Motivations	Mixed differential model	Predictions	Method	Conclusion

# Abstract qualitative model for the genetically regulated lipid metabolism

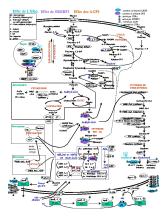
#### O. Radulescu, A. Siegel, E. Pécou, S. Lagarrigue IRISA-CNRS

IHP, January 2006

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Motivations	Mixed differential model	Predictions	Method	Conclusion

# Lipid metabolism in chicken/mouse liver cells



#### • Two antagonistic functioning modes

- synthesis and storage produce reserves (induced by normal feeding)
- lipolysis and oxidation burn reserves and produce energy (induced by a lack of food)

#### • Complex regulations

- intrinsic regulations related to metabolic biochemistry
- genetic regulations of nuclear receptors on enzymes of metabolic pathways
- action of fatty acids (metabolite) on genes controlling their metabolism

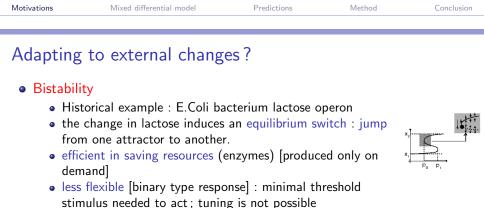
Mixed regulation network whose nodes are metabolites as well as genetic variables

# Modelling mixed regulation networks?

- prokaryotes (lactose operon in E.Coli)
- eukariotes
  - metabolic pathways studied separately from their genetic regulation : problems on long timescales
  - Petri networks : glycolysis [Mastuno et al., Chaouyia et al]
  - Piecewise differential sytems : nutritional stress in E. Coli [Ropers and al.]
  - Simulation of differential models [Chabrier and al.]
  - Hybrid models [Langley et al., King et al.]

Motivations	Mixed differential model	Predictions	Method	Conclusion

# Three main questions (at the moment)



#### • Equilibrium shift

- uniqueness condition is fulfilled
- no jump between attractors; smooth, gradual changes.

**Question 1** : Do the regulations (metabolic, genetic, hormonal) of lipid metabolism produce multistationarity or an unique equilibrium ?

Answer : Unique equilibrium under reasonable biological assumptions.



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# Interactions between metabolic and genetic pathways? Action of PUFA's?

- only a special class (polyunsaturated fatty acids denoted by PUFA) interfere with genes
- PUFA are not synthetized by the organism : produced from essential fatty acids taken from the diet
- Control of metabolism (their own oxidation and synthesis, and oxidation of de novo fatty acids)
- Interactions with nuclear receptors regulating the transcription of genes coding for enzymes involved in the corresponding pathways.

**Question 2** : quantify the effect of PUFA on the lipid metabolism ?

Answer : PPAR knock-out reduces energy buffering and increases PUFA entering during fasting. Interactions between metabolic and genetic pathways? Role of genetic machinery?

- Long timescales : Genetic regulation becomes effective only when transcriptional machinery is activated and processed
- On short timescales genetic variables can be considered to be constant
- Changes of nutritional conditions ask for genetic readjustments [fasting demands a shift from lipogenetic to lipolytic functioning modes]
- Genetic regulation brings slow but larger changes that push the shift further.

**Question 3** : Differences between fast and slow response of the system ?

Answer : Genetic regulations reinforce the energy buffering effect.

Motivations	Mixed differential model	Predictions	Method	Conclusion
Method				
Co	nstruction of a <mark>mixed d</mark>	ifferential mode		
	simplified description : 1	12 main variables	5	
	<ul> <li>includes the energy ava</li> </ul>	ilable to the cell	[variable for AT	Р
	concentration]			

- do not use explicit forms for flux and regulations : only use their variations with respect to the variables
- Study of equilibria : sufficient condition for the uniqueness of equilibrium
- Qualitative validation and prediction
  - effect of suppressing some genetic regulation,
  - role of genetic regulation for energy recovering at fasting.
- Generic explicit model : numerical simulations
- Mathematical framework : successive elimination of variables to compare equilibria

Motivations	Mixed differential model	Predictions	Method	Conclusion

# Construction of the model

Motivations	Mixed differential model	Predictions	Method	Conclusion

# Characteristics of the model

- Integrative model
  - main processes of carbohydrate and lipid metabolism in liver
  - various regulations (metabolic, genetic, hormonal)
- Not explicitly distributed (no space information is taken into account)
- Low complexity abstraction
  - basic features of metabolism in the main nutritional states
  - complex metabolic chains of reactions modeled as a single global reaction
- Keep the model as qualitative as possible
  - no specific numerical values of kinetic constants
  - no specific forms of the functions relating fluxes to concentrations
  - sufficient qualitative conditions chosen as biologically significant as possible

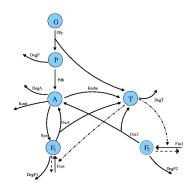
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Motivations	Mixed differential model	Predictions	Method	Conclusion

# Metabolic variables and primitive fluxes

#### Metabolic variables

- Acetyl-CoA [A] (mitochondria)
- De novo synthesized fatty acids [*F*<sub>1</sub>] (produced from Acetyl-CoA)
- Exogenous PUFA [F<sub>2</sub>] (brought by diet)
- Energy (ATP) [T] (energy in the cell)
- Pyruvate [P] (end of glycolysis)
- Parameter : glucose concentration [G] (representing food)
- Primitive fluxes
  - lipid metabolism : Glycolysis, Pdh, Krebs cycle, lipogenesis,  $\beta$ -oxidation
  - ketone bodies exit transfers energy to the outside
  - Outtake/intake flux allows *F*<sub>1</sub> and *F*<sub>2</sub> to exit or enter the liver cell.
  - Degradation of metabolites is needed on the genetic timescale.
  - ATP consumption (energy consumed for living).



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Motivations	Mixed differential model	Predictions	Method	Conclusion

# Genetic variables

#### • Nuclear receptors

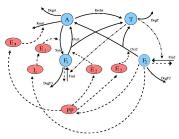
- *PP* : active form of the nuclear receptor PPAR (heterodimer with RXR),
- L : active form of the nuclear receptor LXR
  - (heterodimer with RXR)

#### • Metabolic fluc enzyme

- *E*<sub>1</sub> : abstract enzyme modelling the set of enzymes involved in de novo fatty acids synthesis
- *E*<sub>2</sub> : abstract enzyme modelling de novo acids oxidation,
- $E_3$  : abstract enzyme modelling PUFA oxidation
- $E_4$  : abstract enzyme modelling etone bodies exit

#### Genetic control

- LXR and PPAR control the production of the abstract enzymes *E<sub>i</sub>*
- PUFA control the production of active LXR and PPAR.



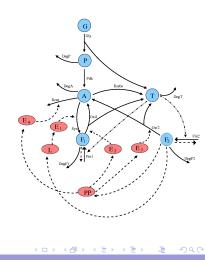
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# Main products and fluxes

Variable (Concentration)	Symbol	d product
Acetyl Co-A	Α	Φ <sub>A</sub>
Pyruvate	Р	$\Phi_{\rm P}$
De novo synthesized fatty acids	F <sub>1</sub>	Φ <sub>F1</sub>
PUFA	F <sub>2</sub>	$\Phi_{F_2}$
Energy ATP	Т	ΦT
Active form of PPAR	PP	$  \Psi_1$
Active form of LXR	L	$\Psi_2$
Enzymes of de novo fatty acids synthesis	$E_1$	$\Psi_3$
Enzymes of de novo fatty acids oxidation	$E_2$	$\Psi_4$
Enzymes of PUFA oxidation	E <sub>3</sub>	$\Psi_5$
Enzymes of Ketone body exit	$E_4$	$\Psi_6$

Parameter Symbol Glucose G

Glacose	
Primitive flux	Symbol
Glycolysis	Gly
Pyruvate dehydrogenase reaction	Pdh
Krebs cycle	Krebs
Ketone bodies exit	Kout
Lipogenesis	Syn
$\beta-$ oxidation of de novo fatty acids	Oxi1
$\beta$ -oxidation of PUFA	Oxi2
De Novo fatty acids intake/outake	Fin1
PUFA fatty acids intake/outake	Fin2
ATP consumption	DegT
Degradation of a metabolite V	DegV
$(V = P, A, F_1, F_2)$	



Motivations	Mixed differential model	Predictions	Method	Conclusion

# Differential model?

#### Express the flux of each variable in terms of primitive fluxes

- Production of metabolic variables : sum of primitive fluxes that produce or consume the metabolite.
- Linear degradation reactions (exept for ATP)
- No details on variations of the genetic variables [unknown mechanisms]

$$\begin{array}{l} \frac{dP}{dA} = \mathrm{Gly}(\mathrm{G},\mathrm{T}) - \mathrm{Pdh}(\mathrm{P}) - \delta_{\mathrm{P}}\mathrm{P} \\ \frac{dA}{dA} = \mathrm{Pdh}(\mathrm{P}) + \mathrm{Oxil}(\mathrm{F}_{1},\mathrm{T},\mathrm{E}_{2}) + \mathrm{Oxi2}(\mathrm{F}_{2},\mathrm{T},\mathrm{E}_{3}) - \mathrm{Krebs}(\mathrm{A},\mathrm{T}) - \mathrm{Kout}(\mathrm{A},\mathrm{E}_{4}) - \mathrm{Syn}(\mathrm{A},\mathrm{T},\mathrm{E}_{1}) - \delta_{\mathrm{A}}\mathrm{A} \\ \frac{dF_{1}}{dF_{1}} = \mathrm{Syn}(\mathrm{A},\mathrm{T},\mathrm{E}_{1}) - \mathrm{Oxil}(\mathrm{F}_{1},\mathrm{T},\mathrm{E}_{2}) + \mathrm{Fin1}(\mathrm{F}_{1},\mathrm{T}) - \delta_{\mathrm{F}_{1}}\mathrm{F}_{1} \\ \frac{dF_{2}}{dF_{2}} = -\mathrm{Oxi2}(\mathrm{F}_{2},\mathrm{T},\mathrm{E}_{3}) + \mathrm{Fin2}(\mathrm{F}_{2},\mathrm{T}) - \delta_{\mathrm{F}_{2}}\mathrm{F}_{2} \\ \frac{dT}{dF_{2}} = \alpha_{\mathrm{G}}\mathrm{Gly}(\mathrm{G},\mathrm{T}) + \alpha_{\mathrm{K}}\mathrm{Krebs}(\mathrm{A},\mathrm{T}) + \alpha_{\mathrm{O1}}\mathrm{Oxil}(\mathrm{F}_{1},\mathrm{T},\mathrm{E}_{2}) + \alpha_{\mathrm{O2}}\mathrm{Oxi2}(\mathrm{F}_{2},\mathrm{T},\mathrm{E}_{3}) - \mathrm{DegT}(\mathrm{T}) \\ \frac{dP_{\mathrm{P}}}{dF_{2}} = \tilde{\Psi}_{1}(\mathrm{F}_{2}) - \delta_{\mathrm{PP}}\mathrm{PP} \\ \frac{dF_{\mathrm{H}}}{dF_{\mathrm{H}}} = \tilde{\Psi}_{2}(\mathrm{F}_{2}) - \delta_{\mathrm{L}}\mathrm{L} \\ \frac{dE_{\mathrm{H}}}{dF_{\mathrm{H}}} = \tilde{\Psi}_{3}(\mathrm{L}) - \delta_{\mathrm{E}_{1}}\mathrm{E}_{1} \\ \frac{dE_{\mathrm{H}}}{dF_{\mathrm{H}}} = \tilde{\Psi}_{4}(\mathrm{PP}) - \delta_{\mathrm{E}_{2}}\mathrm{E}_{2} \\ \frac{dE_{\mathrm{H}}}{dF_{\mathrm{H}}} = \tilde{\Psi}_{5}(\mathrm{PP}) - \delta_{\mathrm{E}_{3}}\mathrm{E}_{3} \\ \frac{dE_{\mathrm{H}}}{dF_{\mathrm{H}}} = \tilde{\Psi}_{6}(\mathrm{PP}) - \delta_{\mathrm{E}_{4}}\mathrm{E}_{4} \end{array}$$

**Remark** : Only fluxes are modelled here. No regulation information is provided yet. What is the sign of each  $\frac{\partial flux}{\partial variable}$ ?

Motivations	Mixed differential model	Predictions	Method	Conclusion
	$\begin{array}{l} \text{differential mod} \\ y(G, T) - Pdh(P) - \delta_P P \\ h(P) + Oxi1(F_1, T, E_2) + Oxi1(F_1, T, E_2) + Oxi2(F_2, T, E_3) + Fin2(F_2, T_3) \\ gdly(G, T) + \alpha_K Krebs(A, T_4) \\ gdly(G, T) + \alpha_E Krebs(A, T_4) \\ gdly(G, T) + \alpha_E Fin_4 \\ gdly(G, T) + \alpha_$			
$\begin{array}{c} \frac{\partial  \text{flux}}{\partial  \text{variable}} \\ P \\ A \\ F_1 \\ F_2 \\ T \\ P \\ L \\ E_1 \\ E_2 \\ E_3 \\ E_4 \\ G \end{array}$	$\begin{array}{c c c c c c c c c c c c c c c c c c c $	$\begin{array}{c c c c c c c c c c c c c c c c c c c $	$\begin{array}{c c c c c c c c c c c c c c c c c c c $	3) 3 900

Motivations	Mixed differential model	Predictions	Method	Conclusion
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#### Constraints on the model : biological arguments

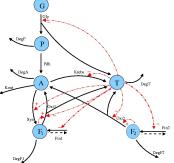
- Metabolic regulations
  - Substrate effect.
  - Passive or active transport effects.
- ATP constraints; hormonal regulations
  - ATP increases ATP consumption [substrate effect]
  - Product negative feed-back : ATP controls negatively fluxes producing ATP [metabolic and hormonal response to glucagon]
  - control of ATP on de novo acids synthesis [substrate effect and insulin mediated stimulation]
  - Hormonal effect on fat intake : a drop in ATP stimulates lipolysis and fat intake [triggers glucagon and epinephrine production]
- Genetic regulations [long time scale]
  - Abstract enzymes  $E_i$  regulate their corresponding fluxes.
  - PUFA activates PPAR and inhibits active-LXR
  - LXR or PPAR triggers abstract enzymes production.
  - Degradation effects occurs on each genetic variable.

Motivations	Mixed differential model	Predictions	Method	Conclusion

# Metabolic (without genetic regulation) model

- Genetic regulation only occurs at long timescales.
- Non genetically regulated model (short timescales) : enzymes have a constant concentration.

$$\begin{array}{l} \frac{dP}{dt} = \operatorname{Gly}(G,\,\mathrm{T}) - \delta_{\mathrm{P}}\,\mathrm{P} - \operatorname{Pdh}(\mathrm{P}) \\ \frac{dA}{dt} = \operatorname{Pdh}(\mathrm{P}) + \operatorname{Oxil}_{qs}(\mathrm{F}_1,\,\mathrm{F}_2,\,\mathrm{T}) + \operatorname{Oxil}_{qs}(\mathrm{F}_2,\,\mathrm{T}) \\ - \operatorname{Krebs}(\mathrm{A},\,\mathrm{T}) - \operatorname{Kout}_{qs}(\mathrm{A},\,\mathrm{F}_2) - \operatorname{Syn}_{qs}(\mathrm{A},\,\mathrm{F}_2,\,\mathrm{T}) - \delta_{\mathrm{A}}\,\mathrm{A} \\ \frac{dF_1}{dt} = \operatorname{Syn}_{qs}(\mathrm{A},\,\mathrm{F}_2,\,\mathrm{T}) - \operatorname{Oxil}_{qs}(\mathrm{F}_1,\,\mathrm{F}_2,\,\mathrm{T}) + \operatorname{Fin1}(\mathrm{F}_1,\,\mathrm{T}) - \delta_{\mathrm{F}_1}\mathrm{F}_1 \\ \frac{dF_2}{dt} = -\operatorname{Oxi2}_{qs}(\mathrm{F}_2,\,\mathrm{T}) + \operatorname{Fin2}(\mathrm{F}_2,\,\mathrm{T}) - \delta_{\mathrm{F}_2}\mathrm{F}_2 \\ \frac{dT}{dt} = \alpha_{\mathrm{G}}\operatorname{Gly}(\mathrm{G},\,\mathrm{T}) + \alpha_{\mathrm{K}}\operatorname{Krebs}(\mathrm{A},\,\mathrm{T}) + \alpha_{\mathrm{O1}}\operatorname{Oxi1}_{qs}(\mathrm{F}_1,\,\mathrm{F}_2,\,\mathrm{T}) \\ + \alpha_{\mathrm{O2}}\operatorname{Oxi2}_{qs}(\mathrm{F}_2,\,\mathrm{T}) - \operatorname{DegT}(\mathrm{T}) \end{array}$$



$\frac{\partial \text{ flux}}{\partial \text{ variable}}$	Gly	Pdh	Krebs	Kout	qs Syn	<sub>qs</sub>  Oxi1	<sub>qs</sub>  Oxi2	<sub>qs</sub>  Fin1	l Fin2	DegT
Р	0	+	0	0	0	0	0	0	0	0
A	0	0	+	+	+	0	0	0	0	0
F <sub>1</sub>	0	0	0	0	0	İ +	0	i –	0	0
$F_2$	0	0	0	0	j 0	j 0	j +	j 0	i —	0
T	-	0	i —	0	i +	i –	i –	i –	i –	İ +
G	+	0	0	0	0	0	0	0	0	0

Motivations	Mixed differential model	Predictions	Method	Conclusion

## Generic model : illustrations

Quantitative versions are used as illustrations of robust dynamical behaviors.

- Rather generic choice of the form of the functions, including numerical constants.
- Check that the constraints are satisfied.
- Low complexity abstractions : only robust features of dynamics of the model are meaningful.

$$\begin{array}{rcl} \frac{d\mathbf{P}}{dt} &=& \frac{l_{\rm Gly}}{l_{\rm Gly}+T^2} \frac{k_{\rm Gly} \mathbf{G}}{k_{\rm Gly}+\mathbf{G}} - \frac{k_{\rm Pdh} \mathbf{P}}{k_{\rm Pdh}+\mathbf{P}} - \delta_{\rm P} \mathbf{P} \\ \\ \frac{d\mathbf{A}}{dt} &=& \frac{k_{\rm Pdh} \mathbf{P}}{k_{\rm Pdh}+\mathbf{P}} + \frac{l_{\rm Oxil}}{l_{\rm Oxil}+T^2} \frac{k_{\rm Oxil} \mathbf{E}_{\rm P} \mathbf{1}}{k_{\rm Oxil}+\mathbf{F}_{\rm 1}} + \frac{l_{\rm Oxil}}{l_{\rm Oxil}+\mathbf{T}_{\rm 2}} \frac{k_{\rm Oxil} \mathbf{E}_{\rm F} \mathbf{1}}{k_{\rm Oxil}+\mathbf{F}_{\rm 1}} + \frac{l_{\rm Oxil}}{l_{\rm Oxil}+\mathbf{T}_{\rm 2}} \frac{k_{\rm Oxil} \mathbf{E}_{\rm S} \mathbf{1}}{k_{\rm Oxil}+\mathbf{F}_{\rm 1}} - \delta_{\rm A} \mathbf{A} \\ \\ \\ \frac{d\mathbf{F}_{\rm 1}}{dt} &=& \frac{k_{\rm Syn} \mathbf{E}_{\rm 1} \mathbf{A}}{k_{\rm Syn}+\mathbf{A}} \frac{l_{\rm Syn} \mathbf{T}^2}{l_{\rm Syn}+\mathbf{T}^2} - k_{\rm Fin1} \mathbf{F}_{\rm 1} + \frac{l_{\rm Fin1}}{l_{\rm Fin1}+\mathbf{T}_{\rm 2}} - \frac{l_{\rm Oxil}}{l_{\rm Oxil}+\mathbf{T}_{\rm 2}} \frac{k_{\rm Oxil} \mathbf{E}_{\rm 2} \mathbf{F}_{\rm 1}}{k_{\rm Oxil}+\mathbf{F}_{\rm 1}} - \delta_{\rm F_{\rm 1}} \mathbf{F}_{\rm 1} \\ \\ \frac{d\mathbf{F}_{\rm 2}}{dt} &=& -k_{\rm Fin2} \mathbf{F}_{\rm 2} + \frac{l_{\rm Fin2}}{l_{\rm Syn}+\mathbf{T}_{\rm 2}} - \frac{l_{\rm Oxil}}{l_{\rm Oxil}+\mathbf{T}_{\rm 2}} \frac{k_{\rm Oxil} \mathbf{E}_{\rm 2} \mathbf{F}_{\rm 1}}{k_{\rm Oxil}+\mathbf{F}_{\rm 1}} - \delta_{\rm F_{\rm 1}} \mathbf{F}_{\rm 1} \\ \\ \frac{d\mathbf{F}_{\rm 2}}{dt} &=& -k_{\rm Fin2} \mathbf{F}_{\rm 2} + \frac{l_{\rm Fin2}}{l_{\rm Gyi}+\mathbf{T}_{\rm 2}} - \frac{l_{\rm Oxil}}{l_{\rm Oxil}+\mathbf{T}_{\rm 2}} \frac{k_{\rm Oxil} \mathbf{E}_{\rm 2} \mathbf{F}_{\rm 2}}{k_{\rm Oxil}+\mathbf{F}_{\rm 2}} - \delta_{\rm F_{\rm 2}} \mathbf{F}_{\rm 2} \\ \\ \frac{d\mathbf{T}}{dt} &=& \alpha_{\rm G} \frac{l_{\rm Gly}}{l_{\rm Gy}+\mathbf{T}_{\rm 2}} \frac{k_{\rm Gly} \mathbf{G}}{k_{\rm Gly} \mathbf{G}} + \alpha_{\rm K} \frac{l_{\rm Krebs}}{l_{\rm Krebs}+\mathbf{T}_{\rm 2}} \frac{k_{\rm Krebs} \mathbf{A}}{k_{\rm Krebs}+\mathbf{A}} + \alpha_{\rm OI} \frac{l_{\rm Oxil}}{l_{\rm Oxil}+\mathbf{T}_{\rm 2}} \frac{k_{\rm Oxil} \mathbf{E}_{\rm 2} \mathbf{F}_{\rm 1}}{k_{\rm Oxil}+\mathbf{F}_{\rm 1}} \\ \\ &+ \alpha_{\rm O2} \frac{l_{\rm Oxil}}{l_{\rm Oxil}+\mathbf{T}_{\rm 2}} \frac{k_{\rm Oxil} \mathbf{E}_{\rm 3} \mathbf{F}_{\rm 2}}{k_{\rm Oxil}+\mathbf{F}_{\rm 2}} - \delta_{\rm T} \mathbf{T} \\ \\ &+ \alpha_{\rm N} \mathbf{F}_{\rm 2} \frac{l_{\rm Oxil}}{\mathbf{F}_{\rm 2}} + \frac{k_{\rm Oxil}}{k_{\rm Oxil}+\mathbf{F}_{\rm 2}}} - \delta_{\rm T} \mathbf{T} \\ \end{array} \end{array}$$

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Motivations	Mixed differential model	Predictions	Method	Conclusion

# Predictions of the model

# Existence of an equilibrium

**Proposition 1** : The genetically regulated model of lipid metabolism admits at least a quasi-stationnary state and an equilibrium state for every parameter G, provided that the following conditions are satisfied

- Fluxes are irreversible [except fatty acids intake/outake]
- The fluxes satisfy the differential constraints
- Degradation terms are linear (except T)
- Irreversible fluxes vanish when there is no substrate.
- All fluxes except degradation saturate at high concentrations
- ATP consumption is an increasing function of ATP with no saturation effect [cells can not store ATP]
- Recovery effect on each metabolic variable : if a variable is zero, then at leastone elementary flux that produces the variable is activated [if the cell contains no PUFA, then PUFA enter the cell]

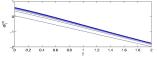
Motivations	Mixed differential model	Predictions	Method	Conclusion

# Uniqueness of equilibrium

- The interaction graph of the model always has a positive circuit.
- Compute a sufficient condition for unicity of equilibrium in terms of derivatives of fluxes.

**Proposition 2** : Both the equilibrium and the quasi-stationnary state of the model are unique if the following condition is fulfilled

 $\begin{array}{l} \label{eq:matrix} \mbox{Mathematic condition } \frac{d\Phi_T^{(2)}}{dT} < 0 \\ \frac{d\Phi_T^{(2)}}{dT} = \alpha_{\rm G} \frac{\partial {\rm Gly}}{\partial {\rm F}_1} + \alpha_{\rm K} (\frac{\partial {\rm Krebs}}{\partial {\rm A}} \frac{\partial {\rm A}^{(2)}}{\partial {\rm T}} + \frac{\partial {\rm Krebs}}{\partial {\rm A}}) + \alpha_{\rm OI} (\frac{\partial {\rm Oxi1}}{\partial {\rm F}_1} \frac{\partial {\rm F}_1^{(2)}}{\partial {\rm T}} + \frac{\partial {\rm Oxi2}}{\partial {\rm T}}) + \alpha_{\rm OI} (\frac{\partial {\rm Oxi1}}{\partial {\rm F}_1} \frac{\partial {\rm F}_1^{(2)}}{\partial {\rm T}} + \frac{\partial {\rm Oxi1}}{\partial {\rm T}}) + \alpha_{\rm OI} (\frac{\partial {\rm Oxi1}}{\partial {\rm F}_2} \frac{\partial {\rm F}_1^{(2)}}{\partial {\rm T}} + \frac{\partial {\rm Oxi1}}{\partial {\rm T}}) - \delta_{\rm T} \end{array}$ 



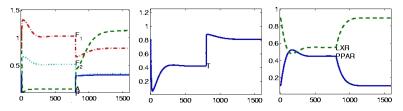
Numerical checking

#### **Biological sufficient conditions**

- Condition on ATP production : oxidation produces much more energy than the Krebs cycle
- Strong lipolytic response condition : when energy is forced to decrease, the total amount of fatty acids increases [intake (insured by lipolysis) overcomes outtake and consumption]

Motivations	Mixed differential model	Predictions	Method	Conclusion

### Simulation : fasting/refeeding protocols



Fasting up to t=750; followed by refeeding

- increase of fatty acids (equilibrium value) after fasting
- overshoot after the beginning of fasting; undershoot after the beginning of refeeding
- Energy (ATP) has an abrupt fall, then it recovers slowly as a result of oxidation
- LXR (equilibrium value) diminishes and PPAR is amplified at fasting

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## Prediction : fatty acids concentration increase at fasting

The following properties are valid for rapid (at quasi-stationarity) as well as for slow (at equilibrium) response as soon as unicity and extra conditions are fulfilled

**Prediction 1** : *ATP decreases during fasting and increases during feeding.* 

**Biological observation** mass of regulating PUFA in the hepatic cell increase during fasting (Lee et al., 2004)

**Prediction 2** : *PUFA increase at fasting iff the intake control overcomes the oxidation control for PUFA.* 

**Prediction 3** : *The curves representing PUFA concentration during refeeding must show an overshoot* : the increase in concentration is greater immediately at quasi-stationarity than later at equilibrium.

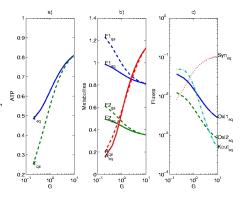
$$\left(\left|\frac{d\mathrm{F}_{2}^{(3)}}{d\mathrm{G}}\right|_{qs} > \left|\frac{d\mathrm{F}_{2}^{(3)}}{d\mathrm{G}}\right|_{eq}\right)$$

Motivations	Mixed differential model	Predictions	Method	Conclusion

#### Simulation : response curves when food G is changing

- Energy T increases with food, fatty acids concentrations decrease with food
- antagonistic relation between synthesis and oxidation : when food G decreases, the synthesis dominated regime changes to an oxidation dominated regime
- buffering effect (effet tampon) : energy T is not zero when food G is zero
- Strong buffering effect : the slope of the dependence of T on G is weaker at equilibrium than at quasi-stationarity.

Genetic regulation increases buffering.

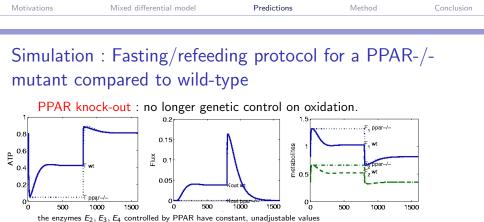


Motivations	Mixed differential model	Predictions	Method	Conclusion
Prediction :	genetic regulation	n reinforce	es energy bu	ffering
at fasting	0 0		0,	U
at lasting				
If unicity co	onditions and control cond	ditions are ful	filled :	
	lipolytic response condition a	nd condition on	the ATP production	l,
• $(R_{\rm T}^{\rm Fin2})$	$\left(-R_{\mathrm{T}}^{\mathrm{Oxi2}}\right)_{eq,qs}>0,$			
$\bullet  \left(\frac{1 - \rho_{\rm F}^{\rm O}}{\rho_{\rm F_1}^{\rm Ox}}\right)$	$R_{\rm F_2}^{\rm Dxi1} = R_{\rm F_2}^{\rm Oxi1} - (1 - \rho_{\rm A}^{\rm Syn}) R_{\rm F_2}^{\rm Syn} - (1 - \rho_{\rm A}^{\rm Syn}) R_{\rm F_2}^{\rm Syn}$	$\left( \rho_{\mathrm{A}}^{\mathrm{Syn}} \mathcal{R}_{\mathrm{F}_{2}}^{\mathrm{Kout}} \right)_{eq}$	> 0	

# **Prediction 4.** Then genetic regulation reinforces the energy buffering effect

- $\bullet\,$  The buffering effect is the variation of T for a fixed variation of G.
- Increasing energy variations is performed by boosting oxidation at fasting.
- Stimulating the decrease of T with the decrease of G is performed by the energy losses by ketone exits and diminished synthesis.

• 
$$\left(\frac{d\mathrm{T}^{(3)}}{d\mathrm{G}}\right)_{qs} > \left(\frac{d\mathrm{T}^{(3)}}{d\mathrm{G}}\right)_{ec}$$



dot curves : mutant type

- incapacity to recover energy on fasting : inefficient oxidation
- no ketone production :  $E_4$  is not produced in mutants
- the fatty acids increase is accentuated under fasting in mutants

3

 the overshoot is replaced by a flat plateau connecting quasi-stationary and equilibrium values

# Predictions about PPAR knock-out

**Biological Observation** : Experiments on transgenic mice : 72h-fast, *fatty acids concentration increases at a higher extent in PPAR knocked-out cells* with respect to wild type cells [Barnouin 2004, Lee 2004]

**Prediction 5** : *PUFA concentration increase under fasting is stronger in PPAR* 

 $\frac{knocked-out \ cells \ compared \ to \ the \ same \ increase \ in \ wild \ type \ cells.}{\left|\frac{dF_2^{(3)}}{dG}\right|_{eq,PPAR-/-}} > \left|\frac{dF_2^{(3)}}{dG}\right|_{eq,WT}.$ 

Prediction 6 : PPAR knock-out reduces energy buffering.

$$\left(\frac{d\mathrm{T}^{(3)}}{d\mathrm{G}}\right)_{eq,PPAR-/-}>\left(\frac{d\mathrm{T}^{(3)}}{d\mathrm{G}}\right)_{eq,WT}$$

Motivations	Mixed differential model	Predictions	Method	Conclusion

# Mathematical framework : successive elimination of variables

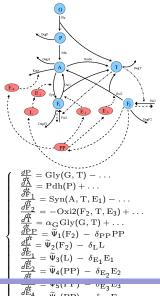
# Study of equilibria

- (Main) Remark 1 : The predictions concern equilibria states and not dynamical properties.
- Remark 2 : Equilibria are characterized by a set of equations equal to zero.
- Remark 3 : One can equilibriate any equation before any other. This does not change the equilibrium state at the end of the process.

# Successive reduction of models !

- Successively eliminate one or several variables.
- Criterion of elimination : existence and unicity of the variable at equilibrium with respect to the remaining variables.
- Compute the constraints of the new model by using the implicit fonction theorem.
- The reduced models have no dynamical meaning but they have the same equilibrium state as the first model.
- The order of reduction can be not intuitive : first reduce the genetic variables. Then some metabolites...

# equilibration of genetic variables



equilibriate genetic variables

$$\begin{array}{ll} \displaystyle \frac{d \underline{P} \underline{P}}{d \underline{t}} = \widetilde{\Psi}_1(\mathbf{F}_2) - \delta_{\mathrm{PP}} \mathrm{PP} & = 0 \\ \displaystyle \frac{d \underline{t}}{d \underline{t}} = \widetilde{\Psi}_2(\mathbf{F}_2) - \delta_{\mathrm{L}} \mathbf{L} & = 0 \\ \displaystyle \frac{d \underline{E}_1}{d \underline{t}} = \widetilde{\Psi}_3(\mathbf{L}) - \delta_{\mathrm{E}_1} \mathbf{E}_1 & = 0 \\ \displaystyle \frac{d \underline{E}_2}{d \underline{t}} = \widetilde{\Psi}_4(\mathrm{PP}) - \delta_{\mathrm{E}_2} \mathbf{E}_2 & = 0 \\ \displaystyle \frac{d \underline{E}_3}{d \underline{t}} = \widetilde{\Psi}_5(\mathrm{PP}) - \delta_{\mathrm{E}_3} \mathbf{E}_3 & = 0 \\ \displaystyle \frac{d \underline{E}_4}{d \underline{t}} = \widetilde{\Psi}_6(\mathrm{PP}) - \delta_{\mathrm{E}_4} \mathbf{E}_4 & = 0 \end{array}$$

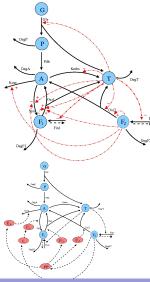
existence and unicity of a solution with respect to the other variables

$$\label{eq:pppeq} \begin{split} PP_{\rm peq}, L_{\rm peq}, E_{\rm 1peq}, E_{\rm 2peq}, E_{\rm 3peq}, E_{\rm 4peq} = \\ \\ \text{fonction}(F_2) \end{split}$$

$$\begin{array}{ll} \frac{\partial \operatorname{Syn}_{\operatorname{peq}}}{\partial F_2} < 0, & \frac{\partial \operatorname{Oxi}_{\operatorname{peq}}}{\partial F_2} > 0\\ \frac{\partial \operatorname{Oxi}_{\operatorname{2peq}}}{\partial F_2} > 0, & \frac{\partial \operatorname{Kout}_{\operatorname{peq}}}{\partial F_2} > 0.\\ & (\Box \rightarrow \langle \overrightarrow{O} \rangle \langle \overrightarrow{a} \rangle \langle$$

Motivations	Mixed differential model	Predictions	Method	Conclusion

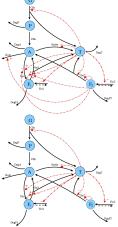
## Partial equilibrium model



- Model of lipid metabolism in which genetic variables are equilibrated
- The constraint table integrate the implicit equilibrated constraints.
- The model has no dynamical meaning
- Same equilibrium states than the extended model

$$\begin{array}{rcl} \frac{dP}{dt} &=& \mathrm{Gly}(\mathrm{G},\mathrm{T}) - \delta_{\mathrm{P}}\mathrm{P} - \mathrm{Pdh}(\mathrm{P}) \\ \frac{dF}{dt} &=& \mathrm{Pdh}(\mathrm{P}) + \mathrm{Oxi1}_{\mathrm{peq}}(\mathrm{F}_{1},\mathrm{F}_{2},\mathrm{T}) + \mathrm{Oxi2}_{\mathrm{peq}}(\mathrm{F}_{2},\mathrm{T}) \\ &-\mathrm{Krebs}(\mathrm{A},\mathrm{T}) - \mathrm{Kout}_{\mathrm{peq}}(\mathrm{A},\mathrm{F}_{2}) - \mathrm{Syn}_{\mathrm{peq}}(\mathrm{A},\mathrm{F}_{2},\mathrm{T}) - \mathrm{d} \\ \frac{dF_{1}}{dt} &=& \mathrm{Syn}_{\mathrm{peq}}(\mathrm{A},\mathrm{F}_{2},\mathrm{T}) - \mathrm{Oxi1}_{\mathrm{peq}}(\mathrm{F}_{1},\mathrm{F}_{2},\mathrm{T}) + \mathrm{Fin1}(\mathrm{F}_{1},\mathrm{T}) - \\ \frac{dF_{2}}{dT} &=& -\mathrm{Oxi2}_{\mathrm{peq}}(\mathrm{F}_{2},\mathrm{T}) + \mathrm{Fin2}(\mathrm{F}_{2},\mathrm{T}) - \delta_{\mathrm{F}_{2}}\mathrm{F}_{2} \\ \frac{dT}{dt} &=& \alpha_{\mathrm{G}}\mathrm{Gly}(\mathrm{G},\mathrm{T}) + \alpha_{\mathrm{K}}\mathrm{Krebs}(\mathrm{A},\mathrm{T}) + \alpha_{\mathrm{O1}}\mathrm{Oxi1}_{\mathrm{peq}}(\mathrm{F}_{1},\mathrm{F}_{2},\mathrm{T}) \\ \frac{\partial\mathrm{flux}}{\partial \mathrm{variable}} & \mathrm{GlyPdh}\mathrm{Krebs}\mathrm{Kout}_{\mathrm{peq}}\mathrm{Syn}_{\mathrm{peq}}\mathrm{Oxi1}_{\mathrm{peq}}\mathrm{Oxi2}_{\mathrm{peq}}\mathrm{Fin1}\mathrm{Fin2}\mathrm{De} \\ \\ \frac{\partial}\mathrm{F}_{1} & 0 & 0 & 0 & 0 & 0 & 0 \\ \mathrm{F}_{2} & 0 & 0 & 0 & + & + & + & 0 & 0 & 0 \\ \mathrm{F}_{2} & 0 & 0 & 0 & + & - & + & + & 0 & - & 0 \\ \\ \mathrm{T} & - & 0 & - & 0 & + & - & + & + & 0 & - & 0 \\ \end{array} \right]$$

Motivations	Mixed differential model	Predictions	Method	Conclusion			
Compare non genetically and genetically regulated models							
The equilibrium states of the non genetically regulated and partial equilibriate							
models check the qame equations with a different table of constraints.							
G	$\begin{pmatrix} \frac{dP}{dt} = 0 \\ \frac{dA}{dA} \end{pmatrix}$	$Gly(G, T) - \delta_P P - Pc$	lh(P)				



$$\begin{array}{lll} \frac{dP}{dt} &=& \operatorname{Gly}(\operatorname{G},\operatorname{T}) - \delta_{\operatorname{P}}\operatorname{P} - \operatorname{Pdh}(\operatorname{P}) \\ \frac{dA}{dt} &=& \operatorname{Pdh}(\operatorname{P}) + \operatorname{Oxil}_{\operatorname{peq},gnr}(\operatorname{F}_1,\operatorname{F}_2,\operatorname{T}) + \operatorname{Oxil}_{\operatorname{peq},gnr}(\operatorname{F}_2,\operatorname{T}) \\ &\quad -\operatorname{Krebs}(\operatorname{A},\operatorname{T}) - \operatorname{Kout}_{\operatorname{peq},gnr}(\operatorname{A},\operatorname{F}_2) - \operatorname{Syn}_{\operatorname{peq},gnr}(\operatorname{A},\operatorname{F}_2,\operatorname{T}) - \\ \frac{dF_1}{dt} &=& \operatorname{Syn}_{\operatorname{peq},gnr}(\operatorname{A},\operatorname{F}_2,\operatorname{T}) - \operatorname{Oxil}_{\operatorname{peq},gnr}(\operatorname{F}_1,\operatorname{F}_2,\operatorname{T}) + \operatorname{Fin1}(\operatorname{F}_1,\operatorname{T}) - \\ \frac{dF_2}{dt} &=& -\operatorname{Oxi2}_{\operatorname{peq},gnr}(\operatorname{F}_2,\operatorname{T}) + \operatorname{Fin2}(\operatorname{F}_2,\operatorname{T}) - \delta_{\operatorname{F}_2}\operatorname{F}_2 \\ \frac{dT}{dt} &=& \alpha_{\operatorname{G}}\operatorname{Gly}(\operatorname{G},\operatorname{T}) + \alpha_{\operatorname{K}}\operatorname{Krebs}(\operatorname{A},\operatorname{T}) + \alpha_{\operatorname{O1}}\operatorname{Oxi1}_{\operatorname{peq},gnr}(\operatorname{F}_1,\operatorname{F}_2,\operatorname{T}) \\ &\quad + \alpha_{\operatorname{O2}}\operatorname{Oxi2}_{\operatorname{peq},gnr}(\operatorname{F}_2,\operatorname{T}) - \operatorname{DegT}(\operatorname{T}) \end{array}$$

<u>∂ flux</u> ∂ variable	Gly	Pdh	Krebs	$\operatorname{Kout}_{\operatorname{peq}}$	$syn_{peq}$	Oxi1 <sub>peq</sub>	Oxi2 <sub>pe</sub>	<sub>4</sub> Fin1	Fin2	DegT
				gnr	gnr	gnr	gnr			
P	0	+	0	0	0	0	0	0	0	0
A	0	0	+	+	+	0	0	0	0	0
F <sub>1</sub>	0	0	0	0	0	+	0	—	0	0
$\mathrm{F}_2 \stackrel{gnr}{\underset{peq}{peq}}$	0	0	0	0 +	0	0 +	+	0	_	0
Т	_	0	_	0	+	_	_	_	_	+
G	+	0	0	0	0	0	0	0	0	0

Compare the equilibrium states of the models to understand the role of genetic regulations

Motivations	Mixed differential model	Predictions	Method	Conclusion
• Eliminate F $P^{(1)}(G, T)$ • Eliminate A $\Phi_A(P^{(1)}(G, T))$ The system $(A^{(2)}(G, T))$ theorem.	$ \begin{array}{l} (A,F_{1},F_{2},T) = 0; \ \Phi_{F_{1}}(A,F_{1},F_{1},F_{2},F_{$	T) = 0 has a uniq city deduced from $P_2, T$ ) = 0; $\Phi_{F_2}(F_2, T)$ = because of the Gal	$\frac{\partial \Phi_{\rm P}}{\partial {\rm P}} < 0$ ) = 0 le-Nikaido	
Jacobian $J_{s}$ system $f_{x} =$ Reduce T v	lo : If $(x, y, z) \rightarrow (f_x, f_y, f_z)$ , such that all the principal $f_y = f_z = 0$ has a unique with respect to G $(G, T), F_1^{(2)}(G, T), F_2^{(2)}(G)$	minors of $-J$ are solution if a solution	positive, the 🍈	
Unicity con	dition : sufficient condition	n for $\frac{d\Phi_{\rm T}}{d{ m T}} < 0.$		$\smile$
	ty condition is satisfied, co I values in different models ant).			(豆) 豆 のQ(の)
:				

Motivations	Mixed differential model	Predictions	Method	Conclusion
Conclusi	on			

Conclusion

- Abstract model : only 12 variables to describe the regulations and main fluxes in lipid metabolism.
- Qualitative model : differential equations together with a table of constraints on elementary fluxes.
- Simulations : provide rough behavior of the system
- Reduction method : allows to make predictions on the static properties of model even if the model is not explicit.
- Compatible with observations : behavior of fatty acids; PPAR mutants; understand the role of regulation.

Motivations	Mixed differential model	Predictions	Method	Conclusion	
To do					

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- Find the most efficient sequence of equilibration
- Study the stability of equilibria
- Distinguish between the different types of fatty acids
- Relation with extended models (KEGG and genetic regulations)
- Other species or tissues?