Algorithmic complexity and ABM for sustainability

07 June 2024

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Training

- Engineering degree on Computational Systems
- Masters degree on Computer Science
- PhD in informatics
- 10+ years of experience in Sustainability / LCA

Caveat

Not traditional "algorithmic complexity"

- O(n) , o(n)
- Kolmogorov complexity
- Etc.

Rather

Including "complexity" in simulation for sustainability.

Complexity?

A “complex system” is in general any system comprised of
a great number of heterogeneous entities, among which local
interactions create multiple levels of collective structure and organization.

[*Chavalarias et al.* , *2009*]

ABM approach for complexity

- Computational nature: it requires simulation to obtain answers for the questions that the models were built for.
- “To an observer B, an object A* is a model of an object A to the extent that B can use A* to answer questions that interest him about A.” *[Minsky, 1968]*
- Models are “simulated”: set of instructions, rules, equations or constraints to generate the input and output behaviour *[Zeigler et al., 2000]*
- An agent can be a physical or virtual entity that can act, perceive its environment (in a partial way) and communicate with others, is autonomous and has skills to achieve its goals and tendencies. *[Ferber 1999]*

Structure

- Control of complex systems
- Applications
  - Mobility
  - Agriculture
- Conclusions

Control of complex systems

How to avoid or favor specific behaviours ?

Challenges

- Many points of view
- Pre-existing systems
- Need for models

Hypothesis Gouvernance

- Relax optimality by using multiple models

Hypothesis Exogenous

- External control

Hypothesis Multi-agent models

- Useful for *modelling* complex systems

Principles

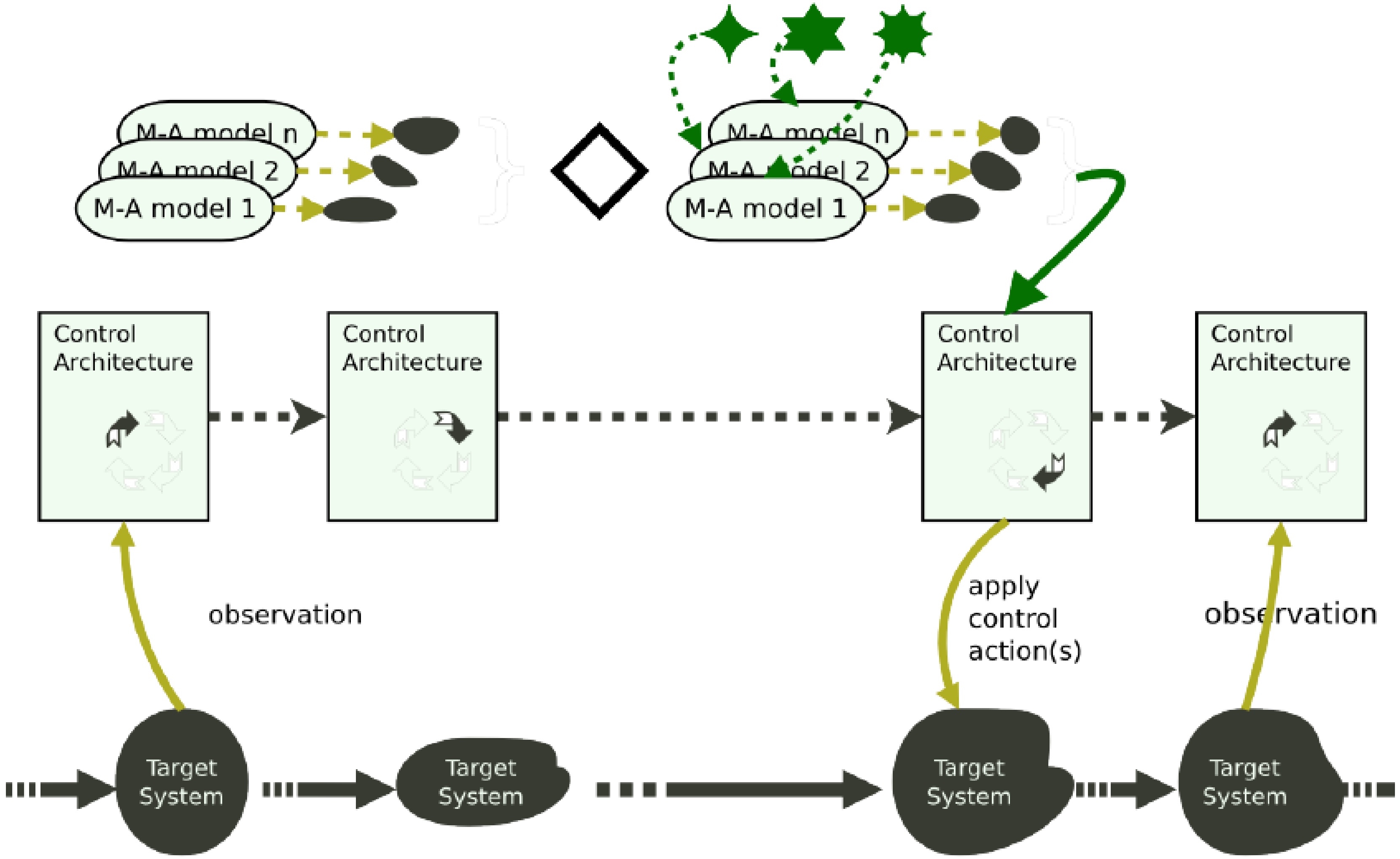
A COHERENT EXOGENOUS ARCHITECTURE

INTEGRATING MULTI-AGENT SIMULATION

IN A CONTROL LOOP

USING THE EQUATION-FREE APPROACH SAMAEY (2010) .

Workflow



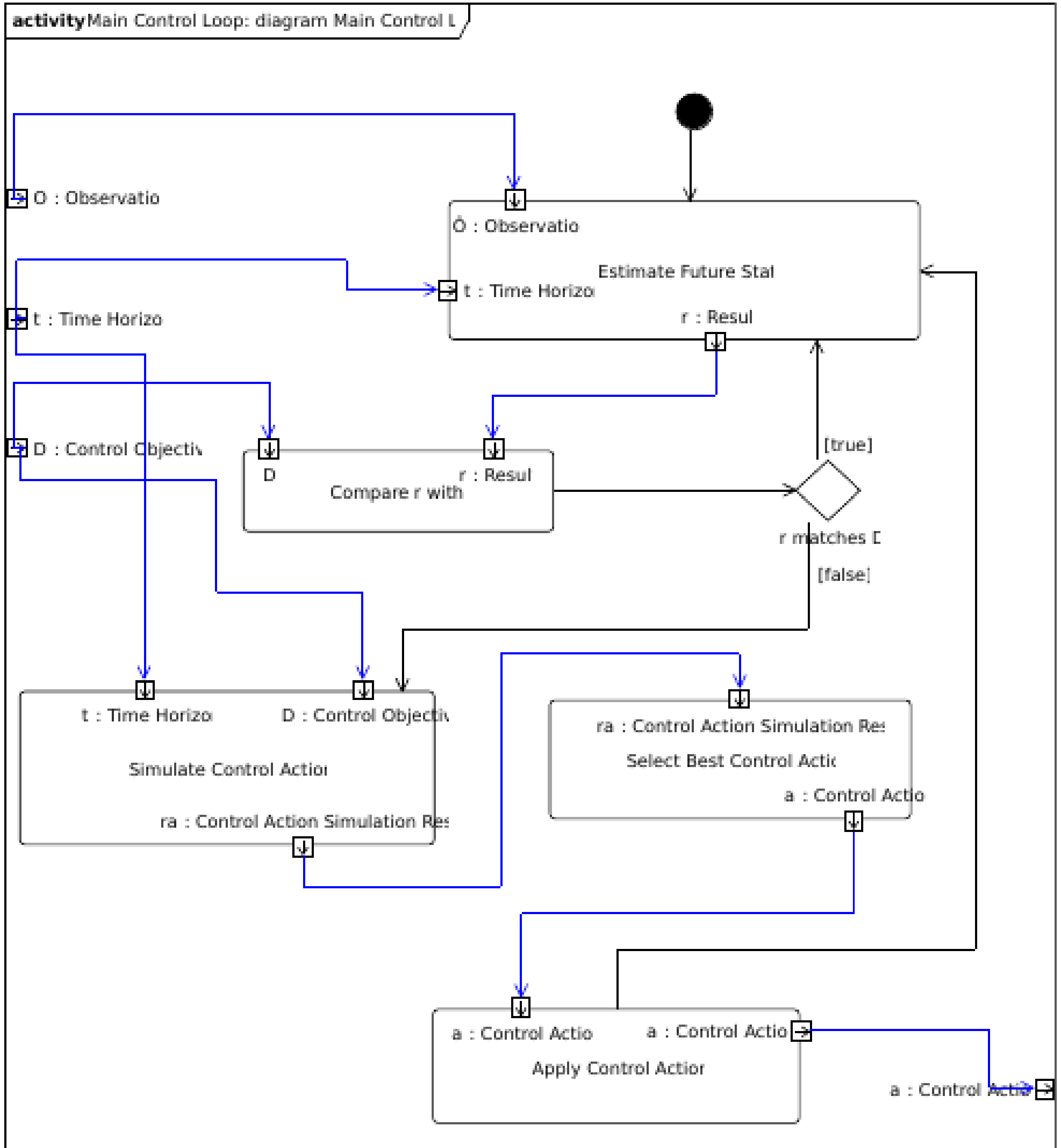
M-A model n
M-A model 2
M-A model 1
M-A model n
M-A model 2
M-A model 1
Control Architecture
Control Architecture
Control Architecture
Control Architecture
observation
apply control action(s)
observation
Target System
Target System
Target System
Target System

Implementation

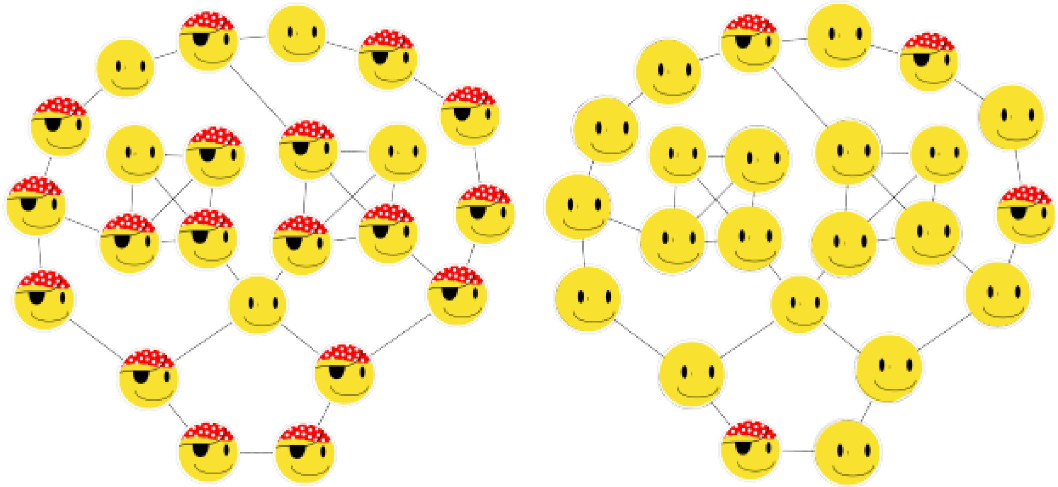
Modules

- Observation
- Future state Estimation
- Simulation
- Control action selection

Formalized by using SysML



Control experiments : Avoid a target system with a majority of “free-riders”



Experimental Approach

Target system w/majority of free-riders + Control Architecture → Target system w/majority of sharing peers

First conclusions

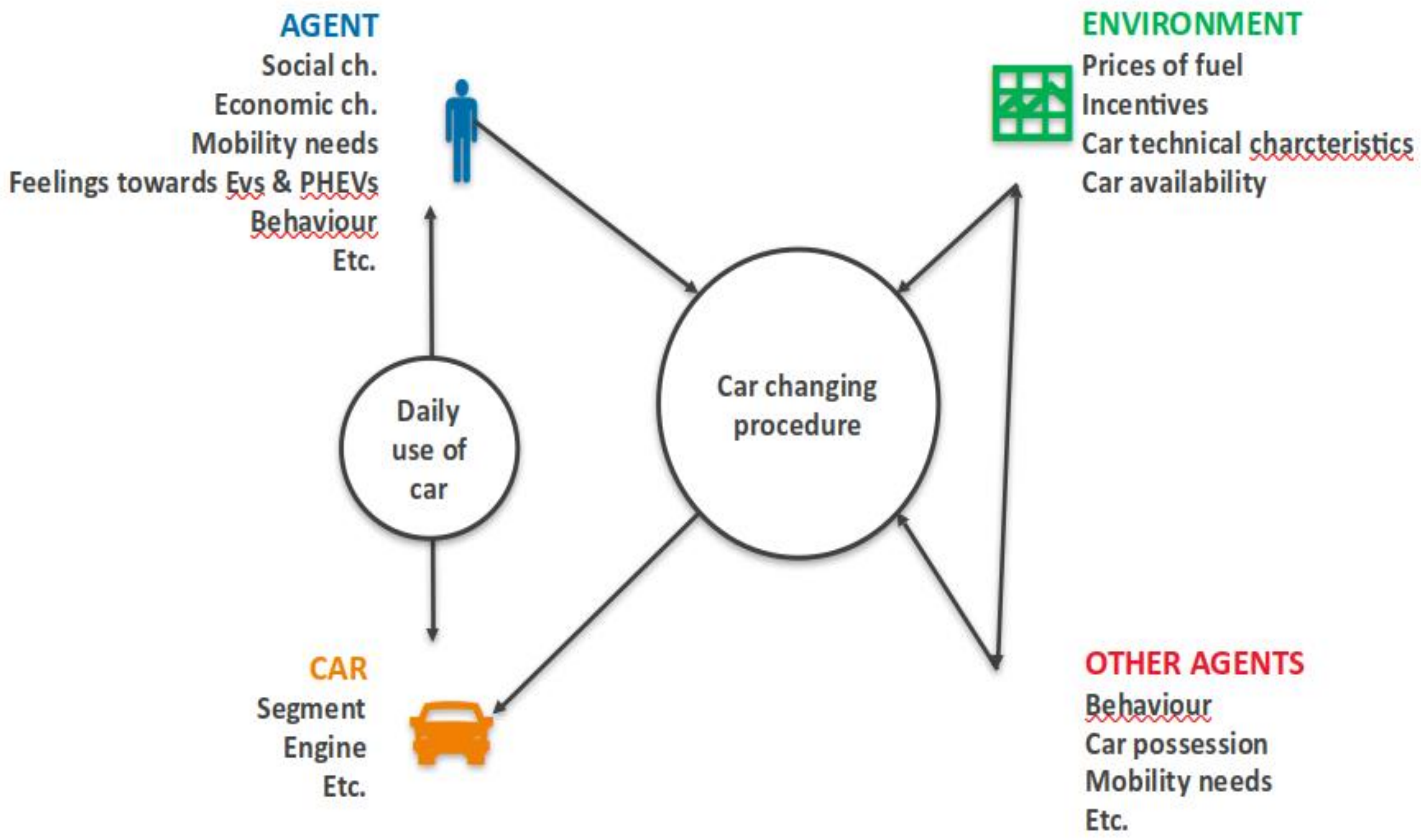
General question : Control of pre-existing complex systems

- We proposed a control architecture for complex systems, with an equation-free approach using multi-agent model simulation

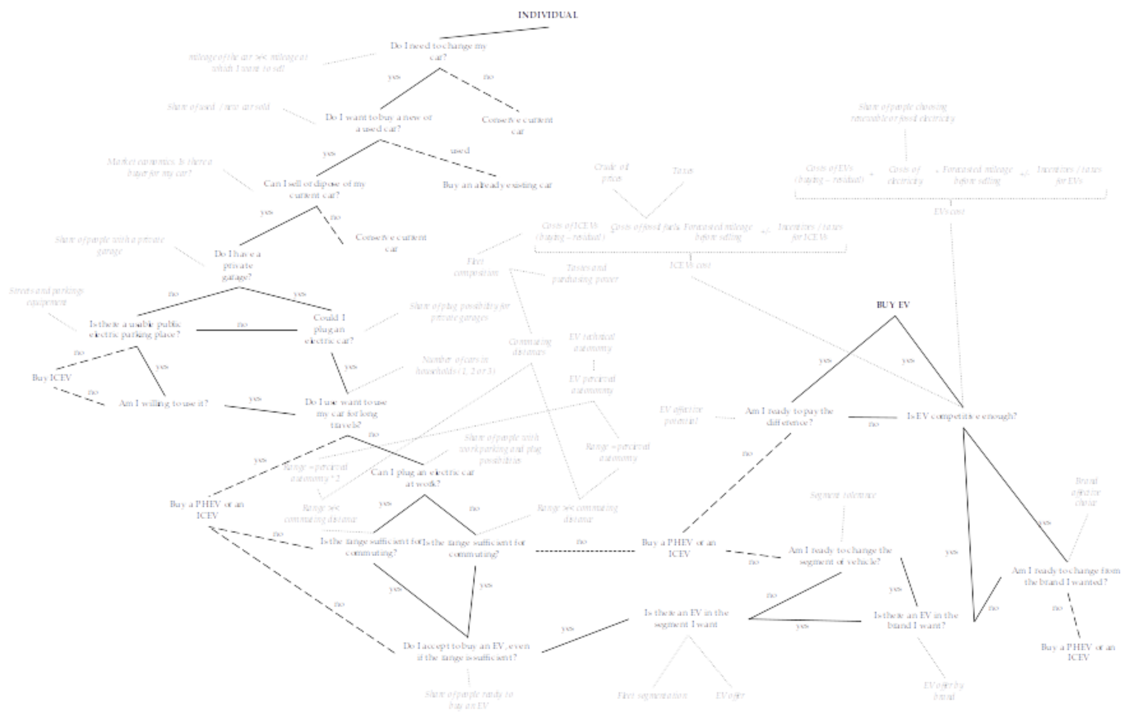
Specific question : Influence of working hypotheses in the context of control

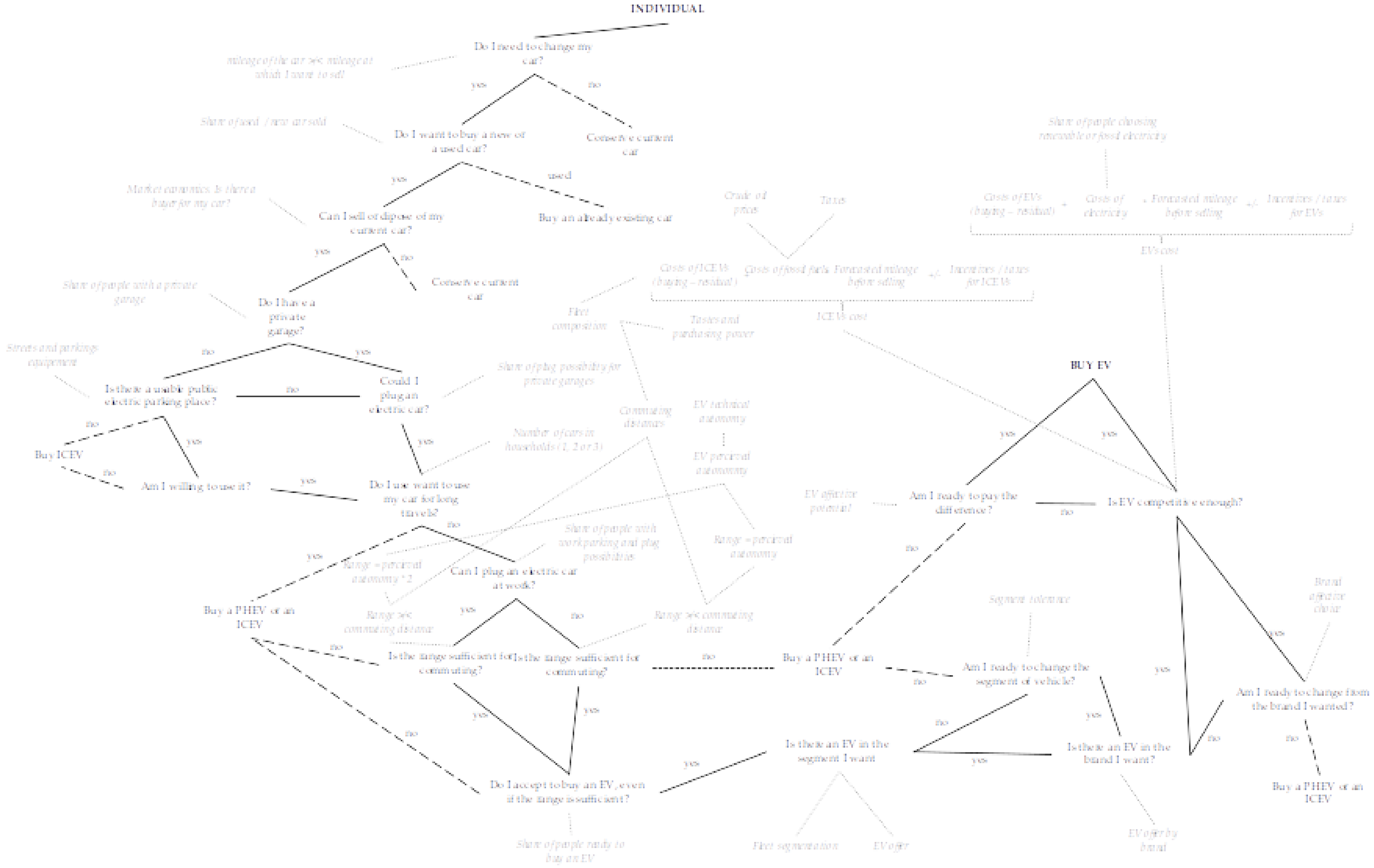
- The modular and formal design of the architecture allows to make explicit the questions of validity, calibration, correspondence and selection of models.

Application: Mobility



Decision tree for buying a new personal EV





INDIVIDUAL
Do I need to change my car?
Mileage of the car >/< mileage at which I want to sell
yes
no
Do I want to buy a new or a used car?
Share of used / new car sold
Conserve current car
yes
used
Can I sell or dispose of my current car?
Market dynamics: Is there a buyer for my car?
Buy an already existing car
yes
no
Conserve current car
Do I have a private garage?
Share of people with a private garage
no
yes
Streets and parkings equipment
Is there a usable public electric parking place?
no
Could I plug an electric car?
Share of plug possibility for private garages
no
yes
yes
Buy ICEV
no
Am I willing to use it?
yes
Number of cars in households (1, 2 or 3)
Do I use/want to use my car for long travels?
yes
no
Buy a PHEV or an ICEV
Range = perceived autonomy * 2
Can I plug an electric car at work?
Share of people with work parking and plug possibilities
yes
no
Range >/< commuting distance
Range >/< commuting distance
no
Is the range sufficient for commuting?
Is the range sufficient for commuting?
no
yes
yes
no
Do I accept to buy an EV, even if the range is insufficient?
Share of people ready to buy an EV
yes
Fleet composition
Taxes and purchasing power
Commuting distance
EV technical autonomy
EV perceived autonomy
Range = perceived autonomy
Crude oil prices
Taxes
Costs of ICEVs (buying – residual)
Costs of fossil fuels
Forecasted mileage before selling
Incentives / taxes for ICEVs
ICEVs cost
Share of people choosing renewable or fossil electricity
Costs of EVs (buying – residual)
Costs of electricity
Forecasted mileage before selling
Incentives / taxes for EVs
EVs cost
BUY EV
yes
yes
EV affective potential
Am I ready to pay the difference?
no
Is EV competitive enough?
no
Buy a PHEV or an ICEV
no
Segment tolerance
Am I ready to change the segment of vehicle?
no
yes
Is there an EV in the segment I want
yes
Fleet segmentation
EV offer
Is there an EV in the brand I want?
EV offer by brand
yes
yes
no
Brand affective choice
Am I ready to change from the brand I wanted?
no
Buy a PHEV or an ICEV

Conclusions 3

We showed that it is feasible to couple LCA and ABM, even for complex large scale systems such as mobility. Here, the ABM is not only used for scenario elaboration but also to obtain a life cycle inventory that encompasses all the variability of the car characteristics and uses.

Attributional LCAs of single vehicles cannot be scaled up to assess large scale policies as the conclusions on a single model can be misleading.

The impact of policies aiming at deploying EVs have mixed consequences, depending on the impact considered, but we recommend pursuing them, while encouraging all solutions increasing battery lifetime and promoting renewable electricity.

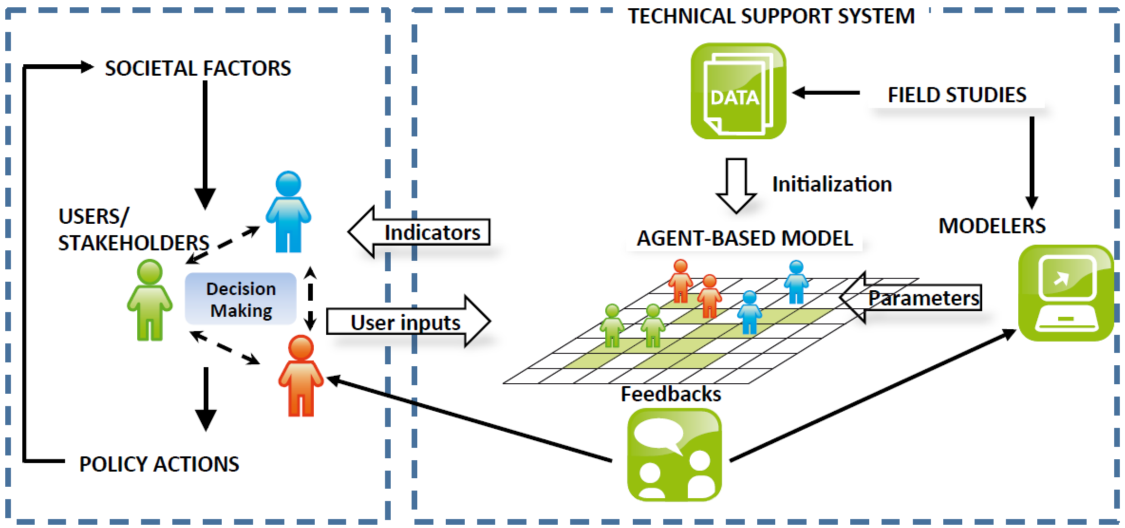
We think that the large amounts of data generated by the coupling of ABM and LCA could clearly be beneficial for the LCA community

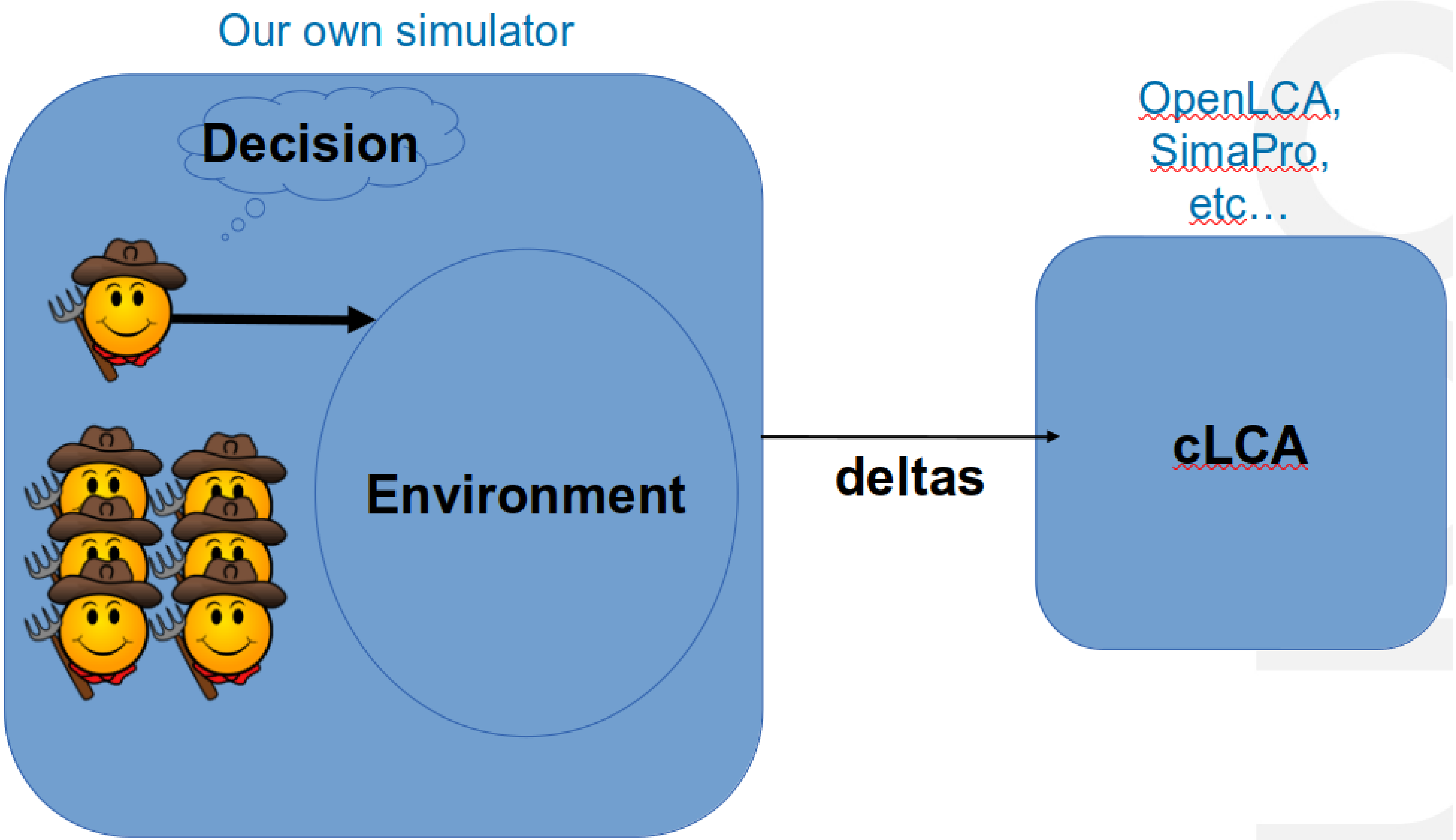
Application: Agriculture

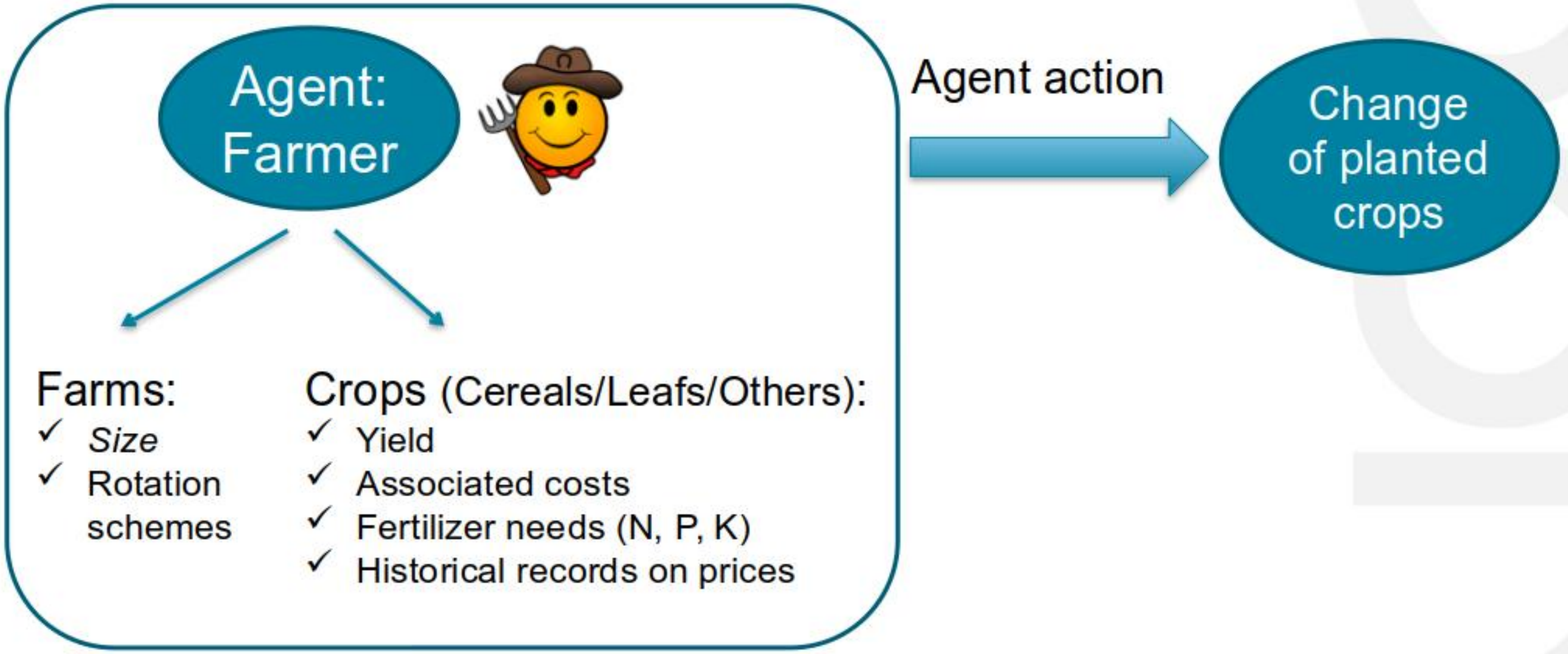
- Evaluate environmental consequences of agricultural policies…
    - Subsidies
    - Taxes
    - Regulation (crop proportions)
- … taking into consideration the individual level behaviour of farmers
- Incentive mechanisms to increase the area under maize in Luxembourg to produce biofuels

C-LCA:

- Identifying the changes (Δ), in terms of potential environmental impacts induced into a system, caused by human driven actions, most often related to policy or strategic decisions.

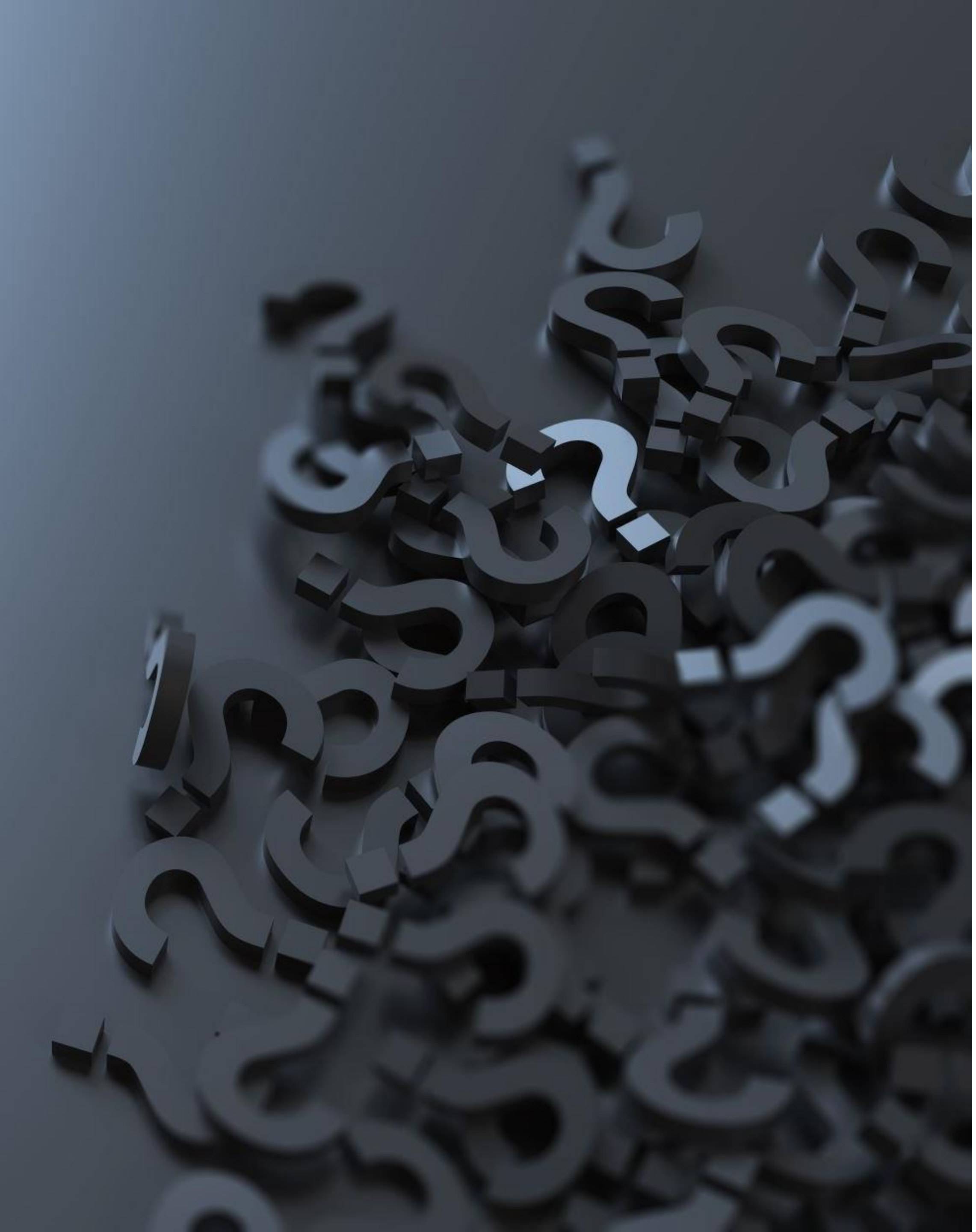



Our own simulator
Decision
Environment
deltas
OpenLCA,
SimaPro,
etc…
cLCA


Agent:
Farmer
Farms:
✓ *Size*
✓ Rotation schemes
Crops (Cereals/Leafs/Others):
✓ Yield
✓ Associated costs
✓ Fertilizer needs (N, P, K)
✓ Historical records on prices
Agent action
Change of planted crops

Conclusions 3

- We have evidence in the form of aggregated data.
- Actual farming landscape includes other highly important entities
- Price Discovery mechanisms
- Agent interaction
- Events (Shock)
- “behavioural” facet => we conduct a survey
- Animal farms, mixed systems
- Farmers share knowledge



Final remarks

- Complexity aproaches (ABM, equation-free) allow to observe multiple levels
    - Microscopic
    - Mesoscopic
    - Macroscopic
- Identification of emergent characteristics of the system
- Validity not only on the "do the results match historical records"
    - Model structure also for validity
- Experimental approach feasible
    - Test multiple hypotheses on behaviour or scenario conditions