

# Robust Portfolio Decisions for Financial Institutions

Ioannis Baltas<sup>1,3</sup>, Athanasios N. Yannacopoulos<sup>2,3</sup> & Anastasios Xepapadeas<sup>4</sup>

<sup>1</sup>Department of Financial and Management Engineering  
University of the Aegean

<sup>2</sup>Department of Statistics  
Athens University of Economics and Business

<sup>3</sup>Stochastic Modeling and Applications Laboratory  
Athens University of Economics and Business

<sup>4</sup>Department of International and European Economic Studies  
Athens University of Economics and Business

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# It's all about robustness

*Robust grass endures mighty winds;  
loyal ministers emerge through ordeal.*

**Li Shimin, 568-649 A.D.  
Tang Dynasty of China**

# The model: Financial Market

Suppose that we have a financial market on the fixed time horizon  $[0, T]$  with  $T > 0$  and two investment possibilities :

- A risk free asset (bond or bank account) with unit price  $S_0(t)$  at time  $t$  and dynamics described by the ordinary differential equation

$$\boxed{dS_0(t) = rS_0(t)dt, \quad S_0(0) = 1} \quad (1)$$

- A risky asset (stock or index) with unit price  $S_1(t)$  at time  $t$  which evolves according to the stochastic differential equation

$$\boxed{dS_1(t) = \mu S_1(t)dt + \sigma S_1(t)dW(t), \quad S_1(0) > 0} \quad (2)$$

Here,  $r > 0$ ,  $\mu$  (with  $\mu > r$ ) and  $\sigma > 0$ , are given constants.

## The model: Cash Flow

- In collective risk theory, a sound mathematical model for describing the surplus of a large portfolio of claims is the Cramer-Lundberg model:

$$Y(t) = Y(0) + P(t) - L(t) \quad (3)$$

- In some situation, it is easier to work with its diffusion approximation.
- Here, the cumulative claims process is modeled by

$$\boxed{dL(t) = \alpha dt - \beta dB(t)} \quad (4)$$

where  $\alpha$  and  $\beta$  are positive constants.

- The drift term can be interpreted as the mean claims up to time  $t$ .
- The stochastic term can be interpreted as the fluctuations around the mean claims.

# The setting

- We consider a financial firm, who, at time  $t = 0$ , starts with some initial wealth  $x_0 > 0$ .
- The risk manager of the firm decides the proportion  $\pi(t)$  of its wealth  $X(t)$  to be invested in the risky asset (2).
- The remaining proportion  $(1 - \pi(t))X(t)$  is invested in the risk-less asset (1).
- The firm is designed to offer some very specific services to its clients (e.g., financial investments consultancy, pension fund management, insurance, etc) by entering a contract.
- In exchange for its services, the firm collects compensation (continuously) at the constant rate  $c_0\alpha$ , where  $c_0 \geq 1$ .

# The setting

- However, such a contract also generates a stochastic cash flow of liabilities (e.g., long term payments, operating costs, etc) that evolves according to (4).
- As a means of reducing this additional exposure, the risk manager of the firm has the ability to transfer a proportion of its liabilities to another party (e.g. external investor, financial fund, reinsurance firm, e.t.c).
- The risk manager decides the proportion  $q(t)$  of its claims process to be covered, by entering a contract with the third party.
- In exchange for this coverage, the third party collects an income continuously at the constant rate  $c_1 \alpha q(t)$ , where  $c_1 \geq c_0$ .

# Stochastic Differential Equations of firm's wealth

- To sum up, the wealth process corresponding to the strategy  $\eta_1 = (\pi(t), q(t))$ , is denoted as  $X^{\eta_1}(t)$  and is defined as the solution of the following linear stochastic differential equation

$$dX^{\eta_1}(t) = \pi(t)X^{\eta_1}(t)\frac{dS_1(t)}{S_1(t)} + (1 - \pi(t))X^{\eta_1}(t)\frac{dS_0(t)}{S_0(t)} + dR(t),$$

where

$$\begin{aligned}dR(t) &= (c_0 - c_1)dt - dL(t) + q(t)dL(t) \\ &= \alpha(\theta - \eta)q(t)dt + \beta(1 - q(t))dB(t).\end{aligned}$$

- Therefore, in view of (1-4)

$$\begin{aligned}dX^{\eta_1}(t) &= \left[ X^{\eta_1}(t)(r + (\mu - r)\pi(t)) + \alpha(\theta - \eta)q(t) \right] dt \\ &\quad + \beta(1 - q(t))dB(t) + \sigma\pi(t)X^{\eta_1}(t)dW(t),\end{aligned}$$

with initial condition  $X^{\eta_1}(0) = x_0 > 0$ .

# The original problem

- The risk manager aims to choose the control process so as to maximize some certain goal, e.g., the expected utility from her terminal wealth:

$$\sup_{\pi, q \in \mathcal{A}^{\mathbb{F}}} \mathbb{E} \left[ U(X^{\eta_1}(T)) \right],$$

subject to the state process

$$\begin{aligned} dX^{\eta_1}(t) = & \left[ X^{\eta_1}(t)(r + (\mu - r)\pi(t)) + \alpha(\theta - \eta q(t)) \right] dt \\ & + \beta(1 - q(t))dB(t) + \sigma\pi(t)X^{\eta_1}(t)dW(t). \end{aligned}$$

- A standard way to proceed is by employing the techniques of stochastic optimal control.



# Model uncertainty aspects

- Stochastic optimal control theory is an indispensable part of mathematical economics and modern financial management.
- Great importance and wide range of applicability !

## **Assumption**

The decision maker has complete faith in her model !

L.P.Hansen (Nobel Prize in Economics, 2013) and T.Sargent (Nobel Prize in Economics, 2011):

- Questioning the validity of your model is the first step towards realistic modeling: Model uncertainty aspects.

**Solution**: Robust control theory!

# Stochastic Control vs Robust Control



Figure: Stochastic Optimal Control Theory

# Stochastic Control vs Robust Control



Figure: Robust Optimal Control Theory

# Introduction to Robust Control Theory

Robust control theory is a mixture of two things:

- Stochastic control theory.
- Model selection techniques.

## Main Philosophy:

Solve an optimal control problem under the worst possible scenario.

⇒ Using the model that may provide the worst case for the problem at hand.

In Mathematical terms:

Model  $\sim$  Probability Measure

## Model uncertainty aspects

- We assume that the risk manager is uncertain as to the true nature of the stochastic processes  $W$  and  $B$  in the sense that the exact law of  $W$  and  $B$  is not known.
- There exists a "true" probability measure related to the true law of the processes  $W$  and  $B$ , the risk manager is unaware of, and a probability measure  $Q$ , which is her idea of what the exact law of  $W$  and  $B$  looks like.
- The manager is uncertain about the validity of  $Q$ :

$$\inf_{Q \in \Omega} \mathbb{E}_Q \left[ U(X^{\eta_1}(T)) \right],$$

- As a result, the manager faces the robust control problem

$$\sup_{\pi, q \in \mathcal{A}^{\mathbb{F}}} \inf_{Q \in \Omega} \mathbb{E}_Q \left[ U(X^{\eta_1}(T)) \right],$$

# The class of measures $\mathcal{Q}$

## Definition (The set $\mathcal{Q}$ )

The set of acceptable probability measures  $\mathcal{Q}$  for the agent is a set enjoying the following two properties:

- (i) Considering the stochastic process  $W$  under the reference probability measure  $\mathbb{P}$  and under the probability measure  $\mathbb{Q}$  results to a change of drift to the Brownian motion  $W$ .
- (ii) There is a maximum allowed deviation of the managers measure  $\mathbb{Q}$  from the reference measure  $\mathbb{P}$ . In other words, the manager is not allowed to freely choose between various probability models as every departure will be penalized by an appropriately defined penalty function, a special case of which is the Kullback-Leibler relative entropy  $\mathcal{H}(\mathbb{P}|\mathbb{Q})$ .

## Change of measure - Girsanov

### Theorem

Assume that  $y_1, y_2 \in \mathcal{Y} \subset \mathbb{R}^2$  satisfy the condition

$$\mathbb{E} \left[ \exp \left( \frac{1}{2} \int_0^T y_1^2(s) + y_2^2(s) ds \right) \right] < \infty.$$

Then, the stochastic processes  $\widetilde{W}$  and  $\widetilde{B}$  with decomposition given by

$$\widetilde{W}(t) = W(t) - \int_0^t y_1(s) ds,$$

and

$$\widetilde{B}(t) = B(t) - \int_0^t y_2(s) ds,$$

are  $(\mathbb{F}, \mathbb{Q})$  Brownian motions.

# The robust control problem

$$\begin{aligned} & \sup_{\pi, q \in \mathcal{A}^{\mathbb{F}}} \inf_{Q \in \mathcal{Q}} J(t, x) \\ &= \sup_{\pi, q \in \mathcal{A}^{\mathbb{F}}} \inf_{y_1, y_2 \in \mathcal{Y}} \mathbb{E}_Q \left[ U(\tilde{X}^{\eta_1, \eta_2}(T)) + \frac{1}{2\lambda} \int_t^T y_1^2(s) + y_2^2(s) ds \right], \end{aligned} \quad (5)$$

subject to the state dynamics

$$\begin{aligned} d\tilde{X}^{\eta_1, \eta_2}(s) &= \left[ r\tilde{X}^{\eta_1, \eta_2}(s) + (\mu - r)\pi(s)\tilde{X}^{\eta_1, \eta_2}(s) + \alpha(\theta - \eta q(s)) \right. \\ &\quad \left. + \sigma\pi(s)y_1(s)\tilde{X}^{\eta_1, \eta_2}(s) + \beta(1 - q(s))y_2(s) \right] ds \\ &\quad + \sigma\pi(s)\tilde{X}^{\eta_1, \eta_2}(s)d\tilde{W}(s) + \beta(1 - q(s))d\tilde{B}(s), \end{aligned} \quad (6)$$

with initial condition  $\tilde{X}^{\eta_1, \eta_2}(s) = x_0 > 0$ .



# Solution Procedure

1. Derive the Hamilton-Jacobi-Bellman-Isaacs equation (HJBI) for the problem at hand. This is a partial differential equation (PDE) for an unknown function, e.g.  $V$ .
2. Fix an arbitrary point in time-space and solve the resulting static optimization problems (minimization  $\rightarrow$  maximization).
3. From s2 we get a candidate for the optimal control laws.
4. This yields to a second order (for the problem at hand) PDE.
5. Solve the PDE of s4.
6. Verification theorem: The solution of the HJBI equation ( $V$ ) is the value function of the problem at hand and the control choices we found earlier are indeed the optimal ones.

# On the solvability of the HJBI

Is it possible to find a (smooth) solution to the HJBI ?

**NOT IN GENERAL !!**

There are three ways to proceed:

1. Guess a solution and pray !
2. Numerical Approximation.
3. Weak solutions (viscosity, mild, etc)

# Robust Control Problem = Stochastic Differential Game



Figure: World Chess Championship 2016

# Stochastic Differential Games

- The evolution of the underlying system is described by a Stochastic differential equation.
- The system is controlled by two (or more) players with conflicting goals.
- The controllers decide their control process so as to drive the system to a desired state.

A robust control problem is written as a SDG:

- **Player I.** Decision maker: Chooses the control process.
- **Player II.** Imaginary player (Nature): Chooses the model (the measure)

## Theorem (Main Result)

Suppose that the risk manager has preference for robustness as described by the non-negative constant  $\lambda$ . The optimal robust strategy is to invest in the risky asset proportion of the firm's wealth equal to

$$\pi^*(t, x) = -\frac{\mu - r}{\sigma^2 x} \frac{V_x}{V_{xx} - \lambda V_x^2},$$

and purchase proportional coverage for the firm's claims, equal to

$$q^*(t, x) = 1 + \frac{\alpha \eta}{\beta^2} \frac{V_x}{V_{xx} - \lambda V_x^2}.$$

On the other hand, Nature chooses the worst-case scenario defined by

$$y_1^*(t, x) = \frac{\mu - r}{\sigma} \frac{\lambda V_x^2}{V_{xx} - \lambda V_x^2} \quad \text{and} \quad y_2^*(t, x) = \frac{\alpha \eta}{\beta} \frac{\lambda V_x^2}{V_{xx} - \lambda V_x^2}.$$

In this case, the optimal robust value function is a smooth solution of the following non-linear partial differential equation

$$V_t + [rx + \alpha(\theta - \eta)]V_x - \frac{1}{2} \left[ \left( \frac{\mu - r}{\sigma} \right)^2 + \left( \frac{\alpha \eta}{\beta} \right)^2 \right] \frac{V_x^2}{V_{xx} - \lambda V_x^2} = 0,$$

with boundary condition  $V(T, x) = U(x)$ .

## Theorem (Exponential Utility)

Assume Exponential preferences ( $u(x) = -\frac{\delta}{\gamma} e^{-\gamma x}$ ). The optimal robust value function admits the form:

$$V(t, x) = -\frac{\delta}{\gamma} \exp \left[ -\gamma x e^{r(T-t)} + g(t) \right], \quad (7)$$

where

$$g(t) = \alpha \gamma (\theta - \eta) \frac{1 - e^{r(T-t)}}{r} - \frac{\gamma}{2(\lambda + \gamma)} \left[ \left( \frac{\mu - r}{\sigma} \right)^2 + \left( \frac{\alpha \eta}{\beta} \right)^2 \right] (T - t). \quad (8)$$

In this case, the optimal robust strategy for the risk manager is to invest in the risky asset the constant amount

$$\pi^*(t, x) = \frac{\mu - r}{\sigma^2 x} \frac{e^{-r(T-t)}}{\lambda + \gamma}, \quad (9)$$

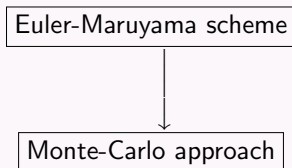
and purchase proportional coverage for the firm's claims, equal to

$$q^*(t, x) = 1 - \frac{\alpha \eta}{\beta^2} \frac{e^{-r(T-t)}}{\lambda + \gamma}. \quad (10)$$

On the other hand, Nature chooses the worst-case scenario defined by

$$y_1^*(t, x) = -\frac{\mu - r}{\sigma} \frac{\lambda}{\lambda + \gamma} \quad \text{and} \quad y_2^*(t, x) = -\frac{\alpha \eta}{\beta} \frac{\lambda}{\lambda + \gamma}. \quad (11)$$

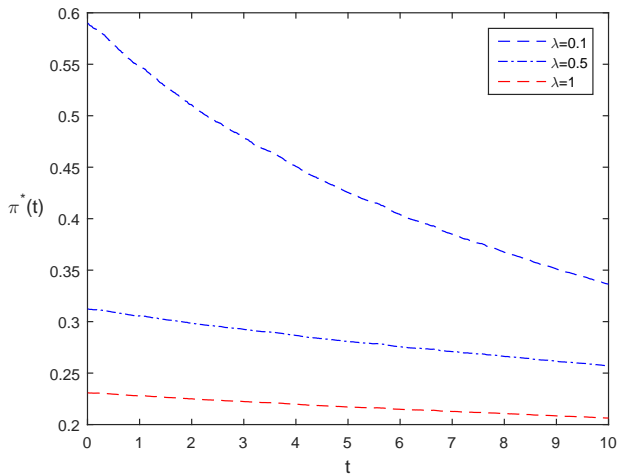
# Numerical study of the optimal investment strategy



**E-M:** For a time step of size  $\Delta t = T/N$  with  $N = 2^{11}$  points, we define the step size in the Euler-Maruyama scheme as  $\delta t = \Delta t$ .

**M-C:** Simulate a large number  $M$  of paths of  $\pi^*$  and  $q^*$  in the time interval  $[0, T]$  and at each time point we plot the average of  $M$  different values. We also use for each path  $N = 2^\alpha$  number of points (here  $N = 2^{11}$  and  $M = 6000$  paths).

We let  $M = 6000$ ,  $T = 10$  months,  $X(0) = 1.5$ ,  $\gamma = 0.5$  and  $\lambda = 0.2$ . The parameters of the financial market are chosen as  $\mu = 12\%$ ,  $r = 6\%$ ,  $\sigma = 40\%$ . The parameters for the insurance market are chosen as  $\alpha = 1$ ,  $\beta = 0.2$  and  $c_1 = 1.1$ .



**Figure:** Average of 6000 optimal investment strategy paths for various levels of the preference for robustness parameter, in the case of the exponential utility function.



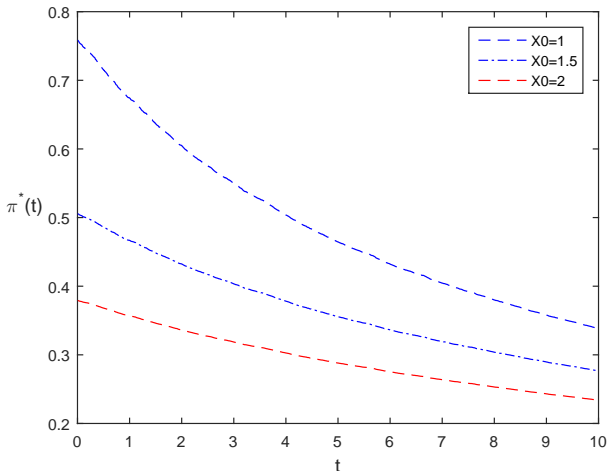


Figure: Average of 6000 optimal investment strategy paths for various levels of the initial wealth, in the case of the exponential utility function.

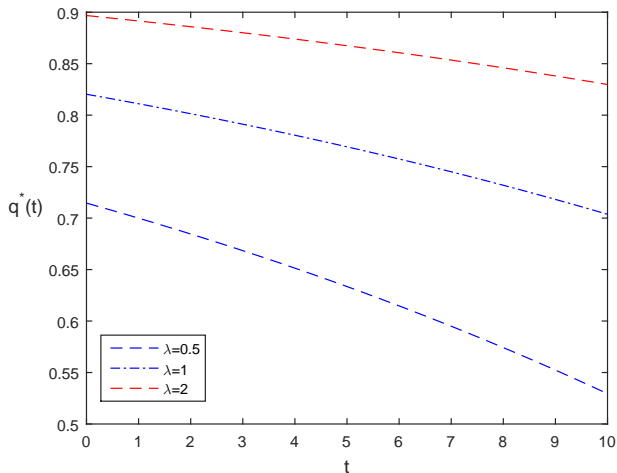


Figure: Average of 6000 optimal proportional coverage strategy paths for various levels of the preference for robustness parameter, in the case of the exponential utility function.

## Limiting behavior: Cases $\lambda \rightarrow 0$ and $\lambda \rightarrow \infty$

- It is well known (see e.g. Anderson, Hansen and Sargent) that as  $\lambda \rightarrow 0$  the decision maker fully trusts her model and exhibits no preference for robustness.
- As  $\lambda \rightarrow +\infty$ , the decision maker has no faith in the model she is offered and is willing to consider alternative models with larger relative entropy.
- The vast majority of the available works examines the limiting behavior of the optimal robust strategies, after the problem has been solved.
- Here, we are concerned with the structural behavior of the robust control problem itself in these limiting cases (well-posedness?)

## Theorem (Limiting behavior as $\lambda \rightarrow 0$ )

The optimal robust strategy for the risk manager is to invest in the risky asset proportion of the firm's wealth equal to

$$\pi^*(t, x) = -\frac{\mu - r}{\sigma^2} \frac{V_x}{V_{xx}}, \quad (12)$$

and also, to purchase proportional coverage for the firm's liabilities, equal to

$$q^*(t, x) = 1 - \frac{\alpha(1 - c_1)}{\beta^2} \frac{V_x}{V_{xx}}. \quad (13)$$

On the other hand, Nature chooses the myopic worst-case scenario defined by

$$y_1^*(t, x) = y_1^*(t, x) = 0. \quad (14)$$

In this case, the optimal robust value function is a smooth solution of the following non-linear partial differential equation

$$V_t + [rx + \alpha(\theta - \eta)]V_x - \frac{1}{2} \left[ \frac{(\mu - r)^2}{\sigma^2} + \frac{\alpha^2(1 - c_1)^2}{\beta^2} \right] \frac{V_x^2}{V_{xx}} = 0, \quad (15)$$

with boundary condition  $V(T, x) = U(x)$ , assuming that such a solution exists.

## Limiting behavior I: Case $\lambda \rightarrow 0$

We have some interesting findings

- The risk manager has complete faith in the model described by Equations (2) and (4).
- Operates under the probability measure  $\mathbb{P}$ .
- The controls (12), (13) and the PDE (15), are the optimal Markovian control laws and PDE associated with the stochastic optimal control problem:

$$\sup_{\pi, q \in \mathcal{A}^{\mathbb{F}}} \mathbb{E}_{\mathbb{P}} \left[ U(X^{\pi_1}(T)) \right],$$

subject to the original state dynamics.

- Robust Control Problem  $\rightarrow$  Optimal Control Problem.

## Theorem (Limiting behavior as $\lambda \rightarrow +\infty$ )

Assume that  $\mathcal{Y}$  is the rectangle  $[\underline{y}_1, \bar{y}_1] \times [\underline{y}_2, \bar{y}_2]$ . The optimal robust strategy for the risk manager is to invest in the risky asset proportion of the firm's wealth equal to

$$\pi^*(t, x) = -\left(\frac{\mu - r}{\sigma} + \underline{y}_1\right) \frac{V_x}{\sigma x V_{xx}}, \quad (16)$$

and to purchase proportional coverage for the firm's liabilities, equal to

$$q^*(t, x) = 1 + \left(\frac{\alpha(c_1 - 1)}{\beta} + \underline{y}_2\right) \frac{V_x}{\beta V_{xx}}. \quad (17)$$

On the other hand, Nature chooses the myopic worst-case scenario defined by

$$y_1^*(t, x) = \underline{y}_1, \quad \text{and} \quad y_2^*(t, x) = \underline{y}_2. \quad (18)$$

In this case, the optimal robust value function is a smooth solution of the following non-linear partial differential equation

$$V_t + [rx + \alpha(c_0 - c_1)]V_x - \frac{1}{2} \left[ \left(\frac{\mu - r}{\sigma} + \underline{y}_1\right)^2 + \left(\frac{\alpha(c_1 - 1)}{\beta} + \underline{y}_2\right)^2 \right] \frac{V_x^2}{V_{xx}} = 0, \quad (19)$$

with boundary condition  $V(T, x) = U(x)$ , assuming that such a solution exists.

## Solution break-down

- We construct a case where loss of convexity leads to break-down of the solution of the HJBI equation.
- For simplicity we assume that  $c_0 = c_1$ .
- The HJBI equation is restated as

$$V_t + rxV_x - A(\underline{y}_1, \underline{y}_2) \frac{V_x^2}{V_{xx}} = 0, \quad (20)$$

where

$$A(\underline{y}_1, \underline{y}_2) := \frac{1}{2} \left[ \left( \frac{\mu - r}{\sigma} + \underline{y}_1 \right)^2 + \left( \frac{\alpha(c_1 - 1)}{\beta} + \underline{y}_2 \right)^2 \right] \geq 0.$$

- We assume that the risk manager operates under quadratic preferences, that is a utility function of the form

$$U(x) = \kappa \frac{x^\rho}{\rho}, \quad (21)$$

for some  $\kappa > 0$  and  $0 < \rho < 1$ .

## Solution break-down

1. Assume that the PDE (20) admits a classical solution  $V \in \mathcal{C}^{1,2}(\mathbb{S})$ .
2. We look for a solution using the guess

$$V(t, x) = e^{-\delta t} \tilde{V}(x),$$

where  $\tilde{V} \in \mathcal{C}^{1,2}(\mathbb{S})$ . Differentiating the above expression with respect to  $(t, x)$ , yields

$$V_t = -\delta e^{-\delta t} \tilde{V}(x)$$

$$V_x = e^{-\delta t} \tilde{V}_x$$

$$V_{xx} = e^{-\delta t} \tilde{V}_{xx}.$$



## Solution break-down

4. Substituting these expressions back in the partial differential equation (20), results to the elliptic partial differential equation

$$\delta \tilde{V} - r x \tilde{V}_x + A(\underline{y}_1, \underline{y}_2) \frac{\tilde{V}_x^2}{\tilde{V}_{xx}} = 0. \quad (22)$$

5. We propose a solution to the partial differential equation of the form

$$\tilde{V}(x) = \kappa \frac{x^\rho}{\rho}.$$

Inserting this trial solution in (22), yields to the following condition for the discounting factor

$$\delta = r\rho - A(\underline{y}_1, \underline{y}_2) \frac{\rho}{\rho - 1},$$

or equivalently

$$A(\underline{y}_1, \underline{y}_2) = \frac{1 - \rho}{\rho} (\delta - r\rho).$$

## Solution break-down

We distinguish the following four cases:

- (i). If  $A(\underline{y}_1, \underline{y}_2) = 0$  and  $\delta = r\rho$ , a solution exists.
- (ii). If  $A(\underline{y}_1, \underline{y}_2) > 0$  and  $\delta = r\rho$ , the solution breaks down.
- (iii). If  $A(\underline{y}_1, \underline{y}_2) = 0$  and  $\delta > r\rho$ , the solution breaks down.
- (iv). If  $A(\underline{y}_1, \underline{y}_2) > 0$  and  $\delta - r\rho > 0$ , as  $\underline{y}_1$  and  $\underline{y}_2$  increase in absolute value, the solution breaks down.

**Thank you for your attention !**