

Optimal control of parabolic equations by spectral decomposition

Martin Lazar
University of Dubrovnik

Osijek, 2018
Seminar za optimizaciju i primjene

Joint work with: C. Molinari,
Universidad Técnica Federico Santa María, Valparaíso, Chile



Outline

- Problem formulation
- Characterisation of the solution
- Numerical recovery
- Numerical examples
- Distributed control

Outline

- Problem formulation
- Characterisation of the solution
- Numerical recovery
- Numerical examples
- Distributed control

The problem framework

An **optimal control** problem for an abstract heat equation:

$$\begin{cases} -y'(t) &= \mathcal{A}y(t) & \text{for } t > 0 \\ y(0) &= u \in H. \end{cases} \quad (1)$$

H - Hilbert space

\mathcal{A} - positive semidefinite, self-adjoint unbounded operator on H ,
- with dense domain $D(\mathcal{A})$,
- with compact resolvent.

Keynote example: $\mathcal{A} = -\Delta$, the Dirichlet Laplacian in $L^2(\Omega)$.

$\{\mathcal{S}_t\}_{t \geq 0}$ - strongly continuous semigroup of non-expansive linear operators generated by $-\mathcal{A}$

Control u - initial datum aiming to:

- (1) steer the solution (arbitrarily closed) to a desired target in a given time horizon,
- (2) minimise a given energy functional.

The system (1) is **controllable** to a *target state* $y^T \in H$ in time $T > 0$ if there is $u \in H$ such that

$$\mathcal{S}_T u = y^T.$$

In general, system (1) is **NOT controllable** to an arbitrary target.

E.g. $\mathcal{A} = -\Delta$, the Dirichlet Laplacian in $L^2(\Omega)$

$$(\forall t > 0) \quad S_t H \subseteq D(\mathcal{A}) = H^2(\Omega) \cap H_0^1(\Omega)$$

– no target state $y^T \in H \setminus D(\mathcal{A})$ can be attained in any time.

System (1) is **approximately controllable**:

for every target time $T > 0$, target state y^T , tolerance $\varepsilon > 0$, there exists an initial datum $u \in H$ such that

$$\|\mathcal{S}_T u - y^T\|_H \leq \varepsilon.$$

The problem

Given a tolerance $\varepsilon > 0$, a control time $T > 0$, and a target state y^T , find

$$(\mathcal{P}) \quad \hat{u} = \operatorname{argmin}_{u \in H} \left\{ J(u) : \|\mathcal{S}_T u - y^T\|_H \leq \varepsilon \right\},$$

where

$$J(u) = \frac{\alpha}{2} \|u\|_H^2 + \frac{1}{2} \int_0^T \beta(t) \|\mathcal{S}_t u - y^d(t)\|_H^2 dt,$$

with

- ▶ $y_d \in L^2(0, T; H)$, target trajectory;
- ▶ $\alpha > 0$, weight of the control cost;
- ▶ $0 \leq \beta \in L^2(0, T)$, weight of the control on the trajectory.

Outline

- Problem formulation
- **Characterisation of the solution**
- Numerical recovery
- Numerical examples
- Distributed control

The solution is unique!

Indeed, by means of the *indicator function*:

$$I_C(y) = \begin{cases} 0 & \text{if } y \in C \\ +\infty & \text{else.} \end{cases}$$

the problem (\mathcal{P}) is restated as

$$\min_{u \in H} \{J(u) + I_{\bar{B}}(\mathcal{S}_T u)\},$$

where $\bar{B} = \overline{B(y^T; \varepsilon)}$.

$J + I_{\bar{B}} \circ \mathcal{S}_T$ is proper, strongly convex and lower-semicontinuous

\implies problem (\mathcal{P}) has a **unique** solution \hat{u} .

Let \tilde{u} denote the unique solution of the **unconstrained** problem

$$\tilde{u} = \operatorname{argmin}_{u \in H} J(u),$$

and $\tilde{y} = \mathcal{S}_T \tilde{u}$ the corresponding final state.

Proposition

If $\|\tilde{y} - y^T\|_H \leq \varepsilon$, then $\hat{u} = \tilde{u}$.

Otherwise, the optimal final state verifies $\hat{y} \in \partial \bar{B}$.

Standard approaches to the problem

$\beta = 0$ (no desired trajectory)

HUM (Hilbert Uniqueness Method), some penalised version:

- based on the dual problem,
- discretisation of the system,
- approximation by a finite dimensional problem,
- iterative algorithm for getting the control.



Glowinski, R., Lions, J. L. Exact and approximate controllability for distributed parameter systems, Acta Numer. (1994), 269-378.



Boyer, F. On the penalized HUM approach and its application to the numerical approximation of null-controls for parabolic problems, ESAIM: Proceedings (2013), no. 41, 15-58.

$\beta \neq 0$

- even a more complex numerical treatment (convex optimisation techniques)

We present a different approach based on **spectral decomposition** of the solution by eigenfunctions of \mathcal{A} ,

Geometrical interpretation

Denote

$$\psi = (J \circ S_{-T}),$$

i.e. $\psi(y) = J(u)$ for $u = S_{-T}(y)$.

Introduce sublevel sets of $\psi = (J \circ S_{-T})$:

$$\begin{aligned} W_c &= \{y \in H : \psi(y) \leq c\} \\ &= \{y \in H : y = \mathcal{S}_T u \text{ for some } u \in H \text{ with } J(u) \leq c\}. \end{aligned}$$

W_c is empty for $c < \tilde{c} = J(\tilde{u})$.

$(W_c)_{c \geq \tilde{c}}$ – a nested family of nonempty closed convex sets centred at \tilde{y} , that increases with c .

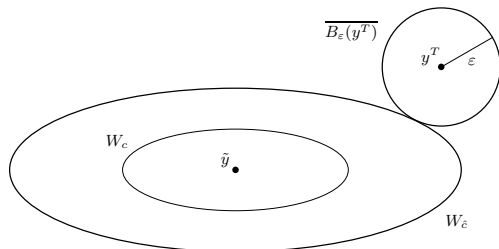


Figure: Sublevel sets W_c and the target ball.

The target ball is hit for the first time by $W_{\hat{c}}$, where $\hat{c} = J(\hat{u})$.
The intersection \hat{y} is the optimal final state.

$$\hat{y} - y^T = -\hat{\gamma} \nabla \psi(\hat{y}),$$

for some $\hat{\gamma} > 0$.

Together with

$$\|\hat{y} - y^T\|_H = \varepsilon$$

we get a fully determined system for $\hat{\gamma}, \hat{y}$.

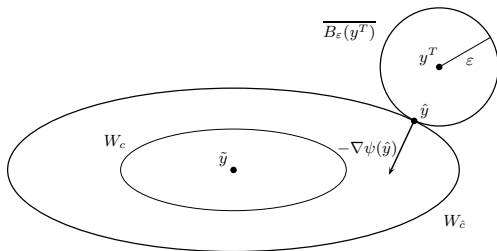


Figure: Optimal final state \hat{y} as intersection of $W_{\hat{c}}$ and $\overline{B_{\varepsilon}(y^T)}$

Spectral decomposition

Denote:

$(\varphi_n)_{n \in \mathbf{N}}$ – an orthonormal basis of H , consisting of **eigenfunctions** of \mathcal{A}

$(\lambda_n)_{n \in \mathbf{N}}$ – a sequence of corresponding (nonnegative) **eigenvalues** λ_n ,

$$\lim_n \lambda_n = +\infty$$

y_n – the n -th **Fourier coefficient** of $y \in H$.

The ellipsoids W_c can be now characterised as

$$W_c = \left\{ \sum_n y_n \varphi_n : \underbrace{\sum_n (a_n y_n^2 + b_n y_n + c_n)}_{\psi(y)=J(u)} \leq c \right\}, \quad (2)$$

where

$$a_n = \left(\frac{\alpha}{2} + \frac{1}{2} \int_0^T \beta(t) e^{-2\lambda_n t} dt \right) e^{2\lambda_n T};$$

$$b_n = -e^{\lambda_n T} \int_0^T \beta(t) e^{-\lambda_n t} y_n^d(t) dt;$$

$$c_n = \frac{1}{2} \int_0^T \beta(t) \left(y_n^d(t) \right)^2 dt.$$

The geometrical interpretation

$$\hat{y} - y^T = -\hat{\gamma} \nabla \psi(\hat{y}),$$

together with

$$(\nabla \psi(y))_n = 2a_n y_n + b_n, \quad n \in \mathbf{N},$$

we get an explicit formula for the Fourier coefficients of the optimal final state \hat{y} :

$$\hat{y}_n = \frac{y_n^T - \hat{\gamma} b_n}{1 + 2\hat{\gamma} a_n}. \quad (3)$$

It remains to determine the constant $\hat{\gamma} > 0$.

Condition $\|\hat{y} - y^T\| = \varepsilon$ together with (3) implies

$$G(\hat{\gamma}) := \sum_n \left(\frac{\hat{\gamma} (2a_n y_n^T + b_n)}{1 + 2\hat{\gamma} a_n} \right)^2 = \varepsilon^2. \quad (4)$$

- G – strictly increasing,
 – $G(0)=0$,
 – $\lim_{\gamma \rightarrow \infty} G(\gamma) = \|\tilde{y} - y^T\| =: \varepsilon_c$.

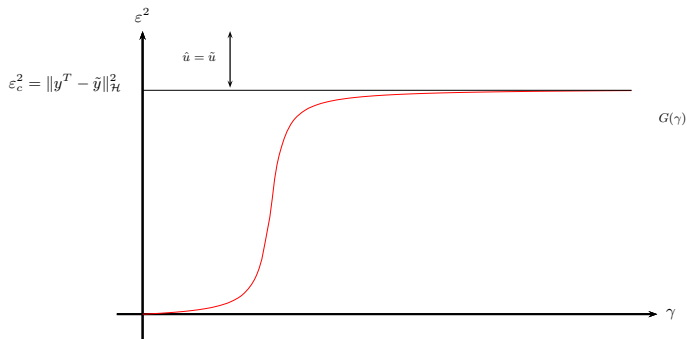


Figure: Function G

The equation

$$G(\hat{\gamma}) = \varepsilon^2$$

has the unique solution for every $\varepsilon \in (0, \|\tilde{y} - y^T\|_H)$.

Theorem [Generalized HUM]*

The solution of the optimal control problem (\mathcal{P}) is given by

$$\hat{u} = \sum_n \hat{u}_n \varphi_n = \sum_n e^{\lambda_n T} \hat{y}_n \varphi_n,$$

where the Fourier coefficients $(\hat{y}_n)_{n \in \mathbf{N}}$ of the final state \hat{y} are given by:

$$\hat{y}_n = \frac{y_n^T - \hat{\gamma} b_n}{1 + 2\hat{\gamma} a_n},$$

$$G(\hat{\gamma}) := \sum_n \left(\frac{\hat{\gamma} (2a_n y_n^T + b_n)}{1 + 2\hat{\gamma} a_n} \right)^2 = \varepsilon^2.$$



L., M., Molinari, C., Peypouquet, J.: Optimal control of parabolic equations by spectral decomposition. Optimization 66 (8), 1359-1381 (2017)

Outline

- Problem formulation
- Characterisation of the solution
- **Numerical recovery**
- Numerical examples
- Distributed control

Obtained explicit formulas incorporate infinite series.

Truncation required.

Introduce the truncated approximation of the optimal final state, \hat{y}^N :

$$\hat{y}^N = \sum_{n=1}^N \hat{y}_n^N \varphi_n, \quad \text{with} \quad \hat{y}_n^N = \frac{y_n^T - \hat{\gamma}_N b_n}{1 + 2\hat{\gamma}_N a_n}. \quad (5)$$

Truncated Fourier series with **approximate** coefficients.

Theorem

The following estimate holds

$$\|\hat{y}^N - \hat{y}\|_H^2 \leq 4\|y^T - y^{T,N}\|_H^2 + \frac{4\|\beta\|_{L^2(0,T)}^2}{\alpha^2 e^{2\lambda_N T}} \|y^d - y^{d,N}\|_{L^2(0,T;H)}^2,$$

where $y^{T,N} = \sum_{n=0}^N y_n^T \varphi_n$ and $y^{d,N}(t) = \sum_{n=0}^N y_n^d(t) \varphi_n$ the truncated series representation of the target final state and the reference trajectory in the distributed cost, respectively.

Numerical algorithm

– produces the approximate optimal final state \hat{y}^N , with precision ρ .

Step 1. Determine N such that

$$\max \left\{ \|y^T - y^{T,N}\|_H^2, \frac{\|\beta\|_{L^2(0,T)}^2}{\alpha^2 e^{2\lambda_N T}} \|y^d - y^{d,N}\|_{L^2(0,T;H)}^2 \right\} \leq \frac{\rho^2}{8}.$$

Step 2. Compute $\varepsilon_N := \lim_{\gamma \rightarrow \infty} G_N(\gamma)$.

Step 3. For $\varepsilon \geq \varepsilon_N$ the approximative solution is $\tilde{u}^N = \sum_{n=1}^N -\frac{b_n}{2a_n} e^{\lambda_n T} \varphi_n$.

Otherwise, proceed to Step 4.

Step 4. Solve equation $G_N(\gamma) = \varepsilon^2$ numerically to find $\hat{\gamma}_N$ (bisection method or other).

Step 5. Compute the approximate optimal final state \hat{y}^N using (5), and the approximate optimal control \hat{u}^N by

$$\hat{u}^N = \sum_{n=1}^N \hat{u}_n^N \varphi_n = \sum_{n=1}^N e^{\lambda_n T} \hat{y}_n^N \varphi_n.$$

Outline

- Problem formulation
- Characterisation of the solution
- Numerical recovery
- **Numerical examples**
- Distributed control

Example 1 - Energy minimisation in 2D

The heat equation on $\Omega = (0, 1) \times (0, 1)$

$$\begin{cases} \frac{d}{dt}y - \Delta y = 0 & \Omega \times (0, T) \\ y = 0 & \partial\Omega \times (0, T) \\ y(0) = u & (0, \pi). \end{cases} \quad (6)$$

Target time $T = 0.001$

We use the eigenfunctions of the Dirichlet Laplacian on the rectangle

$$\varphi_{j,k}(x_1, x_2) = \sin(j\pi x_1) \sin(k\pi x_2), \quad j, k = 1, 2, \dots,$$

with corresponding eigenvalues

$$\lambda_{j,k} = (j\pi)^2 + (k\pi)^2.$$

Example 1 - Energy minimisation in 2D

$$\alpha = 1$$

$\beta = 0$ - no prescribed reference trajectory.

$$(\mathcal{P}) \quad \hat{u} \in \arg \min_{u \in L^2(0, \pi)} \left\{ \frac{1}{2} \|u\|_{L^2}^2 : \mathcal{S}_T u \in \overline{B_\varepsilon(y^T)} \right\}.$$

We choose a reachable final target y^T .

We introduce

$$u(x_1, x_2) = \exp(- (x_1^2 + x_2^2)) \cdot \sin(5\pi x_1^3) \cdot \sin(5\pi x_2^7),$$

and we set $u^T = u^N$, the Fourier representation of u using the first 15×15 coefficients.

The final target, given as $y^T = \mathcal{S}_T u^T$, has a finite series representation.

The aim: Explore the differences between the initial datum u^T that generates the target and the solution \hat{u} for various values of ε .

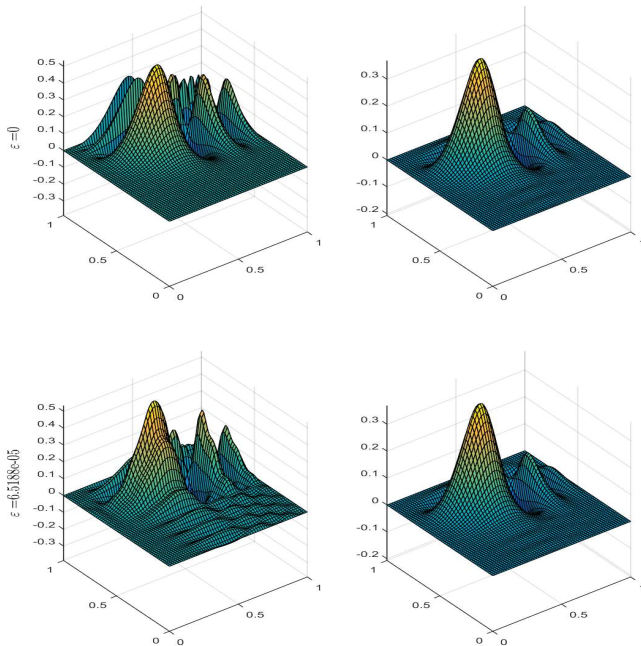


Figure: Initial data (left) and final state (right) for different values of ϵ .

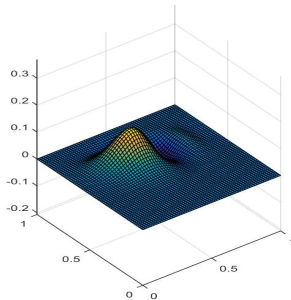
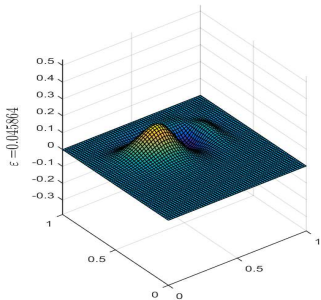
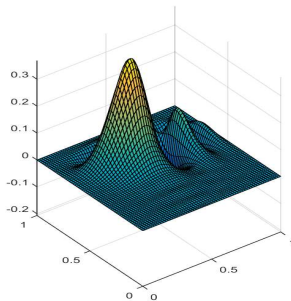
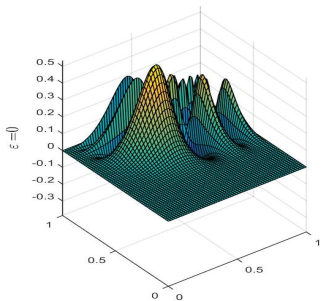


Figure: Initial data (left) and final state (right) for different values of ε .

Example 2 - Energy minimisation and trajectory regulation, 1D

The heat equation on $\Omega = (0, \pi)$, $T = 0.01$

- ▶ $\alpha = 10^{-4}$;
- ▶ $\beta(t) = \mathbb{1}_{[t_1, t_2]}(t)$, with $t_1 = T/3$ and $t_2 = 2T/3$;
- ▶ $y^d(x, t)$ as a smoothing regularisation (through classical mollifier) of the function $x \mapsto \mathbb{1}_{[x_1, x_2]}(x)$, with $x_1 = \pi/5$ and $x_2 = 2\pi/5$;
- ▶ $y^T(x)$ as a smoothing regularisation (again, through mollifier) of the function $x \mapsto \mathbb{1}_{[x_3, x_4]}(x)$, with $x_3 = 3\pi/5$ and $x_4 = 4\pi/5$.

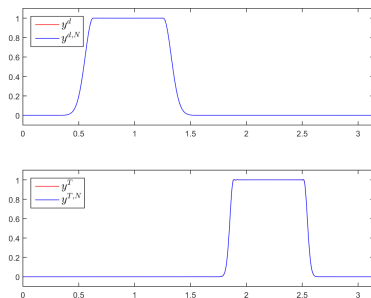


Figure: TOP: reference trajectory y^d for the distributed cost. BOTTOM: target final state y^T , in comparison with their reconstructions after Fourier decomposition with $N=185$ coefficients (indistinguishable).

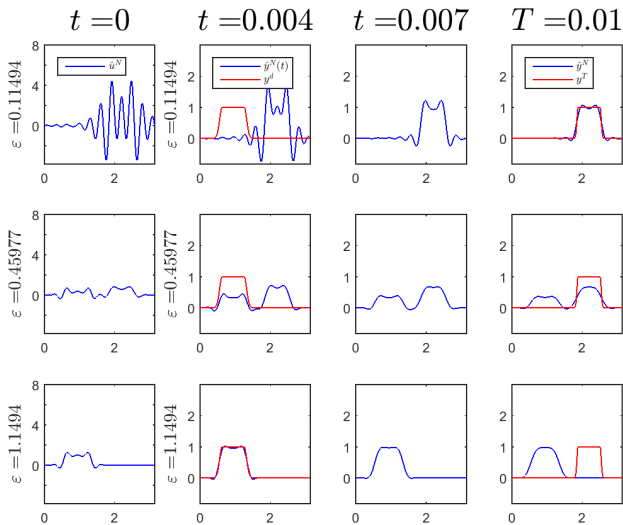


Figure: For the three values of ε : evolution of the solution in time and comparison with the reference trajectory $y^d(t)$ ($t = 0.004$), and with the target y^T ($T = 0.01$).

Outline

- Problem formulation
- Characterisation of the solution
- Numerical recovery
- Numerical examples
- Distributed control

The problem framework*

The constrained minimisation problem

$$(\mathcal{P}) \quad \min_u \left\{ J(u) : y(T) \in \overline{B_\varepsilon(y^T)} \right\},$$

where:

- J is a given cost functional
- y^T is a given target
- y the solution of

$$(\mathcal{E}) \quad \begin{cases} \frac{d}{dt}y(t) + \mathcal{A}y(t) = \mathcal{B}_t u(t) & \text{for } t \in (0, T) \\ y(0) = 0. \end{cases}$$

- H1** The functional J is strictly convex, coercive and lower-semicontinuous.
- H2** The unbounded linear operator $\mathcal{A} : \mathcal{H} \rightarrow \mathcal{H}$ is positive semidefinite, selfadjoint with dense domain $D(\mathcal{A})$ and compact resolvent.
- H3** The operator \mathcal{B}_t belongs to $\mathcal{L}(U, \mathcal{H})$ for each time $t \in (0, T)$; moreover the pair $(\mathcal{A}, \mathcal{B}_t)$ is approximately controllable in time T .

U, H - real Hilbert space



L, M., Molinari, C.: Optimal distributed control of the heat-type equations by spectral decomposition, submitted.

Existing numerical approaches

Optimal control problems involving distributed control:

- usually restricted to a null control problem
- approximation by an auxiliary problem (penalisation one)
- Fenchel-Rockafeller duality
- iterative algorithm for getting the control,
- (finite element) discretisation of the system (convergence issues!),



Fernandez-Cara, Munch: Numerical exact controllability of the 1D heat equation: duality and Carleman weights, JOTA (2014).



Fernandez-Cara, Munch: Strong convergent approximations of null controls for the 1D heat equation, SEMA (2013).



Labbé, Trélat: Uniform controllability of semidiscrete approximations of parabolic control systems, SCL (2006).

Characterisation of the solution by the dual problem

We introduce the Fenchel conjugate J^* of the functional J :

$$J^*(u^*) = \sup_{u \in L^2_{T,U}} \{ \langle u^*, u \rangle_{T,U} - J(u) \} \quad \text{for } u^* \in L^2_{T,U}.$$

Theorem [Generalized HUM]

Let $\bar{y} \in \mathcal{H}$ be a reachable state.

Then

$$\bar{u} \in \operatorname{argmin}_{u \in \mathcal{U}} \{ J(u) : \mathcal{T}u = \bar{y} \}.$$

is of the form $\bar{u} = \nabla J^* (-\mathcal{T}^* \bar{\varphi}^T)$, where

$$\bar{\varphi}^T \in \operatorname{arg min}_{\varphi^T \in \mathcal{H}} \left\{ J^*(-\mathcal{T}^* \varphi^T) + \langle \bar{y}, \varphi^T \rangle_{\mathcal{H}} \right\}.$$

$\mathcal{T} : L^2_{T,U} \rightarrow \mathcal{H}$ is the operator that takes the distributed control and gives the corresponding final state

$$\mathcal{T}u = y(T).$$

$$\mathcal{T}^* \varphi^T = \mathcal{B}^* \varphi,$$

where φ is the solution to the dual problem satisfying $\varphi(T) = \varphi^T$.

Characterisation of the solution by the dual problem

It is enough to restrict minimisation problem (\mathcal{P}) to controls of form

$$u = \nabla J^* (-\mathcal{T}^* \varphi^T).$$

For such u

$$J(u) = F(\varphi^T),$$

where

$$F(\varphi^T) = - \left[\langle \nabla J^* (-\mathcal{T}^* \varphi^T), \mathcal{T}^* \varphi^T \rangle_{L^2_{T,u}} + J^* (-\mathcal{T}^* \varphi^T) \right].$$

Theorem

The solution of problem (\mathcal{P}) is

$$\hat{u} = \nabla J^* (-\mathcal{T}^* \hat{\varphi}^T),$$

where $\hat{\varphi}^T$ is a solution of

$$\min_{\varphi^T \in \mathcal{H}} \left\{ F(\varphi^T) : \|y(T) - y^T\|_{\mathcal{H}} = \varepsilon. \right\}. \quad (7)$$

Optimal control constructive characterisation

For

$$J(u) = \frac{1}{2} \int_0^T \alpha(t) \|u(t)\|_{L^2(\omega)}^2 dt + \frac{1}{2} \int_0^T \beta(t) \|y_u(t) - y^d(t)\|_{L^2(\omega')}^2 dt.$$

we obtain

$$\hat{\varphi}^T = \arg \min_{\varphi^T \in \mathcal{H}} \left\{ F(\varphi^T) \right\} = \arg \min_{\varphi^T \in \mathcal{H}} \left\{ \langle M_T \varphi^T, \varphi^T \rangle_{\mathcal{H}} \right\},$$

where $M_t : \mathcal{H} \rightarrow \mathcal{H}$ is given by:

$$M_t \left(\varphi^T \right) = \int_0^t e^{(s-t)\mathcal{A}} \mathcal{B} \left\{ \left[(C^* C)^{-1} \left(\mathcal{B}^* e^{(\cdot-T)\mathcal{A}^*} \varphi^T \right) \right] (s) \right\} ds, \quad (8)$$

and $C = (C_1, C_2)$:

$$(C_1 u)(t) = \sqrt{\alpha(t)} u(t) \mathbb{1}_{\omega};$$

$$(C_2 u)(t) = \sqrt{\beta(t)} y_u(t) \mathbb{1}_{\omega'}.$$

$$y(T) = -M_T \varphi^T + \tilde{y}(T).$$

Consequently, the original problem (\mathcal{P}) is equivalent to

$$(\mathcal{P}') \quad \min_{\varphi^T \in \mathcal{H}} \left\{ \langle M_T \varphi^T, \varphi^T \rangle_{\mathcal{H}} : \underbrace{\|M_T \varphi^T - \tilde{y}(T) + y^T\|_{\mathcal{H}}}_{= \varepsilon} = \varepsilon \right\}.$$