvilinear abscissa of  $(\xi, h(\xi))$  and  $y$  be equal to  $\dot{x}$  —i.e.  $x = \int_0^\xi \sqrt{1 + (\varphi'(z))^2} dz$  and  $y = \dot{\xi} \sqrt{1 + (\varphi'(\xi))^2}$ . Then, system (2) rewrites:

$$\begin{cases} \dot{x} = y \\ m\dot{y} = u - \alpha y - mg \sin(\theta(x)) \end{cases} \quad (3)$$

where  $\theta(x)$  is the  $C^1$  function that accounts for the road profile — $h = \varphi(\xi)$  is recovered from  $\theta(x)$ .

## 1.2 Cost function

The cost function is the energy consumed to steer the vehicle from a starting position to some final position in time  $T_f$ . Let  $D(t)$  be the energy flow rate. The associated cost function is simply

$$\int_0^{T_f} D(\tau) d\tau.$$

Now, let  $A$  be the absolute work of the propulsion force. It is given by

$$A = \int_0^{T_f} |\dot{\xi} u| \sqrt{1 + (\varphi'(\xi))^2} d\tau$$

The associated absolute instantaneous power writes  $\frac{dA}{dt}$  and is connected to the flow rate with the help of a yield function  $\rho(\cdot)$ :  $\frac{dA}{dt} = D(t)\rho(\cdot)$ . We assume that the yield function is as follows (examples are shown in Figure 2):

- its argument is the speed of the vehicle —i.e.  $y = \dot{\xi} \sqrt{1 + (\varphi'(\xi))^2}$ ;
- it takes its values in the interval  $]0, 1]$ , for all  $y \in \mathbb{R}$ ;
- it has one of the two following behaviours for all  $y \in \mathbb{R}^+$  (respectively  $\mathbb{R}^-$ ):
  1.  $\rho(y)$  is identically constant;
  2.  $\rho(y)$  admits a maximum at  $y^+$ , is increasing on  $]0, y^+[$  and decreasing on  $]y^+, +\infty[$ ;  
( $\rho(y)$  admits a maximum at  $y^-$ , is decreasing on  $]y^-, 0[$  and increasing on  $] -\infty, y^- ]$ );
- it is differentiable as many times as needed.

Finally, the cost function is denoted by  $J(u)$  and has the following expression:

$$J(u) = \int_0^{T_f} \frac{|\dot{\xi}u|}{\rho(\dot{\xi}\sqrt{1+(\varphi'(\xi))^2})} \sqrt{1+(\varphi'(\xi))^2} d\tau = \int_0^{T_f} \frac{|yu|}{\rho(y)} d\tau \quad (4)$$

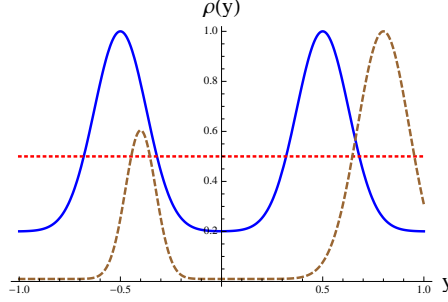


Figure 2: Yield function examples.

**Remark 1.** *The proposed model for the running cost may not feel very realistic since the energy consumption is the same while accelerating ( $u > 0$ ) or braking ( $u < 0$ ). First of all, let us mention that our goal is to capture the influence of the non-differentiability on the optimal strategy. As such, the energy that a decelerating electric engine would send back to the accumulators is not considered for simplicity. Also, the considered cost models small robots not equipped with regenerative braking systems. Moreover, in order to better model an internal combustion engine where braking costs almost nothing, phases when  $u < 0$  can be discriminated with the help of a function of the form:*

$$v(u) = \begin{cases} \alpha u & \text{for } u \geq 0 \\ -\beta u & \text{for } u < 0 \end{cases} \quad \text{with } 0 < \beta \leq \alpha \quad \text{and} \quad J(u) = \int_0^{T_f} \frac{|y|v(u)}{\rho(y)} d\tau$$

*This new cost function will have an impact on the several calculations and on the switching times, but not on the qualitative behaviours displayed in the remainder of the article.*

### 1.3 A fixed-time optimal control problem

In the remainder of this paper, we restrict our study to trajectories having a forward destination and a fixed final time  $T_f$ . Also, in order to ease the exposure of the study, we set the parameters  $m$  and  $g$  to 1. The optimal control problem under consideration is:

$$(\mathcal{P}_1) \left\{ \begin{array}{l} \text{Minimise} \quad J(u) = \int_0^{T_f} \frac{|yu|}{\rho(y)} d\tau \\ \text{Subject to} \quad (\Sigma_1) \quad \begin{cases} \dot{x} = y \\ \dot{y} = u - \alpha y - \sin(\theta(x)) \end{cases} \quad \text{for } t \in [0, T_f] \\ \\ X(0) = \begin{pmatrix} x(0) \\ y(0) \end{pmatrix} = \begin{pmatrix} 0 \\ 0 \end{pmatrix}, \quad X(T_f) = \begin{pmatrix} x(T_f) \\ y(T_f) \end{pmatrix} = \begin{pmatrix} x_f \\ 0 \end{pmatrix}, \quad \text{with } x_f > 0 \\ \\ |u(t)| \leq 1 \quad \text{for } t \in [0, T_f] \\ \\ T_f > 0 \text{ is fixed.} \end{array} \right.$$

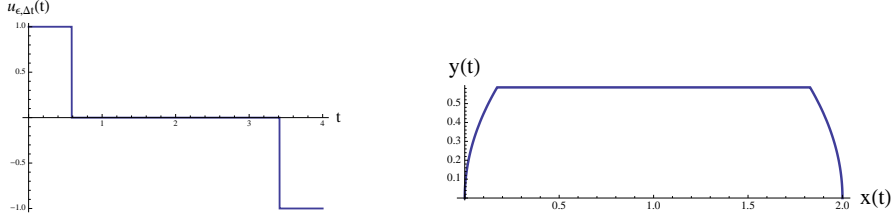


Figure 3: Control strategy of the form  $u_{\epsilon, \Delta t}(t)$ , and associated trajectory.

Following [15, Thm. 4, P. 259], and also [4, 5], the set of solutions to this problem is non-empty as soon as  $T_f$  is greater or equal to the minimum time problem associated to  $(\mathcal{P}_1)$ .

Let us remark that, in order to perform a study in free time,  $(\mathcal{P}_1)$  requires a specific road profile, a cost that penalises the travel time or a specific yield function  $\rho(y)$ . This statement is illustrated in the case of a flat road (i.e.  $\theta \equiv 0$ ) by the following proposition.

**Proposition 1.** *Let us consider problem  $(\mathcal{P}_1)$  with a flat road (that is to say  $\theta \equiv 0$ ). If the final time  $T_f$  is free then the minimum value of the cost function  $J$  is not reached.*

*Proof.* We first detail the case when  $\alpha = 0$ : system  $(\Sigma_1)$  is just a double integrator. Let us now consider the following family of controls —see Figure 3:

$$u_{\epsilon, \Delta t}(t) = \begin{cases} \epsilon & \text{for } t \in [0, \Delta t[ \\ 0 & \text{for } t \in [\Delta t, T_f - \Delta t[ \\ -\epsilon & \text{for } t \in [T_f - \Delta t, T_f] \end{cases} \quad (5)$$

The trajectory of  $(\Sigma_1)$  is easily computed —see Figure 3 for an example. For a given  $x_f$ , we have:

$$x(T_f) = \epsilon \Delta t (T_f - \Delta t) \Rightarrow T_f = \frac{\epsilon \Delta t^2 + x_f}{\epsilon \Delta t}$$

The cost of this trajectory is  $J(u) = \int_0^{\Delta t} \frac{\epsilon y}{\rho(y)} dt + \int_{T_f - \Delta t}^{T_f} \frac{\epsilon y}{\rho(y)} dt$  and tends toward 0 either when  $\Delta t \rightarrow 0$  or  $\epsilon \rightarrow 0$ . In both cases,  $T_f \rightarrow \infty$  and the minimum cost is not reached.

For  $\alpha > 0$ , we consider the family of controls:

$$u_\epsilon(t) = \begin{cases} \epsilon & t \in [0, \Delta t[ \\ -\epsilon & t \in [\Delta t, T_f] \end{cases} \quad (6)$$

Again, the trajectory is easily computed. For a fixed  $\epsilon > 0$ , the constraint  $y(T_f) = 0$  provide the expression  $T_f = \frac{1}{\alpha} \ln(2e^{\alpha \Delta t} - 1)$ . This latter expression is used together with the constraint  $x(T_f) = x_f$  to provide the following expression for  $\Delta t$ :

$$\Delta t = \frac{1}{\alpha} \ln \left( e^{\frac{\alpha^2 x_f}{\epsilon}} + \sqrt{e^{\frac{\alpha^2 x_f}{\epsilon}} \left( e^{\frac{\alpha^2 x_f}{\epsilon}} - 1 \right)} \right)$$

Since  $\Delta t \xrightarrow{\epsilon \rightarrow 0} \infty$ , the same goes for  $T_f$  while  $J(u_\epsilon) \xrightarrow{\epsilon \rightarrow 0} 0$ . As before, the minimum is not reached. An example of such a trajectory is shown in Figure 4.  $\square$

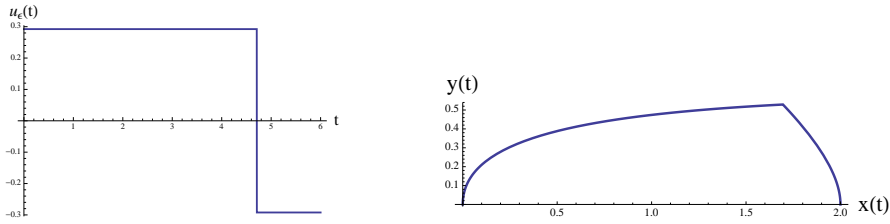


Figure 4: Control strategy of the form  $u_\varepsilon(t)$ , and associated trajectory.

## 2 On the regularity of the problem

In this section, we address two regularity issues:

- a theorem about the regularity of controls that are solution to a class of problems that includes  $(\mathcal{P}_1)$ ;
- a lemma showing that for specific road profiles the search for optimal solutions can be limited to the set of forward trajectories.

### 2.1 Regularity of the control variable

Let  $(\Sigma_0)$  be the following system for all  $t \in [0, T]$  with  $T > 0$  fixed:

$$(\Sigma_0) \quad \dot{x} = F(x) + uG(x)$$

The initial state of  $(\Sigma_0)$  is denoted by  $x_0 \in \mathbb{R}^n$ ,  $n > 0$ . The vector fields  $F(\cdot)$  et  $G(\cdot)$  are assumed real analytic. The control variable is such that  $|u(t)| \leq 1$ . The associated input-output application is:

$$\begin{aligned} \Phi : \mathbb{R}^n \times L^1_{[0,T]} &\longrightarrow C^0_{[0,T]} \\ (x_0, u(t)) &\mapsto x(\cdot) \end{aligned}$$

where  $x(\cdot)$  is the trajectory of  $(\Sigma_0)$  with initial state  $x_0$  and control  $u(\cdot)$ . For a given  $x_0$ , we denote  $\Phi_{x_0}(u) = \Phi(x_0, u)$ . The set  $L^1_{[0,T]}$  is embedded with its natural topology,  $C^0_{[0,T]}$  has the topology of uniform convergence, and  $\mathbb{R}^n$ , the Euclidean metric topology.

Let  $\psi(\cdot)$  be a continuous function. The cost associated to a trajectory of  $(\Sigma_0)$  generated by  $u(\cdot)$  and  $x_0$  is:

$$\begin{aligned} J : \mathbb{R}^n \times L^1_{[0,T]} &\longrightarrow \mathbb{R}^+ \\ (x_0, u(t)) &\mapsto \int_0^T |\psi(x)u| dt \end{aligned}$$

**Lemma 1.**  $\Phi(\cdot)$  and  $J(\cdot)$  are uniformly continuous functions.

*Proof.* For the sake of completeness, the proof of this lemma is given in Appendix A.  $\square$

**Theorem 1.** Let  $\mathcal{PA}$  be the  $L^1_{[0,T]}$ -subset made of piecewise algebraic controls —i.e. algebraic on a finite number of subintervals of  $[0, T]$ . Let us consider an optimal control problem of the

form:

$$(\mathcal{P}_0) \left\{ \begin{array}{l} \text{Minimise} \quad J(u) = \int_0^{T_f} |\psi(x(\tau))u(\tau)| d\tau \\ \text{Subject to} \quad (\Sigma_0) \quad \dot{x}(t) = F(x(t)) + uG(x(t)) \quad \text{for } t \in [0, T_f] \\ \\ x(0) = x_0 \text{ and } x(T_f) = x_f \\ \\ |u(t)| \leq 1 \quad \text{for } t \in [0, T_f] \\ \\ T_f > 0 \text{ is fixed} \end{array} \right.$$

under the hypotheses:

( $\mathcal{H}_0$ )  $\psi(\cdot)$  has a maximum on  $\mathbb{R}^n$ ;

( $\mathcal{H}_1$ )  $J(\cdot)$  has a minimum on  $\mathcal{PA}$ , which we denote by  $J_M$ ;

( $\mathcal{H}_2$ ) the minimum time trajectories of  $(\Sigma_0)$  are given by controls belonging to  $\mathcal{PA}$ ;

( $\mathcal{H}_3$ )  $(\Sigma_0)$  is small time locally controllable at  $x_f$ ;

( $\mathcal{H}_4$ )  $(x_f, u_f)$  is an equilibrium point of  $(\Sigma_0)$  such that  $\psi(x_f)u_f \equiv 0$ .

Then  $J_M$  is the minimum of  $J(\cdot)$  over  $L^1_{[0, T_f]}$ .

The theorem is also true when  $x_f$  is replaced by  $x_0$  in hypotheses ( $\mathcal{H}_3$ ) and ( $\mathcal{H}_4$ ).

*Proof.* Let us fix an initial state  $x_0$  and a final state  $x_f$ . Assume that there exists a control  $u^* \in (L^1_{[0, T_f]} \setminus \mathcal{PA})$  steering  $(\Sigma_0)$  from  $x_0$  to  $x_f$  such that  $J(u^*) < J_M$ . We show that it is in contradiction with ( $\mathcal{H}_1$ ).

First of all, let us remark that there exist  $\varepsilon > 0$  and an interval  $I_\varepsilon$  of measure  $\varepsilon$  such that the trajectory  $x^*$  of  $(\Sigma_0)$  generated by  $u^*$  is not the solution to the minimal time problem on  $I_\varepsilon$ . Indeed, if there is no such  $\varepsilon$ , then  $x^*$  is the solution to the minimal time problem, which contradicts ( $\mathcal{H}_2$ ) since  $u^* \notin \mathcal{PA}$ .

Let  $u_\varepsilon$  be a new control constructed from  $u^*$  as follows.

1. Let  $t_1$  and  $t_2$  denote the boundaries of  $I_\varepsilon$ , with  $0 \leq t_1 < t_2 \leq T_f$ .
2. For all  $t \leq t_1$ ,  $u_\varepsilon(t) = u^*(t)$ .
3. Next,  $u_\varepsilon(t)$  equals the solution to the minimum time problem associated to  $(\Sigma_0)$  with starting point  $x^*(t_1)$  and final point  $x^*(t_2)$ .  
The corresponding travel time is denoted by  $t_{min}$ , and of course  $t_1 + t_{min} < t_2$ .  
Let  $\delta$  denote the time saved in the process —i.e.  $\delta = t_2 - t_1 - t_{min}$ .
4. Since  $(\Sigma_0)$  is time invariant, for  $t \in ]t_1 + t_{min}, \leq T_f - \delta]$ , then  $u_\varepsilon(t) = u^*(t_2 - t_1 - t_{min} + t)$  steers  $x$  from  $x(t_1 + t_{min}) = x(t_2)$  to  $x_f$ .
5. Finally,  $u_\varepsilon(t) = u_f$  for  $t \in ]T_f - \delta, T_f]$ .



The new control variable  $u_\varepsilon$  steers  $x$  from  $x_0$  to  $x_f$ , and the cost difference between the trajectory associated to  $u_\varepsilon$  (denoted by  $x_\varepsilon$ ) and the trajectory associated to  $u^*$  is:

$$\begin{aligned}
J(u^*) - J(u_\varepsilon) &= \int_0^{T_f} |\psi(x(t))u(t)| dt - \int_0^{T_f} |\psi(x_\varepsilon(t))u_\varepsilon(t)| dt \\
&= \underbrace{\int_0^{t_1} |\psi(x(t))u(t)| dt}_A + \underbrace{\int_{t_1}^{t_2} |\psi(x(t))u(t)| dt}_B + \underbrace{\int_{t_2}^{T_f} |\psi(x(t))u(t)| dt}_C \\
&\quad - \underbrace{\int_0^{t_1} |\psi(x_\varepsilon(t))u_\varepsilon(t)| dt}_D - \underbrace{\int_{t_1}^{t_1+t_{min}} |\psi(x_\varepsilon(t))u_\varepsilon(t)| dt}_E \\
&\quad - \underbrace{\int_{t_1+t_{min}}^{T_f-\delta} |\psi(x_\varepsilon(t))u_\varepsilon(t)| dt}_F - \underbrace{\int_{T_f-\delta}^{T_f} |\psi(x_\varepsilon(t))u_\varepsilon(t)| dt}_G
\end{aligned}$$

1. By definition of  $u_\varepsilon$ , we have  $A = D$ .
2. The measures of  $[t_1+t_{min}, T_f-\delta]$  and  $[t_2, T_f]$  are the same —i.e.  $T_f-\delta-t_1-t_{min} = T_f-t_2$ .  
Furthermore
  - (a) for  $t \in [0, T_f - t_2]$ ,  $u_\varepsilon(t_1 + t_{min} + t) = u^*(t_2 + t)$ ,
  - (b)  $x_\varepsilon(t_1 + t_{min}) = x^*(t_2)$ ,
  - (c)  $(\Sigma_0)$  is time invariant.

Thus,  $\forall t \in [0, T_f - t_2]$ ,  $x_\varepsilon(t_1 + t_{min} + t) = x^*(t_2 + t)$ .

And finally, since the function  $\psi(\cdot)$  is also time invariant, then  $C = F$ .

3. since  $(x_\varepsilon, u_\varepsilon) = (x_f, u_f)$  over  $[T_f - \delta, T_f]$ , then  $G = 0$  —cf. hypothesis  $(\mathcal{H}_4)$ .

Those considerations lead to:

$$\begin{aligned}
|J(u^*) - J(u_\varepsilon)| &= \left| \int_{t_1}^{t_2} |\psi(x(t))u(t)| dt - \int_{t_1}^{t_1+t_{min}} |\psi(x_\varepsilon(t))u_\varepsilon(t)| dt \right| \\
&\leq \int_{t_1}^{t_2} \underbrace{|\psi(x(t))|}_{\leq M} \underbrace{|u(t)|}_{\leq 1} dt + \int_{t_1}^{t_1+t_{min}} |\psi(x_\varepsilon(t))| |u_\varepsilon(t)| dt \\
&\leq M(t_2 - t_1) + Mt_{min} \leq 2\varepsilon M
\end{aligned}$$

where  $M > 0$  denotes the maximum of  $\psi(\cdot)$  —cf. hypothesis  $(\mathcal{H}_0)$ .

Henceforth, we fix  $\varepsilon > 0$  such that  $2\varepsilon M < \frac{J(u^*)-J_M}{3}$ , and  $x_\varepsilon$  is the trajectory of  $(\Sigma_0)$  given by  $x_0$  and  $u_\varepsilon$ .

As a consequence, the small time  $\delta > 0$  is now fixed. The same goes for the accessibility set of  $(-\Sigma_0)$  starting<sup>1</sup> from  $x_f$  for times less or equal than  $\delta$ . We denote this set by  $\mathcal{A}_\delta^-(x_f)$ .

Following [13]:

<sup>1</sup> $(-\Sigma_0)$  denotes system  $(\Sigma_0)$  with reversed time.

1. the small time local controllability of  $(\Sigma_0)$ , implies the small time local controllability of  $(-\Sigma_0)$ ;
2. the real analyticity hypothesis for  $F(x)$  and  $G(x)$  leads to the small time self-reachability of  $(-\Sigma_0)$ ;
3. since  $x_f$  is an equilibrium point of  $(-\Sigma_0)$ , then self-reachability is valid in fixed time.

Therefore, for any point in  $\mathcal{A}_\delta^-(x_f)$ , there exist a control  $u_\varepsilon \in \mathcal{PA}$  steering this point to  $x_f$  in a time exactly equal to  $\delta$ . The cost of such a piece of trajectory is:

$$\int_{T_f-\delta}^{T_f} |\psi(x_\varepsilon(t))u_\varepsilon(t)| dt \leq 2\delta M < 2\varepsilon M < \frac{J(u^*) - J_M}{3} \quad (7)$$

Let us now construct a  $L^1_{[0, T_f]}$ -perturbation of  $u_\varepsilon$  that lives in  $\mathcal{PA}$  and denoted by  $u_\delta$ . It is important to point out that the reachable set  $\mathcal{A}_\delta^-(x_f)$  is now independent from the construction that follows. This is a crucial point of the proof.

Firstly, following Luzin's theorem (i.e. [14]), for all  $m > 0$  there is a continuous function  $\mathcal{C}_\delta$  such that  $\{t : \mathcal{C}_\delta(t) \neq u_\varepsilon(t)\}$  is of measure at most  $m$ . Next, the function  $\mathcal{C}_\delta$  is saturated in  $\pm 1$  in order to obtain a continuous function  $\bar{\mathcal{C}}_\delta$  such that  $\|u_\varepsilon - \bar{\mathcal{C}}_\delta\|_{L^1} < 2m$ .

Secondly, there is a sequence of polynomials, denoted by  $\{P_n\}_{n \in \mathbb{N}}$ , that converges uniformly to  $\bar{\mathcal{C}}_\delta$ . Therefore, for all  $\tilde{m} > 0$ , there exists a polynomial  $P_\delta$  taken from  $\{P_n\}_{n \in \mathbb{N}}$  which is  $\tilde{m}$ -close to  $\bar{\mathcal{C}}_\delta$  in the  $L^1_{[0, T_f]}$ -sense. We consider the control variable  $u_\delta(t) \in \mathcal{PA}$  obtained from the polynomial  $P_\delta$  saturated in  $\pm 1$ , then  $\|u_\varepsilon - u_\delta\|_{L^1} < 2m + \tilde{m}$ .

The uniform continuity of  $\Phi_{x_0}(\cdot)$ , and  $J_{x_0}(\cdot)$ , cf. Lemma 1, guarantees that we can choose  $m$  and  $\tilde{m}$  such that:

1.  $|J(u_\varepsilon) - J(u_\delta)| < \frac{J(u^*) - J_M}{3}$ ,
2.  $x_\delta(T_f - \delta)$  is close to  $x_f$ , that is to say  $x_\delta(T_f) \in \mathcal{A}_\delta^-(x_f)$ .

Finally, the following control  $\tilde{u} \in \mathcal{PA}$  steers  $x_0$  to  $x_f$  in a fixed time  $T_f$ :

$$\tilde{u}(t) = \begin{cases} u_\delta(t) & \text{if } 0 \leq t \leq T_f - \delta \\ u_\varepsilon(t) & \text{otherwise} \end{cases}$$

In particular, we have the relations  $J(\tilde{u}) = J(u_\delta) + J(u_\varepsilon)$  and

$$|J(u^*) - J(\tilde{u})| < \underbrace{|J(u^*) - J(u_\varepsilon)|}_{< \frac{J(u^*) - J_M}{3}} + \underbrace{|J(u_\varepsilon) - J(u_\delta)|}_{< \frac{J(u^*) - J_M}{3}} + \underbrace{|J(u_\varepsilon)|}_{< \frac{J(u^*) - J_M}{3}} < J(u^*) - J_M$$

which contradicts the minimality of  $J_M$  over the subset  $\mathcal{PA}$  —i.e. hypothesis  $(\mathcal{H}_1)$ — and concludes the proof.

Now, let us show how this result is preserved when  $(x_0, u_0)$  is the equilibrium point around which  $(\Sigma_0)$  is small time locally controllable.

- The control  $u_\varepsilon(t)$  is constructed the same way, except that it equals  $u_0$  over  $[0, \delta]$ .

- The small time  $\delta$  being fixed during the previous step, the same goes for the reachable set of  $(\Sigma_0)$  starting from  $x_0$ , in time less or equal to  $\delta$ :  $\mathcal{A}_\delta^+(x_0)$ .  
As before, the results on small time self-reachability guarantee the existence of a control on  $\mathcal{PA}$  that steers  $x_0$  to any point of  $\mathcal{A}_\delta^+(x_0)$  in a time that is exactly equal to  $\delta$ . The cost of such a piece of trajectory is less than  $\frac{J(u^*)-J_M}{3}$ .
- $x_\varepsilon(t)$  denotes the trajectory starting from  $x_0$  when the control  $u_\varepsilon$  is applied. We define  $\tilde{x}_\varepsilon(\tau) = x_\varepsilon(T_f - \tau)$  which dynamics is:

$$\frac{d\tilde{x}_\varepsilon}{d\tau} = - \left. \frac{x_\varepsilon(t)}{dt} \right|_{(T_f-\tau)} = -F(\tilde{x}_\varepsilon(\tau)) - u_\varepsilon(T_f - \tau)G(\tilde{x}_\varepsilon(\tau))$$

The control  $\tilde{u}_\varepsilon(\tau) = u_\varepsilon(T_f - \tau)$ , for  $\tau \in [0, T_f - \delta]$ , applied to  $(-\Sigma_0)$  steers  $\tilde{x}(0) = x_f$  to  $\tilde{x}(T_f - \delta) = x_0$ .

Again, we use Luzin's theorem and the density property of polynomials. Since Lemma 1 also applies to system  $(-\Sigma_0)$ , there is therefore a control  $\tilde{u}_\delta \in \mathcal{PA}$  such that  $|J(\tilde{u}_\delta) - J(\tilde{u}_\varepsilon)| < \frac{J(u^*)-J_M}{3}$ , such that  $\tilde{x}_\delta(T_f - \delta) \in \mathcal{A}_\delta^+(x_0)$ .

- With a change of variable similar to the one of the previous step —i.e.  $x_\delta(t) = \tilde{x}_\delta(T_f - t)$ — the control  $u_\delta(t) = \tilde{u}_\delta(T_f - t)$ , for  $t \in [\delta, T_f]$ , applied to  $(\Sigma_0)$ , steers some point  $x_\delta(\delta) \in \mathcal{A}_\delta^+(x_0)$  to  $x_\delta(T_f) = \tilde{x}_\delta(0) = x_f$ .
- Finally, a  $\mathcal{PA}$  control steering  $x_0$  to  $x_f$ , with an associated cost less than  $J_M$  is obtained by firstly joining  $x_0$  to  $x_\delta(\delta) \in \mathcal{A}_\delta^+(x_0)$  for  $t \in [0, \delta]$ , and secondly using  $u_\delta(t)$  for  $t \in [\delta, T_f]$ .  $\square$

**Remark 2.** *The small time self-reachability of  $(\Sigma_0)$  is a key point of the proof. As it can be seen in Corollary 4.15 of [13], the property “ $F(\cdot)$  and  $G(\cdot)$  are real analytic vector fields” can be replaced by “ $F(\cdot)$  and  $G(\cdot)$  are  $\mathcal{C}^1$  and locally bounded”.*

## 2.2 Trajectories without backward arcs

A **backward arc** is understood as a piece of trajectory, defined over a non-trivial interval of time, along which the quantity  $y$  is strictly negative.

**Lemma 2.** *Let us consider a road profile such that Problem  $(\mathcal{P}_1)$  is invariant under a translation along the  $\mathcal{O}x$  axis of the phase diagram of  $(\Sigma_1)$ . Then, trajectories including backward arcs can be disregarded when looking for solutions to  $(\mathcal{P}_1)$ .*

*Proof.* Let  $\Gamma(t) = (x_\Gamma(t), y_\Gamma(t))^t$  be a trajectory of  $(\Sigma_1)$ . According to Theorem 1, in order to be a candidate for optimality, this trajectory is made of a finite number of arcs. Let us assume that  $y_\Gamma(t)$  has only one backward arc —the following argument remains in the case of multiple backward arcs.

$$y_\Gamma(t) = \begin{cases} y_\Gamma(t) < 0 & \text{over } [0, t_1[ \\ y_\Gamma(t) \geq 0 & \text{over } [t_1, T_f] \end{cases}$$

Let  $\Gamma^-$  denote the arc such that  $y < 0$ , and  $\Gamma^+$  the other one. We now construct a new trajectory, denoted by  $\gamma = (x_\gamma, y_\gamma)^t$ , that doesn't include any backward arc and which associated cost is less or equal to the one of  $\Gamma$ . The explanations below are illustrated in Figure 5.

Let us translate the arc  $\Gamma^+$  along the  $\mathcal{O}x$  axis in order to move  $A = (x_\Gamma(t_1), y_\Gamma(t_1))^t$  to  $(0, 0)^t$ . This new curve, denoted by  $\Gamma_{trans}^+$  is the dotted curve in Figure 5. The time instants  $t_2$  and  $t_3$  are defined as follows:

- let  $B$  be the intersection point between  $\Gamma^+$  and  $\Gamma_{trans}^+$ , then  $B = (x_\Gamma(t_3), y_\Gamma(t_3))^t$ ;

- let  $C$  be the translation of  $B$  when  $\Gamma_{trans}^+$  is translated back to  $\Gamma^+$ , then  $C = (x_\Gamma(t_2), y_\Gamma(t_2))^t$ .

The trajectory  $\gamma$  is:

$$\gamma(t) = \begin{cases} \Gamma_{trans}^+(t+t_1) & \text{for } 0 \leq t \leq t_2 - t_1 \\ \Gamma^+(t+t_3) & \text{for } t_2 - t_1 \leq t \leq (t_2 - t_1) + (T_f - t_3) \\ (x_f, 0)^t & \text{for } (t_2 - t_1) + (T_f - t_3) \leq t \leq T_f \end{cases}$$

Let  $u_\Gamma$  (resp.  $u_\gamma$ ) denote the control corresponding to  $\Gamma$  (resp.  $\gamma$ ), and  $J^\Gamma(u)$  (resp.  $J^\gamma(u)$ ) the

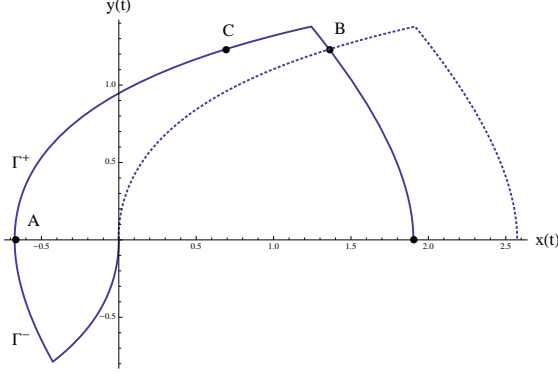


Figure 5: The  $\Gamma(t)$  trajectory.

associated cost:

$$\begin{aligned} J^\Gamma(u) &= \int_0^{T_f} \frac{|y_\Gamma u_\Gamma|}{\rho(y_\Gamma)} dt = \int_0^{t_1} \frac{|y_\Gamma u_\Gamma|}{\rho(y_\Gamma)} dt + \int_{t_1}^{t_2} \frac{|y_\Gamma u_\Gamma|}{\rho(y_\Gamma)} dt + \int_{t_2}^{t_3} \frac{|y_\Gamma u_\Gamma|}{\rho(y_\Gamma)} dt + \int_{t_3}^{T_f} \frac{|y_\Gamma u_\Gamma|}{\rho(y_\Gamma)} dt \\ &\geq \int_{t_1}^{t_2} \frac{|y_\Gamma u_\Gamma|}{\rho(y_\Gamma)} dt + \int_{t_3}^{T_f} \frac{|y_\Gamma u_\Gamma|}{\rho(y_\Gamma)} dt = \int_0^{t_2-t_1} \frac{|y_\gamma u_\gamma|}{\rho(y_\gamma)} dt + \int_{t_2-t_1}^{(t_2-t_1)+(T_f-t_3)} \frac{|y_\gamma u_\gamma|}{\rho(y_\gamma)} dt = J^\gamma(u) \quad \square \end{aligned}$$

### 3 Case studies

In this paper, three configurations of Problem ( $\mathcal{P}_1$ ) are investigated:

1. a flat road without drag;
2. a flat road with drag;
3. a non-flat road profile, and a null drag coefficient.

System ( $\Sigma_1$ ) is linear in the two first configurations, and nonlinear in the third. As we deal with a fixed time control problem, a solution exists only if the final time  $T_f$  is larger than the minimum time ( $T_{min}$ ) needed to reach the prescribed destination. For all those three cases, the minimum time strategy consists in the following control sequence, and the calculation of  $T_{min}$  is straightforward:

$$u_{min}(t) = \begin{cases} 1 & \text{for } 0 \leq t < \Delta t \\ -1 & \text{for } \Delta t \leq T_{min} \end{cases}$$

Both cases (1) and (2) are elementary examples treated in the first chapter of [17], and the formulas are respectively

$$T_{min} = 2\sqrt{x_f} \quad \text{and} \quad T_{min} = -\frac{1}{\alpha} \left( \ln \left( 1 - \sqrt{1 - e^{-\alpha^2 x_f}} \right) - \ln \left( 1 + \sqrt{1 - e^{-\alpha^2 x_f}} \right) \right) \quad (8)$$

The last case is also easily dealt with following the procedure in [17], and the formula is provided in Section 3.3 below.

The study is performed with the help of Pontryagin's Maximum Principle [17, 1, 10, 7]. To this end, we introduce  $\mathcal{P}(t) = (p(t), q(t))^t$ , the adjoint vector of  $X(t) = (x(t), y(t))^t$ , and form the Hamiltonian:

$$\mathcal{H}(X, \mathcal{P}, u, \lambda_0) = py + q(u - \alpha y - \sin(\theta(x))) - \lambda_0 \frac{|yu|}{\rho(y)} \quad \text{with } \lambda_0 \in \{1, 0\}$$

Since  $(\mathcal{P}_1)$  is an autonomous problem, then  $\mathcal{H}(X, \mathcal{P}, u, \lambda_0)$  is constant along extremal trajectories and denoted by  $H$ . Also, still along extremal trajectories, for almost every  $t$ , we have the maximisation condition:

$$H = \max_{|u| \leq 1} \mathcal{H}(X, \mathcal{P}, u, \lambda_0)$$

and the adjoint equations:

$$\dot{p} = -\frac{\partial \mathcal{H}}{\partial x}(X, \mathcal{P}, u, \lambda_0) \quad (9)$$

$$-\dot{q} \in D_y \mathcal{H}(X, \mathcal{P}, u, \lambda_0) \quad (10)$$

where  $D_y \mathcal{H}$  denotes the subdifferential of  $\mathcal{H}$  with respect to  $y$ , cf. [10].

As a consequence, following the maximisation condition, the candidate control strategy **for abnormal extremals** is given by:

$$u(t) = \operatorname{argmax}_{|u| \leq 1} \mathcal{H}(X, \mathcal{P}, u, 0) = \operatorname{sgn}(q)$$

**For normal extremals** the maximisation condition, illustrated in Figure 6, yields:

$$u(t) = \operatorname{argmax}_{|u| \leq 1} \mathcal{H}(X, \mathcal{P}, u, 1) = \operatorname{argmax}_{|u| \leq 1} \left( qu - \frac{|yu|}{\rho(y)} \right) = \begin{cases} 1 & \text{if } q > \frac{|y|}{\rho(y)} \\ u \in [0, 1] & \text{if } q = \frac{|y|}{\rho(y)} \\ 0 & \text{if } -\frac{|y|}{\rho(y)} < q < \frac{|y|}{\rho(y)} \\ u \in [-1, 0] & \text{if } q = -\frac{|y|}{\rho(y)} \\ -1 & \text{if } q < -\frac{|y|}{\rho(y)} \end{cases} \quad (11)$$

A **singular arc** is a piece of extremal trajectory such that either  $q = \frac{|y|}{\rho(y)}$  or  $q = -\frac{|y|}{\rho(y)}$  over a non-trivial interval of time —see for instance [7, 6, 20]. Also, a control  $u(t)$  is said **extremal** if there exists  $\mathcal{P}(0) = (p_0, q_0)$  such that the solution of the Hamiltonian system, formed by  $(\Sigma_1)$ , (9) and (10) is extremal.

### On the properties of singular arcs

Let us write the Hamiltonian along an extremal singular arc. Following the set of rules (11), we have:

$$H = py - q(\sin(\theta(x)) + \alpha y) \quad \text{where } q(t) \text{ is either } \frac{|y(t)|}{\rho(y(t))} \text{ or } -\frac{|y(t)|}{\rho(y(t))}$$

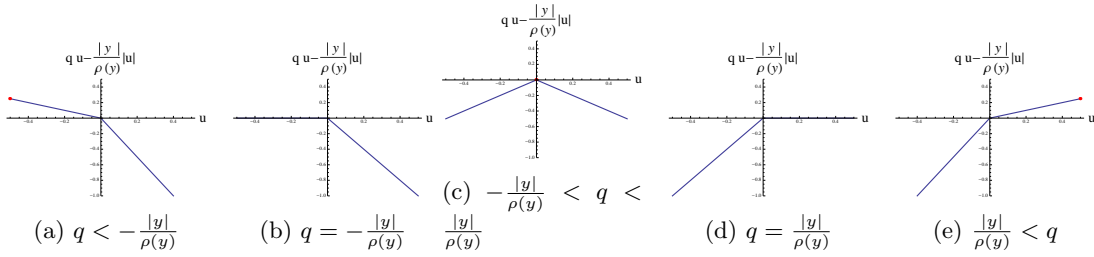


Figure 6: The maximisation condition in the normal case.

As a consequence, if the  $y$  trajectory of an extremal singular arc crosses  $y = 0$ , then  $H = 0$  along the corresponding extremal.

We now consider the case  $q = \frac{|y|}{\rho(y)}$  and  $y > 0$ , then  $u \in [0, 1]$  and the Hamiltonian writes

$$\mathcal{H}(X, \mathcal{P}, u, \lambda_0) = py - \frac{y}{\rho(y)} (\sin(\theta(x)) + \alpha y) \quad (12)$$

Its time derivative is:

$$0 = \dot{y} \left[ p - \sin(\theta(x)) \left( \frac{1}{\rho(y)} - \frac{y\rho'(y)}{\rho^2(y)} \right) - \alpha y \left( \frac{2}{\rho(y)} - \frac{y\rho'(y)}{\rho^2(y)} \right) \right] \text{ where } \rho'(y) = \frac{\partial \rho(y)}{\partial y}$$

This last expression is of the form  $0 = \dot{y} [p - \sin(\theta(x))A - B]$ . Therefore, one possible behaviour for singular arcs is to have  $y$  constant. Over intervals such that  $y$  is not constant, the quantity  $[p - \sin(\theta(x))A - B]$  must vanish. Following equation (9), the time derivative of  $p$  is given by:

$$\dot{p} = q \cos(\theta(x)) \frac{\partial \theta(x)}{\partial x} = \frac{y}{\rho(y)} \cos(\theta(x)) \frac{\partial \theta(x)}{\partial x}$$

If  $\frac{\partial \theta}{\partial x}$  doesn't vanish, the time derivative of  $[p - \sin(\theta(x))A - B]$  is of the form:  $C + \dot{y}D = 0$  where<sup>2</sup> both  $C$  and  $D$  are independent from  $\dot{y}$ . At this point one can investigate possible behaviours for extremal singular arcs by using the differential equation  $\dot{y} = -\frac{C}{D}$ .

If  $\frac{\partial \theta}{\partial x}$  vanishes, then both  $p$  and  $\sin(\theta(x))$  are constants. The time derivative of  $[p - \sin(\theta(x))A - B]$  is of the form  $(\dot{y}D)$  where  $D$  depends on  $y$ ,  $\rho(y)$ ,  $\rho'(y)$  and  $\rho''(y)$ . Since we assumed that  $\dot{y} \neq 0$ , then  $D = 0$ , and the time derivative of  $D$  is computed. It is of the form  $(\dot{y}E)$  where  $E$  depends on  $y$ ,  $\rho(y)$ , and the derivatives of  $\rho$  up to order 3. In fact, there is no new information to be found and an extremal singular arc of this kind exists only if the yield function is of the form given by the Hamiltonian (12), which is almost never the case.

The same conclusions are drawn for  $y < 0$  and in the case  $q = -\frac{|y|}{\rho(y)}$ .

### 3.1 Flat road without drag

In this section, the drag coefficient  $\alpha$  is null and the road is flat —i.e.  $\theta(x) \equiv 0$ . System  $(\Sigma_1)$  is then a simple double integrator and the Hamiltonian associated to Problem  $(\mathcal{P}_1)$  writes:

$$\mathcal{H}(X, \mathcal{P}, u, \lambda_0) = py + qu - \lambda_0 \frac{|yu|}{\rho(y)}$$

<sup>2</sup>The expressions  $C$  and  $D$  are rather long, and as such, we do not reproduce them at this point. It is straightforward to recover them with the help of a symbolic computation software.

System  $(\Sigma_1)$  being linear, there is no abnormal extremal trajectory. Let us write the Hamiltonian, along extremal trajectories at times  $t = 0$  and  $t = T_f$ :

$$\mathcal{H}|_{t=0} = \mathcal{H}|_{t=T_f} = H \Rightarrow H = u(0)q(0) = u(T_f)q(T_f) \quad (13)$$

From Lemma 2,  $y \geq 0$  for all  $t \in [0, T_f]$ . There exist  $t_1$  and  $t_2$  in  $[0, T_f]$  such that  $y(t_1) = y(t_2) = 0$  and  $y(t) > 0$  for all  $t \in ]t_1, t_2[$ . The quantity  $\kappa(t) = \frac{q\rho(y)}{y}$  is well defined over  $]t_1, t_2[$  and the set of rules (11) translates into:

$$u(t) = \begin{cases} 1 & \text{if } \kappa(t) > 1 \\ 0 & \text{if } -1 < \kappa(t) < 1 \\ -1 & \text{if } \kappa(t) < -1 \end{cases} \quad (14)$$

Now, since there is no backward arc, there exists  $\varepsilon > 0$  such that  $u = 1$  over an interval of the form  $]t_1, t_1 + \varepsilon[$ . Remember that  $(\Sigma_1)$  is a double integrator and that  $y(t_2) = 0$ . This means that the control variable must become negative at some point (or equivalently,  $\kappa$  must be less than  $-1$ ), thus there is a time  $t^* \in ]t_1, t_2[$  such that  $\kappa(t^*) = 0$  and  $\dot{\kappa} < 0$ . Let us now compute the time derivative of  $\kappa(t)$ :

$$\begin{aligned} \dot{\kappa}(t) &= \left( \widehat{\frac{q\rho(y)}{y}} \right) = \frac{q\dot{y}y\rho'(y)}{y^2} + \frac{\dot{q}\rho(y)y}{y^2} - \frac{q\rho(y)\dot{y}}{y^2} \\ &= \frac{q\dot{y}\rho'(y)}{y} + \rho(y)\frac{1}{y^2} \underbrace{(\dot{q}y - q\dot{y})}_{-H - \frac{|u|\rho'(y)y^2}{\rho(y)^2}} = -\rho(y)\frac{H}{y^2} + \rho'(y) \left( \frac{q\dot{y}}{y} - \frac{|u|}{\rho(y)} \right) \\ &= -\frac{\rho(y)}{y^2}H + \frac{\rho'(y)}{\rho(y)}(\kappa u - |u|) \end{aligned} \quad (15)$$

Following (14), when  $\kappa = 0$  then  $u = 0$ . Therefore, equation (15) yields  $\dot{\kappa}(t^*) = -\frac{\rho(y)}{y^2}H$  and  $H$  must be strictly positive. Now, relation (13) tells us that  $u(0) = 1$  and  $u(T_f) = -1$ .

Indeed, since  $u(0)q(0) \neq 0$  then  $q(0) \neq 0$ . If  $q(0) < 0$  then  $u(0) = -1$  which contradicts the fact that there is no backward arc. A similar argument yields  $u(T_f) = -1$ .

Going back to equation (15), let us consider the case when  $\kappa = 1$ . According to the set of rules (14),  $u \geq 0$ , therefore  $(\kappa u - |u|) = 0$  and  $\dot{\kappa} = -\frac{\rho(y)}{y^2}H < 0$ . When  $\kappa = -1$ ,  $u \leq 0$  and  $\dot{\kappa}$  is also strictly negative. As a consequence, an extremal trajectory contains no singular arc and has a maximum of 2 commutations. In fact, for a given  $T_f > T_{min}$ , there is only one possible extremal trajectory, the one generated by the control sequence:

$$u(t) = \begin{cases} 1 & \text{for } t \in [0, \Delta t[ \\ 0 & \text{for } t \in [\Delta t, T_f - \Delta t[ \\ -1 & \text{for } t \in [T_f - \Delta t, T_f] \end{cases} \quad (16)$$

The terminal condition  $x_f = \Delta t T_f - \Delta t^2$  allows the explicit computation of  $\Delta t$ :

$$\Delta t = \frac{1}{2} \left( T_f - \sqrt{T_f^2 - 4x_f} \right)$$

This relation is well defined, since the fact that  $T_f > T_{min}$  implies  $(T_f^2 - 4x_f) > 0$  —cf. equation (8).

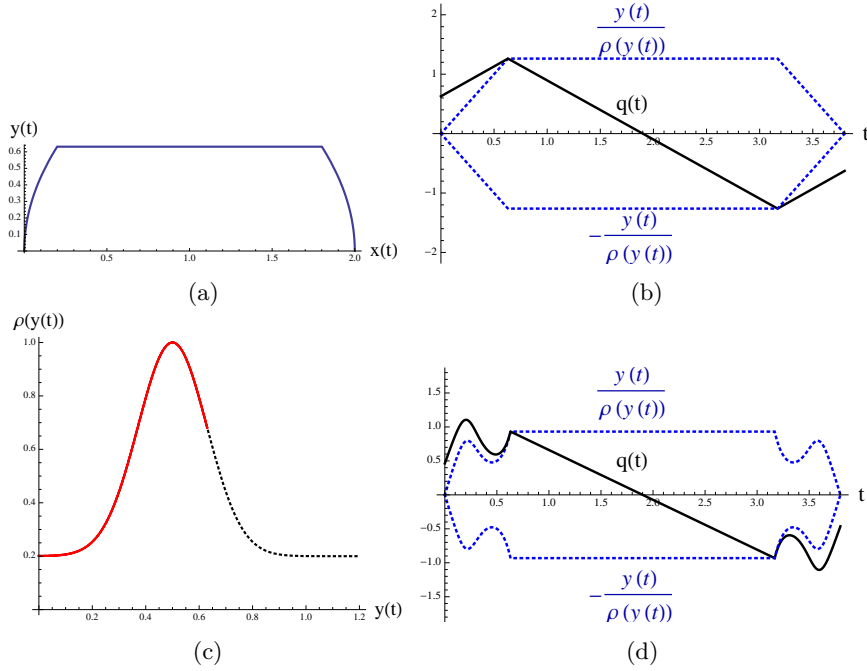


Figure 7: Optimal trajectory in the double integrator case. Parameters:  $x_f = 2$ ,  $T_{min} \approx 2.82$  and  $T_f = 3.8$ .

It is clear from expression (15), that the yield function has no part to play in this specific problem. Actually, the solution to this problem is exactly the same as the one to the problem that consists in minimising  $\int_0^{T_f} |u(t)|dt$  for a double integrator. The interested reader can refer to [18] where this problem is solved.

Figure 7 illustrates this optimal strategy. The trajectory is shown in Figure 7a. Figures 7b and 7d show the switching functions for a constant and a non-constant yield function respectively. Finally, Figure 7c represents the non-constant yield function: the dotted part shows the shape of the yield function, while the plain red part shows the visited values of the yield function.

### 3.2 Flat road with drag

In this second case study a drag coefficient is introduced. Again, system  $(\Sigma_1)$  is linear and writes:

$$\begin{cases} \dot{x} = y \\ \dot{y} = u - \alpha y \end{cases}$$

As before, abnormal extremal trajectories are out of the picture, Lemma 2 applies and optimal trajectories don't include backward arcs. The normal Hamiltonian  $\mathcal{H}$  is:

$$\mathcal{H}(X, \mathcal{P}, u, 1) = py + q(u - \alpha y) - \frac{y|u|}{\rho(y)}$$



As in Section 3.1, we have the relation:  $H = u(0)q(0) = u(T_f)q(T_f)$ , and we define the quantity  $\kappa = \frac{q\rho(y)}{y}$ . It is defined over some open subinterval  $]t_1, t_2[ \subset [0, T_f]$ , such that  $y(t) > 0$  and  $y(t_1) = y(t_2) = 0$ . The time derivative of  $\kappa$  is:

$$\dot{\kappa}(t) = -\frac{\rho(y(t))}{y(t)^2}H - \frac{\rho'(y)}{\rho(y)}|u(t)| + \kappa(t) \left( \alpha + \frac{\rho'(y)}{\rho(y)}(u - \alpha y(t)) \right) \quad (17)$$

As before, there exists  $\varepsilon > 0$  such that  $u = 1$  over an interval of the form  $]t_1, t_1 + \varepsilon[$ , and  $(\Sigma_1)$  is such that the control  $u$  must be negative in order to have  $y(t_2) = 0$ . As a consequence, there is a time  $t^*$  such that  $\kappa(t^*)$  vanishes, and  $\dot{\kappa}(t^*) < 0$ . Following (17):  $\dot{\kappa}(t^*) = -\frac{\rho(y(t^*))}{y(t^*)^2}H$ , and therefore  $H > 0$ ,  $u(0) = 1$  and  $u(T_f) = -1$ .

The rest of this section is divided into two parts. In the first one, the yield function  $\rho(y)$  is assumed equal to some constant  $0 < \bar{\rho} \leq 1$ . This assumption allows us to completely describe the solution to problem  $(\mathcal{P}_1)$  with respect to the value of  $T_f > T_{min}$ . In a second part, we build upon this basis and propose a methodology to obtain the solution to the problem with a non-constant yield function.

### 3.2.1 Constant yield function

First of all, let us remark that the solution to problem  $(\mathcal{P}_1)$  doesn't depend on the value taken by  $\bar{\rho}$ . We therefore set  $\bar{\rho} = 1$ . Up to now, we know the three following facts:

1. the control variable is equal to 1 over an interval of the form  $[0, \varepsilon[$ ;
2. the control variable equals  $-1$  over an interval of the form  $[T_f - \varepsilon, T_f]$ ;
3. there might be singular arcs and such an arc is characterised by  $\dot{y} = 0$  with  $y > 0$ .

An immediate consequence of the third fact is that there are no singular arc of the form  $q = -y$  —i.e. with  $u \in [-1, 0]$ . Indeed,  $\dot{y} = 0$  with  $y > 0$  can only be achieved with a strictly positive control. In the following,  $u_{sing} \in ]0, 1[$  denotes a singular control. The following lemma states several facts allowing us to narrow down the list of candidate strategies.

#### Lemma 3.

1. If the control variable switches to  $u = 0$  then it cannot be strictly positive again.
2. If the control variable switches to  $u = -1$  then it cannot switch back to 0.
3. There can be at most one singular arc.
4. For extremal trajectories comprising a singular arc:

- (a)  $y = \sqrt{\frac{q_0}{\alpha}}$  along the singular arc;
- (b) the corresponding control is  $u_{sing} = \sqrt{\alpha q_0}$ ;
- (c) the following relation holds:  $p = 2\sqrt{\alpha q_0}$ .

*Proof.* 1. We use the quantity  $\kappa(t)$ . A commutation of the control from  $u > 0$  to  $u = 0$  means that, at some time  $t^*$ ,  $\kappa(t^*) = 1$  and  $\dot{\kappa}(t^*) < 0$ . Let us write the expression of  $\dot{\kappa}(t^*)$  —cf. equation (17):

$$\dot{\kappa}(t^*) = \alpha\kappa(t^*) - \frac{H}{y(t^*)^2} < 0$$

Therefore,  $\kappa(t) < \kappa(t^*)$  over a small interval of the form  $[t^*, t^* + \varepsilon[$ . Also, since the control switched to 0, then the same goes for the variable  $y(t)$ . As a consequence, over  $[t^*, t^* + \varepsilon[$ , we have:

$$\dot{\kappa}(t) = \alpha\kappa(t) - \frac{H}{y(t)^2} < \dot{\kappa}(t^*) < 0$$

As a consequence,  $\kappa(t)$  remains less than 1 and the control cannot switch back to a positive value.

2. The second assertion is derived from similar arguments;
3. Assume that there exists an extremal trajectory that includes two singular arcs. Since this cannot happen as soon as  $u = 0$ , then, the control sequence is of the following form —with  $t_4 < T_f$ :

$$\begin{cases} u = 1 & \text{for } t \in [0, t_1[ \\ u_{sing} & \text{for } t \in [t_1, t_2[ \\ u = 1 & \text{for } t \in [t_2, t_3[ \\ u_{sing} & \text{for } t \in [t_3, t_4[ \end{cases}$$

Along a singular arc, we have  $\kappa = 1$  and  $\dot{\kappa} = 0$ , and equation (17) rewrites:

$$0 = -\frac{H}{y(t)^2} + \alpha \quad \Rightarrow \quad y^2 = \frac{H}{\alpha} = \frac{q_0}{\alpha}$$

Since  $y$  is constant along a singular arc, then  $y^2(t_1) = \frac{q_0}{\alpha}$  and  $y^2(t_3) = \frac{q_0}{\alpha}$ . Those two equalities contradict the existence of two singular arcs. Indeed,  $\dot{y} \neq 0$  over  $[t_2, t_3[$ , therefore,  $y(t_1)$  and  $y(t_3)$  are not equal while having the same sign.

4. Items (a) and (b) come directly from the relation  $y^2 = \frac{q_0}{\alpha}$  used in the proof of fact (3). In order to prove item (c) we simply need to remark that, since both  $\dot{\kappa}$  and  $\dot{y}$  are null along a singular arc, the same is true for  $\dot{q}$ :

$$\begin{aligned} 0 = \dot{q} &= -\frac{\partial \mathcal{H}}{\partial y}(X, \mathcal{P}, u, 1) = -p + \alpha q + |u| \\ &= -p + \alpha y + u_{sing} \\ &= -p + 2u_{sing} \quad \square \end{aligned}$$

**Remark 3.** According to the informations gathered so far, control sequences candidate for optimality are:

1.  $u = 1$ , then  $u = 0$  and finally  $u = -1$ ;
2.  $u = 1$ , then  $u = u_{sing}$ ,  $u = 0$  and finally  $u = -1$ ;
3.  $u = 1$ , then  $u = u_{sing}$ ,  $u = 1$ ,  $u = 0$  and finally  $u = -1$ .

**Lemma 4.** The following control sequence, with  $\sqrt{\alpha q_0} \neq 1$ , is not extremal

$$u(t) = \begin{cases} 1 & \text{for } t \in [0, t_1[ \\ \sqrt{\alpha q_0} & \text{for } t \in [t_1, t_2[ \\ 1 & \text{for } t \in [t_2, t_3[ \\ 0 & \text{for } t \in [t_3, t_4[ \\ -1 & \text{for } t \in [t_4, T_f] \end{cases}$$

*Proof.* Let us focus on the subinterval  $[t_2, t_3[$  and show that time  $t_3$  actually doesn't exist. Let  $\bar{t}$  be the quantity  $t - t_2$  and solve  $(\Sigma_1)$  for  $t > t_2$  with  $u = 1$ :

$$y(t) = \left(y(t_2) - \frac{1}{\alpha}\right) e^{-\alpha\bar{t}} + \frac{1}{\alpha} \quad \text{and} \quad q(t) = \left(q(t_2) - \frac{p_0 - 1}{\alpha}\right) e^{\alpha\bar{t}} + \frac{p_0 - 1}{\alpha}$$

The commutation of the control variable at time  $t_2$  implies  $y(t_2) = q(t_2)$ , and the commutation at time  $t_3$  implies  $y(t_3) = q(t_3)$ . Therefore,  $t_3 - t_2$  is the solution to the following equation:

$$\left(y(t_2) - \frac{1}{\alpha}\right) e^{-\alpha\bar{t}} + \frac{1}{\alpha} = \left(q(t_2) - \frac{p_0 - 1}{\alpha}\right) e^{\alpha\bar{t}} + \frac{p_0 - 1}{\alpha}$$

which rewrites, denoting  $q_2 = q(t_2)$ :

$$\left(q_2 - \frac{1}{\alpha}\right) e^{-\alpha\bar{t}} + \frac{1}{\alpha} = \left(q_2 - \frac{p_0 - 1}{\alpha}\right) e^{\alpha\bar{t}} + \frac{p_0 - 1}{\alpha}$$

After a few simplifications, and denoting  $X = e^{\alpha\bar{t}}$ , we obtain:

$$(\alpha q_2 - p_0 + 1)X^2 + (p_0 - 2)X - \alpha q_2 + 1 = 0 \quad (18)$$

We have,  $y(t_2) = y(t_1)$ , which implies  $q_2 = \sqrt{\frac{q_0}{\alpha}}$  —cf. Lemma 3. Also, the Hamiltonian is written at time  $t = t_2$  —i.e.  $\mathcal{H}|_{t=t_2} = \mathcal{H}|_{t=0} = q_0$ . We obtain the relations:

$$q_0 = \alpha q_2^2 \quad \text{and} \quad q_0 = p_0 q_2 - \alpha q_2^2 \quad \xrightarrow{q_2 \neq 0} \quad p_0 = 2\alpha q_2 \quad (19)$$

Therefore, the equation given in (18) becomes:

$$(1 - \alpha q_2)(X - 1)^2 = 0$$

- If  $(1 - \alpha q_2) = 0$ , then  $q_0 = \alpha q_2^2 = \frac{1}{\alpha}$ , and  $\sqrt{\alpha q_0} = 1$  which is a contradiction.
- If  $(X - 1) = 0$ , then  $X = 1$  and  $\bar{t} = 0$ , which means that  $t_3 > t_2$  doesn't exist.

As a consequence, the control strategy under consideration is not an extremal trajectory.  $\square$

**Lemma 5.** *Consider the control sequence:*

$$u(t) = \begin{cases} 1 & \text{for } t \in [0, t_1[ \\ \sqrt{\alpha q_0} & \text{for } t \in [t_1, t_2[ \\ 0 & \text{for } t \in [t_2, t_3[ \\ -1 & \text{for } t \in [t_3, T_f] \end{cases} \quad (20)$$

1. If strategy (20) is extremal, then  $t_3 - t_2 = \frac{1}{\alpha} \ln(1 + \sqrt{2})$ .
2. For given values of parameters  $\alpha$  and  $x_f$ , there is a time  $T_{lim} > 0$  such that for all  $T_f > T_{lim}$ , (20) is a candidate control sequence for optimality.

*Proof.* 1. Using the notation  $y_1 = y(t_1)$ , since the second arc is singular, we know that  $y(t_2) = q(t_2) = y_1$ . Let  $\bar{t}$  be defined by  $\bar{t} = t - t_2$ , the expressions of  $q$  and  $y$  over the interval  $[t_2, t_3]$  are:

$$q(\bar{t}) = y_1 e^{\alpha\bar{t}} - \frac{p_0}{\alpha}(e^{\alpha\bar{t}} - 1) \quad \text{et} \quad y(\bar{t}) = y_1 e^{-\alpha\bar{t}}$$

At time  $t_3$ , the control commutes from 0 to  $-1$ , which corresponds to the relation  $q(t_3) = -y(t_3)$ . We now combine the relation  $p_0 = 2\sqrt{\alpha q_0} = 2u_{sing}$  from Lemma 3, fact (4), with the fact that  $y$  is constant and equals  $y_1$  along the singular arc:  $u_{sing} = \alpha y_1$  and  $p_0 = 2\alpha y_1$ . Let us now compute  $\bar{t}$  such that  $-y(\bar{t}) = q(\bar{t})$  :

$$\begin{aligned} -y_1 e^{-\alpha \bar{t}} &= y_1 e^{\alpha \bar{t}} - \frac{p_0}{\alpha} (e^{\alpha \bar{t}} - 1) \\ -y_1 e^{-\alpha \bar{t}} &= y_1 e^{\alpha \bar{t}} - \frac{2\alpha y_1}{\alpha} (e^{\alpha \bar{t}} - 1) \\ -e^{-\alpha \bar{t}} &= e^{\alpha \bar{t}} - 2(e^{\alpha \bar{t}} - 1) && \text{(since } y_1 > 0) \\ -1 &= e^{2\alpha \bar{t}} - 2(e^{2\alpha \bar{t}} - e^{\alpha \bar{t}}) \\ 0 &= X^2 - 2X - 1 && \text{( with } X = e^{\alpha \bar{t}}) \end{aligned}$$

Therefore  $X = 1 \pm \sqrt{2}$ , which yields  $t_3 - t_2 = \frac{1}{\alpha} \ln(1 + \sqrt{2})$ .

2. Consider the following procedure.

- Let  $t_1 = t_2$ .
- Let  $t_3 - t_2 = \frac{1}{\alpha} \ln(1 + \sqrt{2})$ , set  $T_f - t_3 = T_f - \frac{1}{\alpha} \ln(1 + \sqrt{2}) - t_1$  and solve  $y(T_f) = 0$  for  $t_1$ . It is the following function of  $\alpha$  and  $T_f$ :

$$t_1 = \frac{1}{\alpha} \ln \left[ \left( 1 - \frac{\sqrt{2}}{2} \right) (1 + e^{\alpha T_f}) \right]$$

- For a given final time  $T_f$ , the control strategy (20) leads to:

$$x_f = -\frac{T_f}{\alpha} + \frac{\ln(1 + \sqrt{2})}{\alpha^2} + \frac{2}{\alpha^2} \ln \left( \left( 1 - \frac{\sqrt{2}}{2} \right) (1 + e^{\alpha T_f}) \right)$$

- The above relation is reversed in order to express  $T_f$ , as a function of  $\alpha$  and  $x_f$ . We obtain the following relations, and  $T_{lim}$  is the latter one:

$$\begin{aligned} \frac{1}{\alpha} \ln \left( (1 + \sqrt{2}) e^{\alpha^2 x_f} - 1 - \sqrt{\left( (1 + \sqrt{2}) e^{\alpha^2 x_f} - 1 \right)^2 - 1} \right) &\leq 0 \\ \text{and} \\ \frac{1}{\alpha} \ln \left( (1 + \sqrt{2}) e^{\alpha^2 x_f} - 1 + \sqrt{\left( (1 + \sqrt{2}) e^{\alpha^2 x_f} - 1 \right)^2 - 1} \right) &> 0 \quad \square \end{aligned}$$

The only strategy left to investigate is the following one:

$$u(t) = \begin{cases} 1 & \text{for } t \in [0, t_1[ \\ 0 & \text{for } t \in [t_1, t_2[ \\ -1 & \text{for } t \in [t_2, T_f] \end{cases} \quad (21)$$

For given values of  $\alpha$ ,  $x_f$ ,  $T_f > T_{min}$ , there always exists a control of the form (21) joining  $(0, 0)^t$  to  $(x_f, 0)^t$ . From the two constraints  $y(T_f) = 0$  and  $x(T_f) = x_f$ , we compute the expressions of  $t_1$  et  $t_2$  :

$$\begin{cases} t_1 = \frac{1}{\alpha} \ln \left[ \frac{1}{2} \left( 1 + e^{\alpha T_f} - \sqrt{1 + 2e^{\alpha T_f} + e^{2\alpha T_f} - 4e^{\alpha^2 x_f + \alpha T_f}} \right) \right] \\ t_2 = T_f + \frac{1}{\alpha} \ln \left[ e^{-\alpha T_f} (1 - e^{\alpha t_1} + e^{\alpha T_f}) \right] \end{cases} \quad (22)$$

The trajectory generated by control (21) is clearly optimal when  $T_{min} < T_f < T_{lim}$ . Indeed, there is no other extremal trajectory.

**Theorem 2** (Optimal strategy for a constant yield function).

For a given set of parameters  $\alpha$ ,  $x_f$  and  $T_f$ , let  $X(t) : t \mapsto (x(t), y(t))^t$  denote the trajectory of  $(\Sigma_1)$  steering  $(0, 0)^t$  to  $(x_f, 0)^t$  under a control sequence of the form (21).

1. If  $(X(t), p_0, q(t))$  is an extremal trajectory of Pontryagin's maximum principle, then  $p_0$  and  $q_0$  are given by the following expressions:

$$p_0 = \frac{e^{-\alpha t_2} (e^{\alpha t_1} - 1) (1 + e^{2\alpha(t_2 - t_1)})}{e^{\alpha(t_2 - t_1)} - 1}$$

$$q_0 = \frac{e^{-2\alpha t_1}}{\alpha} (e^{\alpha t_1} - 1) (1 + e^{\alpha t_1} (p_0 - 1))$$

2. For  $T_f > T_{lim}$ , with  $T_{lim}$  as in Lemma 5, then  $(X(t), p_0, q(t))$  is not an extremal trajectory.
3. The solution to the optimal control problem  $(\mathcal{P}_1)$  on a flat road, with drag coefficient  $\alpha$  and constant yield function is:
  - (a) for  $T_{min} < T_f \leq T_{lim}$ , with  $T_{lim}$  as in Lemma 5, the optimal control strategy is (21);
  - (b) for  $T_f > T_{lim}$ , the optimal control strategy is (20).

*Proof.* 1. Parameters  $\alpha$ ,  $x_f$ ,  $T_f$  being fixed, the commutation times  $t_1$  et  $t_2$  of control sequence (21) are given by (22), which allows the computation of  $y(t_1)$  and  $y(t_2)$ .

- (a)  $p_0$  is determined with the help of the expression of  $q(t)$  over the interval  $[t_1, t_2]$ :

$$q(t) = q(t_1) e^{\alpha(t - t_1)} - \frac{p_0}{\alpha} (e^{\alpha(t - t_1)} - 1)$$

Since  $q(t_1) = y(t_1)$ , the equation  $q(t_2) = -y(t_2)$  is solved for  $p_0$ .

- (b)  $q_0$  is determined from the expression of  $q(t)$  over the interval  $[0, t_1]$ :

$$q(t) = q_0 e^{\alpha t} + \frac{1}{\alpha} (1 - p_0) (e^{\alpha t} - 1).$$

In both cases, the derived expression is uniquely determined.

2. For a given set of parameters  $\alpha$ ,  $x_f$ ,  $T_f$ , assume that  $(X(t), p_0, q(t))$  is an extremal trajectory. Then,  $t_1$ ,  $p_0$  et  $q_0$  can be explicitly computed. Therefore, we can determine the expressions of both  $y(t)$  and  $q(t)$  over the interval  $[0, t_1]$ . A commutation takes place if there is a time  $t$  such that  $y(t) = q(t)$ . This equation is then solved for  $t$ .

We obtain two expressions<sup>3</sup>. One of them is exactly formula  $t_1$  given in (22). However, the other one is real and lower than  $t_1$  as soon as  $T_f > T_{lim}$ . In other words, for  $T_f > T_{lim}$  a first commutation of the control happens before time  $t_1$  and consequently the control sequence (21) is not extremal.

3. The analysis performed in the present section showed that there are only two possible extremal strategies. They have the following restrictions:

- the trajectory due to the control sequence (21) is not extremal as soon as  $T_f > T_{lim}$ ;
- the trajectory due to the control sequence (20) doesn't exist for  $T_{min} < T_f \leq T_{lim}$ .  $\square$

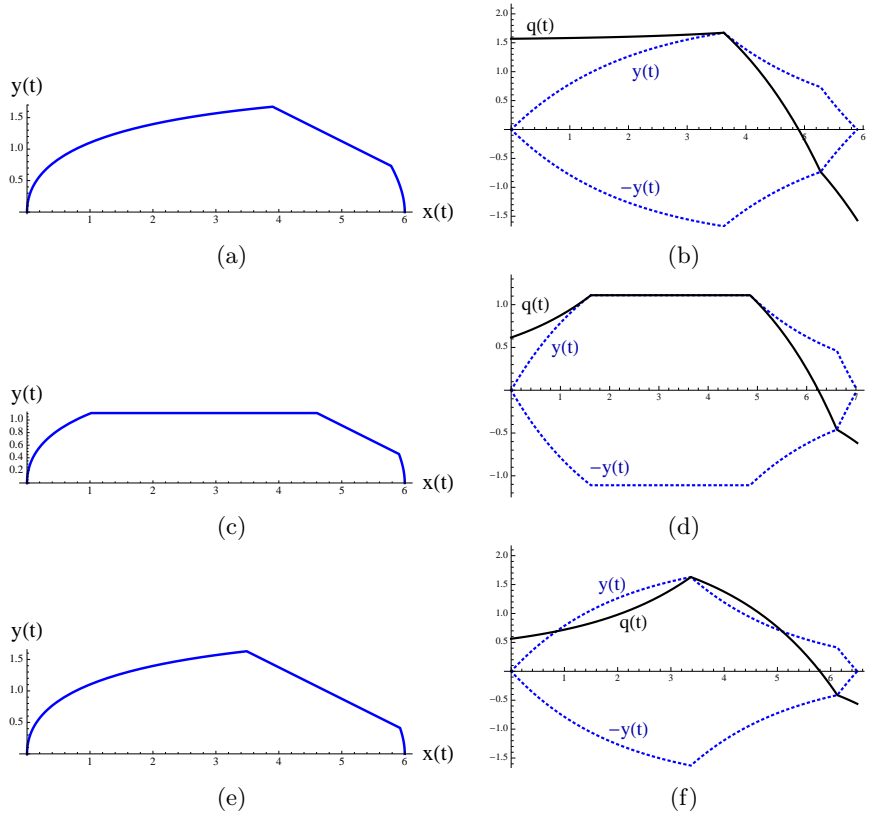


Figure 8: Optimal and non-optimal trajectories for the second case study with a constant yield function. Parameters:  $\alpha = 0.5$ ,  $x_f = 6$ ,  $T_{min} \approx 5.52$  and  $T_{lim} \approx 5.95$ . Figures 8a, and 8b correspond to  $T_f = 5.9$ . Figures 8c to 8f correspond to  $T_f = 6.5$ .

Figure 8 illustrates the claims of Theorem 2 for fixed parameters  $x_f = 6$  and  $\alpha = 0.5$ . The quantity  $T_{lim}$  is determined as explained in Lemma 5. Figures 8a and 8b show the optimal trajectory for  $T_f < T_{lim}$ , and Figures 8c and 8d correspond to the case  $T_f > T_{lim}$ . In particular, Figures 8e and 8f illustrate the fact that strategy (21) is not extremal for  $T_f > T_{lim}$ . Those last two figures are obtained as follows:  $t_1$  and  $t_2$  are determined in order to steer  $X(0)$  to  $X(T_f)$  using strategy (21). When we apply this control to the Hamiltonian system, we see that trajectory  $q(t)$  intersects  $y(t)$  at some time  $0 < t < t_1$ , as expected this trajectory is not extremal.

### 3.2.2 Non-constant yield function

In this section, in order to solve  $(\mathcal{P}_1)$  on a flat road, with drag coefficient  $\alpha > 0$  and a non-constant yield function  $\rho(y)$ , we propose a methodology based on fact (3) of Theorem 2.

1. Compute a trajectory of  $(\Sigma_1)$  given by control sequence (21).
2. If possible, compute a trajectory of  $(\Sigma_1)$  given by control sequence (20).

<sup>3</sup>Since they are quite large, those two expressions are not reproduced here. However, the interested reader can obtain them with the help of a symbolic computation software.

3. Check which trajectory is extremal, and compute the cost explicitly to remove possible ambiguities.
4. It can happen that neither strategy (21) nor strategy (20) yield extremal trajectories. Indeed, the facts of Lemma 3 don't hold anymore and there can be more than one commutation of the control variable between the values  $u = 0$  and  $u = -1$ . When this situation arises, a new control strategy is investigated —see (25) below.

A trajectory of  $(\Sigma_1)$ , given by the control sequence (21), such that  $X(T_f) = (x_f, 0)^t$  is given by relations (22), as before. However, for a trajectory given by control sequence (20), relation  $t_3 - t_2 = \frac{1}{\alpha} \ln(1 + \sqrt{2})$  of Lemma 5 doesn't hold anymore, and we have to rely on a numerical scheme.

### Computing extremal trajectories given by strategy (20)

First, we need to derive usable expressions for  $p_0$  and  $q_0$ . Along a singular arc, since  $\dot{y} = 0$ , then  $\dot{q} = \frac{d}{dt} \left( \frac{y}{\rho(y)} \right) = 0$ . Let  $y_s$  denote the value of  $y(t)$  along the singular arc, then  $u_{sing} = \alpha y_s$  and:

$$0 = \dot{q} = -\frac{\partial}{\partial y} \mathcal{H} = \frac{|u_{sing}|}{\rho(y_s)} - \frac{y_s |u_{sing}| \rho'(y_s)}{\rho^2(y_s)} + \alpha q_s - p_0 \quad \text{where} \quad q_s = \frac{y_s}{\rho(y_s)} \quad \text{and} \quad \rho'(y) = \frac{\partial \rho}{\partial y}(y)$$

$$\Rightarrow p_0 = \frac{2\alpha y_s}{\rho(y_s)} - \frac{\alpha y_s^2 \rho'(y_s)}{\rho^2(y_s)} \quad (23)$$

Now, since  $u_0 = 1$ , and denoting by  $\mathcal{H}_s$  the Hamiltonian function computed along a singular arc, we have:

$$\mathcal{H}|_{t=0} = q_0 = \mathcal{H}_s = p_0 y_s + q_0 (u_{sing} - y_s) - \frac{y_s |u_{sing}|}{\rho(y_s)} \quad \Rightarrow \quad q_0 = p_0 y_s - \frac{\alpha y_s^2}{\rho(y_s)} \quad (24)$$

In order to compute an extremal trajectory associated to (20), the following methodology is proposed:

1. set  $t_1$  to some arbitrary value, then  $y(t_2) = y(t_1) = y_s$  and both  $p_0$  and  $q_0$  can be computed;
2. the duration  $(t_3 - t_2)$  is the solution of  $q(t) = -\frac{y(t)}{\rho(y(t))}$  where  $q(t)$  and  $y(t)$  are the solutions of the Hamiltonian system associated to  $(\mathcal{P}_1)$  with  $u = 0$ ,  $y(0) = y_s$  and  $q(0) = \frac{y_s}{\rho(y_s)}$ ;
3. the duration  $(T_f - t_3)$  comes from the constraint  $y(t) = 0$  where  $y(t)$  is the solution of  $(\Sigma_1)$  with  $u = -1$  and setting  $y(0)$  to the value taken by  $y$  in the previous step when we solved equation  $q(t) = -\frac{y(t)}{\rho(y(t))}$ ;
4.  $t_1$  is determined in order to solve the equation  $x(T_f) = x_f$ , with the duration of the singular arc (i.e.  $t_2 - t_1$ ) given by  $T_f$  minus the length of the three other arcs.

**Remark 4.** • *Each step of this methodology is achieved with a simple dichotomy.*

- *For a given set of parameters  $\alpha$  and  $x_f$ , the minimum time  $T_{lim}$  for the existence of a singular strategy (20) is determined with a similar methodology: the singular arc is reduced to a point but the constraints are kept. Time  $t_1$  is determined such that  $x(T_f) = x_f$ , which yields the value of  $T_{lim} = T_f$ .*
- *In practice, if a singular strategy exists, then the basic strategy (21) is not extremal.*

### Trajectories having a two-step braking behaviour

The two control strategies presented so far —i.e. (20) and (21)— are not sufficient to account for all the situations we encountered during the resolution of this case. Since Lemma 3 doesn't guarantee anymore that each type of commutation happens at most once, we considered a strategy of the form (25) below.

Let us remember that the running cost is  $\frac{|yu|}{\rho(y)}$ . On the one hand, the fact that it tends to zero when  $y$  tends to 0 points out the interest of braking at low speed. On the other hand, a non-null control is expected to take place when the yield function's value is the largest. Actually, strategies (20) and (21) both realise a tradeoff between those two behaviours, and the fact that both strategies aren't extremal hints toward a two-step braking strategy. In other words,  $u = -1$  a first time when the yield function is large enough, and a second time when the speed is low enough.

Strategy (25) below actually produces extremal trajectories when (20) and (21) don't. Those trajectories are calculated with a methodology adapted from the one used for strategy (20).

$$u(t) = \begin{cases} 1 & \text{when } t \in [0, t_1[ \\ \alpha y_1 & \text{when } t \in [t_1, t_2[ \\ 0 & \text{when } t \in [t_2, t_3[ \\ -1 & \text{when } t \in [t_3, t_4[ \\ 0 & \text{when } t \in [t_4, t_5[ \\ -1 & \text{when } t \in [t_5, T_f] \end{cases} \quad (25)$$

Figures 9, 10 and 11 illustrate the optimal trajectories calculated following the above methodology for fixed parameters  $x_f = 6$  and  $\alpha = 0.5$ . Figure 9 corresponds to the case  $T_{min} < T_f < T_{lim}$ , and Figures 10 and 11 to  $T_f > T_{lim}$ . For  $T_f = 10$ , neither (21) nor (20) produce extremal trajectories, but the new strategy (25) does. It is illustrated in Figure 11. In fact, this situation happens only for  $T_f$  within a rather small interval of time. In Figures 9c, 10c and 11c the visited values of the yield function are displayed in red. The blue sections in Figure 11c correspond to the two braking periods.

**Remark 5.** *Let us remark that extremal trajectories such as the one displayed in Figure 11f don't exist for all type of non-constant yield functions. Indeed, in the case of the yield function shown in Figure 7c, that is with  $\rho(0) = 0.2$ , there is no such extremal. This can be understood as a translation of the fact that because the ratio between the maximum and the minimum of the yield is not significant, it is much more interesting to only brake at low speed.*

### 3.3 Non-flat road

In this third case study, we consider a non-flat road and no drag coefficient. System  $(\Sigma_1)$  writes:

$$(\Sigma_1) \begin{cases} \dot{x} = y \\ \dot{y} = u - \sin(\theta(x)) \end{cases}$$

The road profile under consideration, represented in Figure 12, has the following behaviour:

$$\begin{cases} \theta(x) \text{ is constant for } x \geq -1 \\ \theta(x) \text{ is increasing for } x \in ]-6.5, -1[ \\ \theta(x) \text{ is decreasing for } x \in [-10, -6.5[ \end{cases}$$



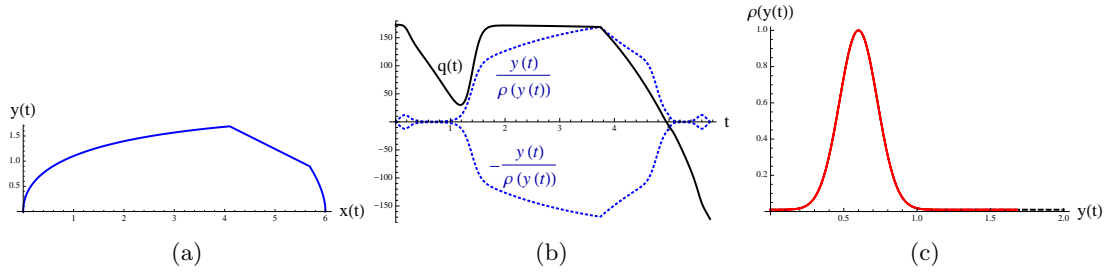


Figure 9: Optimal trajectory for the second case study with a non-constant yield function. Parameters:  $\alpha = 0.5$ ,  $x_f = 6$ ,  $T_{min} \approx 5.52$ ,  $T_{lim} \approx 5.8$  and  $T_f = 5.75$ .

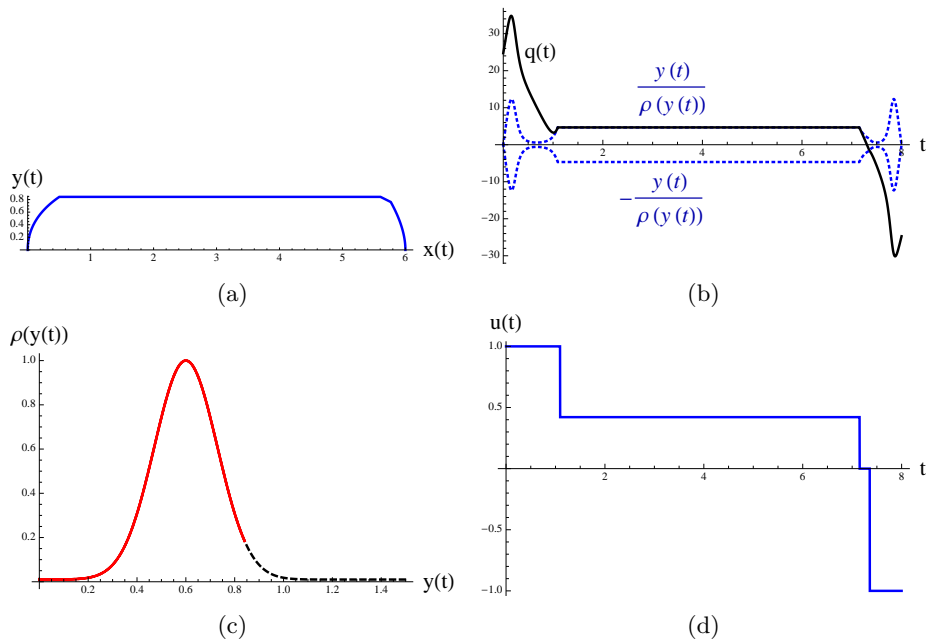


Figure 10: Optimal trajectory for the second case study with a non-constant yield function. Parameters:  $\alpha = 0.5$ ,  $x_f = 6$ ,  $T_{min} \approx 5.52$ ,  $T_{lim} \approx 5.8$  and  $T_f = 8$ .

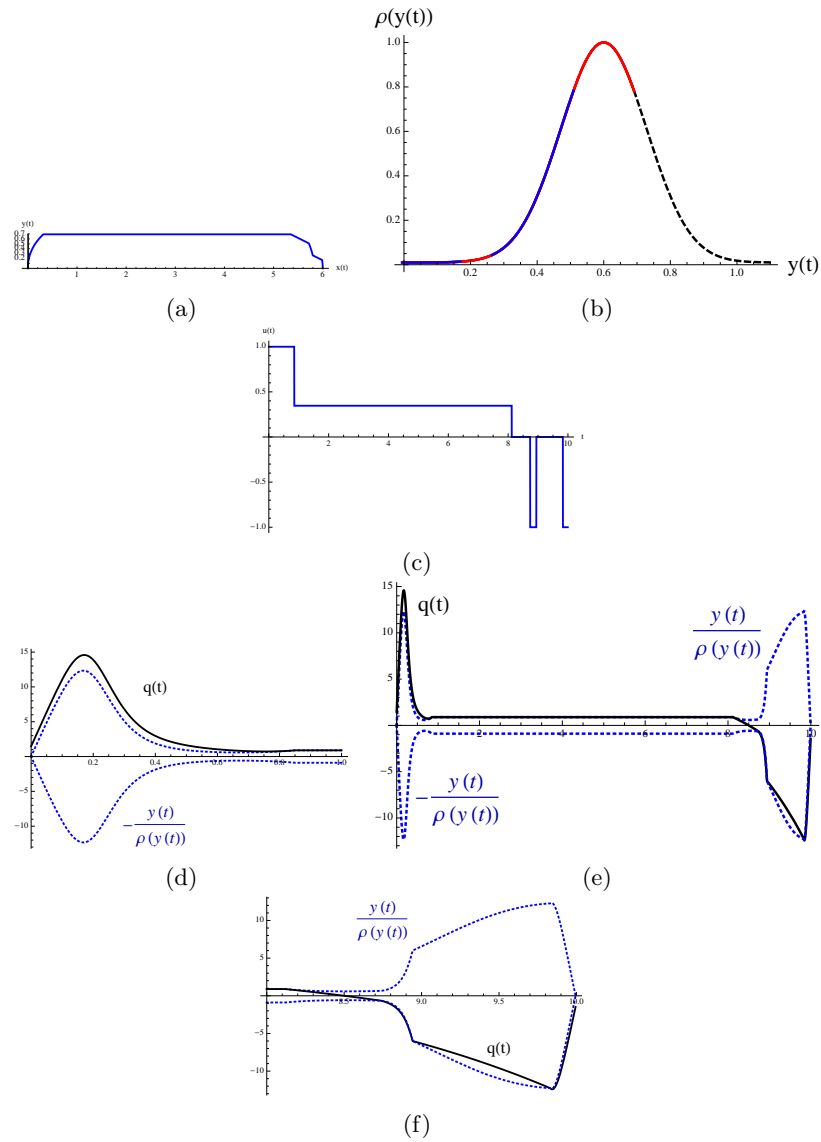


Figure 11: Optimal trajectory for the second case study with a non-constant yield function. Parameters:  $\alpha = 0.5$ ,  $x_f = 6$ ,  $T_{min} \approx 5.52$ ,  $T_{lim} \approx 5.8$  and  $T_f = 10$ .

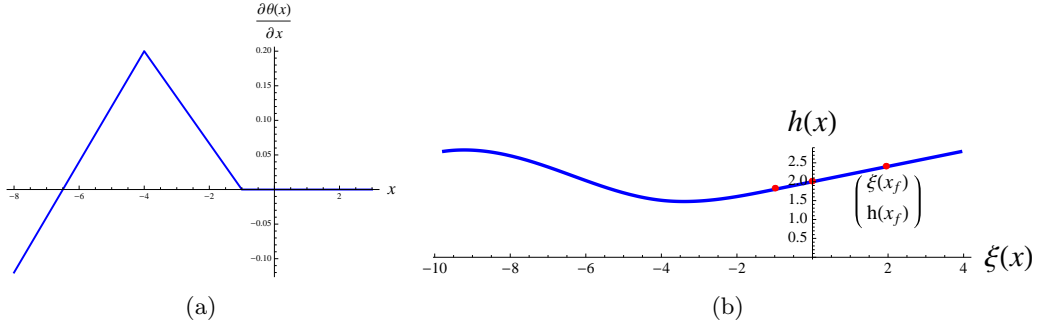


Figure 12: Derivative of  $\theta$  with respect to  $x$ , and road profile in the  $(\xi, h)^t$  coordinates. The red dots appearing on the road profile correspond to  $x = -1$ ,  $x = 0$  and  $x = x_f$ .  
 $T_{min} \approx 2.885$ ,  $(T_{min} + T_{back}) \approx 4.177$  and  $T_f^{1,0} \approx 5.01$ .

In order to simplify notations when there is no ambiguity, we denote  $K = \sin(\theta(x))$  for  $x \geq -1$ . The minimum time is  $T_{min} = \frac{2\sqrt{x_f}}{\sqrt{1-K^2}}$ , and we set  $x_f = 2$ .

As before, abnormal extremals are out of the picture. First, let  $T_f^{1,0}$  be the time needed in order to reach  $X = (x_f, 0)^t$  with the strategy

$$u(t) = \begin{cases} 1 & \text{for } t \in [0, t_c[ \\ 0 & \text{for } t \in [t_c, T_f^{1,0}] \end{cases} \quad (26)$$

**Lemma 6.** 1. If the control sequence (26) is extremal, then the Hamiltonian  $H$  is null along the corresponding trajectory of  $(\Sigma_1)$ ;

2. we have the following equivalence:

$$\rho'(y(t_c)) \geq 0 \quad \iff \quad (26) \text{ is an extremal strategy}$$

3. for all  $T_f > T_f^{1,0}$  the following strategy is also extremal:

$$u(t) = \begin{cases} K & \text{for } t \in [0, t_1[ \\ 1 & \text{for } t \in [t_1, t_1 + t_c[ \\ 0 & \text{for } t \in [t_1 + t_c, T_f - t_2[ \\ K & \text{for } t \in [T_f - t_2, T_f[ \end{cases} \quad (27)$$

where  $t_1 \geq 0$ ,  $t_2 \geq 0$  and  $t_1 + t_2 = T_f - T_f^{1,0}$ .

*Proof.* 1. The normal Hamiltonian, with  $x \geq -1$ , writes  $\mathcal{H}(X, \mathcal{P}, u, 1) = -\frac{|yu|}{\rho(y)} + py + q(u - K)$ . For an extremal trajectory given by (26),  $u(T_f) = 0$  and  $\frac{y(T_f)}{\rho(y(T_f))} \leq q(T_f) \leq -\frac{y(T_f)}{\rho(y(T_f))}$ . Since  $y(T_f) = 0$  then  $q(T_f) = 0$ , and the Hamiltonian expressed at time  $T_f$  yields  $H = 0$ .

2. **Let us assume**  $\rho'(y_c) \geq 0$ , **with**  $y_c = y(t_c)$ . Since  $u = 1$  over  $[0, T_c[$ , then  $y \geq 0$  over  $]0, t_c[$ . Let  $p = p_0$  be a constant, and  $q(t)$  be the solution of

$$\dot{q} = -\frac{\partial}{\partial y} \left( -\frac{y}{\rho(y)} + py + q(1 - K) \right) \quad \text{with } q(0) = 0$$

We now compute the time derivative of  $\mathcal{H}(X, \mathcal{P}, u, 1)$  over  $]0, t_c[$ . Recall that  $y > 0$  and  $u$  is constant, which yields  $\dot{\mathcal{H}} = 0$ . Therefore,  $\mathcal{H}$  is constant over  $[0, t_c]$  by continuity. Now, since we've set  $q_0 = 0$ , then  $\mathcal{H}|_{t=0} = 0$ , and therefore  $\mathcal{H}|_{t=t_c} = 0$ .

The commutation at time  $t_c$  happens if  $q(t_c) = \frac{y_c}{\rho(y_c)} = 0$ . This is true if  $p_0 = \frac{K}{\rho(y_c)}$ . In order to show that (26) is an extremal strategy, we still have to show that:

- (a)  $q(t) > \frac{y}{\rho(y)}$  over  $]0, t_c[$ ;
- (b)  $-\frac{y}{\rho(y)} < q(t) < \frac{y}{\rho(y)}$  over  $]t_c, T_f^{1,0}[$ .
- Over  $]0, t_c[$ :

$$-\frac{y}{\rho(y)} + p_0 y + q(1 - K) = 0 \iff q = \frac{y}{1 - K} \left( \frac{1}{\rho(y)} - p_0 \right)$$

After few manipulations, and replacing  $p_0$  by  $\frac{K}{\rho(y_c)}$ , we obtain the expression:

$$q - \frac{y}{\rho(y)} = \frac{K}{1 - K} y \left( \frac{1}{\rho(y)} - \frac{1}{\rho(y_c)} \right)$$

Since  $\rho'(y_c) \geq 0$  and  $0 < y(t) < y_c$  over  $]0, t_c[$ , then  $\left( \frac{1}{\rho(y)} - \frac{1}{\rho(y_c)} \right) > 0$  and  $q > \frac{y}{\rho(y)}$ .

- Over  $]t_c, T_f^{1,0}[$ :  
we have  $u = 0$ . Let  $\bar{t} = t - t_c$ , then  $y(\bar{t}) = -K\bar{t} + y_c$  and  $q(\bar{t}) = -p_0\bar{t} + q(t_c) = -\frac{K}{\rho(y_c)}\bar{t} + \frac{y_c}{\rho(y_c)}$ . Hence  $T_f^{1,0} - t_c = \frac{K}{y_c}$ ,  $q(T_f^{1,0}) = 0$  and trivially  $-\frac{y}{\rho(y)} < q$  over  $]t_c, T_f^{1,0}[$ .

Let us now determine the sign of  $q - \frac{y}{\rho(y)}$ :

$$\begin{aligned} q - \frac{y}{\rho(y)} &= \frac{y_c}{\rho(y_c)} - \frac{K}{\rho(y_c)}\bar{t} - \frac{y}{\rho(y)} \\ &= \frac{y_c}{\rho(y_c)} - \frac{K}{\rho(y_c)}\bar{t} - \frac{y_c - K\bar{t}}{\rho(y)} \\ &< \frac{y_c}{\rho(y_c)} - \frac{K}{\rho(y_c)}\bar{t} - \frac{y_c - K\bar{t}}{\rho(y_c)} = 0 \quad (\text{since } y < y_c \text{ and } (y_c - K\bar{t}) > 0) \end{aligned}$$

This proves the result, and strategy (26) is extremal.

**Let us assume  $\rho'(y_c) < 0$ , with  $y_c = y(t_c)$ .** As we've done before, we consider the quantity  $\kappa(t) = \frac{q\rho(y)}{y}$  over an interval of time that contains  $t_c$  and such that  $y > 0$ . We assume that (26) is an extremal strategy and compute the time derivative of  $\kappa(t)$  over this interval:

$$\dot{\kappa}(t) = -\frac{H\rho(y)}{y^2} - \frac{|u|\rho'(y)}{\rho(y)} + \kappa(t) \frac{\rho'(y)}{\rho(y)} \dot{y} \quad (28)$$

When  $t = t_c$ ,  $\kappa(t_c) = 1$  and  $u \geq 0$ , which yields  $\dot{\kappa}(t_c) = -\frac{\rho'(y(t_c))}{\rho(y(t_c))} K$  since  $H = 0$ . As a consequence, a commutation of the control cannot take place since  $\dot{\kappa}(t_c) > 0$ . This contradicts the fact that (26) is extremal.

3. This item comes from the two following facts.

- (a) An extremal trajectory having a singular arc of the form  $y = 0$ ,  $\dot{y} = 0$  implies  $H = 0$ .
- (b) If (26) is an extremal strategy, then  $H = 0$ .  $\square$

We are now left with the following question: *what happens when  $\rho'(y_c) < 0$  ?* We know from Lemma 6 that this strategy cannot be extremal. From the experience gained with the preceding case study, searching for singular arcs comes to mind. As we have seen at the beginning of Section 3: since  $\theta(x)$  is constant then singular arcs are of the form  $\dot{y} = 0$ . A possible strategy is:

$$u(t) = \begin{cases} 1 & \text{for } t \in [0, t_c[ \\ K & \text{for } t \in [t_c, t_c + t_{sing}[ \\ 0 & \text{for } t \in [t_c + t_{sing}, T_f^{1,s,0}] \end{cases} \quad (29)$$

The associated trajectory of  $(\Sigma_1)$  has a singular arc over the time interval  $[t_c, t_c + t_{sing}[$  which can be as large as needed in order to meet the constraint  $x(T_f) = x_f$ . In fact, if we assume that strategy (29) is extremal, we have the following facts:

1.  $H = 0$  since  $u(t) = 0$  for  $t \in [t_c + t_{sing}, T_f]$ ;
2. the time derivative of the quantity  $\kappa = \frac{q\rho(y)}{y}$ , computed at time  $t_c$  is  $\dot{\kappa}(t_c) = -\frac{\rho'(y(t_c))}{\rho(y(t_c))}K$  —see formula (28)— which shows that a singular arc can happen only if  $\rho'(y(t_c)) = 0$ .

The final time  $T_f^{1,s,0}$  is uniquely determined by the following procedure, and the corresponding trajectory is proven extremal by using the same arguments as in Lemma 6:

- $t_c$  is such that  $\rho(\cdot)$  reaches its maximum over  $\mathbb{R}^{+,*}$  at  $y(t_c)$ ;
- $t_{sing}$  and  $T_f^{1,s,0}$  are such that  $X(T_f^{1,s,0}) = (x_f, 0)^t$ .

As before, if (29) is an extremal strategy, then for all  $T_f > T_f^{1,s,0}$  the following strategy is also extremal:

$$u(t) = \begin{cases} K & \text{for } t \in [0, t_1[ \\ 1 & \text{for } t \in [t_1, t_1 + t_c[ \\ K & \text{for } t \in [t_1 + t_c, t_1 + t_c + t_{sing}[ \\ 0 & \text{for } t \in [t_1 + t_c + t_{sing}, T_f - t_2[ \\ K & \text{for } t \in [T_f - t_2, T_f] \end{cases} \quad (30)$$

where  $t_1 \geq 0$ ,  $t_2 \geq 0$  and  $t_1 + t_2 = T_f - T_f^{1,s,0}$ . This strategy is illustrated in Figure 13.

Let us now define  $T_{back}$  as the the minimum time needed for system  $(\Sigma_1)$  to reach the abscissa  $x = -1$ . We call **small time trajectory** a trajectory having a final time  $T_f$  within the interval  $]T_{min}, T_{min} + T_{back}]$ .

**Lemma 7 (Small time trajectories).** 1. *An optimal small time trajectory of  $(\mathcal{P}_1)$  has no backward arc.*

2. *Small time extremals of  $(\mathcal{P}_1)$  do not contain singular arcs of the form  $y = 0$ .*

3. *Let  $y_s$  be the constant speed of the singular arc of a small time extremal, then  $\frac{\partial \rho}{\partial y}(y_s) < 0$ .*

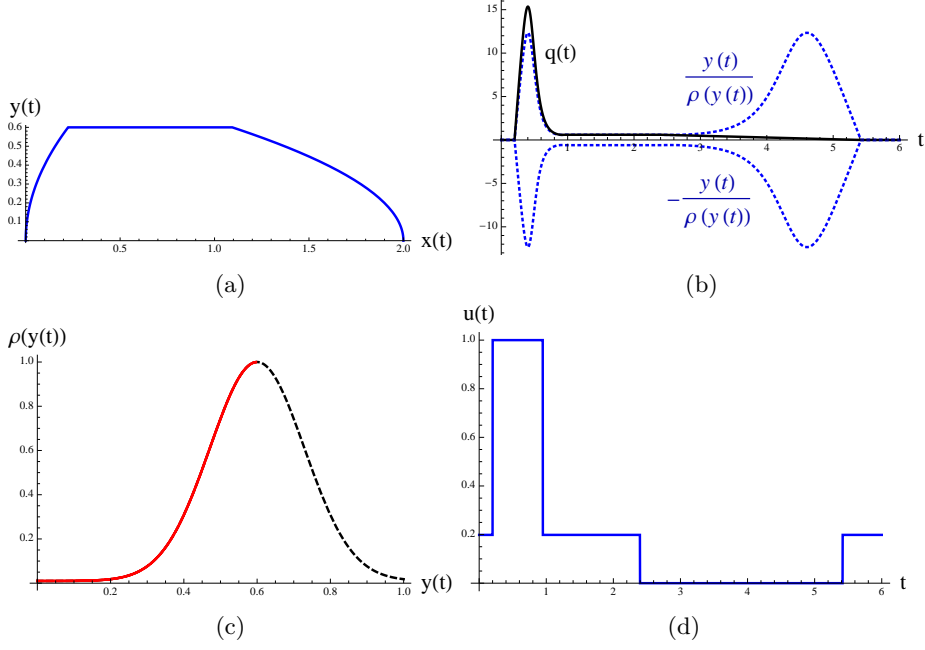


Figure 13: Optimal trajectory for the third case study. Parameters:  $T_f^{1,s,0} \approx 5.21$  and  $T_f = 6$ . The associated cost equals 3.605.

4. Consider a small time extremal trajectory containing a singular arc, and denote  $y_s$  the constant speed, then:

$$q_0 = \frac{K y_s^2 \rho'(y_s)}{(K-1)\rho(y_s)^2} \quad \text{and} \quad p_0 = K \frac{\rho(y_s) - y_s \rho'(y_s)}{\rho(y_s)^2}$$

*Proof.* 1. Since  $T_f < T_{min} + T_{back}$ , trajectories  $(x(t), y(t))^t$  of  $(\mathcal{P}_1)$  starting from  $(0, 0)^t$  can reach  $(x_f, 0)^t$  only by staying on portions of road such that  $\theta(x(t)) \equiv \text{constant}$ . Then,  $(\mathcal{P}_1)$  can be viewed as invariant with respect to translations along the  $\mathcal{O}x$  axis. According to Lemma 2, an optimal trajectory has no backward arc.

2. In the problem under consideration,  $T_{min} + T_{back} < T_f^{1,0}$ . As a consequence, for a small time extremal,  $y(T_f) = 0$  cannot be achieved with a strategy of the form (26), and  $u$  must be negative over some time interval. Hence, there exists a non-trivial interval of the form  $]\tilde{t}, \bar{t}[$  such that:

- $y > 0$  for all  $t \in ]\tilde{t}, \bar{t}[$  and the quantity  $\kappa(t) = \frac{q\rho(y)}{y}$  exists for all  $t \in ]\tilde{t}, \bar{t}[$ ;
- $\kappa(\tilde{t}) = 1$  and  $\kappa(\bar{t}) = -1$
- there is a  $t^* \in ]\tilde{t}, \bar{t}[$  such that  $\kappa(t^*) = 0$  and  $\dot{\kappa}(t^*) < 0$ .

The time derivative of  $\kappa(t)$ , over this interval is, again, equation (28). When  $\kappa(t) = 0$ , then  $u = 0$  and  $\dot{\kappa}(t^*) = -\frac{H\rho(y)}{y^2}$  which implies that  $H$  must be strictly positive in order to achieve  $\dot{\kappa}(t^*) < 0$ . A singular arc with  $y = 0$  cannot exist since it implies  $H = 0$ .

- As before, we define the quantity  $\kappa(t) = \frac{q\rho(y)}{y}$  over intervals where  $y \neq 0$ , and we derive an expression for  $\dot{\kappa}(t)$  —see equation (28) above. Along a singular arc, we have  $\kappa(t) = 1$  and  $\dot{\kappa}(t) = 0$ , following expression (28) we obtain equality:

$$0 = -\frac{H\rho(y)}{y^2} - \frac{|u|\rho'(y)}{\rho(y)}$$

which can only be true if  $\rho'(y)$  is negative.

- The two expressions are easily obtained as follows:

- solve the equation  $0 = -\frac{H\rho(y_s)}{y_s^2} - \frac{|u|\rho'(y_s)}{\rho(y_s)}$  for  $H$  and set  $u = K$  since  $\dot{y} = 0$  along a singular arc;
- the relation  $H = q_0(u(0) - K) = q_0(1 - K)$  yields the expression of  $q_0$ ;
- finally, writing  $H$  along a singular arc,  $H = p_0 y_s - \frac{y_s}{\rho(y_s)} K$ , provides the expression of  $p_0$ .  $\square$

Based on the informations gathered in Lemma 7, small time optimal trajectories are searched following the methodology exposed in Section 3.2.2. This is illustrated in Figure 14.

Finally, we propose the following methodology in order to address the optimal control problem ( $\mathcal{P}_1$ ) in the case of the road profile displayed in Figure 12.

- Consider strategy (26), check the sign of  $\frac{\partial \rho}{\partial y}(y(t_c))$  and decide which strategy between (26) and (29) is relevant. We denote by  $\bar{T}_f$  the corresponding final time.
- For  $T_f > \bar{T}_f$ , either strategies of the form (27) or strategies of the form (30) are extremal and therefore candidate to optimality. Items (1) and (2) are illustrated in Figure 13.
- For  $T_{min} < T_f < T_{min} + T_{back}$ , compute a forward extremal trajectory as in Section 3.2.2. As explained in Lemma 7, such trajectories are optimal extremals. This is illustrated in Figure 14 with a small time trajectory having no singular arc.
- For  $T_{min} + T_{back} < T_f < \bar{T}_f$ , as in the preceding item, forward extremal trajectory as in Section 3.2.2 can be searched. This is illustrated in Figure 15 with an extremal trajectory having a two-step braking behaviour.
- Finally, with the help of a numerical study, extremal trajectories having backward arcs are searched. For instance, for  $T_f = 4.48$ , we didn't find any extremal having a backward arc and as such, the trajectory displayed in Figure 15 is considered optimal. Extremal trajectories having backward arcs are shown in Figures 16 and 17.

In order to better understand this last step, numerical exploration was performed via the manipulation of the values of  $p_0$  and  $q_0$ . As expected, extremal trajectories having backward arcs do exist. An interesting fact being that such extremals are not necessarily optimal. In Figure 16, an example of an optimal trajectory with backward arcs is displayed. The yield function is the same as the one used to determine the trajectory of Figure 13. In this case, the backward strategy of Figure 16 costs less than the forward strategy of the form (30)—since the arcs with  $y = 0$  have a null running cost, strategy (30) costs the same regardless of the value of  $T_f > T_f^{1,s,0}$ .

On the other hand, Figure 17 shows an extremal trajectory having backward arcs obtained for a yield function such that  $\rho(0)$  is 20 times larger than the one used in Figure 16 —this is the only

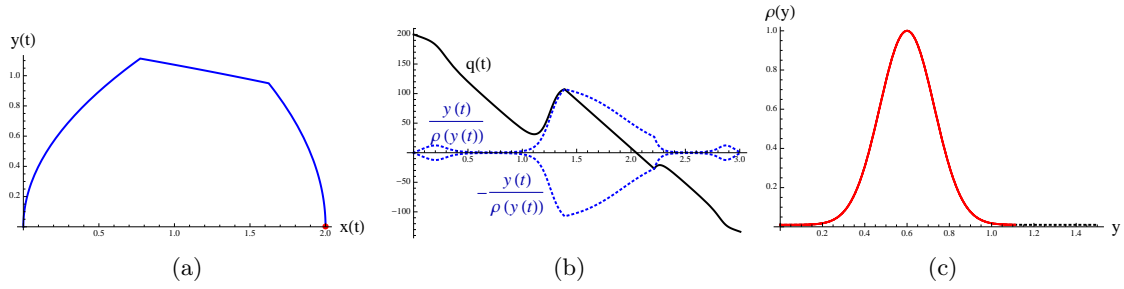


Figure 14: Optimal trajectory in the third case case study in small time. Parameters:  $T_{min} \approx 2.885$ ,  $(T_{min} + T_{back}) \approx 4.177$  and  $T_f = 3$ .

parameter that is changed in the design of  $\rho$ . The two maximums of the cost function are the same, and are reached for the same value of  $y$ . In this case, the cost associated to the strategy (30) is equal to 0.73, and the strategy of Figure 17 is not optimal. In Figures 16d and Figures 17d values of the yield functions visited when  $u = -1$  are highlighted. In Figures 16e and 17e values of the yield functions visited when  $u = 1$  are highlighted. The different colours used can be related to Figures 16c and 17c.

## A Proof of Lemma 1

First of all, let us remark that both  $\mathbb{R}^n \times L^1_{[0,T]}$  and  $C^0_{[0,T]}$  are metrisable sets, and as such sequential continuity implies uniform continuity.

1. Let  $(u_n(t))_{n \in \mathbb{N}}$  be a sequence of controls that converges to  $u(t)$  in  $L^1_{[0,T]}$ , and  $x_0^{(n)}$  be a  $\mathbb{R}^n$  sequence converging to  $x_0$ . We denote by  $x_n(t)$  the trajectory of  $(\Sigma_0)$  given by  $x_0^{(n)}$  and  $u_n(t)$ , and  $x(t)$  the trajectory given by  $x_0$  and  $u(t)$ . In other words, we have:

$$x_n(t) = x_0^{(n)} + \int_0^t F(x_n(\tau)) + u_n(\tau)G(x_n(\tau))d\tau, \text{ and } x(t) = x_0 + \int_0^t F(x(\tau)) + u(\tau)G(x(\tau))d\tau.$$

Let us now write down the expression of  $E_n(t) = x(t) - x_n(t)$ :

$$E_n(t) = \underbrace{(x_0 - x_0^{(n)})}_A + \underbrace{\int_0^t F(x) - F(x_n)d\tau}_B + \underbrace{\int_0^t uG(x) - u_nG(x_n)d\tau}_C.$$

Expression  $C$  is rewritten:

$$C = \underbrace{\int_0^t (u - u_n)G(x)d\tau}_{C_1} + \underbrace{\int_0^t u_n(G(x) - G(x_n))d\tau}_{C_2}$$

Next

$$\|E_n(t)\| \leq \|A\| + \|B\| + \|C_1\| + \|C_2\| \quad (31)$$

When restricted to a compact subset,  $X$  et  $Y$  are both Lipschitz with constants  $K_1$  and  $K_2$  respectively, and we have the inequalities:



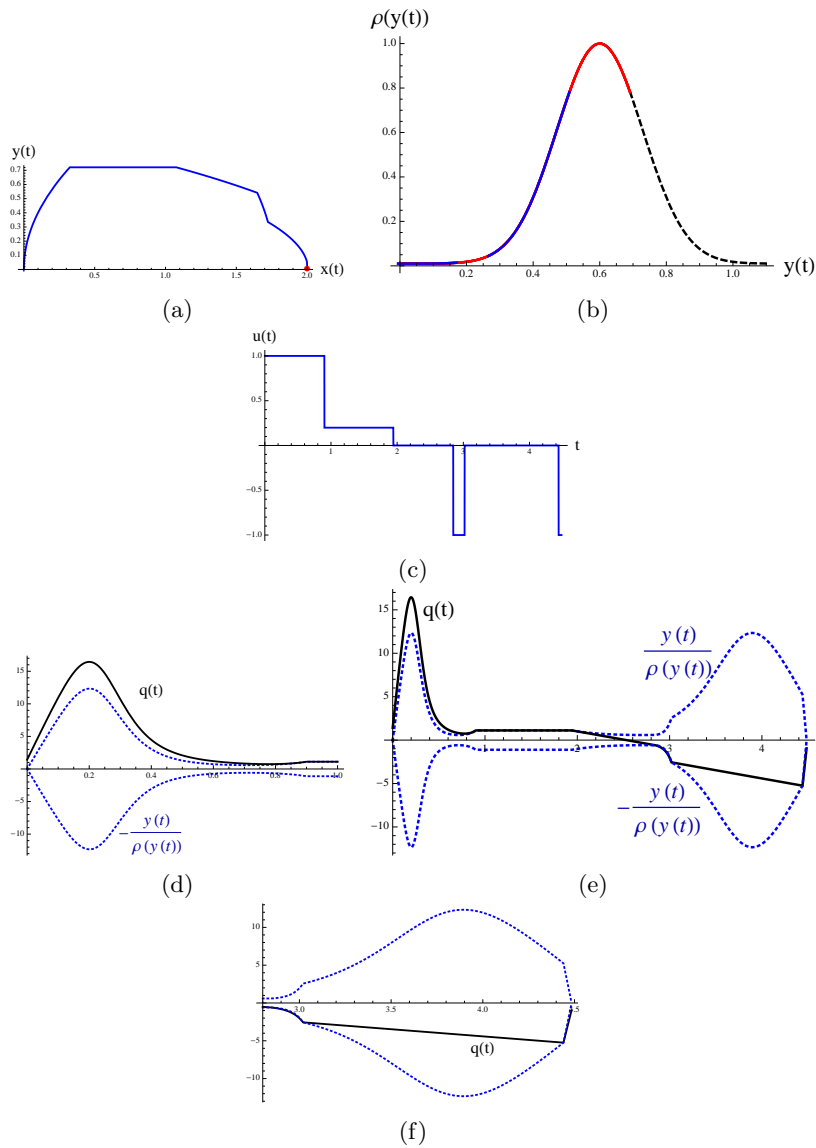


Figure 15: Optimal trajectory for the third case study. Parameters:  $(T_{min} + T_{back}) \approx 4.177$  and  $T_f = 4.48$ . Figure 15b: the blue parts of the graph corresponds to moments when  $u = -1$ .

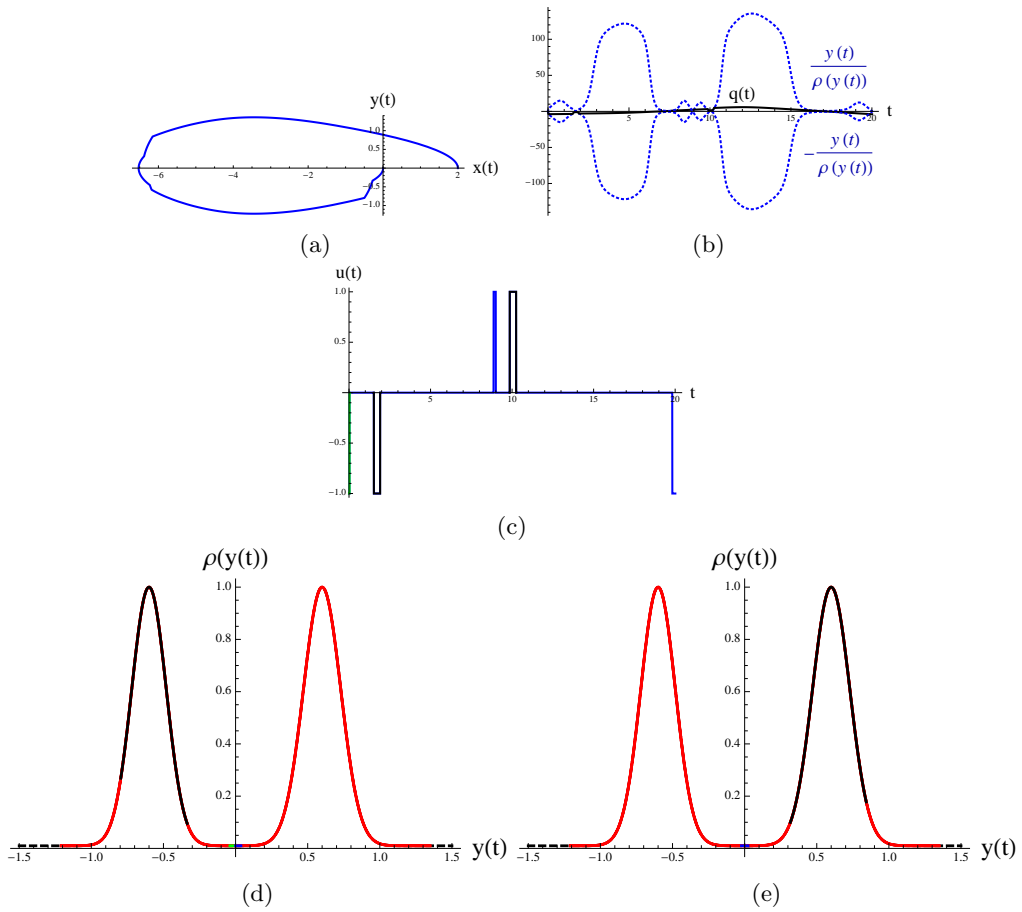


Figure 16: Optimal trajectory for the third case study for  $T_f \approx 17.75$ . The associated cost equals  $\approx 1.61$  while it equals 3.605 for strategy (30) —cf. Figure 13.

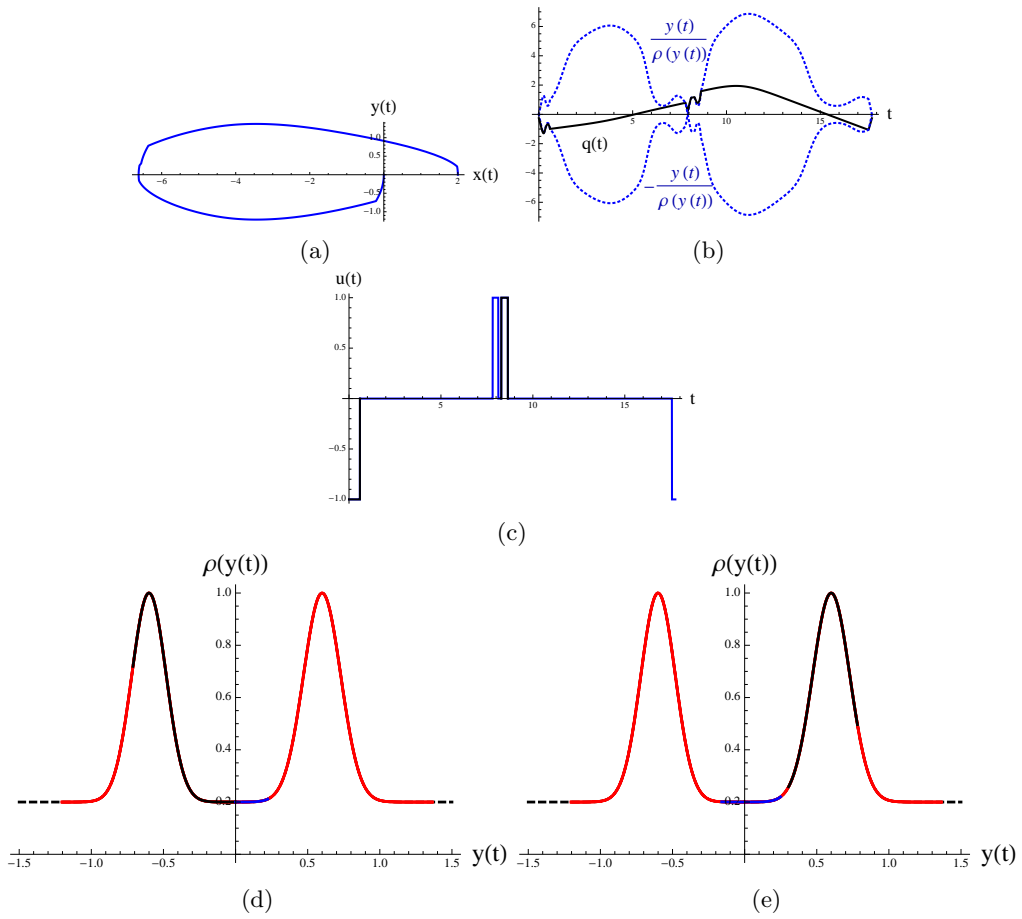


Figure 17: Extremal trajectory for the third case study for  $T_f \approx 17.75$ . The associated cost equals  $\approx 1.02$  while it equals 0.73 for strategy (30) with the yield function of Figures 17d and 17e.

- (a) for all  $\bar{\varepsilon} > 0$ , there exists  $\bar{N} \in \mathbb{N}$  such that  $\forall n > \bar{N}$ ,  $\|A\| < \bar{\varepsilon}$ ;  
(b) since  $X$  is Lipschitz:  $\|B\| \leq \int_0^t \|F(x) - F(x_n)\| d\tau \leq K_1 \int_0^t \|E_n(\tau)\| d\tau$ ;  
(c) on  $[0, T]$ ,  $Y$  is bounded from above (by some constant  $\tilde{K}$ ), which yields:

$$\|C_1\| \leq \tilde{K} \int_0^t \|u_n(\tau) - u(\tau)\| d\tau;$$

- (d) finally, for all  $n$ ,  $|u_n| \leq 1$ , and since  $Y$  is Lipschitz, we have  $\|C_2\| \leq K_2 \int_0^t \|E_n(\tau)\| d\tau$ .

Therefore, inequality (31) becomes:

$$\|E_n(t)\| \leq \|x_0 - x_0^{(n)}\| + K_1 \int_0^t \|E_n(\tau)\| d\tau + \tilde{K} \int_0^t \|u_n(\tau) - u(\tau)\| d\tau + K_2 \int_0^t \|E_n(\tau)\| d\tau \quad (32)$$

Since  $(u_n)$  converges in  $L^1_{[0, T]}$ : for all  $\tilde{\varepsilon} > 0$ , there is a  $\tilde{N}$  such that  $\forall n > \tilde{N}$ :  $\tilde{K} \int_0^t \|u_n - u\| d\tau < \tilde{\varepsilon}$ . Thus, for  $n > \max(\bar{N}, \tilde{N})$ , inequality (32) rewrites:

$$\|E_n(t)\| \leq (\bar{\varepsilon} + \tilde{\varepsilon}) + (K_1 + K_2) \int_0^t \|E_n(\tau)\| d\tau \leq (\bar{\varepsilon} + \tilde{\varepsilon}) + (K_1 + K_2) \int_0^T \|E_n(\tau)\| d\tau.$$

Gronwall's lemma, for  $t \in [0, T]$  gives:

$$\|E_n(t)\| \leq (\bar{\varepsilon} + \tilde{\varepsilon})e^{(K_1 + K_2)T} \quad \forall n > \tilde{N}.$$

In other words, for a given  $\varepsilon > 0$ , we can choose  $(\bar{\varepsilon} + \tilde{\varepsilon})$  such that, for all  $n > N = \max(\bar{N}, \tilde{N})$ ,  $\|E_n(t)\| < \varepsilon$  for all  $t \in [0, T]$ .

Which proves the continuity of  $\Phi(\cdot, \cdot)$ .

2. In this second part, we use the preceding continuity result and the continuity of  $u \mapsto |u|$  for the  $L^1_{[0, T]}$  topology.

As before,  $u_n(t)$  is a  $L^1_{[0, T]}$ -sequence of controls converging to  $u(t)$ ,  $x_0^{(n)}$  converges to  $x_0$ , and  $x_n$  (resp.  $x$ ) is the trajectory generated by  $x_0^{(n)}$  and  $u_n$  (resp.  $x_0$  et  $u$ ). Let us now write the difference:

$$\begin{aligned} |J(u_n) - J(u)| &= \left| \int_0^T |\psi(x_n)u_n| dt - \int_0^T |\psi(x)u| dt \right| \\ &= \left| \int_0^T |\psi(x_n)| (|u_n| - |u|) dt - \int_0^T |u| (|\psi(x_n)| - |\psi(x)|) dt \right| \end{aligned}$$

Since  $x_n(t)$  tends uniformly to  $x(t)$  in  $C^0_{[0, T]}$ , there are a constant  $M > 0$ , and an integer  $N(M)$  such that for all  $n > N(M)$ , we have  $|\psi(x_n)| < M$ . For a given  $\varepsilon > 0$ , there are a rank  $N(\frac{\varepsilon}{2MT})$  and a rank  $N(\frac{\varepsilon}{2T})$  such that;

- (a)  $\left| |u_n| - |u| \right| < \frac{\varepsilon}{2MT}$  for all  $n > N(\frac{\varepsilon}{2MT})$ ,

$$(b) \left| |\psi(x_n)| - |\psi(x)| \right| < \frac{\varepsilon}{2T} \text{ for all } n > N\left(\frac{\varepsilon}{2T}\right).$$

Consequently, there exists a rank  $N(\varepsilon)$  such that for all  $n > N(\varepsilon)$

$$|J(u_n) - J(u)| < M \int_0^T \frac{\varepsilon}{2MT} dt + \int_0^T \frac{\varepsilon}{2T} dt = \varepsilon$$

which gives us the sequential continuity of  $J(\cdot)$ .

## Conclusion

The energy consumption optimisation problem allowed us to study an optimal control problem with a running cost including an absolute value function and a yield function. This problem has been addressed in fixed time and decomposed into several case studies, three of which were considered in the present article. For each one of them, the influence of the yield function upon optimal trajectories have been discussed. In particular, in the case of a flat road and a null drag coefficient, the yield function plays no role. Then, when the drag coefficient isn't null anymore, singular arcs may appear even in the case of a constant yield function. We also noticed that for some yield functions two-step braking strategies are optimal. In the last case study, involving a non-flat road profile, the yield function plays a role with respect to singular arcs, since singular arcs heavily depend on the sign of the yield function's derivative.

Finally, subsequent works on this topic should include investigations on extremal trajectories having both backward and singular arcs, especially arcs such that  $y$  is not constant. The introduction of the drag coefficient in the case of a non-flat road, and different road profiles should also be covered.

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