# MULTILEVEL CONTROL OF LINEAR SYSTEMS 

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## ABSTRACT

The "satisfaction approach" of Takahara [5] reduces the complexity of the computation of the control for a large scale system. Its aim is not to reach the optimum, but, given a reference control, to compute a new control such as to improve the performance. The fact that the optimum point is not reached is compensated by the fact that the computation is simplified. The numerical application of this technique is studied here (Chapter 2). This viewpoint of the problem leads (in Chapter 3) to an algorithm which improves the performance and deals with each subsystem separately. The iteration of this algorithm is shown to give the optimum, if some assumptions are satisfied.

Another approach for this kind of problem is the "decomposition technique": it reaches the optimal control of a large system by dealing with each subsystem separately and then coordinating the results. This technique was applied by $S$. Reich [3] in the case of linear systems with quadratic performances and is extended (Chapter 4) to the use of linear systems with disturbances. Moreover, with regard to the solution of the global system, the results do not show any reduction in the computing time of the optimal solution.

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| A | Positive self adjoint linear operator from X into X . |
| :---: | :---: |
| B | Positive self adjoint linear operator from M into M . |
| $C(T)$ | Set of continuous real-valued functions defined on [T]. |
| $D(T)$ | Set of continuous real-valued functions defined on [T]. |
| E | Expectation operator. |
| H | Hamiltonian. |
| $\mathrm{H}_{\mathrm{m}}$ | $\frac{\partial H}{\partial m}$ |
| M | Set of manipulated variables. |
| $M_{i}$ | $i \frac{\text { th }}{}$ projection of $M$. |
| m | Element of M 二 manipulated variable. |
| $m^{r}$ | Reference control for the first level. |
| $m_{j}^{r}$ | $\mathrm{P}_{\mathrm{j}} \mathrm{m}^{r}$. |
| n | Number of the subsystems of the first level. |
| N | Vector Wiener Process: Noise in the system. |
| $\mathrm{N}_{\mathrm{i}}$ | $P_{i} N .$ |
| $\mathrm{P}_{\mathrm{i}}$ | ith projection operator. |
| q | Performance index on Mx U . |
| $q_{j}$ | Performance index of the $j \frac{\text { th }}{}$ subsystem on |
|  | $M_{j} \times U_{j}$ |
| r | Desired value of a state variable. |
| $r_{j}$ | $j \frac{\text { th }}{}$ projection of $r$. |

```
\(S_{i} \quad\) First kind of sensitivity functional for the ith subsystem.
Sm( \(t\) ) Segment of \(m(t)\).
\(s_{j}\)
Sensitivity (first kind) of the \(j \frac{\text { th }}{}\) subsystem Uncertainty of the \(j \frac{\text { th }}{}\) subsystem.
Time index set : \(\left[0, t_{e}\right]\).
t Time index.
\(t_{S(i)}\) Starting time of the \(i \frac{t h}{}\) adaptation.
\(t_{e}\) End time of control.
V Uncertainty set - Posterior variance
= \(E\left[(x-\bar{x})(x-\bar{x})^{T}\right]=\operatorname{matrix}(n, n)\)
\(v_{j} \quad\) Set of \(v_{j}\).
\(v_{i j}\) Element of the matrix \(v\).
\(v_{j}\) Uncertainty for the \(j \underline{\text { th }}\) subsystem.
X Set of state vector.
\(X_{i} \quad i \frac{\text { th }}{}\) projection of \(X\).
\(x_{i} \quad\) Element of \(X_{i}\).
\(x^{r} \quad\) State vector corresponding to \(\mathrm{m}^{r}\).
\(\bar{x}_{i} \quad E\left(x_{i}\right)\).
\(\overline{\mathrm{x}} \quad \mathrm{E}(\mathrm{x})=\) posterior mean.
Y Observation of the system.
Z Vector Wiener Process: Noise in the measurements.
\(z_{i} \quad P_{i} Z\).
\(\}_{j} \quad\) coordination variable for the \(j \frac{\text { th }}{}\) subsystem.
\(t\) Time index.
\(\phi \quad\) Performance functional on \(\mathrm{X} \times \mathrm{M}\).
```

| $\quad \phi_{i} \quad$ Performance functional of the $i \underline{\text { th }}$ subsystem |  |
| :--- | :--- |
|  | on $X_{i} \times M_{i}$. |
| $s(q) \quad$ Ordering relation on $M$. |  |
| $s(q j) \quad$ Ordering relation on $M_{j}$. |  |

NOTATIONS
$A^{T}=\quad$ Transpose of $A$.
$\dot{Y}_{(t)}=$ Time derivative of $y(t)$.
\&. 6, f. (? Time varying matrices defining the successive sweep method.
$h(t), w_{1}, w_{2}$ : Time varying vectors defining the successive sweep method.
$g_{1}, g_{2}:$ Real valued functions defined on $T$.
$W \quad: \quad \frac{1}{d t}\left[d N(t) \cdot d N^{T}(t)\right]$.
$Q \quad: \quad \frac{1}{d t}\left[d z(t) \quad d z^{T}(t)\right]$.
$v_{11}^{\prime}, v_{22}^{\prime}, \bar{x}_{1}^{\prime}, \bar{x}_{2}^{\prime}, v_{12}^{\prime}, v_{12}^{\prime \prime}:$ Dummy variables.

## INTRODUCTION

This thesis is concerned with the decomposition of the computation of optimal controls for large scale systems.

There are two parts:
The first part (Chapters 2 and 3) deals with a particular technique, the "satisfaction approach" studied by Takahara [5]. The satisfaction approach proceeds as follows: it allows performance improvement of a large system by dealing with separate subsystems, and the interconnections between the subsystems are viewed as internal disturbances. The second chapter is an application of the satisfaction approach to linear quadratic systems. The third chapter is another way of improving the performance by dealing with separate subsystems. With some assumptions this heuristic is shown to lead by iterations to the optimal control.

The second part (Chapter 4) deals with the use of the decomposition technique in large systems with disturbances. This decomposition technique is derived from a technique developed by Dantzig and Wolfe [1], and by Arrow [2]. The technique was studied and used by S. Reich [3] for deterministic linear systems, and deterministic linear systems with non-linear coupling. In this chapter, noises are introduced in an additive
way, both in the processes and the measurements. The noises are supposed to be Gaussian, uncorrelated, and their characteristics (mean and variance) are supposed to be known. The noises in the measurements introduce a new kind of interconnection between the subsystems so the decomposition technique cannot be applied directly. The Kalman technique [4] allows, however, in some specific cases the transformation of a stochastic problem into a deterministic one. Once the deterministic equations are found, the application of the decomposition technique presents no computational difficulty. However, it was not shown that this computation, based on a saddlevalue argument should, in the general case, converge to the optimal point.

In all the numerical examples, the computation technique is the successive sweep method for the global method and the first level of the decomposition technique. The gradient method is used for the second level. The notations for the computation are those explained in Appendix 1.

## CHAPTER II

THE SATISFACTION TECHNIQUE

APPLICATION TO LINEAR SYSTEMS
2.1 Goals and Methods of the Satisfaction Approach:

The decomposition technique is a way to break a large scale system into subsystems and then by a multilevel procedure find the overall optimum.

This is not the only way to approach the problem. The satisfaction approach, with the notion of "internal disturbances" leads to another multilevel procedure, dealing with separate subsystems. All the details on the method are taken from Takahara [5].

A multilevel system is a control system where a given controlled system is controlled by a group of goal seeking systems in a hierarchic arrangement.

By referring to Table $l$ we find that: $G_{11}, G_{12}, G_{2}$ are goal seeking systems or controllers. $G_{11}, G_{12}$ belong to the first level. $G_{2}$ belong to the second level.


Table 1
Integrated Controlled System
$G_{11}, G_{12}$ are assumed to control $S_{11}$ and $S_{12}$ separately. But in general $S_{11}$ and $S_{12}$ are interacting. So we must introduce a goal seeking $G_{2}$ in order to coordinate the $G_{11}, G_{12} . G_{2}$ improves the integrated performance by compensating the negligences of the interactions through the controllers $G_{11}, G_{12}$. Since these interactions are unknown for $G_{11}$ and $G_{12}$, they are called internal disturbances (the term "external disturbances" being used for the noises).

The satisfaction approach uses a so-called on-line coordination, i.e., a coordination which does not use an iteration technique. The reason is that the use of an iteration technique, in a so-called off-line coordination technique supposes an harmoniously coordinable system, i.e., the system is such that there exists a best value for the coordination variable and this value can be reached by iteration technique.

Therefore, the goal of the satisfaction technique is not to get the optimum solution of the problem but to improve the overall performance, with respect to a reference control.

In a given control system, each controller has its own mathematical model for the control purpose.


The whole problem is to determine a mathematical model for each goal seeking system in relation to the integrated mathematical model.

We can repeat the problem of the satisfaction approach in the following way:

Let $S$ be a real normed linear space on which an inner product is defined. The inner product is assumed to be continuous with respect to the topology derived from the norm. Let $U, M$ and $X$ be subsets of $S$. The relative topologies are defined on them. Let $\Psi$ and $\phi$ be continuous mappings such that:

$$
\begin{aligned}
& \Psi: M \times U \\
& \phi: X \times M \\
& \operatorname{Let} q(m, u)=\phi(\Psi(m, u), m)
\end{aligned}
$$

The satisfaction approach consists in finding:

1) If there exists $m^{*} \in M$ such that:

$$
\forall u \in U \quad q(m *, u)=v(u)
$$

where $V(u)$ is the satisfaction threshold.
2) If m* exists, then it is desired to find it explicitly.

### 2.2 Mathematical Formulation.

Hypothesis and Assumptions:
We consider a multilevel deterministic system in a real Banach space B. Let $X$ and $M$ be subsets of $B$; we call them the state set and the manipulated variable set. The linear manifolds spanned by $X$ and $M$ will be written as $\underline{X}$ and M . Let the system have as its state equation

$$
x=\psi(m)
$$

and performance functional:

$$
q(m)=\phi(\Psi \quad(m), m) .
$$

Assumptions:

1. $\psi$ and $\phi$ have Frechet derivatives.
2. $M$ and $X$ are convex sets in $B$ and $X=\underline{X}$ Int (m) $\neq \phi$. with respect to the relative topology.
3. $M=M_{1} \oplus M_{2}$ ( +1 ( $+M_{n}$
(4) represents the direct sum operation.

$$
M_{i}=P_{i} M
$$

4. Let us call $\mathrm{F}_{1}$ and $\mathrm{F}_{2}$ the Frechet derivatives of $\phi$ with respect to $x$ and $m_{1}$. We assume that $F_{1}$ and $F_{2}$ have also continuous Frechet derivatives.

With these assumptions we can give some definitions very helpful for the classification of multilevel systems:
-The operator $K_{i}: M \rightarrow X$ such that

$$
K_{i}: P_{i} \Psi(m)-\Psi(m) P_{i}
$$

where $P_{i}$ is the projection operator, is called the first kind of interaction operator.

If $K_{i}=0$, we can write $x_{i}=\psi\left(m_{i}\right)+x_{0}^{i}$ where $x_{0}^{i}$ is a constant, i.e., the subsystems of the first level are isolated.
-The bounded linear functional $S_{i}: M \rightarrow R$ such that: $\quad S_{i}=K_{i}^{*} F_{1}(x, m)$ where $K_{i}^{*}$ is the adjoint of $K_{i}$ and $F_{1}(x, m)$ is the Frechet derivative of $\phi$ with respect to $x$ is called the first kind of sensitivity functional.

It can be shown that the variations of $q$ with respect to the variations of $m_{i}$ consist of two parts: one is the direct consequence of $\delta \mathrm{m}_{i}$ on $\mathrm{x}_{\mathrm{i}}$. The second, $\left\{-\left(s_{i}, \delta m_{i}\right)\right\}$ (inner product), is the consequence of the interactions among the subsystems.

Lastly we can deal with the interactions in the integrated performance functional with the help of the second kind of interaction operators, i.e.,

$$
\begin{array}{ll}
R_{i l}: X \rightarrow \underline{X}^{\prime} & R_{i 2}: X \rightarrow \underline{M}^{\prime} \\
T_{i 1}: M \rightarrow \underline{X}^{\prime} & T_{12}: M \rightarrow \underline{M}^{\prime}
\end{array}
$$

with $\underline{X}^{\prime}, \underline{M}^{\prime}$ conjugate spaces of the linear manifold spanned by $X$ and $M$, and such that:

$$
\begin{aligned}
& R_{i j}=P_{i}^{*} D_{x} F_{j}(x, m)-D_{x} F_{j}(x, m) P_{i} \\
& T_{i j}=P_{i}^{*} D_{m} F_{j}(x, m)-D_{m} F_{j}(x, m) P_{i}
\end{aligned}
$$

where:

$$
P_{i}^{*} \text { is the adjoint of } P_{i} \text {. }
$$

$\mathrm{F}_{1}$ is the Frechet derivative of $\phi$ with respect
to x .
$\mathrm{F}_{2}$ is the Frechet derivative of $\phi$ with respect
to m .
$\mathrm{D}_{\mathrm{x}} \mathrm{F}_{\mathrm{j}}$ is the Frechet derivative of $\mathrm{F}_{\mathrm{j}}$ with
respect to x .

We say that $\phi(x, m)$ is additive if $\phi(x, m)$ is represented as $\phi(x, m)=\sum_{i=1}^{n} \phi_{i}\left(x_{i}, m_{i}\right)$.
It was proved [5] that $\phi(x, m)$ is additive if and only if $R_{i j}\left(I-P_{i}\right)=0$ and $T_{i j}\left(I-P_{i}\right)=0$.

So, if the two kinds of interactions, $K_{i}$ on one hand, $R_{i j}$ and $T_{i j}$ on the other hand, are equal to zero, then, the interactions are zero, the system can be reduced to $n$ independent control subsystems. If any one of these is not zero, then we have interactions called internal disturbances.

In order to give a mathematical formulation of the subsystems we have to make some more assumptions on the system:

The integrated system is given as follows:

$$
\begin{aligned}
x=\Psi m+x^{F} & \text { state equation } \\
\phi(x, m)=[x-r, A(x-r)]+(m, B m) & \text { performance } \\
& \text { functional. }
\end{aligned}
$$

Supplementary assumptions:
-M is compact.
$-q(m)=\phi(\Psi(m), m)$ is convex and it takes its unique unitical point in the interior of $M$.
$-\Psi$ is a linear operator such that: $\Psi: M \rightarrow X$.
-A and $B$ are linear, bounded, self adjoint positive operators.
$-r \in X$ is a constant.
$-\phi(x, m)$ is additive, i.e., $\phi$ can be rewritten in the following form:

$$
\begin{aligned}
\phi(x, m) & =\left(x_{1}-r_{1}, A_{1}\left(x_{1}-r_{1}\right)\right)+\ldots+\left(x_{n}-r_{n}, A_{n}\left(x_{n}-r_{n}\right)\right) \\
& +\left(m_{1}, B_{1} m_{1}\right)+\ldots \ldots \ldots+\left(m_{n}, B_{n} m_{n}\right)
\end{aligned}
$$

With these assumptions, we can write the following
formulation:
The $j$ th subsystem control problem of the first level is defined as follows:

$$
x_{j}=\Psi_{j} m_{j}+v_{j}+x_{j}^{F}
$$

$\min _{m_{j} \in M_{j}} \phi_{j}\left(x_{j}, m_{j}, s_{j}\right)=\left(x_{j}-r_{j}, A_{j}\left(x_{j}-r_{j}\right)\right)+\left(m_{j}, B^{\prime} m_{j}\right)$

$$
q_{j}\left(m_{j}, v_{j}, s_{j}\right)=\phi_{j}\left(\Psi_{j} m_{j}+v_{j}+x_{j}^{F} m_{j}, s_{j}\right)
$$

where

$$
x_{j} \in x_{j^{\prime}} v_{j} \in v_{j} \subset x_{j}, m_{j} \in M_{j^{\prime}} s_{j} \in S_{j}
$$

and

$$
\begin{aligned}
& \Psi j=\Psi+P_{j} \Psi-\Psi P_{j} \cdot \\
& x_{j}^{F}=P_{j} x^{F} \\
& B_{j}=B_{j}+K_{j}^{*} A K_{j}
\end{aligned}
$$

$$
N_{j}=k_{j} \bar{m}_{j}
$$

It was proved [5] that:
If

$$
m^{\prime \prime} \& m^{\prime} \in \text { admissible set of controls }
$$

and
$q_{i}\left(m_{i}^{\prime \prime}, v_{i}, s_{i}\right) \leq q_{i}\left(m_{i}^{\prime}, v_{i}, s_{i}\right) \forall_{i} \forall v_{i} \in v_{i}, \forall s_{i} \in S_{i}$ then

$$
q\left(m^{\prime \prime}\right) \leq q\left(m^{\prime}\right) .
$$

But the following theorem is also true and the demonstration is exactly the same:

Theorem: For $m^{\prime \prime}$ and $m^{\prime} \varepsilon$ admissible set of controls, such that:

$$
q_{i}\left(m_{i}^{\prime \prime}, v_{i}^{\prime \prime}, s_{i}^{\prime \prime}\right) \leq q_{i}\left(m_{i}^{\prime}, v_{i}^{\prime \prime}, s_{i}^{\prime \prime}\right) \forall_{i}
$$

we have:

$$
q\left(m^{\prime \prime}\right) \leq q\left(m^{\prime}\right)
$$

with

$$
\begin{aligned}
v_{i}^{\prime \prime} & =k_{i} \bar{m}_{i}^{\prime \prime} \\
s_{i}^{\prime \prime} & =2\left(K_{i}^{*} A\left(x^{\prime \prime}-r\right)+k_{i}^{*} A K_{i} m^{\prime \prime}\right)
\end{aligned}
$$

This formulation of the problem, i.e., the
mathematical models of the subsystems, is a second order approximation of the integrated system. Sirice the integrated system we shall deal with is assumed to be linear-quadratic a second order approximation can represent the global property precisely and if a general system
can be approximated by a linear quadratic system, then this formulation will be applicable.
2.3 Theoretical Way of Applying the Satisfaction Technique We shall study a linear example:

$$
\frac{d x}{d t}=c x+m
$$

or

$$
\left\{\begin{array}{l}
\frac{d x_{1}}{d t}=c_{11} x_{1}+c_{12} x_{2}+m_{1} \\
\frac{d x_{2}}{d t}=c_{21} x_{1}+c_{22} x_{2}+m_{2}
\end{array}\right.
$$

with the performance:

$$
\phi=\int_{0}^{t} e\left\{(x-r)^{T} A(x-r)+m^{T} B m\right\} d t
$$

with

$$
A=\left[\begin{array}{cc}
{ }^{A} 1 & 0 \\
0 & A_{2}
\end{array}\right] \quad B=\left[\begin{array}{ll}
B_{1} & 0 \\
0 & B_{2}
\end{array}\right]
$$

## Notations:

For a linear example like the one we are studying we can write:

$$
x_{1}(t)=x_{1}^{f}+\left(\Psi_{1} m_{1}\right)(t)+\left(K_{1} m_{2}\right)(t) .
$$

with

$$
\begin{aligned}
\mathrm{x}_{1}^{\mathrm{f}} & =\text { free movement of the subsystem } 1 . \\
\Psi_{1} \mathrm{~m}_{1} & =\text { control action within subsystem } 1 . \\
\mathrm{K}_{1} m_{2} & =\text { interaction between the two subsystems. }
\end{aligned}
$$

This can be shown in the following way: $x(t)$, solution of a linear differential equation can be written:

$$
x(t)=\varphi(t) x(0)+\int_{0}^{t} \varphi(t-) m() d
$$

with $\varphi(t)=$ transition matrix.
If we call

$$
\varphi=\left[\begin{array}{ll}
\varphi_{11} & \varphi_{12} \\
\varphi_{21} & \varphi_{22}
\end{array}\right]
$$

we get

$$
\left\{\begin{array}{l}
x_{1}^{f}(t)=\varphi_{11}(t) x_{1}(0)+\varphi_{12}(t) x_{i}(t) \\
\Psi_{1} m_{1}(t)=\int_{0}^{t} \varphi_{11}(t-\tau) m_{1}(\tau) d^{\prime} \tau \\
K_{1} m_{2}(t)=\int_{0}^{t} \varphi_{12}(t-\tau) m_{2}(\tau) d \tau
\end{array}\right.
$$

Fundamental theorem:
Given a reference control $\left[\mathrm{m}_{1}^{r}, m_{2}^{r}\right]$, the internal disturbances $v_{1}^{r}=K_{1} m_{2}^{r}$

$$
\begin{aligned}
& \mathrm{v}_{2}^{r}=\mathrm{K}_{2} \mathrm{~m}_{1}^{r} \\
& \mathrm{~s}_{1}^{r}=2\left[\mathrm{~K}_{1}^{\star} A\left(\mathrm{x}^{r}-r\right)+\mathrm{K}_{1}^{*} A K_{1} m^{r}\right] \\
& \mathrm{s}_{2}^{r}=2\left[\mathrm{~K}_{2}^{\star} A\left(\mathrm{x}^{r}-r\right)+K_{2}^{\star} A K_{2} m^{r}\right]
\end{aligned}
$$

and the following systems, equations and performances: -sub system 1:

$$
\left\{\begin{array}{l}
x_{1}=\Psi_{1} m_{1}+x_{1}^{f}+v_{1}^{r} \\
\phi_{1}\left(x_{1}, m_{1}\right)=\int_{0}^{t} e_{\left\{A_{1}\left(x_{1}-r_{1}\right)^{2}+B_{1}^{\prime} m_{1}^{2}-s_{1}^{r} m_{1}\right\} d t} \\
=q\left(m_{1}, v_{1}^{r}, s_{1}^{r}\right)
\end{array}\right.
$$

$$
\begin{aligned}
& x_{2}=\Psi_{2} m_{2}+x_{2}^{f}+v_{2}^{r} \\
& \begin{aligned}
\phi\left(x_{2}, m_{2}\right)=\int_{0}^{t} e \\
\left(A_{2}\left(x_{2}-r_{2}\right)^{2}+B_{2}^{\prime} m_{2}^{2}-s_{2}^{r} m_{2}\right) d t
\end{aligned} \\
& \quad=q_{2}\left(m_{2}, v_{2}^{r}, s_{2}^{r}\right) .
\end{aligned}
$$

If we can find controls $m_{1}^{\prime}(t)$ and $m_{2}^{\prime}(t)$ such that
and $\left\{\begin{array}{l}q_{1}\left(m_{1}^{\prime}, v_{1}^{r}, s_{1}^{r}\right) \leq q_{1}\left(m_{1}^{r}, v_{1}^{r}, s_{1}^{r}\right) \\ q_{2}\left(m_{2}^{\prime}, v_{2}^{r}, s_{2}^{r}\right) \leq q_{2}\left(m_{2}^{r}, v_{2}^{r}, s_{2}^{r}\right)\end{array}\right.$
Then we have, for the overall problem:

$$
q\left(m^{\prime}\right) \leq q(m)
$$

Proof: This is exactly the fundamental theorem we stated in the preceeding paragraph.

The heuristic is now obvious:
1 $\frac{\text { st }}{}$ leve1 - 1 st subsystem - ith stage:
equation $\mathrm{x}_{1}={ }_{\Psi_{1}} \mathrm{~m}_{1}-\mathrm{x}_{1}^{f}+\mathrm{v}_{1}^{\mathrm{r}}$
performance:

$$
\phi\left(i, x_{1}, m_{1}\right)=q_{1}\left(i, m_{1}, v v_{1}^{r}, s_{1}^{r}\right)=\int_{t_{S}(i)}^{t_{e}}\left\{A_{1}\left(x_{1}-r_{1}\right)^{2}+B_{1}^{\prime} m_{1}^{2}-s_{1}^{r_{1}} m_{1}\right\} d t
$$

Given $m_{1}^{r}, v_{l}^{r}, s_{1}^{r}$ by the second level, find:
$m_{i}^{\prime}(t)$ such that:
$q_{1}\left(i, m_{1}^{\prime}, v_{1}^{r}, s_{1}^{r}\right) \leq q_{1}\left(i, m_{i}^{r}, v_{1}^{r}, s_{1}^{r}\right)$.
$2^{\text {nd }}$ level - ith stage:
Let us call $m(i, t)$ the $i \frac{t h}{}$ adaptation stage control
of the first level, $q(i, m)$ the first level performance
index for the $i \underline{\text { th }}$ adaptation stage, $t_{S}(i)$ the starting time of the $i \frac{\text { th }}{}$ adaptation stage and

$$
\begin{aligned}
& \operatorname{Sm}^{r}(i-1, t) \text { the restriction of } m^{r}(i-1, t) \text { to } \\
& {\left[t_{S}(i), t_{e}\right]}
\end{aligned}
$$

Let us call $\mathrm{Sm}^{\prime}(i-1, t)$ the restriction of $\mathrm{m}^{\prime}(i-1, t)$ to

$$
\left[t_{S}(i), t_{e}\right]
$$

Given the control in the following way:

$$
m^{r}(i, t)=\lambda S m^{r}(i-1, t)+(1-\lambda) S m^{\prime}(i-1, t)
$$

and the system:

$$
x^{r}(i, t)=\Psi(i) m^{r}(i, t)+x^{f}(i, t)
$$

the performance:

$$
\phi=\int_{t_{S}(i)}^{t_{e}}\left\{\left(x^{r}-r\right)^{T} A\left(x^{r}-r\right)+m^{r^{T}} B m^{r}\right\} d t
$$

Find:

$$
\begin{aligned}
&-\lambda_{0} \text { such that: } \lambda_{0} \text { minimizes } \phi \\
& \text {-Compute: } v_{1}^{r}=K_{1} m_{2}^{r} \quad v_{2}^{r}=K_{2} m_{1}^{r} \\
& s_{1}^{r}=2\left[K_{1}^{*} A\left(x^{r}-r\right)+K_{1}^{*} A K_{1} m^{r}\right] \\
& s_{2}^{r}=2\left[K_{2}^{*} A\left(x^{r}-r\right)+K_{2}^{*} A K_{2} m^{r}\right]
\end{aligned}
$$

With this scheme we have:

$$
\begin{aligned}
& q\left[i, S m^{r}(i-1)\right] \\
& q\left[i, s m^{\prime}(i-1)\right]
\end{aligned} \quad q\left[i, m^{r}(i) \geq q\left[i, m^{\prime}(i)\right]\right.
$$

This scheme is perfect from a theoretical point of view, but not easy to implement with a computer.

### 2.4 A Heuristic for the Satisfaction Technique

In this paragraph, no new concept is introduced. The preceeding theoretical scheme is adapted in order to be computable.

This computation scheme is an adaptation of the scheme outlined in [5].

The system we study is always the same, i.e., a linear quadratic system. But the trick is to exchange the roles of $x$ and $m, i . e .$,

$$
\left\{\begin{array}{l}
m_{1}(t)=\frac{d x_{1}}{d t}-c_{11} x_{1}-c_{12} x_{2} \\
m_{2}(t)=\frac{d x_{2}}{d r}-c_{22} x_{2}-c_{21} x_{1}
\end{array}\right.
$$

with the performance:

$$
\phi=\int_{0}^{t} e\left\{(x-r)^{T} A(x-r)+m^{T} B m\right\} d t
$$

Fundamental theorem:
Given a reference control ( $\mathrm{m}_{1}^{r}, \mathrm{~m}_{2}^{r}$ ) that is to say a reference trajectory $\left(x_{1}^{r}, x_{2}^{r}\right)$ and given the sets of disturbances $V_{1}, V_{2}, S_{1}, S_{2}$ which contain respectively $v_{1}^{r}, v_{2}^{r}, s_{1}^{r}, s_{2}^{r}$ and the following systems, equations and performances:
*subsystem 1:

$$
m_{1}(t)=\frac{d x_{1}}{d t}-c_{11} x_{1}-v_{1}
$$

$$
\begin{aligned}
q_{1}\left(i, x_{1}, v_{1}, s_{1}\right)=\phi_{1}\left(i, x_{1}, m_{1}\right)= & \int_{t_{S}(i)}^{t_{e}}\left[A_{1}+c_{21}^{2} B_{2}\right)\left(x_{1}-r_{1}\right)^{2} \\
& \left.+B_{1} m_{1}^{2}-2 x_{1} s_{1}\right] d t
\end{aligned}
$$

*subsystem 2:

$$
\begin{aligned}
m_{2}(t)=\frac{d x_{2}}{d t}-c_{22} x_{2}- & v_{2} \\
q_{2}\left(i, x_{2}, v_{2}, s_{2}\right)=\phi_{2}\left(i, x_{2}, m_{2}\right)= & \int_{t_{S}(i)}^{t} e \\
& \left.\left.+A_{2}+c_{12}^{2} B_{1}\right)\left(x_{2}-r_{2}\right)^{2}-2 x_{2} s_{2}\right] d t
\end{aligned}
$$

If we can find controls $m_{1}^{\prime}(t)$ and $m_{2}^{\prime}(t)$ such that:

$$
\begin{aligned}
& q_{1}\left(i, x_{1}^{\prime}, v_{1}, s_{1}\right) \leq q_{1}\left(i, x_{1}^{r}, v_{1}, s_{1}\right) \quad \forall v_{1} \in v_{1}, \forall s_{1} \in s_{1} \\
& q_{2}\left(i, x_{2}^{\prime}, v_{2}, s_{2}\right) \leq q_{2}\left(i, x_{2}^{r}, v_{2}, s_{2}\right) \quad \forall v_{2} \in v_{2}, \forall s_{2} \in s_{2}
\end{aligned}
$$

and

Then we have, for the overall problem:

$$
q\left(i, m^{\prime}\right) \leq q\left(i, m^{r}\right)
$$

Proof:

$$
\begin{aligned}
& q_{1}\left(i, x_{1}^{\prime}, v_{1}^{r}, s_{1}^{r}\right)=\int_{t_{S}(i)}^{t_{e}}\left(A_{1}+B_{2} C_{21}^{2}\right)\left(x_{1}^{\prime}-r_{1}\right)^{2} \\
&\left.+B_{1} m_{1}^{2}-2 s_{1}^{r} x_{1}^{\prime}\right] d t
\end{aligned}
$$

But

$$
\begin{aligned}
& v_{1}^{r}=c_{12} x_{2}^{r} \\
& s_{1}^{r}=B_{2} c_{21} m_{2}^{r}+c_{21}^{2} B_{2}\left(x_{1}^{r}-r_{1}\right)
\end{aligned}
$$

Then replacing $v_{1}^{r}, s_{1}^{r}, m_{1}^{\prime}$ by their value, we get:

$$
\begin{aligned}
& q_{1}\left(i, x_{1}^{\prime}, v_{1}^{r}, s_{1}^{r}\right)=\int_{t_{S}(i)}^{t} e \\
& \left\{\left(A_{1}+B_{2} c_{21}^{2}\right)\left(x_{1}^{\prime}-r_{1}\right)+B_{1}\left[\frac{d x_{1}^{\prime}}{d t}-c_{11} x_{1}^{\prime}\right.\right. \\
& \left.-2\left[B_{2} c_{21}^{2} m_{2}^{r}+c_{21}^{2}\left(x_{1}^{r}-r_{1}\right)\right] x_{1}^{\prime}\right\} d t
\end{aligned}
$$

Now we write:

$$
\begin{aligned}
& q_{1}\left(i, x_{1}^{r}, v_{1}^{r}, s_{1}^{r}\right)=\int_{t_{S}(i)}^{t}\left\{\left[A_{1}+B_{2} c_{21}^{2}\right]\left[x_{1}^{r}-r_{1}\right]^{2}+B_{1}\left[\frac{d x_{1}^{\prime}}{d t}-c_{11} x_{1}^{r}\right.\right. \\
& \left.-2\left[B_{2} c_{21} m_{2}^{r}+c_{21}^{2}\left(x_{1}^{r}-r_{1}\right)\right] x_{1}^{r} x_{2}^{r}\right]
\end{aligned}
$$

We call

$$
\delta=\binom{\delta_{1}}{\delta_{2}}=\binom{x_{1}^{r}-x_{1}^{\prime}}{x_{2}^{r}-x_{2}^{\prime}}=x^{r}-x^{\prime} .
$$

By hypothesis we have:

$$
q_{1}\left(i, x_{1}^{\prime}, v_{1}^{r}, s_{1}^{r}\right)-q\left(i, x_{1}^{r}, v_{1}^{r}, s_{1}^{r}\right) \leq 0
$$

Replacing

$$
x_{1}^{\prime} \text { by }\left(x_{1}^{r}-\delta_{1}\right)
$$

and

$$
q_{1}\left(i, x_{1}^{\prime}, v_{1}^{r}, s_{1}^{r}\right), q_{1}\left(i, x_{1}^{r}, v_{1}^{r}, s_{1}^{r}\right)
$$

by their values, we get the following inequality $=$ (2) :

$$
\begin{aligned}
& \int_{t_{S}(i)}^{t_{e}}\left\{\left(A_{1}+B_{2} C_{21}^{2}\right)\left(x_{1}^{r}-\delta_{1}-r_{1}\right)^{2}+B_{1}\left[\frac{d x_{1}^{r}}{d t}-c_{11} x_{1}^{r}-c_{12} x_{2}^{r}\right.\right. \\
& \\
& \left.-\frac{d \delta_{1}}{d t}+c_{11} \delta_{1}\right]^{2} \\
& -2\left[B_{2} c_{21}\left[\frac{d x_{2}^{r}}{d t}-c_{22} x_{2}^{r}-c_{21} x_{1}^{r}\right]+c_{21}^{2}\left(x_{1}^{r}-r_{1}\right)\left[x_{1}^{r}-\delta_{1}\right]\right. \\
& -\left[A_{1}+B_{2} C_{21}^{2}\right)\left[x_{1}^{r}-r_{1}\right]^{2}-B_{1}\left[\frac{d x_{1}^{r}}{d t}-c_{11} x_{1}^{r}-c_{12} x_{2}^{r}\right]^{2} \\
& \left.+2\left[B_{2} c_{21}\left\{\frac{d x_{2}^{r}}{d t}-c_{22} x_{2}^{r}-c_{21} x_{1}^{r}\right]+c_{21}^{2}\left(x_{1}^{r}-r_{1}\right)\right] x_{1}^{r}\right\} d t \leq 0
\end{aligned}
$$

Now we compute:

$$
q\left(x^{r}-\delta_{1}\right)-q\left(x^{r}\right)=
$$

$$
\int_{t_{S}(i)}^{t_{e}}\left\{A_{1}\left(x_{1}^{r}-\delta_{1}-r_{1}\right)^{2}+B_{1}\left[\frac{d x_{1}^{r}}{d t}-c_{11} x_{1}^{r}-c_{12} x_{2}^{r}-\frac{d \delta_{1}}{d t}\right.\right.
$$

$$
\left.+c_{11} \delta_{1}\right]^{2}
$$

$$
+B_{2} c_{21}^{2}\left[x_{1}^{r}-r_{1}-\delta_{1}\right]^{2}-2\left(x_{1}^{r}-r_{1}\right)\left(x_{1}^{r}-\delta_{1}\right)-2 B_{2} c_{21}\left(\frac{d x_{1}^{r}}{d t}-c_{22} x_{2}^{r}\right.
$$

$$
\left.-c_{21} x_{1}^{r}\right)\left(x_{1}^{r}-\delta_{1}\right)
$$

$$
-A_{1}\left(x_{1}^{r}-r_{1}\right)^{2}-B_{2} c_{21}^{2}\left(x_{1}^{r}-r_{1}\right)^{2}-B_{1}\left[\frac{d x_{1}^{r}}{d t}-c_{11} x_{1}^{r}-c_{12} x_{2}^{r}\right]^{2}
$$

$$
+2 x_{1}^{r}\left[B_{2} c_{21}\left(\frac{d x_{2}^{r}}{d t}-c_{22} x_{2}^{r}-c_{21} x_{1}^{r}\right)+c_{21}^{2} B_{2}\left(x_{1}^{r}-r_{1}\right)\right] d t
$$

Developing this expression algebraically we can find that $q\left(x^{r}-\delta_{1}\right)-q\left(x^{r}\right)$ is equal to the left hand side
of the inequality (2).

So

$$
q\left(x^{r}-\delta_{1}\right)-q\left(x^{r}\right) \leq 0
$$

In the same way we could have shown that:

$$
q\left(x^{r}-\delta_{1}-\delta_{2}\right) \leq q\left(x^{r}-\delta_{1}\right)
$$

so

$$
q\left(x^{\prime}\right) \leq q\left(x^{r}\right)
$$

End of the proof.
Corollary:
Given a reference control $\left(m_{1}^{r}, m_{2}^{r}\right)$, i.e., a reference trajectory $\left(x_{1}^{r}, x_{2}^{r}\right)$ and given
$\mathrm{v}_{1}^{r}=\mathrm{c}_{12} \mathrm{x}_{2}^{\mathrm{r}} \quad \mathrm{s}_{1}^{\mathrm{r}}=\mathrm{B}_{2} \mathrm{c}_{21} \mathrm{~m}_{2}^{r}+\mathrm{c}_{21}^{2} \mathrm{~B}_{2}\left(\mathrm{x}_{1}^{\mathrm{r}-\mathrm{r}_{1}}\right)$
$v_{2}^{r}=c_{21} x_{1}^{\prime} \quad s_{2}^{r}=B_{1} c_{12} m_{1}^{\prime}+c_{21}^{2} B_{1}\left(x_{2}^{r}-r_{2}\right)$.
and the following systems, equations and performances:
-subsystem 1:

$$
\begin{gathered}
m_{1}(t)=\frac{d x_{1}}{d t}-c_{11} x_{1}-v_{1}^{r} \\
q_{1}\left(i, x_{1}, v_{1}^{r}, s_{1}^{r}\right)=\phi_{1}\left(i, x_{1}, m_{1}\right)=\int_{t_{S}(i)}^{t_{e}}\left[\left(A_{1}+c_{21}^{2} B_{2}\right)\left(x_{1}-r_{1}\right)^{2}\right. \\
\\
\left.+B_{1} m_{1}^{2}-2 x_{1} s_{1}^{r}\right] d t
\end{gathered}
$$

-subsystem 2:

$$
m_{2}(t)=\frac{d x_{2}}{d t}-c_{22} x_{2}-v_{2}^{r}
$$

$q_{2}\left(i, x_{2}, v_{2}^{r}, s_{2}^{r}\right)=\phi_{2}\left(i, x_{2}, m_{2}\right)=\int_{t_{S}(i)}^{t} e\left[\left(A_{2}+c_{12}^{2} B_{1}\right)\left(x_{2}-r_{2}\right)^{2}\right.$

$$
\left.+\mathrm{B}_{2} \mathrm{~m}_{2}^{2}-2 \mathrm{x}_{2} \mathrm{~s}_{2}^{r}\right] d t
$$

If we can find controls $m_{1}^{\prime}(t)$ and $m_{2}^{\prime}(t)$ such that:

$$
q_{1}\left(i, x_{1}^{\prime}, v_{1}^{r}, s_{1}^{r}\right) s q_{1}\left(i, x_{1}^{r}, v_{1}^{r}, s_{1}^{r}\right)
$$

and

$$
q_{2}\left(i, x_{2}^{\prime}, v_{2}^{r}, s_{2}^{r}\right) \leq q_{2}\left(i, x_{2}^{r}, v_{2}^{r}, s_{2}^{r}\right) .
$$

Then we have for the overall problem:

$$
q\left(i, m^{\prime}\right) \leq q\left(i, m^{r}\right) .
$$

The proof of the corollary is straightforward.
A procedure was derived by Takahara [5] based on
the preceeding theories.
Procedure ( $1 \frac{\text { st }}{}$ stage only):

1. Given the system without any correlation,
(we make $c_{12}=c_{21}=0$ ), we compute the optimal solution, which we call: $x_{1}^{r}(0, t), x_{2}^{r}(0 ; t), m_{1}^{r}(0, t), m_{2}^{r}(0, t)$ with


In this part 1, the problem is divided in two independent sub problems.
2. We compute
$v_{1}^{r}(0, t)=c_{12} x_{2}^{r}(0, t)$
$s_{1}^{r}(0, t)=B_{2} c_{21} m_{2}^{r}(0, t)+c_{21}^{2} B_{2}\left[x_{1}^{r}(0, t)-r_{1}\right]$.
3. subsystem 1 :

$$
\left\{\begin{array}{c}
m_{1}(t)=\frac{d x_{1}}{d t}-c_{11} x_{1}-v_{1}^{r} \\
q_{1}\left(0, x_{1}, v_{1}^{r}, s_{1}^{r}\right)=\phi_{1}\left(0, x_{1}, m_{1}\right)=\int_{t_{S}(0)}^{t} e\left(A_{1}+c_{21}^{2} B_{2}\right)\left(x_{1}-r_{1}\right)^{2} \\
\end{array}\right.
$$

$\min _{m_{1}} \phi_{1}\left(0, x_{1}, m_{1}\right)=\phi_{1}\left(0, x_{1}^{\prime}, m_{1}^{0}\right)$
4. Compute:

$$
\left.\begin{array}{rl}
v_{2}^{r}(0, t)= & c_{21} x_{1}^{\prime} \\
s_{2}^{r}(0, t)= & B_{1} c_{12}\left[\frac{d x_{1}^{\prime}}{d t}-c_{11}\right.
\end{array} \quad x_{1}^{\prime}-c_{12} x_{2}^{r}\right] .
$$

5. subsystem 2:

$$
\begin{aligned}
m_{2}(t)=\frac{d x_{2}}{d t}-c_{22} x_{2}- & v_{2}^{r} \\
q_{2}\left(0, x_{2}, v_{2}^{r}, s_{2}^{r}\right)=\phi_{2}\left(0, x_{2}, m_{2}\right)=\int_{t_{S}(0)}^{t} e & {\left[\left(A_{2}+c_{12}^{2} B_{1}\right)\left(x_{2}-r_{2}\right)^{2}\right.} \\
& \left.+B_{2} m_{2}^{2}-2 x_{2} s_{2}^{r}\right] d t
\end{aligned}
$$

$$
\min _{m_{2}} \phi_{2}\left(0, x_{2}, m_{2}\right)=\phi_{2}\left(0, x_{2}^{\prime}, m_{2}^{0}\right)
$$

$$
\text { 6. Computation of } m_{1}^{\prime}(0, t), m_{2}^{\prime}(0, t) \text {. }
$$

$$
m_{1}^{\prime}(0, t)=\frac{d x_{1}^{\prime}}{d t}-c_{11} x_{1}^{\prime}-c_{12} x_{2}^{\prime}
$$

$$
m_{2}^{\prime}(0, t)=\frac{d x_{2}^{\prime}}{d t}-c_{21} x_{1}^{\prime}-c_{22} x_{2}^{\prime}
$$

7. Computation of the new performance:

$$
\begin{aligned}
q\left[m_{1}^{\prime}(0, t), m_{2}^{\prime}(0, t)\right]=A_{1}\left(x_{1}^{\prime}-r_{1}\right)^{2}+A_{2}\left(x_{2}^{\prime}-r_{2}\right)^{2} & +B_{1} m_{1}^{2} \\
& +B_{2} m_{2}^{2}
\end{aligned}
$$

And at this stage we have:

$$
q\left[m_{1}^{\prime}(0, t), m_{2}^{\prime}(0, t)\right] \leq q\left[m_{1}^{r}(0, t), m_{2}^{r}(0, t)\right]
$$

And the procedure can be applied again with a new reference control; in a new stage:
8. Computation of $\mathrm{m}_{1}^{\mathrm{r}}(1, t), \mathrm{m}_{2}^{\mathrm{r}}(1, t)$ :

Given the feedback information

$$
\begin{aligned}
& \mathrm{Sm}_{1}(i-1, t) \\
& \mathrm{Sm}_{2}(i-1, t)
\end{aligned}
$$

consider the control:

$$
m^{r}(1, t)=\lambda \operatorname{Sm}^{r}(0, t)+(1-\lambda) \operatorname{sm}(0, t)
$$

the system

$$
\frac{d x^{r}}{d t}(1, t)=c x^{r}(1, t)+m^{r}(1, t)
$$

the performance
$\phi=\int_{t_{S}(1)}^{t} e\left\{\left[x^{r}(1, t)-r\right]^{T} A\left[x^{r}(1, t)-r\right]+m^{r^{T}}(1, t) B m^{r}(1, t)\right\} d t$
Find $\lambda$ such that $\min _{\lambda} \phi$
which gives the new reference control for the next stage:

$$
m^{r}(1, t)=\left(\begin{array}{ll}
m_{1}^{r} & (1, t) \\
m_{2}^{r} & (1, t)
\end{array}\right)
$$

Now the cycle is complete: we can start the computation again.

Survey of the procedure:
The procedure is a two level, multistage, updating procedure:

1st level:
steps 1, 3, 5: computation of a better control for the subsystems.
2 nd leve1:

```
steps 2, 4: computation of }\mp@subsup{v}{1}{r}, v ve, s, r, s, s r.
steps 6, 7: computation of the new control, and the new
    performance.
step 8: updating.
```


## 2. 5 Application of the Procedure to 2 Numerical Examples

## Example 1

Let us consider the following integrated system and performance functional:

$$
\begin{gathered}
{\left[\begin{array}{l}
x_{1} \\
x_{1} \\
x_{2}
\end{array}\right]=\left[\begin{array}{ll}
2 & 2 \\
2 & \\
& \\
& \\
x_{2}
\end{array}\right]\left[\begin{array}{l}
x_{1} \\
m_{2}
\end{array}\right]} \\
\phi(x, m)=\int_{0}^{1}\left\{10 \quad\left(x_{1}^{2}+x_{2}^{2}\right)+m_{1}^{2}+m_{2}^{2}\right\} d t \\
x_{1}(0)=5 \quad \text { and } \quad x_{2}(0)=2 .
\end{gathered}
$$

Then

$$
C=\left[\begin{array}{ll}
2 & 2 \\
2 & 3
\end{array}\right] \quad A=\left[\begin{array}{ll}
10 & 0 \\
0 & 10
\end{array}\right] \quad B=\left[\begin{array}{ll}
1 & 0 \\
0 & 1
\end{array}\right]
$$

The procedure is the following:
Step 1
part a

$$
\begin{aligned}
& \left\{\begin{array}{ll}
\text { system } & \dot{x}_{1}=2 x_{1}+m_{1} \\
\text { performance } & \phi_{1}\left(x_{1}, m_{1}\right)=10 x_{1}^{2}+m_{1}^{2} \\
\operatorname{Min}_{m_{1}} & \phi_{1}\left(x_{1}, m_{1}\right)=\phi_{1}\left[x_{1 F}(0, t), m_{1}^{r}(0, t)\right] \\
\begin{cases}\text { system } & x_{2}=3 x_{2}+m_{2} \\
\begin{array}{ll}
\text { performance } \\
m_{2} & \phi_{2}\left(x_{2}, m_{2}\right)=10 x_{2}^{2}+m_{2}^{2}
\end{array} & \phi_{2}\left(x_{2}, m_{2}\right)=\phi_{2}\left[x_{2 F}(0, t), m_{2}^{r}(0, t)\right] .\end{cases}
\end{array} . \begin{array}{l}
\end{array} \quad\right.
\end{aligned}
$$

part b
part $c \quad \frac{d x_{1}^{r}}{d t}=2 x_{1}^{r}+2 x_{2}^{r}+m_{1}^{r}(0, t)$

$$
\frac{d x_{2}^{r}}{d t}=2 x_{1}^{r}+3 x_{2}^{r}+m_{2}^{r}(0, t)
$$

Step 2

$$
\begin{aligned}
& v_{1}^{r}(0, t)=2 x_{2}^{r}(0, t) \\
& s_{1}^{r}(0, t)=2 m_{2}^{r}(0, t)+4\left[x_{1}^{r}(0, t)-r_{1}\right]
\end{aligned}
$$

Step 3

$$
\begin{aligned}
& \text { system } \quad \frac{d x_{1}}{d t}=2 x_{1}+m_{1}+v_{1}^{r}(0, t) \\
& \text { performance } \phi_{1}\left[0, x_{1}, m_{1}\right]=\int_{0}^{t} e_{\left[14\left(x_{1}-r_{1}\right)^{2}+m_{1}^{2}\right.} \\
& \left.-2 x_{1} s_{1}^{r}\right] d t \\
& \text { min } \\
& \phi_{1}\left[0, x_{1}, m_{1}\right]=\phi_{1}\left[0, x_{1}^{\prime}, m_{1}^{0}\right]
\end{aligned}
$$

Step 4

$$
\begin{aligned}
& v_{2}^{r}[0, t]=2 x_{1}^{\prime} \\
& s_{2}^{r}(0, t)=2\left[\frac{d x_{1}^{\prime}}{d t}-2 x_{1}^{\prime}-2 x_{2}^{r}\right]+4\left(x_{2}^{r}-r_{2}\right]
\end{aligned}
$$

## Step 5

$$
\begin{cases}\text { system } & \frac{d x_{2}}{d t}=3 x_{2}+m_{2}+v_{2}^{r}(0, t) \\ \text { performance } & \phi_{2}\left(0, x_{2}, m_{2}\right)=\int_{0}^{t} e_{\left\{14\left(x_{2}-r_{2}\right)^{2}+m_{2}^{2}\right.} \\ \min _{m_{2}} & \left.-2 x_{2} s_{2}^{r}\right\} d t\end{cases}
$$

Step 6

$$
\begin{aligned}
& \frac{d x_{1}^{\prime}}{d t}=2 x_{1}^{\prime}+2 x_{2}^{\prime}+m_{1}^{\prime}(0, t) \\
& \frac{d x_{2}^{\prime}}{d t}=2 x_{1}^{\prime}+3 x_{2}^{\prime}+m_{2}^{\prime}(0, t)
\end{aligned}
$$

Step 7
$\left.q\left[m_{1}^{\prime}(0, t), m_{2}^{\prime}(0, t)\right]=\int_{0}^{t} S_{\{10}\left(x_{1}^{\prime}-r_{1}\right)^{2}+10\left(x_{2}^{\prime}-r_{2}\right)^{2}+m_{1}^{\prime}+m_{2}^{2}\right\} d t$

## Step 8

Given the feedback information

$$
\begin{aligned}
& \mathrm{Sm}_{1}(i-1, t) \\
& \mathrm{Sm}_{2}(i-1, t) \\
& \begin{cases}\text { system } & \frac{d x^{r}}{d I^{r}}(1, t)=c x^{r}(1, t)+m^{r}(1, t) \\
\text { control } & m^{1 r}(1, t)=\lambda \operatorname{sm}^{r}(0, t)+(1-\lambda) \operatorname{Sm}(0, t) \\
\text { performance } & \phi=\int_{t_{S}(1)^{t} e}^{\left\{A_{1}\left(x_{1}^{r}(1, t)-r_{1}\right)^{2}+A_{2}\left(x_{2}^{r}(1, t)\right.\right.} \\
& \left.\left.-r_{2}\right)^{2}+B_{1} m_{1}^{r}(1, t)+B_{2} m_{2}^{r}(1, t)\right\} d t\end{cases}
\end{aligned}
$$

Find $\lambda_{0}$ such that

$$
\min _{\lambda} \quad \phi(\lambda)=\phi\left[\lambda_{0}\right]
$$

Computation:
Step 1:

$$
\begin{aligned}
& \text {-part a: } \\
& H=10 x_{l F}^{2}+\left(m_{1}^{r}\right)^{2}+p_{1}\left(2 x_{1 F}+m_{l}^{r}\right)
\end{aligned}
$$

$$
\begin{aligned}
& A=2 \quad \zeta_{0}=-0.5 \quad \mathrm{w}_{1}=\frac{1}{2} \quad \delta \mathrm{Hm}_{1} \quad \mathscr{Y}=-20 \quad \mathrm{w}_{2}=0 \\
& \quad \text {-part } \mathrm{b}: \\
& \mathrm{H}=10 \mathrm{x}_{2 \mathrm{~F}}^{2}+\left(\mathrm{m}_{2}^{r}\right)^{2}+\mathrm{p}_{2}\left(3 \mathrm{x}_{2 \mathrm{~F}}+\mathrm{m}_{2}^{r}\right) \\
& \dot{b}=3 \quad \dot{C}=-0.5 \quad \mathrm{w}_{1}=0.5 \quad \delta \mathrm{Hm}_{2 \mathrm{r}} \quad \mathscr{L}=-20 \quad \mathrm{w}_{2}=0
\end{aligned}
$$

## Step 3:

$$
\begin{aligned}
& H=14\left(x_{1}^{1}-r_{1}\right)^{2}+\left(m_{1}^{0}\right)^{2}-2 x_{1}^{1} s_{1}^{r}+q_{1}\left(2 x_{1}^{1}+m_{1}^{0}+v_{1}^{r}\right) \\
& A=2 \quad G^{\prime}=-0.5 \quad w_{1}=0.5 \delta \mathrm{Hm}_{11} \quad \mathscr{C}=-28 \quad w_{2}=0
\end{aligned}
$$

## Step 5:

$$
\begin{aligned}
& H=14\left(x_{2}^{\prime}-r_{2}\right)^{2}+\left(m_{2}^{0}\right)^{2}-2 x_{2}^{\prime} s_{2}^{r}+q_{2}\left(3 x_{2}^{\prime}+m_{2}^{0}+v_{2}^{r}\right) \\
& \dot{y}=3 \quad \xi=-0.5 \quad w_{1}=0.5 \quad \delta H_{22} \quad f=-28 \quad w_{2}=0
\end{aligned}
$$

Example 2: A linear system with 5 variables:
The most general system is:

$$
\begin{aligned}
& \frac{d x_{i}}{d t}=\sum_{j=1}^{5} c_{i j} x_{j}+m_{i} \quad i=1,2,3,4,5 . \\
& \phi=\int_{0}^{t} e \sum_{j=1}^{5}\left[A_{j}\left(x_{j}-r_{j}\right)^{2}+B_{j} m_{j}^{2}\right] d t .
\end{aligned}
$$

We break the system in two parts:

$$
\mathscr{x}_{1}=\left[\begin{array}{l}
x_{1} \\
x_{2}
\end{array}\right] \quad \mathscr{b}_{2}=\left[\begin{array}{l}
x_{3} \\
x_{4} \\
x_{5}
\end{array}\right]
$$

$$
\begin{aligned}
& \eta_{1}=\left[\begin{array}{l}
m_{1} \\
m_{2}
\end{array}\right] \quad \eta_{2}=\left|\begin{array}{l}
m_{1} \\
m_{2} \\
m_{3}
\end{array}\right| \\
& C_{11}=\left[\begin{array}{ll}
c_{11} & c_{12} \\
c_{21} & c_{22}
\end{array}\right] \quad C_{12}=\left[\begin{array}{lll}
c_{12} & c_{14} & c_{15} \\
c_{23} & c_{24} & c_{25}
\end{array}\right] \\
& C_{21}=\left[\begin{array}{ll}
c_{31} & c_{32} \\
c_{41} & c_{42} \\
c_{51} & c_{52}
\end{array}\right] \quad C_{22}=\left[\begin{array}{lll}
c_{33} & c_{34} & c_{35} \\
c_{43} & c_{44} & c_{45} \\
c_{53} & c_{54} & c_{55}
\end{array}\right] \\
& Q_{1}=\left[\begin{array}{ll}
A_{1} & 0 \\
0 & A_{2}
\end{array}\right] \quad C_{2}=\left[\begin{array}{ccc}
A_{3} & 0 & 0 \\
0 & A_{4} & 0 \\
0 & 0 & A_{5}
\end{array}\right] \\
& \mathcal{B}_{1}=\left[\begin{array}{ll}
B_{1} & 0 \\
0 & B_{2}
\end{array}\right] \\
& \mathrm{K}_{2}=\left[\begin{array}{ccc}
\mathrm{B}_{3} & 0 & 0 \\
0 & \mathrm{~B}_{4} & 0 \\
0 & 0 & B_{5}
\end{array}\right]
\end{aligned}
$$

The system can now be written:

$$
\begin{aligned}
& \frac{d x_{1}}{d t}=C_{11} \mathscr{x}_{1}+C_{12} \mathscr{F}_{2}+\mathscr{H}_{1} \\
& \frac{\mathrm{~d} \mathscr{X}_{2}}{\mathrm{dt}}=C_{21} \mathscr{x}_{1}+C_{22} \mathscr{x}_{2}+m_{2}
\end{aligned}
$$

We can compute now:

$$
\begin{aligned}
& \mathrm{v}_{1}^{\mathrm{r}}=C_{12} \mathscr{X}_{2}^{\mathrm{r}} \quad \mathrm{v}_{2}^{\mathrm{r}}=C_{21} \mathscr{X}_{1}^{\mathrm{r}} \\
& \mathrm{~s}_{1}^{\mathrm{r}}=C_{21}^{\mathrm{T}} \mathscr{C}_{2} \eta_{2}^{\mathrm{r}}+C_{21}^{\mathrm{T}} \mathscr{R}_{2} C_{21}\left(\mathscr{C}_{1}^{\mathrm{r}}-\mathscr{C}_{1}\right) \\
& \mathrm{s}_{2}^{\mathrm{r}}=C_{12}^{\mathrm{T}} \mathscr{S}_{1} \prod_{1}^{r}+C_{12}^{\mathrm{T}} \mathscr{R}_{1} C_{12}\left(\mathscr{X}_{2}^{\mathrm{r}}-\mathscr{C}_{2}\right)
\end{aligned}
$$

Now we consider the two subsystems:
1 -st subsystem:

$$
\begin{aligned}
& \frac{\mathrm{d} \mathscr{C}_{1}}{\mathrm{dt}}=C_{11} \cdot \mathscr{C}_{1}+v_{1}^{r} \\
& \text { min } \\
& \phi_{1}=\int_{0}^{t} e_{\left\{\left(x_{1}-\mathscr{C}_{1}\right)^{T}\left[A_{1}+c_{21}^{T} \quad \mathscr{C}_{2} \quad c_{21}\right]\left[x_{1}-\mathscr{C}_{1}\right]\right.}^{\mathscr{C}_{2}} \\
& \left.+M_{1}^{T} \hat{R}_{1} M_{1}-2 s_{1}^{r^{T}} \mathscr{X}_{1}\right\} d t
\end{aligned}
$$

$2 \underline{\text { nd }}$ subsystem:

$$
\begin{aligned}
& \frac{a \mathscr{C}_{2}}{d t}=C_{22} \quad x_{2}+v_{2}^{r} \\
& \min _{\mathscr{b}_{2}} \phi_{2}=\int_{0}^{t} e^{\{ }\left(\mathscr{X}_{2}-\mathscr{X}_{2}\right)^{T}\left[a_{2}+c_{12}^{T} \mathscr{S}_{1} C_{12}\right]\left[\mathscr{X}_{2}-\mathscr{C}_{2}\right] \\
& \left.+\mathbb{M}_{2}^{T} \mathscr{\beta}_{2} \quad \mathbb{N}_{2}-2 s_{2}^{r^{T}} \mathscr{K}_{2}\right\} d t
\end{aligned}
$$

For the computation, with the successive sweep
method, we get:
1黑 subproblem:

$$
\mathscr{Q}=\left[\begin{array}{ll}
c_{11} & c_{12} \\
c_{21} & c_{22}
\end{array}\right] \xi=\left[\begin{array}{cc}
-\frac{1}{2} \mathrm{~B}_{1} & 0 \\
0 & -\frac{1}{2} \mathrm{~B}_{2}
\end{array}{ }^{\mathrm{w}_{1}}=\left[\begin{array}{cc}
\frac{1}{2} \mathrm{~B}_{1} & \delta \mathrm{Hm}_{1} \\
\frac{1}{2} \mathrm{~B}_{2} & \delta \mathrm{Hm}_{2}
\end{array}\right]\right.
$$

$$
\mathscr{L}=\left[\begin{array}{ll}
-2\left[A_{1}+B_{3} c_{31}^{2}+B_{4} c_{41}^{2}+B_{5} c_{51}^{2}\right. & -2\left[B_{3} c_{31} c_{32}+B_{4} c_{41} c_{42}\right. \\
-2\left[B_{3} c_{31} c_{32}+B_{4} c_{41} c_{42}+B_{5} C_{51} c_{52}\right. & \left.+B_{5} C_{51} c_{52}\right] \\
& -2\left[A_{2}+B_{3} c_{32}^{2}+B_{4} c_{42}^{2}\right. \\
& +B_{5} c_{52}^{2}
\end{array}\right]
$$

$w_{2}=\left[\begin{array}{l}0 \\ 0\end{array}\right]$
$2^{\text {nd }}$ subproblem:

$$
\begin{aligned}
& A=\left[\begin{array}{ccc}
c_{33} & c_{34} & c_{35} \\
c_{43} & c_{44} & c_{45} \\
c_{53} & c_{54} & c_{55}
\end{array}\right] \zeta=\left[\begin{array}{ccc}
-\frac{1}{2} B_{3} & 0 & 0 \\
0 & -\frac{1}{2} B_{4} & 0 \\
0 & & -\frac{1}{2} \mathrm{C}_{5}
\end{array}\right]
\end{aligned}
$$

$$
\mathrm{w}_{1}=\left[\begin{array}{cc}
\frac{1}{2} \mathrm{~B}_{3} & \delta \mathrm{Hm}_{3} \\
\frac{1}{2} \mathrm{~B}_{4} & \delta \mathrm{Hm}_{4} \\
\frac{1}{2} \mathrm{~B}_{5} & \delta \mathrm{Hm}_{5}
\end{array}\right] \quad \mathrm{w}_{2}=\left[\begin{array}{l}
0 \\
0 \\
0
\end{array}\right]
$$

The program of the computation is shown in Appendix 3, Program 1.

The results of this setisfaction approach are shown and compared to a new heuristic in the following chapter.

## CHAPTER III

## A HEURISTIC FOR A SATISFACTION

APPROACH WITH SEPARATE SUBSYSTEMS

### 3.1 The Method:

Goal of the method:
In the last chapter we saw that the general technique of the satisfaction approach is rather complex when applied to linear systems. It is possible, at least when dealing with difference equations, to find a Heuristic much simpler and with the same advantages as the satisfaction approach.

What are the advantages of the application of the satisfaction approach with deterministic systems? Given a reference control, the technique allows us to find a control which improves the performance of the overall system, and this only by dealing with separate subsystems and considering the interconnections as uncertainties. The reduction of dimensionality and the fact that the computation is done in one iteration are the basic interests of this method. The latter is the one which makes the satisfaction approach different from the decomposition technique. The decomposition technique gets the overall optimum but this needs a second iterative level.

A single Heuristic can be implemented which has these advantages:

Consider the following discrete linear system:

$$
x\left(t_{i+1}\right)=x\left(t_{i}\right)+h\left[A x\left(t_{i}\right)+\operatorname{Bm}\left(t_{i}\right)\right]
$$

with the $t_{i}$ such that

$$
t_{0}=0<t_{1}<t_{2}<\ldots<t_{i}<t_{i+1}<\ldots<t_{m}=t_{e}
$$

and

$$
t_{i+1}-t_{i}=h
$$

with $h$ greater than 0
and the performance functional:

$$
\phi=\phi\left[x\left(t_{0}\right), \ldots, x\left(t_{m}\right), m\left(t_{0}\right) \ldots m\left(t_{m}\right)\right]
$$

We call $x\left(t_{0}\right)$ the vector $\left(x_{1}\left(t_{0}\right) \ldots x_{n}\left(t_{0}\right)\right)$
$x_{j} \quad$ the array $\left(x_{j}\left(t_{0}\right), x_{j}\left(t_{1}\right) \quad \ldots x_{j}\left(t_{m}\right)\right)$
$m\left(t_{0}\right)$ the vector $\left(m_{1}\left(t_{0}\right) \ldots m_{n}\left(t_{0}\right)\right)$
$m_{j}$ the array $\left(m_{j}\left(t_{0}\right), m_{j}\left(t_{1}\right) \ldots m_{j}\left(t_{m}\right)\right)$
We make the following assumptions:
-Assumption 1:
$B$ is non singular.
So we can express $m\left(t_{i}\right)$ as a. function of $x\left(t_{i}\right)$ and $x\left(t_{i+1}\right)$

$$
m\left(t_{i}\right)=B^{-1}\left[\frac{x\left(t_{i+1}\right)-x\left(t_{i}\right)}{h}-A x\left(t_{i}\right)\right]
$$

If we replace $m\left(t_{i}\right)$ by its value in function of $x\left(t_{i}\right)$ and $x\left(t_{i+1}\right)$ in the functional performance, we will get a functional:

$$
\begin{aligned}
\phi\left[x\left(t_{0}\right), \ldots, x\left(t_{m}\right), m\left(t_{0}\right), \ldots,\right. & \left.m\left(t_{m}\right)\right] \\
& =\phi^{\prime}\left[x\left(t_{0}\right), \ldots, x\left(t_{m}\right)\right] \\
& =\phi^{\prime \prime}\left[x_{1}, \ldots, x_{n}\right]
\end{aligned}
$$

-Assumption 2:
$\phi^{\prime \prime}$ is a continuous, non negative function with respect to the $x_{j}$, and it has Frechet derivatives.
-Assumption 3:

$$
\phi^{\prime \prime}\left[x_{1}, \ldots, x_{n}\right] \text { is convex and it takes its unique }
$$

critical point in the interior of $M$.
-Assumption 4:

$$
x \text { is convex and } x=x_{1} \oplus x_{2} \oplus \ldots \text { ( } \oplus x_{n}
$$

$$
\text { with } x=\text { set of the arrays of vectors }\left(x\left(t_{0}\right), \ldots, x\left(t_{m}\right)\right)
$$

$$
x_{1}=\text { set of the arrays: }\left(x_{1}\left(t_{0}\right), \ldots, x_{1}\left(t_{m}\right)\right)
$$

$$
x_{2}=\text { set of the arrays: }\left(x_{2}\left(t_{0}\right), \ldots, x_{2}\left(t_{m}\right)\right)
$$

:

$$
x_{n}=\text { set of the arrays: }\left(x_{n}\left(t_{0}\right), \ldots, x_{n}\left(t_{m}\right)\right)
$$

-Assumption 5:

$$
\forall_{j}, \forall x_{1}^{0}, \ldots, x_{j-1}^{0}, x_{j+1}^{0}, \ldots, x_{n}^{0}
$$

if
$\min$
$\phi\left[x_{1}^{0}, \ldots, x_{j-1}^{0}, x_{j}, x_{j+1}^{0}, \ldots, x_{n}^{0}\right]=$

$$
\phi\left[x_{1}^{0}, \ldots, x_{j-1}^{0}, x_{j}^{0}, x_{j+1}^{0}, \ldots, x_{n}^{0}\right]
$$

then

$$
x_{j}^{o} \in \operatorname{Int}\left(x_{j}\right)
$$

With these assumptions, the procedure is the

## following:

Given a reference control $m_{1}^{r}, \ldots, m_{n}^{r}$ and the corresponding trajectories $x_{1}^{r}, \ldots, x_{n}^{r}$ and performance $\phi^{\prime \prime}\left(x_{1}^{r}, \ldots, x_{n}^{r}\right)$

## Step 1:

We consider the function

$$
f_{1}\left(x_{1}\right)=\phi^{\prime \prime}\left(x_{1}, x_{2}^{r}, \ldots, x_{n}^{r}\right)
$$

By assumption $2, \mathrm{f}_{1}\left(\mathrm{x}_{1}\right)$ is a continuous function of $\mathrm{x}_{1}$.
By assumption 4, if

$$
x_{1} \in x_{1},\left(x_{1}, x_{2}^{r}, \ldots, x_{n}^{r}\right) \in x
$$

So we can compute $x_{1}^{\prime}$ such that:

$$
\min _{x_{1} \in X_{1}} \quad f_{1}\left(x_{1}\right):=f_{1}\left(x_{1}^{\prime}\right)
$$

By assumption 4, we know that ( $x_{1}^{\prime}, x_{2}^{r}, \ldots, x_{n}^{r}$ ) $\in x$. Further, by assumption 5 , we can say that ( $x_{1}^{\prime}, x_{2}^{r}, \ldots, x_{n}^{r}$ )
is not a boundary point of $X$ : So we can say:

$$
\begin{array}{r}
\phi^{\prime \prime}\left(x_{1}^{\prime}, x_{2}^{r}, \ldots, x_{n}^{r}\right)<\phi^{\prime \prime}\left(x_{1}^{r}, x_{2}^{r}, \ldots, x_{n}^{r}\right) \\
\\
\text { if } x_{1}^{\prime} \neq x_{1}^{r}
\end{array}
$$

or

$$
\frac{\partial \phi^{\prime \prime}\left(x_{1}^{\prime}, \ldots, x_{n}^{r}\right)}{\partial x_{1}}=0 \quad \text { if } x_{1}^{\prime}=x_{1}^{r}
$$

We are using too assumption 2 ( $\phi^{\prime \prime}$ has derivatives).

## Step 2:

We consider now the function:

$$
f_{2}\left(x_{2}\right)=\phi^{\prime \prime}\left(x_{1}^{\prime}, x_{2}, x_{3}^{r}, \ldots, x_{n}^{r}\right)
$$

In the same way $f_{2}\left(x_{2}\right)$ is a continuous function of $x_{2}$ and

$$
x_{2} \in x_{2} \rightarrow\left(x_{1}^{\prime}, x_{2}, x_{3}^{r}, \ldots, x_{n}^{r}\right) \in x
$$

We compute $x_{2}^{\prime}$ such that:

$$
\min _{x_{2} \in X_{2}} f_{2}\left(x_{2}\right):=f_{2}\left(x_{2}^{\prime}\right)
$$

We can say again that: ( $x_{1}^{\prime}, x_{2}^{\prime}, x_{3}^{r}, \ldots, x_{n}^{r}$ ) $\in x$ and that: $\left(x_{1}^{\prime}, x_{2}^{\prime}, x_{3}^{r}, \ldots, x_{n}^{r}\right) \in$ Int $x$

$$
\phi^{\prime \prime}\left(x_{1}^{\prime}, x_{2}^{\prime}, x_{3}^{r}, \ldots, x_{n}^{r}\right)<\phi^{\prime \prime}\left(x_{1}^{\prime}, x_{2}^{r}, x_{3}^{r} \ldots x_{n}^{r}\right)
$$

$$
\text { if } x_{2}^{\prime} \neq x_{2}^{r}
$$

or

$$
\frac{\partial \phi^{\prime \prime}}{\partial x_{2}}\left(x_{1}^{\prime}, x_{2}^{\prime}, x_{3}^{r}, \ldots, x_{n}^{r}\right)=0 \quad \text { if } x_{2}^{\prime}=x_{2}^{r} .
$$

We compute n steps in the same way. We have n problems of optimal control., each of which is only one dimensional.
At the $n-$ th step we have: either

$$
\int \phi^{\prime \prime}\left[x_{1}^{\prime}, \ldots ., x_{r}^{\prime}\right]<\phi^{\prime \prime}\left[\begin{array}{lll}
x_{1}^{r}, & \ldots . & \left.x_{n}^{r}\right]
\end{array}\right.
$$

Z with $\quad\left(x_{1}^{\prime}, \ldots ., x_{n}^{\prime}\right) \varepsilon x$ and $\left(x_{1}^{\prime}, \ldots ., x_{n}^{\prime}\right) \varepsilon$ Int $x$.
or

$$
\begin{gathered}
\frac{\partial \phi^{\prime \prime}\left(x_{1}^{\prime} \cdots x_{n}^{\prime}\right)}{\partial x_{1}}=\frac{\partial \phi^{\prime \prime}\left(x_{1}^{\prime} \cdots x_{n}^{\prime}\right)}{\partial x_{2}}= \\
\ldots=\frac{\partial \phi^{\prime \prime}\left(x_{1}^{\prime} \cdots x_{n}^{\prime}\right)}{\partial x_{n}}=0 \\
\text { if } \quad x_{1}^{\prime}=x_{1}^{r} \& x_{2}^{\prime}=x_{2}^{r} \& \cdots \cdots x_{n}^{\prime}=x_{n}^{r}
\end{gathered}
$$

In the first case we improve the performance.
In the second, we got the same point but we know that the reference control is a local minimum, and hence, by assumption 3, the optimal control.

## Iteration of the technique:

At the end of the procedure we improve the performance or we are at the optimum. If we are not at the optimum and if we iterate the procedure we will get $0 \leq \ldots .<\phi^{\prime \prime}\left(x_{1}^{k}, x_{2}^{k}, \ldots, x_{n}^{k}\right)<\phi^{\prime \prime}\left(x_{1}^{k-1}, x_{2}^{k-1}, \ldots, x_{n}^{k-1}\right)<\ldots .$.

$$
<\phi^{\prime \prime}\left(x_{1}^{r}, \ldots x_{n}^{r}\right)
$$

So the iteration will give a sequence of performance functionals. This sequence is monotone decreasing, and has a lower bound (assumption 4). So this sequence is convergent. To compute the limit $\phi\left(x_{1}, \ldots, x_{n}\right)$ we have to write:

$$
\phi^{\prime \prime}\left(x_{1}^{k}, \ldots, x_{n}^{k}\right)=\phi^{\prime \prime}\left(x_{1}^{k-1}, \ldots, x_{n}^{k-1}\right)=\phi^{\prime \prime}\left(x_{1}^{\ell}, \ldots, x_{n}^{\ell}\right)
$$

But by assumption 5, this equality means that:

$$
\rightarrow\left(x_{1}^{k}, \ldots, x_{n}^{k}\right)=\left(x_{1}^{k-1}, \ldots, x_{n}^{k-1}\right)=\left(x_{1}^{\ell}, \ldots, I n^{\ell}\right)
$$

which means, by the preceeding demonstration that:

$$
\left(x_{1}^{\ell}, \ldots ., x_{n}^{\ell}\right)
$$

is the global minimum of the performance functional.
The geometrical interpretation of this iterative heuristic is very simple. Consider the curve $f_{1}\left(x_{1}\right)$ section of the surface $z=\phi^{\prime \prime}\left(x_{1} \ldots x_{n}\right)$ by the curves $x_{2}=x_{2}^{r}, \ldots, x_{n}=x_{n}^{r}$. Then consider on this curve the minimum of $\phi^{\prime \prime}$ call it $x_{1}^{\prime}$, and proceed again with $x_{2}$ in

-Comparison of this technique with iteration and the decomposition technique:

Suppose a linear discrete problem with n state variables. Suppose the performance index is additively separable, and that we want to deal only with one state variable sub-processes. Suppose B has an inverse.

We have:

$$
\begin{aligned}
\phi & =\phi\left[x_{1}, \ldots, x_{n}, m_{1}, \ldots, m_{n}\right] \\
\frac{x\left(t_{i+1}\right)-x\left(t_{i}\right)}{h} & =c x\left(t_{i}\right)+B m\left(t_{i}\right)
\end{aligned}
$$

Since $B$ has an inverse we can write the system in the following way:

$$
\begin{aligned}
& \left\{\begin{aligned}
\phi & =\phi^{\prime \prime}\left[x_{1}, \ldots, x_{n}\right] \\
\frac{x_{k}\left(t_{i+1}\right)-x_{k}\left(t_{i}\right)}{h} & =\sum_{j} c_{k j} x_{k}\left(t_{i}\right)+B_{k k} m_{k}\left(t_{i}\right)
\end{aligned}\right. \\
& \text { or } \\
& \left\{\begin{aligned}
& \frac{x_{1}\left(t_{i+1}\right)-x_{1}\left(t_{i}\right)}{h}=c_{11} x_{1}\left(t_{i}\right)+c_{12} x_{2}\left(t_{i}\right) \\
&+\ldots+c_{1 n} x_{n}\left(t_{i}\right) \\
&+B_{11} m_{1}\left(t_{i}\right) \\
& \frac{x_{n}\left(t_{i+1}\right)-x_{n}\left(t_{i}\right)}{h}=c_{n 1} x_{1}\left(t_{i}\right)+\ldots+c_{n n} x_{n}\left(t_{i}\right)
\end{aligned}\right. \\
& +B_{n n} m_{n}\left(t_{i}\right)
\end{aligned}
$$

The decomposition technique will proceed as follows:

$$
x_{1}=s_{1}, \ldots, x_{n}=s_{n}
$$

1st level:

2 nd level:

$$
\operatorname{maximize}_{\mathrm{K}_{1}, \ldots, \mathrm{~K}_{\mathrm{n}}} \quad \varphi=\phi_{1}^{\prime \prime}+\phi_{2}^{\prime \prime}+\ldots+\phi_{\mathrm{n}}^{\prime \prime}=\varphi^{0}
$$

Once the min-max problem is solved (by a multilevel iteration procedure) we get:

$$
\varphi^{0}=\phi^{\prime \prime} \text { and } x_{1}=s_{1}, x_{2}=s_{2}, \ldots \ldots, x_{n}=s_{n} .
$$

The technique here is to deal with a min-max problem and with subsystems whicr actually do not represent anything for the real system itself. It adapts these subsystems (by the mean of the K 's) in such a way that their optimal points correspond to the optimal real subsystems of the actual problem. But the coincidence takes place only at the cptimum.

The heuristic propcsed will proceed as follows: i- th stage of the iteration:

$$
\begin{aligned}
& \text { s占 } \\
& \text { sub }\left\{\begin{aligned}
\min _{m_{1}} \phi_{1}^{\prime i}=\phi^{\prime \prime}\left[x_{1}^{i}, x_{2}^{i-1}, x_{3}^{i-1}, \ldots, x_{n}^{i-1}\right] \\
\text { system }
\end{aligned} \quad \begin{array}{rl}
\frac{x_{1}^{i}\left(t_{j+1}\right)-x_{1}^{i}\left(t_{j}\right)}{h}= & c_{11} x_{1}^{i}\left(t_{j}\right)+c_{12} x_{1}^{i-1}\left(t_{j}\right) \\
& +\ldots+c_{1 n} x_{n}^{i-1}\left(t_{j}\right) \\
& +B_{11} m_{l}^{i}\left(t_{j}\right)
\end{array}\right.
\end{aligned}
$$

nh
sub
system $\left\{\begin{array}{l}m_{n i n} \phi_{n}^{\prime \prime}=\phi^{\prime \prime}\left[x_{1}^{i}, x_{2}^{i}, \ldots, x_{n}^{i}\right] \\ \frac{x_{n}^{i}\left(t_{j+1}\right)-x_{n}^{i}\left(t_{j}\right)}{h}=c_{n 1} x_{1}^{i}\left(t_{j}\right)+c_{n 2} x_{2}^{i}\left(t_{j}\right)+\ldots\end{array}\right.$ $+c_{n n} x_{n}^{i}\left(t_{j}\right)+B_{n n} m_{n}^{i}\left(t_{j}\right)$
After the last $N$ th iteration we have to compute the controls $m_{1}^{N} \ldots m_{n}^{N}$.

The latter method iss an iteration technique: with n subsystems. But it should be noted:

1) For each subsystem the minimization of the performance is to be computed with respect to one variable, instead of $(n+1)$ in the decomposition technique.
2) We do not have a $2 \underline{\text { nd }}$ level but an iteration technique, which means an easier programming.
3) On the whole, the effectiveness of this heuristic is dependent upon the form of the performance. This heuristic can give the optimal point in one iteration, while with some other surfaces the convergence might be very slow.

$$
\text { system }\left\{\begin{aligned}
\frac{x_{1}\left(t_{i+1}\right)-x_{1}\left(t_{i}\right)}{h}= & c_{11} x_{1}\left(t_{i}\right) \\
& +c_{12} x_{2}\left(t_{i}\right) \\
& +m_{1}\left(t_{i}\right) \\
\frac{x_{2}\left(t_{i+1}\right)-x_{2}\left(t_{i}\right)}{h}= & c_{21} x_{1}\left(t_{i}\right) \\
& +c_{22} x_{2}\left(t_{i}\right) \\
& +m_{2}\left(t_{i}\right)
\end{aligned}\right.
$$

performance

$$
\begin{aligned}
\phi=\sum_{i=0}^{m}\left\{A_{1}\left[x_{1}\left(t_{i}\right)-r_{1}\right]^{2}+A_{2}\left[x_{2}\left(t_{i}\right)-r_{2}\right]^{2}\right. & +B_{1} m_{1}^{2}\left(t_{i}\right) \\
& \left.+B_{2} m_{2}^{2}\left(t_{i}\right)\right\} h
\end{aligned}
$$

global method:

$$
\begin{aligned}
H= & A_{1}\left[x_{1}\left(t_{i}\right)-r_{1}\right]^{2}+A_{2}\left[x_{2}\left(t_{i}\right)-r_{2}\right]^{2}+B_{1} m_{1}^{2}\left(t_{i}\right)+B_{2} m_{2}^{2}\left(t_{i}\right) \\
& +p_{2}\left[c_{21}\left(t_{i}\right) x_{1}\left(t_{i}\right)-c_{22}\left(t_{i}\right) x_{2}\left(t_{i}\right)+m_{2}\left(t_{i}\right)\right]
\end{aligned}
$$

We get:

$$
\downarrow=\left[\begin{array}{ll}
c_{11} & c_{12} \\
& \\
c_{21} & c_{22}
\end{array}\right] \xi=\left[\begin{array}{cc}
-\frac{1}{2} \mathrm{~F}_{1} & \\
& \\
0 & -\frac{1}{2} \mathrm{~B}_{2}
\end{array}\right] \quad{ }^{\mathrm{w}_{1}}=\left[\begin{array}{cc}
\frac{1}{2} \mathrm{~B}_{1} & \delta \mathrm{Hm}_{1} \\
& \\
\frac{1}{2} \mathrm{~B}_{2} & \delta \mathrm{Hm}_{2}
\end{array}\right]
$$

$\mathcal{L}=\left[\begin{array}{cc}-2 A_{1} & 0 \\ 0 & -2 A_{2}\end{array}\right] \quad w_{2}:=\left[\begin{array}{l}0 \\ 0\end{array}\right]$

The program of the computation is shown in Appendix 4,
Program 2.
Use of the Heuristic:
We start with a reference control $\mathrm{m}_{1}^{r}, \mathrm{~m}_{2}^{r}$. We compute the corresponding trajectory $\mathrm{x}_{1}^{r}, \mathrm{x}_{2}^{\mathrm{r}}$ by:

$$
\begin{aligned}
& \frac{x_{1}^{r}\left(t_{i+1}\right)-x_{1}^{r}\left(t_{i}\right)}{h}=c_{11} x_{1}^{r}\left(t_{i}\right)+c_{12} x_{2}^{r}\left(t_{i}\right)+m_{1}^{r}\left(t_{i}\right) \\
& \frac{x_{2}^{r}\left(t_{i+1}\right)-x_{2}^{r}\left(t_{i}\right)}{h}=c_{21} x_{1}^{r}\left(t_{i}\right)+c_{22} x_{2}^{r}\left(t_{i}\right)+m_{2}^{r}\left(t_{i}\right)
\end{aligned}
$$

Then we have:
1 -st subsystem:

$$
\begin{aligned}
& \left(\min _{x_{1}=x_{1}^{\prime}} \phi\left(x_{1}, x_{2}^{r}\right)=\sum_{i=0}^{m}\left\{A_{1}\left[x_{1}\left(t_{i}\right)-r_{1}\right]^{2}+A_{2}\left[x_{2}^{r}\left(t_{i}\right)-r_{2}\right]^{2}\right.\right. \\
& \left.+B_{1} m_{1}^{2}\left(t_{i}\right)+B_{2} m_{2}^{2}\left(t_{i}\right)\right\} . \\
& \text { with } \\
& \left\{\begin{aligned}
& m_{1}\left(t_{i}\right)= \frac{x_{1}\left(t_{i+1}\right)-x_{1}\left(t_{i}\right)}{h}-c_{11} x_{1}\left(t_{i}\right)- \\
& c_{12} x_{2}^{r}\left(t_{i}\right) \\
& m_{2}\left(t_{i}\right)= \frac{x_{2}^{r}\left(t_{i+1}\right)-x_{2}^{r}\left(t_{i}\right)}{h}-c_{21} x_{1}\left(t_{i}\right)- \\
& c_{22} x_{2}^{r}\left(t_{i}\right)
\end{aligned}\right.
\end{aligned}
$$

$2 \underline{\text { nd }}$ subsystem:
Given by $x_{i}^{\prime}$ by the $1 \frac{s t}{}$ system:

$$
\left\{\begin{array}{l}
\min _{x_{2}=x_{2}^{\prime}} \phi\left(x_{1}^{\prime}, x_{2}\right)=\sum_{i=0}^{m}\left\{A_{1}\left[x_{1}^{\prime}\left(t_{i}\right)-r_{1}\right]^{2}+A_{2}\left[x_{2}\left(t_{i}\right)-r_{2}\right]^{2}\right. \\
\left.+B_{1} m_{1}^{2}\left(t_{i}\right)+B_{2} m_{2}^{2}\left(t_{i}\right)\right\} \cdot h
\end{array} \quad \begin{array}{r}
\text { with } \\
\left\{\begin{array}{r}
m_{12}\left(t_{i}\right)=\frac{x_{1}^{\prime}\left(t_{i+1}\right)-x_{1}^{\prime}\left(t_{i}\right)}{h}-c_{11} x_{1}^{\prime}\left(t_{i}\right)- \\
m_{2}\left(t_{i}\right)=\frac{x_{2}\left(t_{i+1}\right)-x_{2}\left(t_{i}\right)}{h}-c_{21} x_{1}^{\prime}\left(t_{i}\right)- \\
c_{22} x_{2}\left(t_{i}\right)
\end{array}\right.
\end{array}\right.
$$

We then have either: $\phi\left(x_{1}^{\prime}, x_{2}^{\prime}\right)<\phi\left(x_{1}^{r}, x_{2}^{r}\right)$

optimum.
We then compute the controls leading to these trajectories:

$$
\begin{aligned}
& m_{1}^{\prime}\left(t_{i}\right)=\frac{x_{1}^{\prime}\left(t_{i+1}\right)-x_{1}^{\prime}\left(t_{i}\right)}{h}-c_{11} x_{1}^{\prime}\left(t_{i}\right)-c_{12} x_{2}^{\prime}\left(t_{i}\right) \\
& m_{2}^{\prime}\left(t_{i}\right)=\frac{x_{2}^{\prime}\left(t_{i+1}\right)-x_{2}^{\prime}\left(t_{i}\right)}{h}-c_{21} x_{1}^{\prime}\left(t_{i}\right)-c_{22} x_{2}^{\prime}\left(t_{i}\right)
\end{aligned}
$$

The program of the computation is shown in Appendix 4, Program 3.

### 3.3 Application of the Heuristic to Slightly Non-Linear

Systems:
By slightly non linear system, we mean the following system:

$$
\left\{\begin{aligned}
\frac{x_{1}\left(t_{i+1}\right)-x_{1}\left(t_{i}\right)}{h}= & c_{11} x_{1}\left(t_{i}\right)+c_{12} x_{2}\left(t_{i}\right) \\
& +D_{11} x_{1}^{2}\left(t_{i}\right)+D_{12} x_{2}^{2}\left(t_{i}\right)+m_{1}\left(t_{i}\right) \\
\frac{x_{2}\left(t_{i+1}\right)-x_{2}\left(t_{i}\right)}{h}= & c_{21} x_{1}\left(t_{i}\right)+c_{22} x_{2}\left(t_{i}\right) \\
& +D_{21} x_{1}^{2}\left(t_{i}\right)+D_{22} x_{2}^{2}\left(t_{i}\right)+m_{2}\left(t_{i}\right)
\end{aligned}\right.
$$

performance:

$$
\begin{aligned}
\phi= & \sum_{i=0}^{m}\left\{A_{1}\left[x_{1}\left(t_{i}\right)-r_{1}\right]^{2}+A_{2}\left[x_{2}\left(t_{i}\right)-r_{2}\right]^{2}\right. \\
& \left.+B_{1} m_{1}^{2}\left(t_{i}\right)+B_{2} m_{2}^{2}\left(t_{i}\right)\right\}
\end{aligned}
$$

The advantage of the heuristic is obvious from the following example. The computation of the coefficients in a successive sweep method for the overall problem is very complex, while, it is simple to do, with this heuristic: subsystem 1:

$$
\begin{aligned}
\min _{x_{1}=x_{1}^{\prime}} \phi\left(x_{1}, x_{2}^{r}\right)= & \sum_{i=0}^{m}\left\{A_{1}\left[x_{1}\left(t_{i}\right)-r_{1}\right]^{2}+A_{2}\left[x_{2}^{r}\left(t_{i}\right)-r_{2}\right]^{2}\right. \\
& \left.+B_{1} m_{1}^{2}\left(t_{i}\right)+B_{2} m_{2}^{2}\left(t_{i}\right)\right\} \cdot h
\end{aligned}
$$

with

$$
\left\{\begin{aligned}
\frac{x_{1}\left(t_{i+1}\right)-x_{1}\left(t_{i}\right)}{h} & =c_{11} x_{1}\left(t_{i}\right)+c_{12} x_{2}^{r}\left(t_{i}\right) \\
& +D_{11} x_{1}^{2}\left(t_{i}\right)+D_{12}\left(x_{2}^{r}\left(t_{i}\right)\right)^{2} \\
& +m_{1}\left(t_{i}\right) \\
\frac{x_{2}^{r}\left(t_{i+1}\right)-x_{2}^{r}\left(t_{i}\right)}{h} & =c_{21} x_{1}\left(t_{i}\right)+c_{22} x_{2}^{r}\left(t_{i}\right) \\
& +D_{21} x_{1}^{2}\left(t_{i}\right)+D_{22}\left(x_{2}^{r}\left(t_{i}\right)\right)^{2} \\
& +m_{2}\left(t_{i}\right)
\end{aligned}\right.
$$

subsystem 2:
Given $x_{1}^{\prime}$ from the subsystem 1 :

$$
\begin{aligned}
\min _{x_{2}=x_{2}^{\prime}} \phi\left(x_{1}^{\prime}, x_{2}\right)= & \sum_{i=0}^{m}\left\{A_{1}\left[x_{1}^{\prime}\left(t_{i}\right)-r_{1}\right]^{2}+A_{2}\left[x_{2}\left(t_{i}\right)-r_{2}\right]^{2}\right. \\
& \left.+B_{1} m_{1}^{2}\left(t_{i}\right)+B_{2} m_{2}^{2}\left(t_{i}\right)\right\} \cdot h
\end{aligned}
$$

with

$$
\left\{\begin{aligned}
\frac{x_{1}^{\prime}\left(t_{i+1}\right)-x_{1}^{\prime}\left(t_{i}\right)}{h} & =c_{11} x_{1}^{\prime}\left(t_{i}\right)+c_{12} x_{2}\left(t_{i}\right) \\
& +I_{11}\left(x_{1}^{\prime}\left(t_{i}\right)\right)^{2}+D_{12} x_{2}^{2}\left(t_{i}\right) \\
& +m_{1}\left(t_{i}\right) \\
\frac{x_{2}\left(t_{i+1}\right)-x_{2}\left(t_{i}\right)}{h} & =c_{21} x_{1}^{\prime}\left(t_{i}\right)+c_{22} x_{2}\left(t_{i}\right) \\
& +I_{21}\left(x_{1}^{\prime}\left(t_{i}\right)\right)^{2}+D_{22} x_{2}^{2}\left(t_{i}\right) \\
& +m_{2}\left(t_{i}\right)
\end{aligned}\right.
$$

We then have

$$
\phi\left(x_{1}^{\prime}, x_{2}^{\prime}\right)<\phi\left(x_{1}^{r}, x_{2}^{r}\right)
$$

$$
\text { or } \left.\quad \begin{array}{rl}
x_{1}^{\prime} & =x_{1}^{r} \\
x_{2}^{\prime} & =x_{2}^{r}
\end{array}\right\} \quad \begin{aligned}
& \text { and the reference control } \\
& \text { is a local minimum. }
\end{aligned}
$$

Application: Appendix 4, Program 4.


### 3.4 Application of the Heuristic to a Linear System

 with 5 Variables. Computational Study of the Heuristic:The system is the most general one:

$$
\begin{array}{r}
\frac{x_{i}\left(t_{k+1}\right)-x_{i}\left(t_{k}\right)}{h}=\sum_{j=-.}^{5} c_{i j} x_{j}\left(t_{k}\right)+m_{i}\left(t_{k}\right) \\
i=1,2,3,4,5 .
\end{array}
$$

$$
\phi=\sum_{k=0}^{m} \sum_{j=1}^{5}\left[A _ { j } \left(x_{j}\left(t_{k} j-r_{j}\right)^{2}+B_{j} m_{j}^{2}\left(t_{k}\right] \cdot h\right.\right.
$$

The computation at the $N^{\frac{t h}{}}$ swage, $j \frac{\text { th }}{}$ step is the following one:

$$
\begin{aligned}
& \begin{aligned}
\frac{x_{j}^{(N)}\left(t_{k+1}\right)-x_{j}^{(N)}\left(t_{k}\right)}{h} & =\sum_{1 \leq i \leq j} c_{j i} x_{i}^{(N)}\left(t_{k}\right) \\
& +\sum_{j<k \leq 5} c_{j k} x_{k}^{(N-1)}\left(t_{k}\right) \\
& +m_{j}^{(N)}\left(t_{k}\right)
\end{aligned} \\
& \min _{x_{j}^{(N)}} \phi_{j}^{(N)}=\sum_{i=0}^{m}\left\{\sum _ { 1 \leq i \leq j } \left[A_{i}\left(x_{i}^{(N)}\left(t_{k}\right)-r_{i}\right)^{2}\right.\right. \\
& \left.+B_{i} m_{i}^{(N)^{2}}\left(t_{k}\right)\right] \\
& +\sum_{j<l \leq 5}\left[A_{l}\left(x_{l}^{(N-1)}\left(t_{k}\right)-r_{l}\right)^{2}\right. \\
& \left.\left.+B_{l} m_{l}^{(N-1)^{2}}\left(t_{k}\right)\right]\right\} \cdot h
\end{aligned}
$$

Program of computation: See Appendix 4, Program 5.
 the refarence applourtion of thic cented sutisflution aprocoll. $\square$
$3 i 828$
steps step4 stip5

| 385 | 31875 |
| :--- | :--- |



| 38791 | 32.791 |
| :--- | :--- |





$1.30 .23 .++$

$$
2^{n!}: \text { iricitio. }
$$

$-3180$

$i^{\text {st }}$ iteration
$2^{\text {rd }}$ 「どatic゙

2
2
2
$t$
$m$
$\sim$
$\cdots$
$r$
2
2
2
2


Prifermanocy

$$
\frac{\text { Eveluth: if the feifermanic versis }}{\text { the nomber of treraticis }}
$$

nefeicnie Peifermance


If, for the same system, we vary $\mathrm{h} / \mathrm{t}_{\mathrm{e}}$ from 0.1 to 0.01 , we can see that:
-The computing time is proportional to the number of intervals in which $\left[t_{0}, t_{e}\right.$ ] is divided, or proportional to $l /\left(h / t_{e}\right)$.
-After 5 iterations, we get almost the same performance.
-When $h$ decreases, we get a smoother curve of the control.
-The difference of the trajectories computed with different $h / t_{e}$ can be neglected. The difference in the controls are more important; but this puts in evidence two facts: For this system, a small variation in the controls will not affect too much the trajectories, and the cost of the control is very little compared to the cost of the deviation from the desired trajectory.

with respect to the step of integration?



Evolution of $m_{2}$ versus rime according to $h$
$m_{2}$

$\stackrel{\rightharpoonup}{\longrightarrow}$


$$
\begin{aligned}
& \mp h / r e=0.01 \\
& h / t_{2}=0.02 \\
& h / r_{2}=0.10
\end{aligned}
$$

Evolution of $m_{4}$ versus time
according to $h$

Evolution of $m_{5}$ versus time according to $h$



## CHAPTER IV

## DECOMPOSITI(ON TECHNIQUE APPLIED

IN PRESENCE OF NOISE

The decomposition technique cannot be applied directly to a system with disturbances, for the noises in the measurements introduce a new kind of correlation between the subsystems. If we consider one subsystem and the measurements related only to this subsystem we are neglecting in this subsystem the information brought by the data of the other subsystems. Hence, the computed control would not be the optimal control computed with all the data given by the measurements.

Nevertheless, in terms of the means and the variances of the state variables, it is possible to use this technique once deterministic equations of the global system are found. We then consider these equations as defining a new system, the state variables of which are the means and the variances of the previous state variables. The examples will show how this can be implemented.
4.1 Case of Linear System with Quadratic Performances
4.1.1 The Deterministic Problem

Part 1 The global method:
The system is the following one:

$\left[\begin{array}{l}d x_{1} \\ d x_{2}\end{array}\right]=\left[\begin{array}{ll}c_{11} & c_{12} \\ c_{21} & c_{22}\end{array}\right]\left[\begin{array}{l}x_{1} \\ x_{2}\end{array}\right] d t+\left[\begin{array}{ll}l_{1} & 0 \\ 0 & l_{2}\end{array}\right]\left[\begin{array}{l}m_{1} \\ m_{2}\end{array}\right] d t$
or

$$
\begin{gathered}
d x=\left(c+c^{\prime}\right) x d t+L m d t . \\
\text { with } c=\left[\begin{array}{ll}
c_{11} & \\
& \\
0 & c_{22}
\end{array}\right] \quad c^{\prime}=\left[\begin{array}{ll}
0 & c_{12} \\
c_{21} & 0
\end{array}\right] \quad L=\left[\begin{array}{ll}
l_{1} & 0 \\
0 & e_{2}
\end{array}\right]
\end{gathered}
$$

The performance criterion is:


$$
\left.+\left(r_{2}-x_{2}\right)^{2}+m_{1}^{2}+m_{2}^{2}\right\} d t
$$

This problem corresponds $=0$ something real:
$\int_{0}^{t} e\left(m_{1}^{2}+m_{2}^{2}\right) d t$ corresponds to the cost of the control
action. $r_{1}(t), r_{2}(t)$ cor:-esponds to the desired trajectories of $x_{1}(t), x_{2}(t)$. $\int_{0}^{t} e_{\left\{\left(r_{1}-x_{1}\right)^{2}+\left(r_{2}-x_{2}\right)^{2}\right\} d t}$
is the cost of deviation From the desired output.
This problem is a classical problem of control which can be solved by well known techniques:

$$
\begin{array}{r}
H=\left(r_{1}-x_{1}\right)^{2}+\left(r_{2}-x_{2}\right)^{2}+m_{1}^{2}+m_{2}^{2}+p_{1}\left[c_{11} x_{1}\right. \\
\left.+c_{12} x_{2}+\ell_{1} m_{1}\right]+p_{2}\left[c_{21} x_{1}+c_{22} x_{2}+\ell_{2} m_{2}\right]
\end{array}
$$

We have to solve the following T. P. B. V. P.:

$$
\begin{cases}\frac{d x_{1}}{d t}=c_{11} x_{1}+c_{12} x_{2}+l_{1} m_{1} & x_{1}(0)=x_{10} \\ \frac{d x_{2}}{d t}=c_{21} x_{1}+c_{22} x_{2}+l_{2} m_{2} & x_{2}(0)=x_{20} \\ \frac{d p_{1}}{d t}=-H x_{1} & p_{1}\left(t_{e}\right)=0 \\ \frac{d p_{2}}{d t}=-H x_{2} & p_{2}\left(t_{e}\right)=0\end{cases}
$$

$$
\mathrm{Hm}_{1}=0 \quad \mathrm{Hm}_{2}=0
$$

-Computation of a numeric:al example:
-Data:

$$
\begin{aligned}
& c_{11}(t)=c_{22}(t)=c_{21}(t)=l_{1}(t)=l_{2}(t)=1 \\
& r_{1}(t)=t \quad r_{2}(t)=2 t \quad t_{e}=0.05 .
\end{aligned}
$$

-Computation:

$$
\begin{aligned}
& \mathscr{D}=\mathcal{D}^{\prime}=\left[\begin{array}{ll}
1 & 1 \\
1 & 1
\end{array}\right] \varepsilon=\left[\begin{array}{cc}
-\frac{1}{2} & 0 \\
0 & -\frac{1}{2}
\end{array}\right] \quad w_{1}=\left[\begin{array}{ll}
\frac{1}{2} & \delta \mathrm{Hm}_{1} \\
\frac{1}{2} & \delta \mathrm{Hm}_{2}
\end{array}\right] \\
&\left.\begin{array}{ll} 
& \\
0 & -2
\end{array}\right]
\end{aligned}
$$

-Results: see Appendix 5, Program 6.

Part 2 The decomposition technique:
The system is decomposed in two subsystems (Appendix
2 and the thesis of $S$. Reich [3]). For this, the chosen system must have the two : =ollowing fundamental properties:
a) It can be split into two subsystems such that the output of one system can be viewed as an input to the other subsystem.
b) The performance is additively separable.

In this case we have the following scheme:


We have:
subsystem 1:

$$
\frac{d x_{1}}{d t}=c_{11} x_{1}+c_{12} t_{2}+l_{1} m_{1}
$$

subsystem 2:

$$
\frac{d x_{2}}{d t}=c_{21} t_{1}+c_{22} x_{2}+\ell_{2} m_{2}
$$

with the supplementary constraints: $x_{2}=t_{2}$

$$
x_{I}=t_{1}
$$

The Lagrangian for the whole system can be written as:

$$
J=\left(r_{1}-x_{1}\right)^{2}+\left(r_{2}-x_{2}\right)^{2}+m_{1}^{2}+m_{2}^{2}+p_{1}\left[c_{11} x_{1}+c_{12} t_{2}\right.
$$

$$
\left.+\ell_{1} m_{1}-\dot{x}_{1}\right]+p_{2}\left[c_{21} t_{1}+c_{22} \dot{x}_{2}+\ell_{2} m_{2}-\dot{x}_{2}\right]
$$

$$
+k_{1}\left(x_{1}-t_{1}\right)+k_{2}\left(x_{2}-t_{2}\right)
$$

This Lagrangian can be split, due to the fact that the performance is additively separable. This leads to
the decomposition technique. It was shown [3] that the decomposition technique and the global method give the same results. The advantage of the decomposition
technique is to break the problem in several subproblem easier to handle by the computer. In this case we have: First Level

Given $k_{1}, k_{2}$ for the 2 nd level we have the two
T. P. B. V. P.:
-subproblem 1:

$$
\begin{aligned}
& J=\left(r_{1}-x_{1}\right)^{2}+m_{1}^{2}+p_{1}\left[c_{11} x_{1}+c_{12} t_{2}+\ell_{1} m_{1}-\dot{x}_{1}\right] \\
& \left\{\begin{aligned}
& \frac{d x_{1}}{d t}= c_{11} x_{1}+\ell_{1} m_{1}+c_{12} t_{1}-k_{2} t_{2} \\
& \frac{d p_{1}}{d t}=-H x_{1}=-\left\{2\left(x_{1}-r_{1}\right)+p_{1} c_{11}+k_{1}\right\} p_{1}\left(t_{e}\right)=0 \\
& 2 m_{1}+p_{1} \ell_{1}= x_{1}(0)=x_{10} \\
& p_{1} c_{12}-k_{2}=0
\end{aligned}\right. \\
& \text {-subproblem 2: }
\end{aligned}
$$

$$
\begin{aligned}
J=\left(r_{2}-x_{2}\right)^{2}+m_{2}^{2}+\rho_{2}\left[c_{21} t_{1}+\right. & \left.c_{22} x_{2}+\ell_{2} m_{2}-\dot{x}_{2}\right] \\
& -k_{1} t_{1}+k_{2} x_{2}
\end{aligned}
$$

$$
\left\{\begin{aligned}
\frac{d x_{2}}{d t}= & c_{21} t_{1}+c_{22} x_{2}+l_{2} m_{2} \quad x_{2}(0)=x_{20} \\
\frac{d p_{2}}{d t} & =-H x_{2}=-\left\{2\left(x_{2}-r_{2}\right)+p_{2} c_{22}+k_{2}\right\} p_{2}\left(t_{e}\right)=0 \\
& 2 m_{2}+p_{2} l_{2}=0 \\
& p_{2} c_{21}-k_{1}=0
\end{aligned}\right.
$$

Second Level or Coordination Level
The 2 nd level coordinates the two subproblems by varying $k_{1}$ and $k_{2}$.

$$
\begin{aligned}
& {\left[k_{1}\right]_{n+1}=\left[k_{1}\right]_{n}-\varepsilon\left(x_{1}-t_{1}\right)} \\
& {\left[k_{2}\right]_{n+1}=\left[k_{2}\right]_{n}-\varepsilon\left(x_{2}-t_{2}\right)}
\end{aligned}
$$

The multilevel procedure consists in solving the first level and making one coordination step at the $2 \frac{\text { nd }}{}$ level. The procedure repeats until $\left|x_{1}-t_{1}\right|$ and $\left|x_{2}-t_{2}\right|$ are within a tolerance limit.

Computation of a numerical example:
-Data:

$$
\begin{aligned}
& c_{11}(t)=c_{21}(t)=c_{22}(t)=l_{1}(t)=l_{2}(t)=1 \\
& r_{1}(t)=t \quad J_{2}(t)=2 t \quad t_{e}=0.05 .
\end{aligned}
$$

-Computation:
subsystem 1:

$$
\begin{aligned}
& \mathscr{D}=\mathcal{D}^{\prime}=1 \quad \mathcal{E}=-\frac{3}{2} \quad w_{1}=\frac{1}{2} \delta \mathrm{Hm}_{1}+\delta H t_{2} \\
& \mathscr{L}=-1 \quad w_{2}=0
\end{aligned}
$$

subsystem 2:

$$
\begin{aligned}
& \mathcal{D}=\mathscr{D}^{\prime}=1 \quad E=-\frac{3}{2} \quad w_{1}=\frac{1}{2} \delta{H m_{2}}^{2}+\delta H t_{1} \\
& \mathcal{E}=-1 \quad w_{2}=0
\end{aligned}
$$

-Results: see Appendix 5, Program 7.
4.1.2 The Stochastic Problem

A Formulation of the Problem:
We take the same system but with noises in the system itself and in the measurements.


The control actions are $m_{1}$ and $m_{2}$.
-The system is:
$\left[\begin{array}{l}d x_{1} \\ d x_{2}\end{array}\right]=\left[\begin{array}{ll}c_{11} & c_{12} \\ c_{21} & c_{22}\end{array}\right]\left[\begin{array}{l}x_{1} \\ x_{2}\end{array}\right] d t+\left[\begin{array}{ll}\ell_{1} & 0 \\ 0 & l_{2}\end{array}\right]\left[\begin{array}{l}m_{1} \\ m_{2}\end{array}\right] d t+\left[\begin{array}{l}d z_{1} \\ d z_{2}\end{array}\right]$
or

$$
d x=\left(C+C^{\prime}\right) x d t+L m d t+d z
$$

The measurements are:

$$
\left[\begin{array}{c}
d M_{1} \\
\\
d M_{2}
\end{array}\right]=\left[\begin{array}{ll}
g_{1} & 0 \\
0 & g_{2}
\end{array}\right]\left[\begin{array}{l}
x_{1} \\
x_{2}
\end{array}\right] \quad d t+\left[\begin{array}{c}
\mathrm{dN}_{1} \\
\\
d N_{2}
\end{array}\right]
$$

or

$$
\mathrm{dM}=\mathrm{G} x \mathrm{dt}+\dot{\mathrm{c}} \cdot \mathrm{~N}
$$

-Assumptions on the noises:
$d N$ and $d z$ are uncorrelatec vector wiener processes, such
that:
For any $t \in T$ and any $s \neq t$ :

$$
\begin{aligned}
& E[d N(t)]=E[d z(t)]=0 \quad E\left[d N(t) \cdot d z^{T}(t)\right]=0 \\
& E\left[d N(t) \cdot d N^{T}(s)\right]=E\left[d N(t) \cdot d z^{T}(s)\right]=E\left[d z(t) \cdot d z^{T}(s)\right]=0 \\
& E\left[d N(t) \cdot d N^{T}(t)\right]=W d t \\
& E\left[d z(t) \cdot d z^{T}(t)\right]=Q d t
\end{aligned}
$$

with

$$
\mathrm{W}=\left[\begin{array}{cc}
\mathrm{w}_{1} & 0 \\
0 & \mathrm{w}_{2}
\end{array}\right] \quad \mathrm{Q}=\left[\begin{array}{ll}
\mathrm{q}_{1} & 0 \\
0 & \mathrm{q}_{2}
\end{array}\right]
$$

-Notations:

$$
\begin{gathered}
\bar{x}=E(x)=\left[\begin{array}{l}
\bar{x}_{1} \\
\\
x_{2}
\end{array}\right]=\left[\begin{array}{l}
E\left(x_{1}\right) \\
E\left(x_{2}\right)
\end{array}\right] \\
V=E\left\{(x-\bar{x}) \cdot(x-\bar{x})^{T}\right\}=\left[\begin{array}{ll}
v_{11} & v_{12} \\
v_{21} & v_{22}
\end{array}\right]
\end{gathered}
$$

-Performance criterion:
We use the same performance criterion as in the deterministic case but with an expectation:

$$
\begin{gathered}
\phi=E\left\{\int_{0}^{t} e\left[\left(r_{1}-x_{1}\right)^{2}+\left(r_{2}-x_{2}\right)^{2}+m_{1}^{2}+m_{2}^{2}\right] d t\right. \\
=\int_{0}^{t} e\left\{\left(m_{1}^{2}+\left(r_{1}-\bar{x}_{1}\right)^{2}+v_{11}\right)+\left(m_{2}^{2}+\left(r_{2}-\bar{x}_{2}\right)^{2}+v_{22}\right)\right\} d t
\end{gathered}
$$

B Solution of the global problem:
To solve the global problem we need to know an expression of $\bar{x}_{1}, v_{1}, \bar{x}_{2}, v_{2}$ which are in the formulation of the performance criterion. To compute these values
we shall use the method of Kalman [4]. This method will be explained in detail in this section. In the following demonstrations only the main steps of the calculation will be written.

We will solve the problem first with the vectorial notation, which will give $\bar{x}$ and $v$. Taking the elements of $\bar{x}$ and $V$ we will get $\bar{x}_{1}, v_{1}, \bar{x}_{2}, v_{2}$. Prior mean and variance of $: \bar{x}$ and $V$. Posterior mean and variance of : $\bar{x}$ and $\underline{V}$.

We approximate the continuous-time model by a finite time difference model:
$\delta x=x(t+\delta t)-x(t)=\left(c+C^{\prime}\right) x \delta t+L m \delta t+\delta z$.
$\delta M=M(t+\delta t)-M(t)=G x \delta t+\delta N$.
Now we proceed in two stages: the first stage is the determination of the conditional probability density of $\delta x$ just after an observation $\delta M$ during the time $\delta t$, in terms of the conditional probability density of $\delta \mathrm{x}$ just before the observation $\delta \mathrm{M}$. These conditional probabilities are known respectively as posterior and prior. In the second stage the effect of the dynamics of the process are taken in account and determine the transformation between the prior conditional probability density at time $t+\delta t$ and the posterior conditional probability density of $x$ at time $t$.

It is assumed, and it can be shown inductively
that the conditional probability densities of $x(t)$ are gaussian.

Stage 1: The effect of the observation:
Bayes rule gives:
$f(x, t+\delta t / t+\delta t)=\frac{f\left[x_{1}-\delta t ; \delta M / t\right]}{E(\delta M / t)}$

which gives:
$\exp \left[-\frac{1}{2}(x-\bar{x})^{T} V^{-1}(x-\bar{x})\right]=k^{\prime} \exp \left[-\frac{1}{2}(\delta M-G x \delta t)(W \delta t)^{-1}\right.$

$$
\begin{equation*}
(\delta M-G x \quad \delta t)] x \exp \left[-\frac{1}{2}(x-\underline{\bar{x}})^{T} \underline{V}^{-1}(x-\underline{\bar{x}})\right] \tag{4}
\end{equation*}
$$

Where all the terms are evaluated at $t+\delta t$. By equating coefficients of $x$ in (4), we get:
(5) $\left.\quad V=\left[\underline{V}^{-1}+G^{T} W^{-1} G \delta t\right]^{-1}\right\}$ where all the terms are
(6) $\overline{\mathrm{x}}=\mathrm{V} \mathrm{\underline{V}}^{-1} \underline{\mathrm{x}}+\mathrm{VGG}^{T} \mathrm{~W}^{-1} \delta \mathrm{M}$ evaluated at $t+\delta t$.

Expanding (5) in a matrix raylor's series, we get:
(7) $\int V=\underline{V}-\underline{V} G^{T} W^{-1} G \underline{V} \delta t+0(\delta t)$.
(6) $\left\{\bar{x}=V^{-1} \underline{\bar{x}}+V G^{T} W^{-1} \delta M\right.$

Taking the conditional moments of (1), we get:
(8) $\underline{\bar{x}}(t+\delta t)=\left[I+\left(c+C^{\prime}\right) \delta t\right] \bar{x}(t)+L m \delta t$
(9) $\underline{V}(t+\delta t)=\left[I+\left(C+C^{\prime}\right) \delta t\right] V(t)\left[I+\left(C+C^{\prime}\right) \delta t\right]^{T}$

$$
+Q \delta t .
$$

Substituting (9) in (7), we get:

$$
\begin{aligned}
v(t+\delta t)=V(t)+\delta t\left\{\left(c+c^{\prime}\right) V\right. & +V\left(C+c^{\prime}\right)^{T}+Q \\
& \left.-V G^{T} W^{-1} G V\right\}+0(\delta t) .
\end{aligned}
$$

which gives:
(10) $\frac{d V}{d t}=\left(C+C^{\prime}\right) V+V\left(C+C^{\prime}\right)^{T}+Q-V G^{T} W^{-1} G V$ Similarly eliminating $\underline{\bar{x}}(t+\delta t) \underline{V}(t+\delta t)$ from (6), we get:
(11) $\frac{d \bar{x}}{d t}=\left(C+C^{\prime}\right) \bar{x}+L m-V G^{T} W^{-1} G \bar{x}+V G^{T} W^{-1} \frac{d M}{d t}$

Taking the components of (10) and (11) we get the solution of the problem or more precisely its statement:
-system:
$\frac{d v_{11}}{d t}=2 c_{11} v_{11}+2 c_{12} v_{12}+q_{1}-\frac{v_{11}^{2} g_{1}^{2}}{w_{1}}-\frac{v_{12}^{2} g_{2}^{2}}{w_{2}}$
$\frac{d v_{22}}{d t}=2 c_{22} v_{22}+2 c_{21} v_{12}+q_{2}-\frac{v_{12}^{2} g_{1}^{2}}{w_{1}}-\frac{v_{22}^{2} g_{2}^{2}}{w_{2}}$
$\frac{d v_{21}}{d t}=\left(c_{11}+c_{22}\right) v_{12}+c_{12} v_{22}+c_{21} v_{11}-\frac{v_{11} v_{12}}{w_{1}} g_{1}^{2}$

$$
-\frac{v_{22} v_{12}}{w_{2}} g_{2}^{2}
$$

$$
\begin{aligned}
\frac{d \bar{x}_{1}}{d t}=c_{11} \bar{x}_{1}+c_{12} \bar{x}_{2} & +\ell_{1} m_{1}-\frac{v_{11} g_{1}^{2} \bar{x}_{1}}{w_{1}}-\frac{v_{12} g_{2}^{2} \bar{x}_{2}}{w_{2}} \\
& +\frac{v_{1} g_{1}}{w_{1}} \frac{d M_{1}}{d t}+\frac{v_{12} g_{2}}{w_{2}} \frac{d M_{2}}{d t} \\
\frac{d \bar{x}_{2}}{d t}=c_{22} \bar{x}_{2}+c_{21} \bar{x}_{1} & +\ell_{2} m_{2}-\frac{v_{12} g_{1}^{2}}{w_{1}} \bar{x}_{1}-\frac{v_{22} g_{2}^{2}}{w_{2}} \bar{x}_{2} \\
& +\frac{v_{12} g_{1}}{v_{1}} \frac{d M_{1}}{d t}+\frac{v_{22} g_{2}}{w_{2}} \frac{d M_{2}}{d t}
\end{aligned}
$$

-Performance criterion:
$\phi=\int_{0}^{t} e\left\{m_{1}^{2}+m_{2}^{2}+\left(r_{1}-\bar{x}_{1}\right)^{2}+\left(r_{2}-\bar{x}_{2}\right)^{2}+v_{11}+v_{22}\right\} d t$
The endpoint conditions are:

$$
\left\{\begin{array}{l}
\bar{x}_{1}(0)=x_{10} \\
\bar{y}_{1}(0)=y_{10} \\
v_{11}(0)=0 \\
v_{22}(0)=0 \\
v_{12}(0)=0 \\
v_{21}(0)=0
\end{array}\right.
$$

The problem is now fcrmulated in terms of a deterministic problem. It can be solved easily.
[Note: p. 83 missing from original. Could just be mis-numbering. RC]

Computation of a numerical example:
-Data:
$c_{11}(t)=c_{12}(t)=c_{22}(t)=0 \quad c_{21}(t)=1 \quad l_{1}(t)=1 \quad l_{2}(t)=0$
$t_{e}=0.05 \quad r_{1}(t)=t \quad r_{2}(t)=2 t \quad \frac{d M_{1}}{d t}=t+0.01$ Sinh

$$
\frac{d M_{2}}{d t}=2 t+0.01 \text { sint } \quad w_{1}=w_{2}=0.2 \quad q_{1}=q_{2}=0.3
$$



$$
\begin{aligned}
& \boldsymbol{C}=\left[\begin{array}{ccccc}
0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & -\frac{1}{2} & 0 \\
0 & 0 & 0 & 0 & -\frac{1}{2}
\end{array}\right] \quad w_{1}=\left[\begin{array}{l}
0 \\
0 \\
0 \\
\delta H x_{1} \\
\frac{2}{2} \\
\frac{\delta H x_{2}}{2}
\end{array}\right] \\
& \boldsymbol{\sigma}=\left[\begin{array}{ccccc}
10 p_{1} & 0 & 5 p_{3} & 5 p_{4} & 0 \\
0 & 10 p_{2} & 5 p_{3} & 0 & 5 p_{5} \\
5 p_{3} & 5 p_{3} & 10\left(p_{1}+p_{2}\right) & 5 p_{5} & 5 p_{4} \\
5 p_{4} & 0 & 5 p_{5} & -2 & 0 \\
0 & 5 p_{5} & 5 p_{4} & 0 & -2
\end{array}\right] w_{2}=\left[\begin{array}{l}
0 \\
0 \\
0 \\
0 \\
0
\end{array}\right]
\end{aligned}
$$

-Results: see Appendix 5, Program 8.


C Application of the decomposition technique:
If we consider the equations derived in the preceeding paragraph we can draw some conclusions: -A linear system with noises will give a linear system.
-The noise increases the difficulty of the problem: if the former state vector was $n$-dimensional, the new one will be $\left[n+\frac{n^{2}+n}{2}\right]$-dimensional $[n$ for the means, $\frac{n^{2}+n}{2}$ for the variances].
-The deterministic formulation of the stochastic problem shows that the two subproblems are not separated now: in particular when we compute $\mathrm{x}_{1}$ we have to know the measurements of $\mathrm{x}_{2}$ and viceversa. So if we want to use all the data given by the measurements we rave to deal with the whole system and transform it in a deterministic problem as we did in the preceeding paragraph and then apply the decomposition technique.

For that we introduce dummy variables:

$$
\left\{\begin{array}{l}
v_{11}^{\prime}=v_{11} \\
v_{22}^{\prime}=v_{22} \\
\bar{x}_{1}^{\prime}=\bar{x}_{1} \\
\bar{x}_{2}^{\prime}=x_{2}
\end{array}\right.
$$

$$
\left\lvert\, \begin{array}{ll}
v_{12}^{\prime} & =v_{12} \\
v_{12}^{\prime \prime} & =v_{12} .
\end{array}\right.
$$

Now we can state the problem:

$$
\begin{aligned}
& \int_{0}^{t} e\left\{\frac{1}{2}\left[r_{2}-\bar{x}_{2}\right]^{2}+m_{2}^{2}+v_{22}+\frac{1}{2}\left[r_{2}-\bar{x}_{1}^{\prime}\right]^{2}\right\} d t .
\end{aligned}
$$

With the following constraints:
Lagrange
multiplier

$$
\begin{aligned}
& \left\{\begin{aligned}
\frac{d v_{11}}{d t}=2 & c_{11} v_{11}+2 c_{12} v_{12}+q_{1} \\
& -\frac{v_{11}^{2} g_{1}^{2}}{w_{1}}-\frac{v_{12}^{\prime}{ }^{2} g_{2}^{2}}{w_{2}}
\end{aligned}\right. \\
& \frac{d v_{12}^{\prime}}{d t}=\left(c_{11}+c_{22}\right) v_{!-2}^{\prime}+c_{12} v_{22}^{\prime}+c_{21} v_{11} \\
& -\frac{v_{11} v_{12}^{\prime} g_{1}^{2}}{w_{1}}-\frac{v_{22}^{\prime} v_{12}^{\prime} g_{2}^{2}}{w_{2}} \\
& \frac{d \bar{x}_{1}}{d t}=c_{11} \bar{x}_{1}+c_{12} \bar{x}_{2}^{\prime}+\ell_{1} m_{1}-\frac{v_{11} g_{1}^{2} \bar{x}_{1}}{w_{1}} \\
& -\frac{v_{12}^{\prime} g_{2}^{2} \bar{x}_{2}^{\prime}}{w_{2}}+\frac{v_{11} g_{1}}{w_{1}} \frac{d m_{1}}{d t}+\frac{v_{12}^{\prime} g_{2}}{w_{2}} \frac{d m_{2}}{d t}
\end{aligned}
$$

$$
\begin{aligned}
& \left(\frac{d v_{22}}{d t}=2 c_{22} v_{22}+2 c_{21} v_{12}^{\prime \prime}+q_{2}-\frac{v_{12}^{\prime \prime} g_{1}^{2}}{w_{1}}\right. \\
& -\frac{v_{22}^{2} g_{2}^{2}}{w_{2}} \\
& \frac{d v_{12}^{\prime \prime}}{d t}=\left(c_{11}+c_{22}\right) v_{12}^{\prime \prime}+c_{12} v_{22}+c_{21} v_{11}^{\prime} \\
& -\frac{v_{11}^{\prime} v_{12}^{\prime \prime} g_{1}^{2}}{w_{1}}-\frac{v_{22} v_{12}^{\prime \prime} g_{2}^{2}}{w_{2}} \\
& \frac{d \bar{x}_{2}}{d t}=c_{22} \bar{x}_{2}+c_{21} \bar{x}_{1}^{\prime}+\ell_{2} m_{2}-\frac{v_{12}^{\prime \prime} g_{1}^{2} \bar{x}_{1}}{w_{1}} \\
& -\frac{v_{22} g_{2}^{2} \bar{x}_{2}}{w_{2}}+\frac{v_{12}^{\prime \prime} g_{1}}{w_{1}} \frac{d M_{1}}{d t}+\frac{v_{22} g_{2}}{w_{2}} \frac{d M_{2}}{d t} \\
& \bar{x}_{1}-\bar{x}_{1}=0 \\
& \bar{v}_{11}^{2}-\bar{v}_{11}^{2}=0 \\
& \bar{x}_{2}-\bar{x}_{2}^{\prime}=0 \\
& v_{22}^{2}-v_{22}^{2}=0
\end{aligned}
$$

Now we can apply the decomposition technique:
Level 1:
subproblem 1:
Given $R_{1}, R_{2}, K_{1}, K_{2}$ by the $2 \frac{\text { nd }}{}$ level, we have:
-Control variables : $m_{1}, \bar{x}_{2}^{\prime}, v_{22}^{\prime}$.
-State variables : $\bar{x}_{1}, v_{1}, v_{12}^{\prime}$.
-Hamiltonian:

$$
\begin{aligned}
H & =\frac{1}{2}\left[r_{1}-\bar{x}_{1}\right]^{2}+m_{1}^{2}+\frac{1}{\overline{2}_{1}}\left[r_{2}-\bar{x}_{2}^{\prime}\right]^{2}+R_{1} \bar{x}_{1}+R_{2} v_{11} \\
& -k_{1} \bar{x}_{2}^{\prime}-k_{2} v_{22}^{\prime}+p_{1}\left[2 c_{11} v_{11}+2 c_{12} v_{12}^{\prime}+q_{1}\right. \\
& \left.-\frac{v_{11}^{2} g_{1}^{2}}{w_{1}}-\frac{v_{12}^{\prime 2} g_{2}^{2}}{w_{2}}\right]+p_{2}\left[\left(c_{11}+c_{22}\right) v_{12}^{\prime}+c_{12} v_{22}^{\prime}\right. \\
& +c_{21} v_{11}-\frac{v_{11} v_{12}^{\prime} g_{1}^{2}}{w_{1}}-\frac{v_{22}^{\prime} v_{12}^{\prime} g_{2}^{2}}{w_{2}}+p_{3}\left[c_{11} \bar{x}_{1}\right. \\
& +c_{12} \bar{x}_{2}^{\prime}+l_{1} m_{1}-\frac{v_{11} g_{1}^{2} \bar{x}_{1}}{w_{1}}-\frac{v_{12}^{\prime} g_{2}^{2} \bar{x}_{2}^{\prime}}{w_{2}} \\
& \left.+\frac{v_{11} g_{1}}{w_{1}}-\frac{d m_{1}}{d t}+\frac{v_{12}^{\prime} g_{2}}{w_{2}} \frac{d M_{2}}{d t}\right]
\end{aligned}
$$

subproblem 2:
Given $R_{1}, R_{2}, K_{1}, K_{2}$ by the $2 \underline{\text { nd }}$ level, we have:
-Control variables : $m_{2}, \bar{x}_{1}, \bar{v}_{11}^{\prime}$.
-State variables : $\bar{x}_{2}, v_{22},{ }^{\prime}{ }_{12}$.
-Hamiltonian:

$$
\begin{aligned}
H & =\frac{1}{2}\left[r_{2}-\bar{x}_{2}\right]^{2}+m_{2}^{2}+v_{22}+\frac{1}{2}\left[r_{1}-\bar{x}_{1}^{\prime}\right]^{2}-R_{1} \bar{x}_{1}^{\prime} \\
& -R_{2} v_{11}^{\prime}+k_{1} \bar{x}_{22}+k_{2} v_{22}+q_{1}\left[2 c_{22} v_{22}\right. \\
& \left.+2 c_{21} v_{12}^{\prime \prime}+q_{2}-\frac{v_{12}^{\prime 2} g_{1}^{2}}{w_{1}}-\frac{v_{22}^{2} g_{2}^{2}}{w_{2}}\right]
\end{aligned}
$$

$$
\begin{aligned}
& +q_{2}\left[\left(c_{11}+c_{22}\right) v_{12}^{\prime \prime}+c_{12} v_{22}+c_{21} v_{11}^{\prime}\right. \\
& \left.-\frac{v_{11}^{\prime} v_{12}^{\prime \prime} g_{1}^{2}}{w_{1}}-\frac{v_{22} v_{12}^{\prime \prime} g_{2}^{2}}{w_{2}}\right]+q_{3}\left[c_{22} \bar{x}_{2}+c_{21} \bar{x}_{1}^{\prime}\right. \\
& +\ell_{2} m_{2}-\frac{v_{12}^{\prime \prime} g_{1}^{2} \bar{x}_{1}^{\prime}}{w_{1}}-\frac{v_{22} g_{2}^{2} \bar{x}_{2}}{w_{2}}+\frac{v_{12}^{\prime \prime} g_{1}}{w_{1}} \frac{d M_{1}}{d t} \\
& \left.+\frac{v_{22} g_{2}}{w_{2}} \frac{d M_{2}}{d t}\right]
\end{aligned}
$$

Level 2 or coordination level:
We vary $K_{1}, K_{2}, R_{1}, R_{2}$ according to:

$$
\begin{aligned}
& {\left[K_{1}\right]_{n+1}=\left[K_{1}\right]_{n}+\varepsilon *\left[\bar{x}_{2}-\bar{x}_{2}^{\prime}\right]} \\
& {\left[K_{2}\right]_{n+1}=\left[K_{2}\right]_{n}+\varepsilon *\left[v_{22}^{2}-v_{22}^{\prime 2}\right]} \\
& {\left[R_{1}\right]_{n+1}=\left[R_{1}\right]_{n}+\varepsilon *\left[\bar{x}_{1}-\bar{x}_{1}^{\prime}\right]} \\
& {\left[R_{2}\right]_{n+1}=\left[R_{2}\right]_{n}+\varepsilon *\left[v_{11}^{2}-v_{11}^{\prime}\right]}
\end{aligned}
$$

Computation of a numerical example:
-Data:

$$
\begin{aligned}
& c_{11}(t)=c_{12}(t)=c_{22}(t)=0 c_{21}(t)=1 \quad l_{1}(t)=1 l_{2}(t)=0 \\
& t_{e}=0.05 \quad r_{1}(t)=t \quad r_{2}(t)=2 t \quad \frac{d M_{1}}{d t}=t+0.01 \sin t
\end{aligned}
$$

$$
\frac{d m_{2}}{d t}=2 t+0.01 \sin t \quad w_{1}=w_{2}=0.2 \quad q_{1}=q_{2}=0.3
$$

-Computation:
subsystem 1:

$$
\begin{aligned}
& \mathcal{Z}=\left[\begin{array}{lll}
-2 \frac{v_{11}}{w_{1}} & -2 \frac{v_{12}^{\prime}}{w_{2}} & 0 \\
1-\frac{v_{12}^{\prime}}{w_{1}} & -\frac{v_{11}}{w_{1}}-\frac{v_{22}^{\prime}}{w_{2}}-\frac{v_{12}^{\prime} p_{2}}{2 K_{2} w_{2}^{2}} & 0 \\
-\frac{\bar{x}_{1}}{w_{1}}+\frac{1}{w_{1}} \frac{d M_{1}}{d t} & -\frac{x_{1}^{\prime}}{w_{2}}+\frac{1}{w_{2}} \frac{d M_{2}}{d t}-\frac{2 p_{3} v_{12}^{\prime}}{w_{2}^{2}} & -\frac{v_{1}}{w_{1}}
\end{array}\right] \\
& \mathcal{C}=\left[\begin{array}{lll}
0 & 0 & 0 \\
0 & -\frac{v_{12}^{\prime 2}}{2 K_{2} w_{2}^{2}} & 0 \\
0 & 0 & -\frac{2 v_{12}^{\prime 2}}{w_{2}^{2}}-1
\end{array}\right] w_{1}=\left[\begin{array}{l}
0 \\
-\frac{v_{12}^{\prime}}{2 \mathrm{~K}_{2} w_{2}} \delta \mathrm{Hv}_{22}^{\prime} \\
\delta \mathrm{Hm}_{1}-\frac{2 \mathrm{v}_{12}}{\mathrm{w}_{2}} \delta \mathrm{H}_{2}^{\prime}
\end{array}\right] \\
& <\left[\begin{array}{lll}
\frac{2 p_{1}}{w_{1}}-2 k_{1} & \frac{p_{2}}{w_{1}} & \frac{p_{3}}{w_{1}} \\
\frac{p_{2}}{w_{1}} & \frac{2 p_{1}}{w_{2}}+\frac{p_{2}^{2}}{2 k_{2}}+\frac{2 p_{3}}{w_{2}^{2}} & 0 \\
\frac{p_{3}}{w_{1}} & 0 & -0.5
\end{array}\right] w_{2}=\left[\begin{array}{l}
0 \\
\frac{p_{2}}{2 K_{2} w_{2}}+\frac{2 p_{3}}{w_{2}} \delta H_{x_{2}}^{\prime} \\
0
\end{array}\right]
\end{aligned}
$$

subsystem 2:

$$
\begin{aligned}
& \mathcal{D}=\left[\begin{array}{ccc}
-2 \frac{v_{22}}{w_{2}} & 2\left(1-\frac{v_{12}^{\prime \prime}}{w_{1}}\right) & 0 \\
-\frac{v_{12}^{\prime \prime}}{w_{2}} & -\frac{v_{11}^{\prime}}{w_{1}}-\frac{v_{22}}{w_{2}}-\frac{q_{2}}{2{K_{1}}_{1}}\left(1-\frac{v_{12}^{\prime \prime}}{w_{1}}\right) & 0 \\
-\frac{\bar{x}_{2}}{w_{2}}+\frac{1}{w_{2}} \frac{d M_{2}}{d t} & -\frac{\bar{x}_{1}}{w_{1}}+\frac{1}{w_{1}} \frac{d M_{1}}{d t}+\left(1-\frac{v_{12}^{\prime \prime}}{w_{1}}\right) \frac{2 q_{3}}{w_{1}} & -\frac{v_{2}}{w_{2}}
\end{array}\right] \\
& \ell=\left[\begin{array}{lll}
0 & 0 & 0 \\
0 & \frac{1}{2}{K_{1}}_{1}\left(1-\frac{v_{12}^{\prime \prime}}{w_{1}}\right)^{2} & 0 \\
0 & 0 & -2\left(1-\frac{v_{12}^{\prime \prime}}{w_{1}}\right)^{2}
\end{array}\right] \quad{ }^{w_{1}}=\left[\begin{array}{l}
0 \\
-\frac{1}{2} K_{1}\left(1-\frac{v_{12}^{\prime \prime}}{w_{1}}\right) \delta H v_{11}^{\prime} \\
2\left(1-\frac{v_{12}^{\prime \prime}}{w_{1}}\right) \delta H \bar{x}_{1}^{\prime}
\end{array}\right]
\end{aligned}
$$

-Results: see Appendix 5, Program 9.



We can make the following observations: -The decomposition technique for deterministic systems is based on a saddle value point argumentation. Since we are dealing with another kind of problem, i.e., a stochastic problem, it should be shown that the optimum point is a saddle value point. This argument is still true since we transformed the stochastic problem into a more complex but deterministic linear quadratic problem. -The advantages of the decomposition technique are the same as in the deterministic case. -To find the equations of the subsystems we had first to compute the ecuations of the global system. The set of equations of the two subsystems is equivalent to the set of equations of the global system. So the solutions will be the same. In particular, the information about the measurements of the global system are included in the equations of each subsystem.
4.2 A Case of Linear System With Non-Linear Coupling In this section we deal with a numerical example of linear system with non-linear coupling. It is the case of slightly non-linear systems, the non-linearity of which can be expanded in a Taylor's series for which all the terms $\left\{x^{n} / n \geq 3\right\}$ are neglected.

### 4.2.1 The Deterministic Problem

## Part 1: global method:

-system:

$$
\begin{aligned}
& \dot{x}_{1}=m \\
& \dot{x}_{2}=x_{1}+0.1 x_{1}^{2}
\end{aligned}
$$

-Control variable : m.
-State variables : $\mathrm{x}_{1}+\mathrm{x}_{2}$.
-performance:

$$
\phi=\int_{0}^{t} e \frac{1}{2}\left[x_{1}^{2}+x_{2}^{2}+m_{l}^{2}\right] d t
$$

-Computation:

$$
\begin{aligned}
& \mathscr{L}=\left[\begin{array}{ll}
0 & 0 \\
1+0.2 x_{1} & 0
\end{array}\right] \quad \varepsilon=\left[\begin{array}{ll}
-1 & 0 \\
0 & 0
\end{array}\right] \quad{ }^{w_{1}}=\left[\begin{array}{l}
\delta \mathrm{Fm} \\
0
\end{array}\right] \\
& L_{0}=\left[\begin{array}{cc}
-\left(1+0.2 p_{2}\right) & 0 \\
0 & -1
\end{array}\right] \quad w_{2}=\left[\begin{array}{l}
0 \\
0
\end{array}\right]
\end{aligned}
$$

-Results: see Appendix 5, Program 10.

## Part 2: decomposition technique:

Level 1:
subsystem 1:

$$
\dot{x}_{1}=m H=\frac{1}{2} m^{2}+\frac{1}{2} x_{1}^{2}+K x_{1}\left(1+0.1 x_{1}\right)+p_{1} m
$$

subsystem 2:

$$
\dot{x}_{2}=t_{1} \quad H=\frac{1}{2} x_{2}^{2}-K=12+p_{2} t_{1}
$$

Level 2:

$$
[K]_{n+1}=[K]_{n}+\varepsilon *\left[x_{1}+0.1 x_{1}^{2}-t_{1}\right]
$$

Computation:
subsystem 1:
9) $=0 \quad \mathcal{E}=-1 \quad \mathrm{w}_{1}=8 \mathrm{Hm} \quad \mathscr{O}=-(1+0.2 \mathrm{k}) \quad \mathrm{w}_{2}=0$
subsystem 2:
$\mathscr{L}=0 \quad \mathcal{E}=-\frac{2 t_{1}^{2}}{p_{2}-k} \quad w_{1}=\frac{t_{1} \delta H t_{1}}{p_{2}-K} \quad \mathscr{b}=-1 \quad w_{2}=0$
-Results: see Appendix 5, Program 11.
4.2.2 The Problem with Noises.

A Statement of the problem:
System:

$$
\int d x_{1}=x_{1} d t+d z_{1}
$$

$$
\left(d x_{2}=\left(x_{1}+0.1 x_{1}^{2}\right) d t+d z_{2}\right.
$$

Measurements:

$$
\left\{\begin{array}{l}
d M_{1}=x_{1} d t+d N_{1} \\
d m_{2}=x_{2} d t+d N_{2}
\end{array}\right.
$$

$d z, d z_{2}, d N_{1}, d N_{2}$ are uncorrelated noises with gaussian probability such that: Vt, $V$ s $\neq t$, we have

$$
\begin{array}{ll}
E\left[d z_{1}(t)\right]=E\left[d z_{2}(t)\right]=E\left[d N_{1}(t)\right]=E\left[d N_{2}(t)\right]=0 \\
E\left[d z_{1}(t)^{2}\right]=q_{1} d t & E\left[d N_{1}^{2}(t)\right]=w_{1} d t \\
E\left[d z_{2}(t)^{2}\right]=q_{2} d t & E\left[d N_{2}^{2}(t)\right]=w_{2} d t
\end{array}
$$

We are assuming too that the variables $\mathrm{x}_{1}, \mathrm{x}_{2}$ have a two dimensional normal distribution, which, in fact, is not true, because of the nonlinear term. But we shall consider that the coefficients of this term is small enough and does not greatly affect the distribution of $x$, the density function of which is given by:

$$
\begin{aligned}
F\left(x_{1}, x_{2}\right)= & \frac{1}{2 \pi \sqrt{v_{11} v_{22}-v_{12}^{2}}} \operatorname{Exp}\left\{\frac{-1}{2\left(1-\frac{v_{12}^{2}}{v_{11} v_{22}}\right)}\right. \\
& {\left.\left[\frac{\left(x_{1}-\bar{x}_{1}\right)^{2}}{v_{11}}-\frac{2\left(x_{1}-\bar{x}_{1}\right)\left(x_{2}-\bar{x}_{2}\right) v_{12}}{v_{11} v_{22}}+\frac{\left(x_{2}-\bar{x}_{2}\right)^{2}}{v_{22}}\right]\right\} }
\end{aligned}
$$

which means:

$$
\begin{gathered}
E\left[\left(x_{1}-\bar{x}_{1}\right)^{2}\left(x_{2}-\bar{x}_{2}\right)\right]=E\left\{\left[x_{2}-\bar{x}_{2}\right]^{2}\left[x_{1}-\bar{x}_{1}\right]\right\} \\
=E\left\{\left[x_{1}-\bar{x}_{1}\right]^{2 K+1}\right\}=E\left\{\left[x_{2}-\bar{x}_{2}\right]^{2 K+1}\right\}=0 \\
E\left\{\left(x_{1}-\bar{x}_{1}\right)^{2}\left(x_{2}-\bar{x}_{2}\right)^{2}\right\}=\frac{v_{11} \frac{v_{22}\left(v_{11} v_{22}+2 v_{12}^{2}\right)}{2\left(v_{11} v_{22}-v_{12}^{2}\right)}}{l}
\end{gathered}
$$

B The global method.
The method is the same as in the linear case. We have the following steps:

$$
\begin{aligned}
& \bar{x}_{1}(t+\delta t)=\bar{x}_{1}(t)+m_{1}(t) \delta t \\
& \underline{\underline{x}}_{2}(t+\delta t)=\bar{x}_{2}(t)+\delta t\left[\bar{x}_{1}(t)+0.1 v_{1}(t)+0.1 x_{1}(t)^{2}\right] \\
& \underline{v}_{1}(t+\delta t)=v_{1}(t)+q_{1} \delta t \\
& \underline{v}_{2}(t+\delta t)=v_{2}(t)+\delta t\left[2.4 v_{12}(t)+q_{2}\right] \\
& \underline{v}_{12}(t+\delta t)=v_{12}(t)+v_{1}(t)\left(1+0.2 \bar{x}_{1}(t)\right) \\
& \text { The assumption of a normal distribution gives: } \\
& \\
& \left(v_{11}=\frac{v_{11}}{}-\frac{v_{11}^{2}}{\frac{w_{1}}{w_{1}} \delta t .-\frac{v_{12}^{2}}{w_{2}} \delta t}\right.
\end{aligned}
$$

$$
\begin{aligned}
& \begin{array}{l}
\text { variables }\{ \\
\text { evaluated }
\end{array}\left\{v_{22}=\frac{v_{22}}{-\frac{v_{12}^{2}}{\overline{w_{1}}} \delta t-\frac{v_{22}}{\overline{w_{2}}} \delta t}\right. \\
& \text { at } \\
& t+\delta t . \\
& \begin{array}{r}
\overline{\mathrm{x}}_{1}=\overline{\mathrm{x}}_{1}=\frac{\overline{\mathrm{x}}_{1}{ }^{v_{11}}}{\mathrm{w}_{1}} \delta t-\frac{\overline{\mathrm{x}}_{2}{ }^{v_{12}}}{\mathrm{w}_{2}} \delta t+\frac{\mathrm{v}_{11}}{\mathrm{w}_{1}} \delta M_{1} \\
\\
+\frac{v_{12}}{w_{2}} \delta M_{2} . \\
\overline{\mathrm{x}}_{2}=\overline{\mathrm{x}}_{2}-\frac{\overline{\mathrm{x}}_{1}{ }^{v_{12}}}{\mathrm{w}_{1}} \delta t-\frac{\overline{\mathrm{x}}_{2}{ }^{v_{22}}}{w_{2}} \delta t+\frac{v_{12}}{w_{1}} \delta M_{1}
\end{array} \\
& +\frac{\mathrm{v}_{22}}{\mathrm{w}_{2}} \delta \mathrm{M}_{2} .
\end{aligned}
$$

Finally the equations of the system are:

$$
\left\{\begin{array}{l}
\frac{d v_{11}}{d t}=q_{1}-\frac{v_{11}^{2}}{w_{1}}-\frac{v_{12}^{2}}{w_{2}} \\
\frac{d v_{12}}{d t}=v_{11}\left(1+0.2 \bar{x}_{1}\right)-\frac{v_{11} v_{12}}{w_{1}}-\frac{v_{22} v_{12}}{w_{2}} \\
\frac{d v_{22}}{d t}=2.4 v_{12}+q_{2}-\frac{v_{12}^{2}}{w_{1}}-\frac{v_{22}^{2}}{w_{2}} \\
\frac{d \bar{x}_{1}}{d t}=m_{1}-\frac{\bar{x}_{1} v_{11}}{w_{1}}-\frac{\bar{x}_{2} v_{12}}{w_{2}}+\frac{v_{11}}{w_{1}} \frac{d M_{1}}{d t}+\frac{v_{12}}{w_{2}} \frac{d M_{2}}{d t}
\end{array}\right.
$$

$$
\begin{aligned}
\frac{d \bar{x}_{2}}{d t}=\bar{x}_{1}+0.1 v_{11}+0.1 \bar{x}_{1}^{2} & -\frac{\bar{x}_{1} v_{12}}{w_{1}}-\frac{\bar{x}_{2} v_{22}}{w_{2}} \\
& +\frac{v_{12}}{w_{1}} \frac{d M_{1}}{d t}+\frac{v_{22}}{w_{2}} \frac{d M_{2}}{d t}
\end{aligned}
$$

Criterion of performance:

$$
\phi=\int_{0}^{t} e \frac{1}{2}\left[\bar{x}_{1}^{2}+\bar{x}_{2}^{2}+v_{11}+v_{22}+m_{1}^{2}\right] d t
$$



Computation of the solution (con't)

$$
\begin{aligned}
& \mathcal{E}=\left[\begin{array}{lllll}
0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & -1 & 0 \\
0 & 0 & 0 & 0 & 0
\end{array}\right] \quad{ }^{w_{1}}=\left[\begin{array}{l}
0 \\
0 \\
0 \\
\delta \mathrm{Hm}_{1} \\
0
\end{array}\right] \\
& \text { - }=\left[\begin{array}{lllll}
\frac{2 p_{1}}{w_{1}} & \frac{p_{2}}{w_{1}} & 0 & \frac{p_{4}}{w_{1}}-0.2 p_{2} & 0 \\
\frac{p_{2}}{w_{1}} & \frac{2 p_{1}}{w_{2}}+\frac{2 p_{3}}{w_{1}} & \frac{p_{2}}{w_{2}} & \frac{p_{5}}{w_{1}} & \frac{p_{4}}{w_{2}} \\
0 & \frac{p_{2}}{w_{2}} & \frac{2 p_{3}}{w_{2}} & 0 & \frac{p_{5}}{w_{2}} \\
0 & \frac{p_{4}}{w_{2}} & \frac{p_{5}}{w_{2}} & 0 & \\
& & & & \\
& & & &
\end{array}\right] \\
& w_{2}=\left[\begin{array}{l}
0 \\
0 \\
0 \\
0 \\
0
\end{array}\right] \\
& \text { C The decomposition technique: } \\
& \text { As before we take the dummy variables: }
\end{aligned}
$$

$$
\left\{\begin{aligned}
\bar{x}_{1}^{\prime} & =\bar{x}_{1} \\
\bar{x}_{2}^{\prime} & =\bar{x}_{2} \\
v_{11}^{\prime} & =v_{11} \\
v_{22}^{\prime} & =v_{22} \\
v_{12}^{\prime} & =v_{12}^{\prime}=v_{12}
\end{aligned}\right.
$$

we get:
Level 1:
*subsystem 1:
-Control variables : $m_{1}, v_{22}^{\prime}, \bar{x}_{2}^{\prime}$.
-performance:

$$
\begin{array}{r}
\int_{0}^{t} e^{2}\left\{\frac{1}{2}\left[\frac{1}{2} \bar{x}_{1}^{2}+\frac{1}{2} \bar{x}_{2}^{2}+v_{11}+m_{1}^{2}\right]+R_{1} \bar{x}_{1}+R_{2} v_{11}^{2}-k_{1} \bar{x}_{2}^{\prime}\right. \\
\left.-k_{2} v_{22}^{\prime 2}\right\} d t
\end{array}
$$

-constraints:

Lagrange multipliers

$$
\left\{\begin{array}{l}
\frac{d v_{11}}{d t}=-\frac{v_{11}^{2}}{w_{1}}-\frac{v_{12}^{\prime 2}}{w_{2}} \\
\frac{d v_{12}^{\prime}}{d t}=v_{11}\left(1+0.2 \bar{x}_{1}\right)-\frac{v_{11} v_{12}^{\prime}}{w_{1}}-\frac{v_{22}^{\prime} v_{12}^{\prime}}{w_{2}} p_{2}
\end{array}\right.
$$

$$
\begin{array}{r}
\frac{d \bar{x}_{1}}{d t}=m_{1}-\frac{\bar{x}_{1} v_{11}}{w_{1}}-\frac{\bar{x}_{2}^{\prime} v_{12}^{\prime}}{w_{2}}+\frac{v_{11}}{w_{1}} \frac{d M_{1}}{d t} \\
+\frac{v_{12}^{\prime}}{w_{2}} \frac{d M_{2}}{d t}
\end{array}
$$

$$
\mathrm{p}_{3}
$$

*subsystem 2:
-Control variables : vil', $\bar{x}_{1}^{\prime}$
-performance:

$$
\int_{0}^{t} e_{\{ } \frac{1}{2}\left[\frac{1}{2} \bar{x}_{1}^{2}+\frac{1}{2} \bar{x}_{2}^{2}+v_{22}\right]+k_{1} \bar{x}_{2}+k_{2} v_{22}^{2}-R_{1} \bar{x}_{1}^{\prime}
$$

$$
-R_{2} v_{11}^{\prime 2}
$$

-constraints:

Lagrange multipliers

$$
\left\{\begin{array}{l}
\frac{d v_{22}}{d t}=2.4 v_{12}^{\prime \prime}+q_{2}-\frac{v_{12}^{\prime \prime 2}}{w_{1}}-\frac{v_{22}^{2}}{w_{2}} \\
\frac{d v_{12}^{\prime \prime}}{d t}=v_{11}^{\prime}\left(1+0.2 \bar{x}_{1}^{\prime}\right)-\frac{v_{11}^{\prime} v_{12}^{\prime \prime}}{w_{1}} \\
\\
-\frac{v_{22} v_{12}^{\prime \prime}}{w_{2}} \\
\frac{d \bar{x}_{2}}{d t}= \\
\bar{x}_{1}^{\prime}+0.1 v_{11}^{\prime}+0.1 \bar{x}_{1}^{2}-\frac{\bar{x}_{1}^{\prime} v_{12}^{\prime \prime}}{w_{1}} \\
-\frac{\bar{x}_{2} v_{22}}{w_{2}}+\frac{v_{12}^{\prime \prime}}{w_{1}} \frac{d M_{1}}{d t}+\frac{v_{22}}{w_{2}} \frac{d M_{2}}{d t}
\end{array}\right.
$$

$q_{2}$
$q_{3}$

Level 2 or coordination level:
We vary $R_{1}, R_{2}, K_{1}, K_{2}$ according to:

$$
\begin{aligned}
& {\left[R_{1}\right]_{n+1}=\left[R_{1}\right]_{n}+\varepsilon *\left[\bar{x}_{1}-\bar{x}_{1}^{\prime}\right]} \\
& {\left[R_{2}\right]_{n+1}=\left[R_{2}\right]_{n}+\varepsilon *\left[v_{11}^{2}-v_{11}^{\prime 2}\right]} \\
& {\left[K_{1}\right]_{n+1}=\left[K_{1}\right]_{n}+\varepsilon *\left[\bar{x}_{2}-\bar{x}_{2}^{\prime}\right]} \\
& {\left[K_{2}\right]_{n+1}=\left[K_{2}\right]_{n}+\varepsilon *\left[v_{22}^{2}-v_{22}^{\prime}\right]}
\end{aligned}
$$

Computation of the solution:
subsystem 1:

$$
\mathscr{L}=\left[\begin{array}{lll}
-\frac{2 v_{11}}{w_{1}} & -\frac{2 v_{12}^{\prime}}{w_{2}} & 0 \\
1+0.2 \bar{x}_{1}-\frac{v_{12}^{\prime}}{w_{1}} & -\frac{v_{11}}{w_{1}}-\frac{v_{22}^{\prime}}{w_{2}}+\frac{p_{2}^{\prime} v_{12}^{\prime}}{2 k_{2} w_{2}^{2}} & 0.2 v_{11} \\
-\frac{\bar{x}_{1}}{w_{1}}+\frac{1}{w_{1}} \frac{d M_{1}}{d t} & -\frac{\bar{x}_{2}^{\prime}}{w_{2}}+\frac{j}{w_{2}} \frac{d M_{2}}{d t}-\frac{2 p_{3} v_{12}^{\prime}}{w_{2}^{2}}-\frac{v_{11}}{w_{1}}
\end{array}\right]
$$

$$
\begin{aligned}
& \zeta=\left[\begin{array}{lll}
0 & 0 & 0 \\
0 & \frac{v_{12}^{\prime 2}}{2 \mathrm{~K}_{2} \mathrm{w}_{2}^{2}} & 0 \\
0 & 0 & -1-\frac{2 \mathrm{v}_{12}^{\prime 2}}{\mathrm{w}_{2}^{2}}
\end{array}\right] \mathrm{w}_{1}=\left[\begin{array}{l}
0 \\
\frac{v_{12}^{\prime}}{2 \mathrm{~K}_{2} \mathrm{w}_{2}^{2}} \delta \mathrm{H}_{22}^{\prime} \\
\delta \mathrm{Hm}_{1}-\frac{2 \mathrm{v}_{12}^{\prime}}{\mathrm{w}_{2}} \delta \mathrm{Hx}_{2}^{\prime}
\end{array}\right] \\
& \mathcal{L}=\left[\begin{array}{lll}
-2 p_{2}+\frac{2 p_{1}}{w_{1}} & \frac{p_{3}}{w_{1}} & \frac{p_{3}}{w_{1}}-0.2 p_{2} \\
\frac{p_{2}}{w_{1}} & \frac{2 p_{1}}{w_{2}}-\frac{p_{2}^{2}}{2 k_{2} w_{2}^{2}}+\frac{2 p_{3}^{2}}{w_{2}^{2}} & 0 \\
-0.2 p_{2}+\frac{p_{3}}{w_{1}} & 0 & -0.5+2 k_{1}
\end{array}\right] \\
& \mathrm{w}_{2}=\left[\begin{array}{ll}
0 & \\
-\frac{\mathrm{p}_{2}}{2 \mathrm{~K}_{2} \mathrm{w}_{2}} & \delta \mathrm{Hv}_{22}^{\prime}+\frac{2 \mathrm{p}_{3}}{\mathrm{w}_{2}} \delta \mathrm{H} \bar{x}_{2}^{\prime} \\
0
\end{array}\right]
\end{aligned}
$$

subsystem 2:
The equations are far more complex. Only the equations were derived:

$$
\begin{aligned}
& \delta \bar{x}_{1}^{\prime}=\frac{1}{1+0.4 q_{3}}\left[-0.4 q_{2} \delta v_{11}^{\prime}+\frac{2 q_{3}}{w_{1}} \delta v_{12}^{\prime \prime}-0.4 v_{11}^{\prime} \delta q_{2}\right. \\
& \left.-2\left(1+0.2 \bar{x}_{11}-\frac{v_{12}^{\prime \prime}}{w_{1}}\right) \delta q_{3}+2 \delta \mathrm{Hx}_{1}\right] \\
& \delta v_{11}^{\prime}=\frac{1}{2} R_{2}\left[-\frac{q_{2}}{w_{1}} \delta v_{12}^{\prime \prime}+\left(1+0.2 \bar{x}_{1}^{\prime}-\frac{v_{12}^{\prime}}{w_{1}}\right) \delta q_{2}+0.1 \delta q_{3}\right. \\
& \left.-\delta H v_{11}^{\prime}+0.2 q_{2} \delta \bar{x}_{1}^{1}\right]
\end{aligned}
$$

$$
\begin{aligned}
& \delta \dot{\bar{x}}_{2}=\left(-\frac{\bar{x}_{2}}{w_{2}}+\frac{1}{w_{2}} \frac{d M_{2}}{d t}\right) \delta v_{22}+\left(-\frac{\bar{x}_{1}}{w_{1}}+\frac{1}{w_{1}} \frac{d M_{1}}{d t}\right) \delta v_{12}^{\prime \prime} \\
& -\frac{v_{22}}{w_{2}} \delta \bar{x}_{2}+0.1 \delta v_{11}^{\prime}+\left(1.0 .2 \bar{x}_{1}-\frac{v_{12}^{\prime}}{w_{1}}\right) \delta \bar{x}_{1} . \\
& \int \delta \dot{q}_{1}=-\left\{\left(2 \mathrm{~K}_{2}-\frac{2 q_{1}}{w_{2}}\right) \delta v_{22}-\frac{q_{2}}{w_{2}} \delta v_{12}^{\prime \prime}-\frac{2 v_{22}}{w_{2}} \delta q_{1}\right. \\
& \left\{-\frac{v_{12}^{\prime \prime}}{w_{2}} \delta q_{2}+\left(-\frac{x_{2}}{w_{2}}+\frac{1}{w_{2}} \frac{d M_{2}}{d t}\right) \delta q_{3}-\frac{q_{3}}{w_{2}} \delta \bar{x}_{2}\right\}
\end{aligned}
$$

$$
\left\{\begin{array}{l}
\delta \dot{q}_{2}=-\left\{-\frac{q_{2}}{w_{2}} \delta v_{22}-\frac{2 q_{1}}{w_{1}} \delta v_{12}^{\prime \prime}+\left(2.4-\frac{2 v_{12}^{\prime \prime}}{w_{1}}\right) \delta q_{1}\right. \\
\left.\quad+\left(-\frac{v_{11}^{\prime}}{w_{1}}-\frac{v_{22}}{w_{2}}\right) \delta q_{2}+\left(-\frac{\bar{x}_{1}^{\prime}}{w_{1}}+\frac{1}{w_{1}} \frac{d M_{1}}{d t}\right) \delta q_{3}-\frac{q_{3}}{w_{1}} \delta \bar{x}_{1}^{\prime}\right\} \\
\delta \dot{q}_{3}=-\left\{-\frac{q_{3}}{w_{2}} \delta v_{22}+0.5 \delta \bar{x}_{2}\right\} .
\end{array}\right.
$$

4.3

Let us consider a general system with additive noise:
system:

$$
\left\{\begin{array}{l}
\dot{x}_{1}=f_{1}\left(x_{1}, x_{2}, m_{1}, m_{2}, t\right)+\frac{d Z_{1}}{d t} \\
\dot{x}_{2}=f_{2}\left(x_{1}, x_{2}, m_{1}, m_{2}, t\right)+\frac{d z_{2}}{d t}
\end{array}\right.
$$

measurements:

$$
\left\{\begin{array}{l}
\frac{d M_{1}}{d t}=x_{1} \div \frac{d N_{1}}{d t} \\
\frac{d M_{2}}{d t}=x_{2}+\frac{d N_{2}}{d t}
\end{array}\right.
$$

performance:

$$
\int_{0}^{t} e \varphi\left[v_{11}, v_{22}, v_{12}, \bar{x}_{1}, \bar{x}_{2}\right]
$$

controls : $m_{1}, m_{2}$.
state variables $: x_{1}, x_{2}$.

We shall call

$$
\begin{aligned}
& g_{1}\left[v_{11}, v_{22}, v_{12}, \bar{x}_{1}, \bar{x}_{2}, m_{1}, m_{2}, t\right]=E\left\{f_{1}\right\} . \\
& g_{2}\left[v_{11}, v_{22}, v_{12}, \bar{x}_{1}, \bar{x}_{2}, m_{1}, m_{2}, t\right]=E\left\{f_{2}\right\} .
\end{aligned}
$$

$$
\begin{aligned}
g_{3}\left[v_{11}, v_{22}, v_{12}, \bar{x}_{1}, \bar{x}_{2}, m_{1}, m_{2}, t\right]= & E\left\{\left(f_{1}-g_{1}\right)\right. \\
& \left.\left(x_{1}-\bar{x}_{1}\right)\right\} . \\
g_{4}\left[v_{11}, v_{22}, v_{12}, \bar{x}_{1}, \bar{x}_{2}, m_{1}, m_{2}, t\right]= & E\left\{\left(f_{2}-g_{2}\right)\right. \\
& \left.\left(x_{2}-\bar{x}_{2}\right)\right\} . \\
g_{5}\left[v_{11}, v_{22}, v_{12}, \bar{x}_{1}, \bar{x}_{2}, m_{1}, m_{2}, t\right]= & E\left\{\left(f_{2}-g_{2}\right)\right. \\
& \left.\left(x_{1}-\bar{x}_{1}\right)\right\} . \\
& \\
g_{6}\left[v_{11}, v_{22}, v_{12}, \bar{x}_{1}, \bar{x}_{2}, m_{1}, m_{2}, t\right]= & E\left\{\left(f_{1}-g_{1}\right)\right. \\
& \left.\left(x_{2}-\bar{x}_{2}\right)\right\} .
\end{aligned}
$$

Two strong assumptions have to be done on the system:
-The possibility of using the decomposition technique for the deterministic problem, i.e., we must check the argumentation based on a saddle value point at the optimal.
-we assume during all the demonstration that the variable ( $\mathrm{x}_{1}, \mathrm{x}_{2}$ ) has a two dimensional normal distribution which is unlikely if the system is strongly non-linear.

We have:

$$
\begin{aligned}
& x_{1}(t+\delta t)=x_{1}(t)+f_{1} \delta t+\delta Z_{1} \\
& x_{2}(t+\delta t)=x_{2}(t)+f_{2} \delta t+\delta z_{2} .
\end{aligned}
$$

Taking the expectations, we get:

$$
\left\{\begin{array}{l}
\bar{x}_{1}(t+\delta t)=\bar{x}_{1}(t)+g_{1} \delta t \\
\bar{x}_{2}(t+\delta t)=\bar{x}_{2}(t)+g_{2} \delta t
\end{array}\right.
$$

$$
\left\{\begin{array}{l}
\underline{v}_{1}(t+\delta t)=v_{1}(t)+\delta t\left(2 g_{3}+q_{1}\right) \\
\underline{v}_{2}(t+\delta t)=v_{2}(t)+\delta t\left(2 g_{4}+q_{2}\right) \\
\underline{v}_{12}(t+\delta t)=v_{12}(t)+\delta=\left(g_{5}+g_{6}\right)
\end{array}\right.
$$

As before, the assump=ion of a normal distribution gives us:

$$
\left\{\begin{array}{l}
v_{1}=\frac{v_{1}}{-\frac{v_{1}^{2}}{w_{1}} \delta t-\frac{v_{12}^{2}}{w_{2}} \delta t} \\
v_{12}=\frac{v_{12}}{-\frac{v_{11}}{w_{1}} \frac{v_{12}}{w_{1}} \delta t-\frac{v_{22}}{w_{2}} \frac{v_{12}}{w_{2}} \delta t} \\
v_{22}=\frac{v_{22}}{-\frac{v_{12}^{2}}{w_{1}} \delta t-\frac{v_{22}^{2}}{w_{2}} \delta t}
\end{array}\right.
$$

$$
\left\{\begin{array}{c}
\bar{x}_{1}=\bar{x}_{1}-\frac{\bar{x}_{1}{ }^{v_{11}}}{w_{1}} \delta t-\frac{\bar{x}_{2}{ }^{v_{12}}}{w_{2}} \delta t+\frac{v_{11}}{w_{1}} \delta M_{1}+\frac{v_{12}}{w_{2}} \delta M_{2} \\
\bar{x}_{2}=\bar{x}_{2}-\frac{\bar{x}_{1}{ }^{v_{12}}}{w_{1}} \delta t-\frac{\bar{x}_{2}{ }^{v_{12}}}{w_{1}} \delta t-\frac{\bar{x}_{2} v_{2}}{w_{2}} \delta t+\frac{v_{12} \delta M_{1}}{w_{1}} \\
+\frac{v_{22} \delta H_{2}}{w_{2}}
\end{array}\right.
$$

Combining the two systems of: equations, we get:

$$
\left\{\begin{array}{l}
\left\{\begin{array}{l}
\frac{d v_{11}}{d t}=2 g_{3}+q_{1}-\frac{v_{11}^{2}}{w_{1}} g_{1}^{2}-\frac{v_{12}^{2}}{w_{2}} g_{2}^{2} \\
\frac{d v_{12}}{d t}=g_{5}+g_{6}-\frac{v_{11} v_{12}}{w_{1}} g_{1}^{2}-\frac{v_{22} v_{12}}{w_{2}} g_{2}^{2} \\
\frac{d v_{22}}{d t}=2 g_{4}+q_{2}-\frac{v_{12}^{2} g_{1}^{2}}{w_{1}}-\frac{v_{22}}{w_{2}} v_{12} \\
g_{2}^{2}
\end{array}\right. \\
\frac{d \bar{x}_{1}}{d t}=g_{1}-\frac{\bar{x}_{1} v_{11}}{w_{1}}-\frac{\bar{x}_{2} v_{12}}{w_{2}}+\frac{v_{11}}{w_{1}} \frac{d M_{1}}{d t}+\frac{v_{12}}{w_{2}} \frac{d M_{2}}{d t} \\
\frac{\bar{x}_{2}}{d t}=g_{2}-\frac{v_{12}}{w_{1}}-\frac{\bar{x}_{2} v_{22}}{w_{2}}+\frac{v_{12}}{w_{1}} \frac{d M_{1}}{d t}+\frac{v_{22}}{w_{2}} \frac{d M_{2}}{d t}
\end{array}\right.
$$

We succeeded in transforming the problem with stochastic variables in a deterministic problem. So we can apply the decomposition technique:

Leve1 1:
*subproblem 1:

$$
\begin{aligned}
& \text {-State variables }: \bar{x}_{1}, v_{11}, v_{12}^{\prime} \\
& \text {-Controls }: m_{1}, \bar{x}_{2}^{\prime}, v_{22}^{\prime}
\end{aligned}
$$

system:

$$
\left\{\begin{array}{l}
\frac{d v_{11}}{d t}=2 g_{3}+q_{1}-\frac{v_{11}^{2}}{w_{1}} g_{1}^{2}-\frac{v_{12}^{2} g_{2}^{2}}{w_{2}} \\
\frac{d v_{12}^{\prime}}{d t}=g_{5}+g_{6}-\frac{v_{11} v_{12}^{\prime}}{w_{1}} g_{1}^{2}-\frac{v_{22}^{\prime} v_{12}^{\prime}}{w_{2}} g_{2}^{2} \\
\frac{d \bar{x}_{1}}{d t}=g_{1}-\frac{\bar{x}_{1} v_{11}}{w_{1}}-\frac{x_{2} v_{12}^{\prime}}{w_{2}}+\frac{v_{11}}{w_{1}} \frac{d m_{1}}{d t}+\frac{v_{12}^{\prime}}{w_{2}} \frac{d M_{2}}{d t}
\end{array}\right.
$$

performance:
$\phi=\int_{0}^{t} e^{t} \frac{1}{2} \varphi\left[v_{11}, v_{22}, v_{12}^{\prime}, \bar{x}_{1}, \bar{x}_{2}^{\prime}\right]+R_{1} x_{1}+R_{2}{ }^{v_{11}}$
$\left.-K_{1} \bar{x}_{2}^{\prime}-K_{2} v_{22}^{\prime}\right\} d t$
*subproblem 2:
-State variables : $\bar{x}_{2}, v_{22}, v_{12}^{\prime \prime}$
-controls : $m_{2}, v_{1}^{\prime}, \bar{x}_{1}^{\prime}$
system:

$$
\left\{\begin{array}{l}
\frac{d v_{22}}{d t}=2 g_{4}+q_{2}-\frac{v_{12}^{\prime \prime 2} g_{1}^{2}}{w_{1}^{\prime}}-\frac{v_{22} v_{12}^{\prime \prime}}{w_{2}} g_{2}^{2} \\
\frac{d v_{12}^{\prime \prime}}{d t}=g_{5}+g_{6}-\frac{v_{11}^{\prime}{ }^{v_{12}^{\prime \prime}}}{w_{1}} g_{1}^{2}-\frac{v_{22}{ }^{v_{12}^{\prime \prime}}}{w_{2}} g_{2}^{2} \\
\frac{d \bar{x}_{2}}{d t}=g_{2}-\frac{\bar{x}_{1}^{\prime} v_{12}^{\prime \prime}}{w_{1}}-\frac{\bar{x}_{2} v_{22}}{w_{2}}+\frac{v_{12}^{\prime \prime}}{w_{1}} \frac{d M_{1}}{d t}+\frac{v_{22}}{w_{2}} \frac{d M_{2}}{d t}
\end{array}\right.
$$

performance:

$$
\begin{aligned}
& \phi=\int_{0}^{t} e_{\{ } \frac{1}{2} \varphi\left[v_{11}^{\prime}, v_{22}, v_{12}^{\prime \prime}, \bar{x}_{1}^{\prime}, \bar{x}_{2}\right]-R_{1} \bar{x}_{1}^{\prime}-R_{2} v_{11}^{\prime} \\
&\left.+k_{1} \bar{x}_{2}+k_{2} v_{22}\right\} d t .
\end{aligned}
$$

Level 2 or coordination level:

$$
\begin{aligned}
& \text { We vary } K_{1}, K_{2}, R_{1}, R_{2} \text { according to: } \\
& {\left[R_{1}\right]_{n+1}=\left[R_{1}\right]_{n}+\varepsilon *\left[\bar{x}_{1}-\bar{x}_{1}^{\prime}\right]} \\
& {\left[R_{2}\right]_{n+1}=\left[R_{2}\right]_{n}+\varepsilon *\left[v_{11}-v_{11}^{\prime}\right]} \\
& {\left[K_{1}\right]_{n+1}=\left[K_{1}\right]_{n}+\varepsilon *\left[\bar{x}_{2}-\bar{x}_{2}^{\prime}\right]} \\
& {\left[K_{2}\right]_{n+1}=\left[K_{2}\right]_{n}+\varepsilon *\left[v_{22}-v_{22}^{\prime}\right]}
\end{aligned}
$$

## CHAPTER V

## CONCLUSIONS

The application of the satisfaction approach of Takahara to linear quadratic systems was easy to implement, once it was shown that the set of internal disturbances could be reduced to one point. To extend this technique to non linear systems, a way of formulating the mathematical models of the first level and of implementing the coordination must be found first.

A heuristic dealing wi-th discrete linear systems was studied in Chapter 3. rohe main advantage of this heuristic lies in the fact that the programming of the computation of the optimal control is much easier to do than with the general method. This heuristic dealing with separate subsystems, should be of some interest from a computing time point of view. But this has to be proved. One can expect, too, that., with some more assumptions, this heuristic converges for linear continuous systems.

In Chapter 4, the decomposition technique was applied to linear systems with disturbances, with the help of the Kalman technique. No signi:\#icant reduction in the computing time was given by the application of the technique, but it should be remembered that the technique is efficient for large scale systems, which was not the case here. For non linear systems, the state variable
is not likely to have a gaussian distribution, and the Kalman technique cannot be used. So the problem of application of the decomposition technique to non linear systems with disturbances has still to be solved.

## APPENDIX I

A COMPUTATIONAL TECHNIQUE USE TO SOLVE OPTIMAL PROGRAMMING
PROBLEMS: THE SUCCESSIVE SWEEP METHOD.
A complete study of the successive sweep method can be found in reference [6]. The method will be explained briefly here in order to define the notations which will. be used later.

Consider the system:

$$
\dot{x}=f(x, m, t) \quad x(0)=x_{0}
$$

The performance can be written as:

$$
\phi=\int_{0}^{t} e\left[H(p, x, m)-p^{T} \cdot x\right] d t
$$

with:
$x(t): n-c o m p o n e n t$ state vector.
$m(t): m$-component control vector.
$p(t): n$-component Lagrange multiplier vector.
The necessary conditiors for an extremal path are:

$$
\begin{align*}
\dot{p} & =-\mathrm{H}_{\mathrm{x}}  \tag{1}\\
\mathrm{H}_{\mathrm{m}} & =0  \tag{2}\\
p\left(t_{e}\right) & =0 \tag{3}
\end{align*}
$$

If some arbritrary control function $m(t)$ is chosen, then equation (2) will not be satisfied. We consider a perturbation around $m(t)$ : we get:

$$
\left\{\begin{align*}
\delta \dot{x} & =f_{x} \delta_{x}+f_{m} \delta_{m}  \tag{4}\\
\dot{p} & =-H_{x x} \delta_{x}=f_{x}^{T} \delta_{p}-H_{x m} \delta_{m} \\
\delta H_{m} & =H_{m x} \delta_{x}+H_{m m} \delta_{m}+f_{m}^{T} \delta_{p}
\end{align*}\right.
$$

Solving (6) for $\delta m(t)$ gives:

$$
\begin{equation*}
\delta m(t)=-H_{m m}^{-1}\left[-\delta H_{m}+H_{m x} \delta_{x}+f_{m}^{\prime} \delta_{p}\right] \tag{7}
\end{equation*}
$$

We can now write:

$$
\begin{align*}
& \dot{\delta} \dot{x}=\mathscr{2} \delta_{x}+\mathcal{L}^{?} \delta_{p}+w_{1}  \tag{8}\\
& \delta \dot{p}=\mathscr{p _ { y }} \delta_{y} \mathscr{2}^{T} \delta_{p}+w_{2} \tag{9}
\end{align*}
$$

with:

$$
\begin{aligned}
\mathscr{L} & =f_{x}-f_{m} H_{m m}^{-1} H_{m x} \\
\mathcal{E} & =-f_{m} H_{r n m}^{-1} f_{m}^{T} \\
\& & =-H_{x x}+H_{x m} H_{m m}^{-1} H_{m x} \\
w_{1} & =f_{m} H_{m m}^{-1} \delta H_{m} \\
w_{2} & =-H_{x m} H_{m m}^{-1} \delta H_{m}
\end{aligned}
$$

To solve this problem we use the usual matrix
Riccati transformation: we express $\delta_{p}$ as a function of $\delta_{x}$ such that (8) and (9) are satisfied.

$$
\begin{equation*}
\delta p(t)=T(t) \quad \delta x(t)+h(t) \tag{10}
\end{equation*}
$$

The result of this transformation yields the following equations:

$$
\begin{aligned}
& \dot{T}=-6 T+T \mathcal{L} T+\underset{\sim}{2} \\
& T\left(t_{e}\right)=0 \\
& h=-(\mathcal{D}+\mathrm{T} \ell) \mathrm{h}-\mathrm{T} \mathrm{w}_{1}+\mathrm{w}_{2} \\
& h\left(t_{e}\right)=0
\end{aligned}
$$

Substituting (10) into (7) gives an equation for $\delta m$ which will produce a change $\delta \mathrm{H}_{\mathrm{m}}$ in $\mathrm{H}_{\mathrm{m}}$ as required.
$\delta m(t)=-H_{m m}^{-1}\left\{\left[H_{m x}+f_{m}^{T} T\right] \delta x+\left[-\delta H_{m}+f_{m}^{T} h\right]\right\}$
Because of the boundary conditions, $\dot{x}(t)$ is integrated forward in time while $\dot{p}(t), \vec{T}(t)$, and $\dot{h}(t)$ are integrated backward in time.

By repeating this forward-backward sweep $N$ times we can bring $\mathrm{H}_{\mathrm{m}}$ to zero. A reasonable policy is to choose for each step:

$$
\delta H_{m}^{(j)}(t)=-\frac{J}{N} H_{m}^{(j-1)}(t)
$$

where $j$ is the step number.
In this way larger and larger reductions are made with each step, and with the last step the whole remaining correction is made.

## APPENDIX II

THE DECOMPOSITION TECHNIQUE
This brief summary and explaination of the decomposition technique for Jinear quadratic deterministic problems is done in order to precise the method and the notations used in Chapter 4. For more details on the decomposition technique, refer to [3].

The decomposition technique can be presented using a saddle value argument on the variational form of a control problem.

Consider the following systern:

$$
\left\{\begin{array}{l}
\dot{x}_{1}=c_{11} x_{1}+c_{12} t_{2}+\ell_{1} m_{1} \\
\dot{x}_{2}=c_{21} t_{1}+c_{22} x_{2}+\ell_{2} m_{2}
\end{array}\right.
$$

or

$$
\dot{x}=C x+C^{\prime} t+L m
$$

with the following constraints:

$$
x_{2}=t_{2} \quad x_{1}=t
$$

This system can be represented in two ways:
1)

2)


The cost function is:

$$
\int_{0}^{t} e\left\{A_{1}\left(r_{1}-x_{1}\right)^{2}+A_{2}\left(x_{2}-x_{2}\right)^{2}+B_{1} m_{1}^{2}+B_{2} m_{2}^{2}\right\} d t
$$

Proceeding directly to the solution the Lagrangian form for the integrated system is given by:

$$
\begin{aligned}
& J\left(x_{1}, x_{2}, t_{1}, t_{2}, m_{1}, m_{2}, p_{1}, p_{2}, k_{1}, k_{2}\right)=A_{1}\left(r_{1}-x_{1}\right)^{2} \\
& +A_{2}\left(r_{2}-x_{2}\right)^{2}+B_{1} m_{1}^{2}+B_{2} m_{2}^{2}+k_{1}\left(x_{1}-t_{1}\right)+k_{2}\left(x_{2}-t_{2}\right) \\
& +p_{1}\left[c_{11} x_{1}+c_{12} t_{2}+\ell_{1} m_{1}-\dot{x}_{1}\right]+p_{2}\left[c_{21} t_{1}+c_{22} x_{2}\right. \\
& \left.+\ell_{2} m_{2}-\dot{x}_{2}\right] .
\end{aligned}
$$

For this problem it is known that:

$$
J\left(x_{1}, x_{2}, t_{1}, t_{2}, m_{1}, m_{2}, p_{1}, p_{2}, k_{1}, k_{2}\right)
$$

has a saddle value as follows:

$$
\begin{aligned}
& J^{0}=J\left[x_{1}^{0}, x_{2}^{0}, t_{1}^{0}, t_{2}^{0}, m_{1}^{0}, m_{2}^{0}, p_{1}^{0}, p_{2}^{0}, K_{1}^{0}, k_{2}^{0}\right]= \\
& \begin{array}{c}
\text { Max } \\
\mathrm{p}_{1} \mathrm{p}_{2} \mathrm{~K}_{1} \mathrm{~K}_{2}
\end{array} \\
& J\left[x_{1}, x_{2}, t_{1}, t_{2}, m_{1}, m_{2}, p_{1}, p_{2}, k_{1}, k_{2}\right] .
\end{aligned}
$$

This last equation, together with the separable nature of the problem directly suggests a two-level procedure for the solution:

Level 1:
Given the arbitrary bounded continuous functions $K_{1}(t), K_{2}(t), 0 \leq t \leq t_{e}$ find the optimal solutions $x_{1}^{0}\left(t, K_{1}, K_{2}\right), x_{2}^{0}\left(t, K_{1}, K_{2}\right), t_{1}^{0}\left(t, K_{1}, K_{2}\right), t_{2}^{0}\left(t, K_{1}, K_{2}\right)$, $m_{1}^{0}\left(t, K_{1}, K_{2}\right), m_{2}^{0}\left(t, K_{1}, K_{2}\right)$ which minimize the parametric subproblems subject to the independent subsystems equations.
min
$J\left[x_{1}, x_{2}, t_{1}, t_{2}, m_{1}, m_{2}\right] \equiv \min _{x_{1}, t_{2}, m_{1}} J_{1}+\min _{x_{2}, t_{1}, m_{2}} J_{2}$. with

$$
\begin{aligned}
J_{1}=A_{1}\left(r_{1}-x_{1}\right)^{2}+B_{1} m_{1}^{2}+k_{1} x_{1}- & K_{2} t_{2}+p_{1}\left[c_{11} x_{1}\right. \\
& \left.+c_{12} t_{2}+\ell_{1} m_{1}-\dot{x}_{1}\right]
\end{aligned}
$$

and

$$
\begin{aligned}
J_{2}=A_{2}\left(r_{2}-x_{2}\right)^{2}+B_{2} m_{2}^{2}+k_{2} & x_{2}-k_{1} t_{1}+p_{2}\left[c_{21} t_{1}\right. \\
& \left.+c_{22} x_{2}+l_{2} m_{2}-\dot{x}_{1}\right]
\end{aligned}
$$

Level 2:
Given the optimal solutions from level l:
$x_{1}^{0}\left(t, K_{1}, K_{2}\right), x_{2}^{0}\left(t, K_{1}, K_{2}\right), m_{1}^{0}\left(t, K_{1}, K_{2}\right), m_{2}^{0}\left(t, K_{1}, K_{2}\right)$,
$t_{1}^{0}\left(t, K_{1}, K_{2}\right), t_{2}^{0}\left(t, K_{1}, K_{2}\right)$, find the optimal coordinating functions $K_{1}^{0}(t), K_{2}^{0}(t)$ which maximize
$J\left(K_{1}, K_{2}\right)=J\left[x_{1}^{0}\left(t, K_{1}, K_{2}\right), x_{2}^{0}\left(t, K_{1}, K_{2}\right), t_{1}^{0}\left(t, K_{1}, K_{2}\right)\right.$
$\left.t_{2}^{0}\left(t, K_{1}, K_{2}\right), m_{1}^{0}\left(t, K_{1}, K_{2}\right), m_{2}^{0}\left(t, K_{1}, K_{2}\right), K_{1}, K_{2}\right]$.
The computation technique for this second level is easy to do:

Consider a perturbation in $\mathrm{K}_{1}(t)$ to $\mathrm{K}_{1}(\mathrm{t})+$
$\delta K_{1}(t)$, in $K_{2}(t)$ to $K_{2}(t)+\delta K_{2}(t)$.
$\delta J\left(K_{1}, K_{2}\right)=\frac{\delta J}{\delta m_{1}} \delta m_{1}+\frac{\delta J}{\delta m_{2}} \delta m_{2}+\frac{\delta J}{\delta x_{1}} \delta x_{1}+\frac{\delta J}{\delta x_{2}} \delta x_{2}$
$+\frac{\delta J}{\delta t_{1}} \delta t_{1}+\frac{\delta J}{\delta t_{2}} \delta t_{2}+\frac{\delta J}{\delta K_{1}} \delta K_{1}+\frac{\delta J}{\delta K_{2}} \delta K_{2}+$ higher order
term where $\frac{\delta J}{\delta m_{1}}, \ldots$ denotes the functional derivatives or first derivations.

But when we solve for the optimal subproblems (I工 level) the following conditions are satisfied:

$$
\frac{\delta J}{\delta m_{1}}=\frac{\delta J}{\delta m_{2}}=\frac{\delta J}{\delta x_{1}}=\frac{\delta J}{\delta x_{2}}=\frac{\delta J}{\delta t_{1}}=\frac{\delta J}{\delta t_{2}}=0
$$

Therefore, we get:

$$
\begin{aligned}
\delta J\left(K_{1} K_{2}\right) & =\frac{\delta J}{\delta K_{1}} \delta K_{1}+\frac{\delta J}{\delta K_{2}} \\
& =\left(x_{1}-t_{1}\right) \delta K_{1}+\left(x_{2}-t_{2}\right) \delta K_{2} .
\end{aligned}
$$

Therefore, a gradient method of adjustment for $K_{1}(t), K_{2}(t)$ to give steepest ascent is given by:

$$
\left[\mathrm{K}_{1}\right]_{\mathrm{n}+1}=\left[\mathrm{K}_{1}\right]_{\mathrm{n}}+\varepsilon\left[\mathrm{x}_{1}-\mathrm{t}_{1}\right]
$$

$$
\left[k_{2}\right]_{n+1}=\left[k_{2}\right]_{n}+\varepsilon\left[x_{2}-t_{2}\right] .
$$

where $\varepsilon$ is a number chosen small enough to insure correctness of the first order expansion.

APPENDIX I:.:I, PROGRAM 1
$\square$

$$
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$$

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& \text { LEVEL } 2
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$$

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APPENDIX IV, PROGRAM 2

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$n \cdot v$
$P 1(T E)=C \& P 2(T F)=C S$ $P<(T-1)=P 2(1)-V+(-2+\Delta 2(T) *(\times 2(T)-R 2(T))-P 1(T) * C 1 つ(T)-P 2(T) * C 22(T))$

If J ENI $(!+1)$ THEN GOTC age

$T 11(T-1)=T 11(T)-V *(-2 * C 11(T, * T 11(T)-C 21(T) * T 12(T)-C 21(T) * T 2!(T)+$
 $\left.T_{121} T_{-1}\right)=T 1<(T)-V *(-C 12(T) * T 11(T)-(C 11(T)+C 22(T) 1 * T 12(T)-$

$\left.C \dot{C}!(T)_{*}-22(1)+T \rightarrow 1(T) * T 1+(T) /(2 \star \&!(T))+T 2 つ(T) * T 21 / T\right) /(2 * P \rho(T)$



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OLOCK 2 LEVEL 2

$$
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& 0 \\
& 0 \\
& 0 \\
& \text { w } \\
& w \\
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& \infty
\end{aligned}
$$




APPENDIX IV, PROGRAM 3

$$
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$$
\text { LE.VEL } 1
$$

$$
\text { Level } 2
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APPENDIX I.V, PROGRAM 4


E12 ALUCK 1 LEVEL 1

## APPENDIX IV, PROGRAM 5

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10
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BLOCK 1 LEVEL 1
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M21(T)
$-C 241(T) * Y 4(T)-C 211(T) * Y 1(T)-C 221(T) * Y 2(T)-C 231(T) * Y 3(T)$
















N311T)mnY(T)-CN11(T)*Y(T)-C321(T)*Y2(T)-C331(T)*Y3(T)

ENत*
COMMENT STEH O COMPUTATION OF A REFERENCE CONTROL 3

ENOS


$\left.C 14(T)+X 4 R(T)+C, T(T) * \times 5^{\circ}(T)+M 1 R(T)\right) s$
$\times 2 R(T+1)=X 2 H(T)+V *(C 21(T)+X(R(T) \quad+C 22(T)+X 9 R(T)+$

$\times 3 R(T+1)=X 3 H(T)+V *(C 3 I(T) \neq X 1 R(T)+C 32(T) * \times 2 R(T)+C 33(T) * \times 3 R(T)+$

$C 44(T) * X 4 R(T)+C H 5(T) * \times 5 R(T)+M 4 R(T)) s$
$\times 5 R(T+1)=X 5 K(T)+V *(C 51(T)+X 1 R(T)+C 5)(T) * \times 2 R(T)+$
C53 $(T) * \times 3 R(T)+C=4(T) * \times 4 R(T)+C 55(T) * \times 5 R(T)+M S R(T))$
DELR $(T+1)=D E L R(T)+V *(A 1(T) *((X 1 R(T)-R 1(T)) * * 2)+A 2(T) *((\times 2 R(T)-R 2(T)) * * 2)$
$+A 3(T) *((X 3 H(T)-R 3(T)) * * 2)+A 4(T) *((X 4 R(T)-R(T)) * * 2)$

$T, X 1 R(T): \times 2 H(T), \times 3 R(T), X 4 R(T), X 5 R(T), M 1 R(T), M 2 R(T), M 3 R(T), M 4 R(T), M 5 R(T)$, OELR(T)
ENDS
$\times 11(T)=x 1 R(T) \leqslant X \sim 1(T)=\times 2 R(T) \$ \times 31(T)=\times 3 R(T) \$ \times 41(T)=\times 4 R(T) \$ \times 51(T)=\times 5 R(T) s$
 ERŪ's $N=(1,1, *)$ OR BEGIN

FCR $T=(\cap, 1, T F)$ CO SIL(T) $\mathrm{mm}(\mathrm{T}) \mathrm{s}$
SVP $A, A 2, A 3, A 4, A 5, B 1, P 2, B 3, B 4, P S, C 11, C 12, C 13, C, 4, C 15, C 21, C 22, C 23, C 24$, $R 1, R 2, R 3, R 4, R 5, Y 12, \times 21, \times 31, \times 41, \times S 1, M 1, M 2, M 3, M 4, M E$,
$\times 10, \times 2 n, \times 3 n, \times 40, \times 50, T E, N, N, C 11,5$ $\times 10, \times 2 n, \times 3 n \times 40, \times 50$.TF,N:N, (II)


WRITE, M, STEPZ, INIS
SVP $(A,, A 3, A 4, A K, A 1, B 2, B 3, B 4,85, B 1, C 22, C 23, C 24, C, 25, C 21$,
$C 32, C, 3, C 34, C 3 S, C 31, C 42, C 43, C 44, C 45, C 41, C 52, C 53, C 54, C 55, C 51, C 12, C 13, C 14$,
$C 15, C 1, R 2, N 3, R 4, R 5, R 1, \times 22, Y 31, \times 41, \times 51, \times 12, M 2, M 3, M 4, M 5$, $M 1, \times 2 n, \times 30, \times 40, \times 5 n, \times 1 \mathrm{n}, \mathrm{TF}, \mathrm{V}, \mathrm{I}, S 11) \mathrm{s}$
$\mathrm{ES}=\mathrm{CLOCK}$
FOR $\quad=(\cap, 1, T F)$ NO WRITE $(, M I(T), M 2(T), M 3(T), M 4(T 1, M S(T), \ldots$,
M1 (T), M2 (T), M3(T),M4(T),M5(T))\$

SVP $1 A 3, A 4, A 5, A 1, A 2, B 3,84, B 5, B 1, B 2, C 33, C 34, C 35, C 31, C 32$,
SVP $C A 3, A 4, A 5, A 1, A 2, B 3, R 4, B 5, B 1, B 2, C 33, C 34, C 35, C 31, C 32$,
$C 43, C 44, C 45, C 41, C 42, C 53, C 54, C 55, C 51, C 52, C 13, C 14, C 15, C 11, C 12, C 23, C 24, C 25$,


ES = CLOCKS
$\operatorname{CON} 3=$ C5-
FCR TI (CO 1, TF) CO WRITE (IM1 (T),M2(T),M3(T),M4(T),M5(T), ',
$N_{1}(T), M 2(T), M 3(T), M \Delta(T), M 5(T) / \$$

FOP $T=10$,
$E 0=$ CLORKS
SVP $1 \triangle 4, A 5, A 1, A D, A 3,84,85,81, B 2, B 3, C 44, C 45, C 41, C 42, C 43$,
$C 54, C 55, C 51, C 52, C 53, C 14, C 15, C 11, C 12, C 13, C 24, C 25, C 21, C 22, C 23$, $C 34, C 35, C 31, C 32, C 33, R 4, R 5, R 1, R 2, R 3, \times 42, \times 51, \times 12, \times 22, \times 32$,
$M 4, N S, N 1, M 2, M 3, \times 4 C, \times 5 n, \times 1 \cap, \times 20, \times 30, T F, V, 1, S 111)$
CCM4=天aーFO
WRTTE (ON,STEP E, ', NI)s
FCR $=$ ini:i,if) no SII(T)ams(T)\$
$\mathrm{EO}=\mathrm{Cl}$ Orks
SVP $1 \triangle 5, A 1, A 2, \triangle 3, A 4, B 5 \cdot B 1,82,83 \cdot B 4, C 55, C 51, C 52, C 53, C 54$, C15,C11,C12,C13,C14,C25,C21,C22.C23.C24,
C45,C4, C42,C43,C44,R5,R1,R2,R3.R4, X52,

$5=$ CLCCKS

FOR $T=1 n, 1, I F)$ nO EEGIN
$\times 21(T)_{n} \times 22(T) \$ \times 31(T)=\times 3 ?$

FCR $T=(n, 1,1 F)$ nO WRITE

$T, \times 12(T), \times 22(T), \times \geq 2(T), \times 42(T), \times 52(T), M 1 N(T), M 2 N(T), N 3 N(T), M 4 N(T), M S N(T$ ) 5 COMI +COM2 + COM $3+C O M L+C O M 5 S$
WKITF $, 1,2,3,4,5$, TOT, , CON1,COM2,COM3.COM4,COM5,COMTIS $\stackrel{c}{c}$



APPENDIX V, PROGRAM 6



## APPENDIX V, PROGRAM 7




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APPENDIX V, PROGRAM 8
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APPENDIX V, PROGRAM 10

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REAL-APPAY $X_{1}+X_{2}+X_{1} S+X_{2 S}+P_{1}+P_{2}+M+W M+T_{1}+T+T 2+T 21+T 22+H_{1}+H 2$. ELI-1..101) COMNENT-NON LINFAR COURLTNG_2
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FOR J=11,1,1+1) DO REGIN
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(T) $10 \times 2$ (U) 2 2




COMMENT BACKMARAS INTEGRATIOM S
OR T=1TFI-1, $n$ ) NO REGIN

P2(T-1) $=P 2(T)+V * \times 2(T) s$



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APPENDIX V, PROGRAM 11




1. Dantzig, G., Wolfe, P., "Decomposition Principle for Linear Programs", Operations Research, vol. 8 , No. 1, pp 101-111, 1960.
2. Pfouts, R. W., (editor), "Essays in Economics and Econometrics" Part 1, pp. 34-106, University of North Carolina Press, Chapel Hill.
3. Reich, S., "A Critique of Decomposition Technique for Optimal Control Problens", Systems Research Center, 103-A-67-45, Case ‥nstitute of Technology.
4. Kalman, R. E., "Some Methods of Linear Filtering", J. M. C. C., Dec. 15, 1964.
5. Takahara, Y., "Multilevel Systems and Uncertainties", Systems Research Center, 99-A-66-42, Case Institute of Technology.
6. Mc Reynolds, S. R., Bryson, A. E., "Successive Sweep Method for Solving Optimal Programming Problems", Proc. 1965 J. A. C. C., June, 1965.
