Predation model
Hybridisation_A

Raphael Klein, EPFL

February 19, 2020

This reports the hybridisation of the predation model with the ACF implementation of the policy model. It outlines how the models were hybridised and goes through the initialisation of the models and the experiments that will be run using these models.

Contents

1 The problem tree

Overall, the problem tree is given as follows:

- Policy core problems:
  1. Sheep - The amount of sheep on the grid.
  2. Wolf - The amount of wolves on the grid.
  3. Fully grown grass - The amount of fully grown grass on the grid.
- Secondary problems:
  1. Net sheep population change - This is the difference between initial and final amount of sheep.
  2. Net wolf population change - This is the difference between initial and final amount of wolves.
  3. Net grown grass patch change - This is the difference between initial and final amount of grown grass patches.

Note that the secondary issues and the policy core issues are the same. The main reason behind this choice is the simplicity of the model. The model is so simple that the it is difficult to find any different policy core issues.

2 The policy instruments

The policy instruments within the policy tree are implemented using incremental increases and decreases in the following exogenous parameters.

1. Change sheep reproduction [CR-0.01/+0.01]
2. Change wolf reproduction [WR -0.01/+0.01]
3. Change grass regrowth [GR-2/+2]

3 The steps for model integration

This section presents the steps that are needed to connect a policy context model, in this case the predation model, to the policy process model.

1. Before any coding, define what the belief tree and the policy instruments will be for the predation model.
2. Copy the policy emergence model files into the same folder.
3. In `runbatch.py`, replace the policy context items by the predation model.
4. In `runbatch.py`, make sure to initialise the predation model appropriately.
5. Change the `input goalProfiles` files to have the appropriate belief tree structure of the predation model.
6. In `model module interface.py`, construct the belief tree and the policy instrument array.
7. Make sure that the step function in the `model predation.py` returns the KPIs that will fit in the belief system in the order DC, PC and S. If no DC is considered, then include one value of 0 at least. All KPIs need to be normalised.
8. Modify the step function of the `model predation.py` to include a policy implemented.
9. Introduce the changes that a policy implemented would have on the model in `model predation.py`.

3.1 Code documentation

The following is the documentation for the hybrid model. This includes the script files that are needed to connect the policy context model (electricity model in the present case) with the policy emergence model.

run_batch.py This script is used to simulate the entire hybrid model for different scenario. To this effect, it contains the inputs for all models. This includes the inputs for the hybrid model itself (number of steps, duration of steps, number of repetitions, number of scenarios, ...), the inputs for the policy context, and the inputs for the policy emergence model (actor distribution, actor belief profiles, ...)

This is then followed by the for loop that simulate the hybrid model. This includes the simulation of a warm up round. Then the policy context is simulated n times for every policy process step simulation. Each feeds the other through indicators and policy selection. The results are all extracted using the data collector from each of the model. The files are saved within .csv files.

model_module_interface.py This script is used to connect the policy context to the policy emergence model. This part of the model will change every time a new policy context is considered. For this, two functions are considered:

- `belief_tree_input()`

  This function is used to define the agent issue tree. It includes the specification of the deep core, policy core and secondary issues.

- `policy_instrument_input()`

  This function is used to define the policy instruments that the agents can select.

4 The steps for model simulation

This section presents the steps that are needed to connect a policy context model, in this case the predation model, to the policy process model.

1. For the policy process:
   (a) Define a set of hypotheses to be tested
   (b) Define scenarios that will be needed to assess the hypotheses
   (c) Choose the agent distribution based on the scenarios constructed

(d) Set the preferred states for the active agents and the electorate along with the causal beliefs to be used. This should all be based on the scenarios that have been constructed.

2. For the predation model:

    (a) Define the initial values for the main parameters

    (b) Define the parameters that will be recorded

3. Save the right data from the model.

5 Model hypotheses

Because of the complexity of the model, there are a lot of hypotheses that can be tested with this ACF policy emergence model. However, we will try not to demonstrate the same hypotheses that were demonstrated for the SM. This would be redundant. This includes all of the hypotheses that establish a causal relation between policy change and environment change. The focus will instead be placed on the impact that the new elements, for each of the model variations, has on policy change and on the dynamics of the model. This includes the impact of policy learning and coalitions on policy change.

5.1 The +PL model

The main research question that we want to answer with this model is:

What impact does policy learning have on policy change within the ACF+PL model?

Several hypotheses are considered to answer this question:

- H1: Policy learning leads to policy change.
- H2: The resources distribution will affect the speed and the direction of policy learning.
- H4: The balance of power will affect the speed and the direction of policy learning.

5.2 The +Co model

The main research question that we want to answer with this model is:

What impact do coalitions have on policy change within the ACF+Co model?

Several hypotheses are considered to answer this question:

- H1: Broader coalitions will normalise all of the beliefs around its dominant belief.
- H2: Powerful but restrictive coalition will influence strongly other agents until they are in the same coalition.

6 Model scenarios

We differentiate the scenarios that will be run for the +PL and the +Co models within this section. For each scenario, we have to consider the belief system of the agents, the agent distribution and the resource distribution. Though in the formalisation of the model we do not make a mention of affiliations (except when it comes to the electorate influence), we will still use affiliations here to simplify the initialisation of the agents for the policy emergence model.

6.1 The +PL model

For now only the benchmark scenario and scenario 1 are considered. These basically test the different impact of a change of resources on policy learning and the associated effect on policy change, if any. For each of the scenario, the preferred states of the agents are shown in Table 1, their causal relations are provided in Table 2 and the agents and resources distribution are provided in Table 3.

Note that for now we only allow the agents to influence one another on their preferred states and not on their causal beliefs.

- Scenario 0 - No interactions

  Scenario 0 is a scenario where no interactions are taken into account. It is the SM simulation. This is used to compare with the results from the model with the interactions introduced.

- Scenario 1 - Benchmark interactions

  The benchmark scenario is to be used as a benchmark. It is a simulation of the predation model with the policy emergence model. Two affiliations are considered. Affiliation 0 consists of two policy makers and four policy entrepreneurs (2 PM and 4 PE) with high resources and a preference for sheep favouring policies. Affiliation 1 consists of one policy maker and four policy entrepreneurs (1 PM and 4 PE) with low resources and a preference for wolf favouring policies. The preferred states for the agents are provided in Table 1. The causal beliefs used as given in Table 2.

- Scenario 2 - Different resource distribution

  Have a simulation where the resources distribution is 99 (affiliation 1) to 1 (affiliation 0). This makes one affiliation dominating, the minority one. Observe where the policy learning ends up and see whether that ends up affecting the policy instruments being selected.

- Scenario 3 - External event on a preferred state (policy core)

  Introduce an external event on one of the preferred states of all agents to influence their beliefs and observe whether that makes a difference in their choice of policy selection. This external events happens after tick 4.

- Scenario 4 - External event on a preferred state (secondary issue)

  Introduce an external event on one of the preferred states of all agents to influence their beliefs and observe whether that makes a difference in their choice of policy selection. This external events happens after tick 4.

- Scenario + (for the +PL scenario) - not discussed here

  Future scenarios could also explore the influence of the electorate on actors with more resources. It could look at how a change in the actor distribution might have an impact on the outcomes of the simulation.

6.2 The +Co model

The coalitions introduce three new parameters mainly: a creation coherence parameters that defines the threshold of belief difference for the creation of new coalitions, a parameter that defines the amount of resources that agents provide to coalitions they are joining, and a parameter that defines which policy core issue is the issue that coalitions assemble around. These are all varied in the following scenarios.

- Scenario 5 - Coalition benchmark

  The first scenario considered for the +Co model is seen as a benchmark and will be used to check it against the model without coalitions. The policy core issue of interest is the sheep one (PC0), the threshold for coalition creation is set at 0.15 and the amount of resources shared with a coalition is set to 50% for agents that join coalitions.

- Scenario 6 - Coalition different PC interest

  The second coalition scenario changes the policy core issue of interest to the wolf one (PC1). The rest of the parameters stay the same: the threshold for coalition creation is set at 0.15 and the amount of resources shared with a coalition is set to 50% for agents that join coalitions.

- Scenario 7 - Coalition different PC interest

  The third coalition scenario changes the policy core issue of interest to the grass one (PC2). The rest of the parameters stay the same: the threshold for coalition creation is set at 0.15 and the amount of resources shared with a coalition is set to 50% for agents that join coalitions.

- Scenario 8 - Coalition LHS

  For this last scenario, the two coalition parameters are jumbled with a LHS algorithm. The range for the coalition creation threshold is between 0.01 and 0.25 while the range for the resources shared is set between 5% and 75%. A LHS algorithm is used to create 50 different inputs normally distributed. This simulation will then be repeated only 10 times to generate a total of 500 runs.

6.3 The +PK model

The partial knowledge model is only partially tested both with the benchmark policy learning scenario and the benchmark coalition scenario.

- Scenario 9 - PK with +PL
- Scenario 10 - PK with +Co

	PC1 Sheep	**PC2** Wolves	**PC3** Grass	**S1** Sheep growth	**S2** Wolves growth	**S3** Grass growth
Scenario 0/1/2/5/6/7/8/9/10						
Affiliation 0 - Pro sheep						
Value	400	50	2000	75	-50	200
Norm.	0.80	0.10	0.80	0.88	0.25	0.70
Affiliation 1 - Pro wolves						
Value	200	175	1700	50	25	120
Norm.	0.40	0.35	0.68	0.75	0.63	0.62
Scenario 3 (after)						
Affiliation 0 - Pro sheep						
Value	50	50	250	75	-50	200
Norm.	0.10	0.10	0.10	0.88	0.25	0.70
Scenario 4 (after)						
Affiliation 0 - Pro sheep						
Value	400	50	2000	-80	-50	200
Norm.	0.80	0.10	0.80	0.10	0.25	0.70

Table 1: Preferred states for the policy makers on a the interval [0,1] for scenarios 0 and 1.

7 Initialisation of the model

7.1 The predation model

The parameters that need to be initialised for the predation model are given by:

- Grid height: 50

Scenario 0/1/2/3/4/5/6/7/8			
	PC1	PC2	PC3
-S1	1.00	0.75	-0.75
-S2	-0.75	1.00	0.25
-S3	0.50	0.75	1.00

Table 2: Causal beliefs for the policy makers. These causal relations can be read as: an increase of 1 in S2 will lead to a decrease of 0.75 in PC1. They are all given on the interval [-1,1].

Scenarios	**0/1/3/4/5/6/7/8**		**2**	
Affiliations	0	1	0	1
Policy makers	2	1	2	1
Policy entrepr.	4	4	4	4
Resources	75	25	10	100

Table 3: Agents and resource distribution for each of the scenarios.

- Grid width: 50
- Initial amount of grass: about 50% of the grid
- Initial number of sheep: 250
- Sheep reproduce rate: 4%
- Sheep gain from food: 6
- Initial number of wolves: 25
- Wolf reproduce rate: 5%
- Wolf gain from food: 35
- Grass regrowth time: 30

Note that the initial parameter as chosen such that if only the predation model is run, it has a stable configuration. Furthermore the onus is placed on the simulation of the policy process, therefore no scenarios are placed on the predation model side of the simulation.

7.2 The policy process model

7.3 The hybrid model

Conflict level thresholds ...

Resources spent

8 Results

There are a number of results we can look at:

1. Predation model results (count of sheep and wolves)
2. Policy selection
3. Belief evolution (both policy core and secondary preferred states) per affiliation of course - This is the new part in this part of the simulation - This can be used to track the policy learning happening within the system.

The figures are presented in an order that builds the model with first the preferred state evolution and then selection of the policy core issues. This is followed by the preferred state evolution and then selection of the secondary issues. This is followed by the policy instrument selection, and then the outcome changes in the predation model.

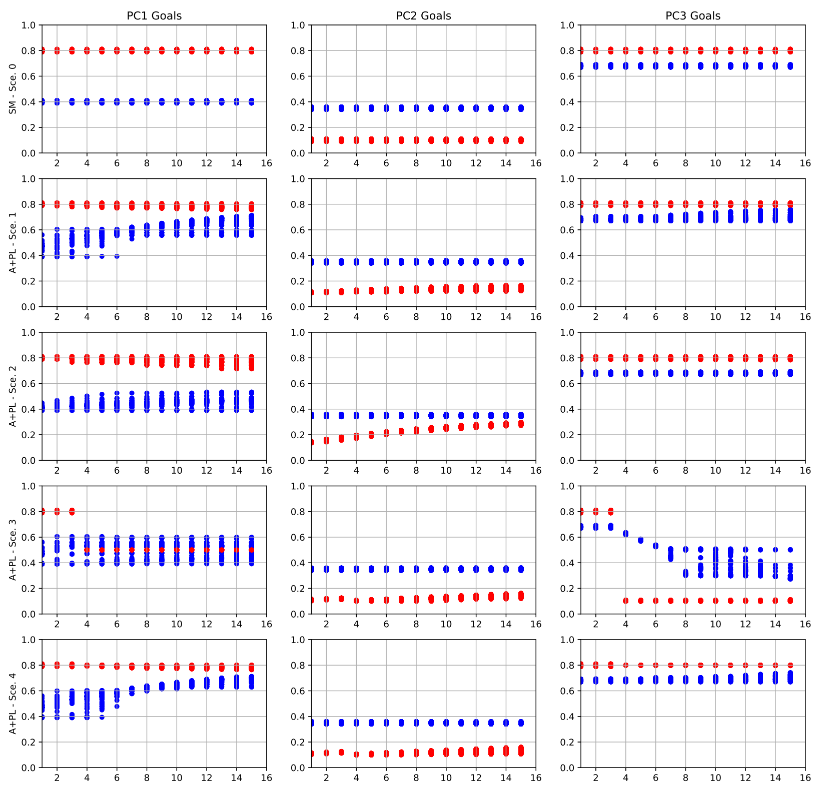

Figure 1: Policy core issue goals.

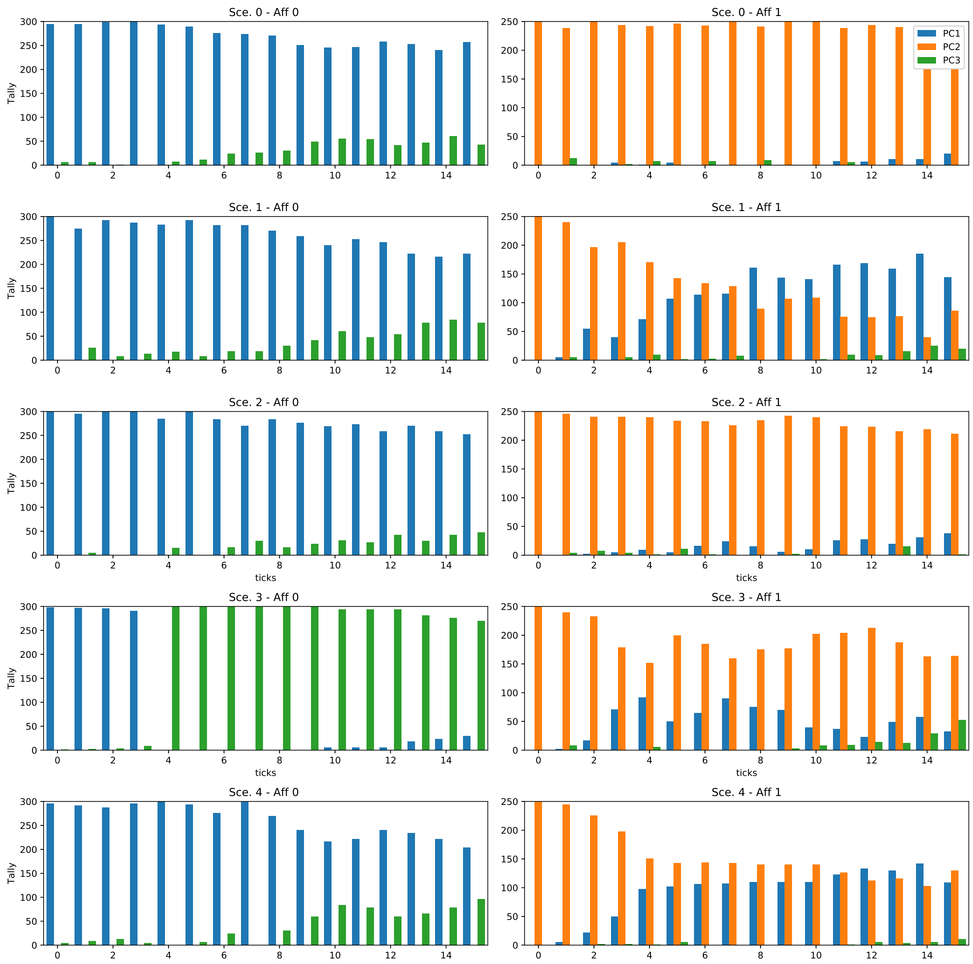

Figure 2: Policy core issues selected.

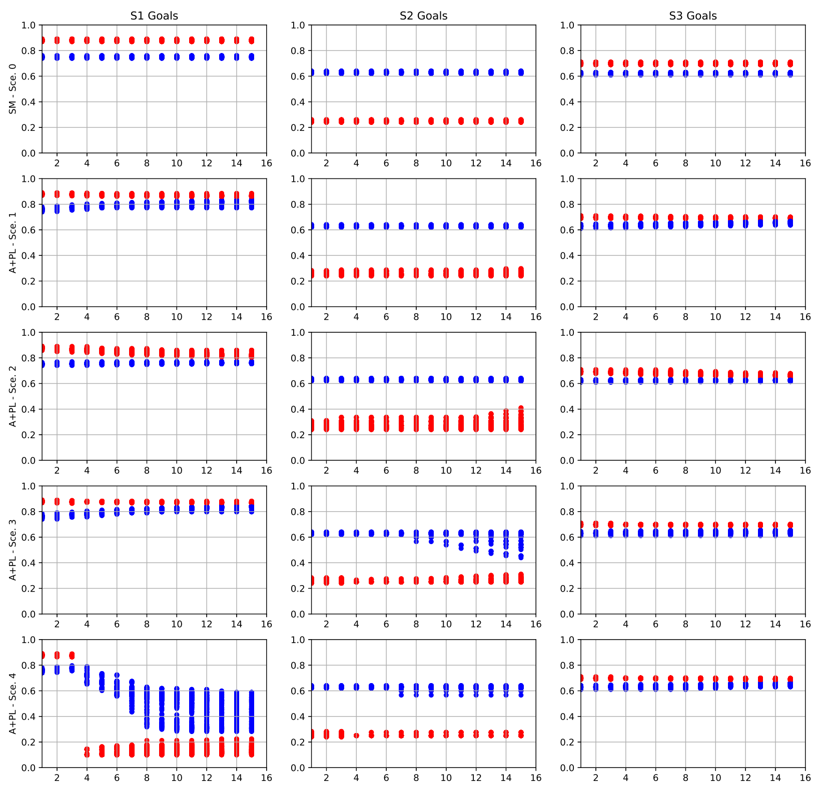

Figure 3: Secondary issue goals.

Figure 4: Secondary issue selected.

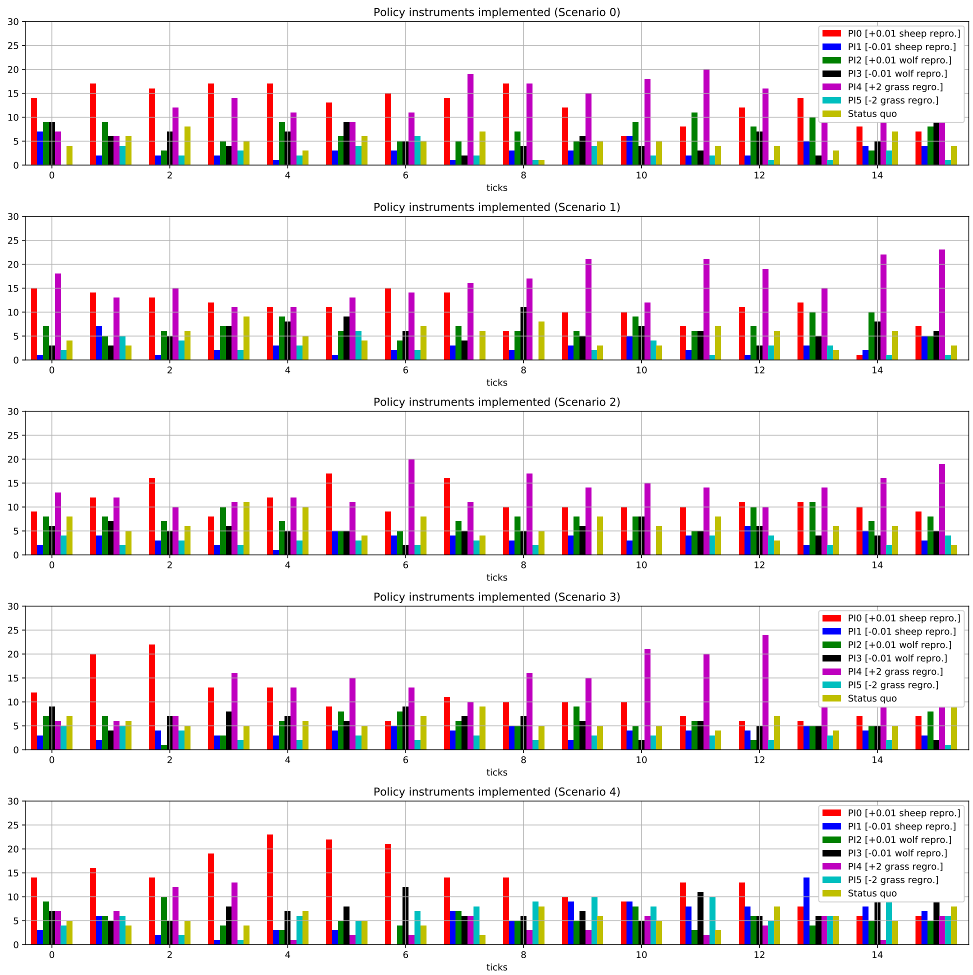

Figure 5: Policy instruments selected.

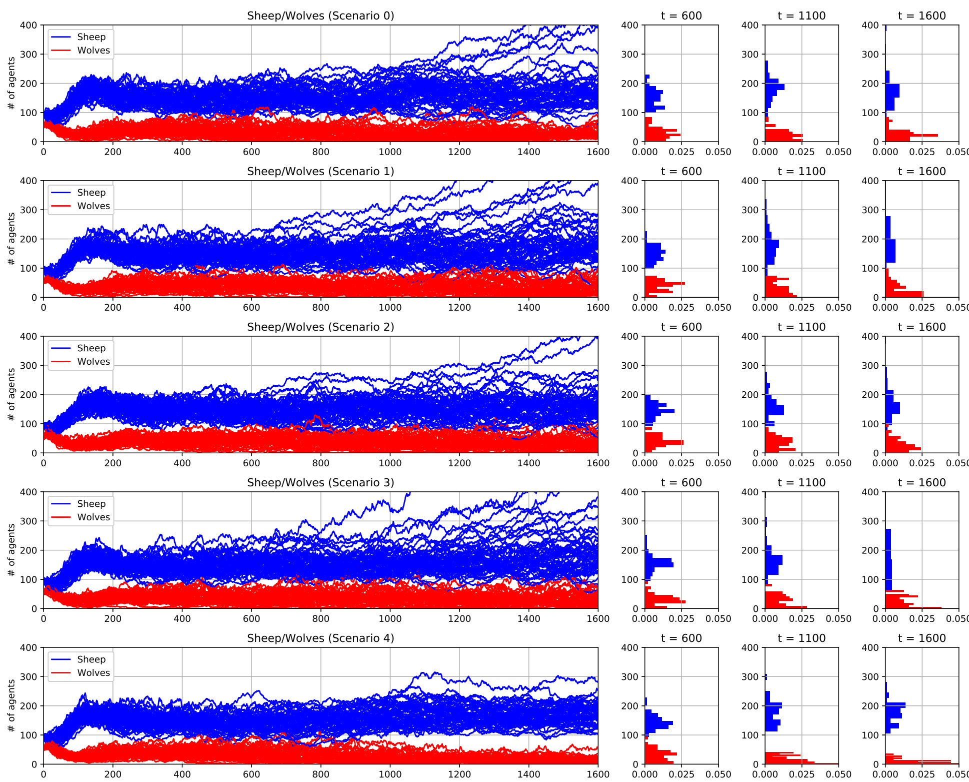

Figure 6: Predation model results - wolf and sheep.

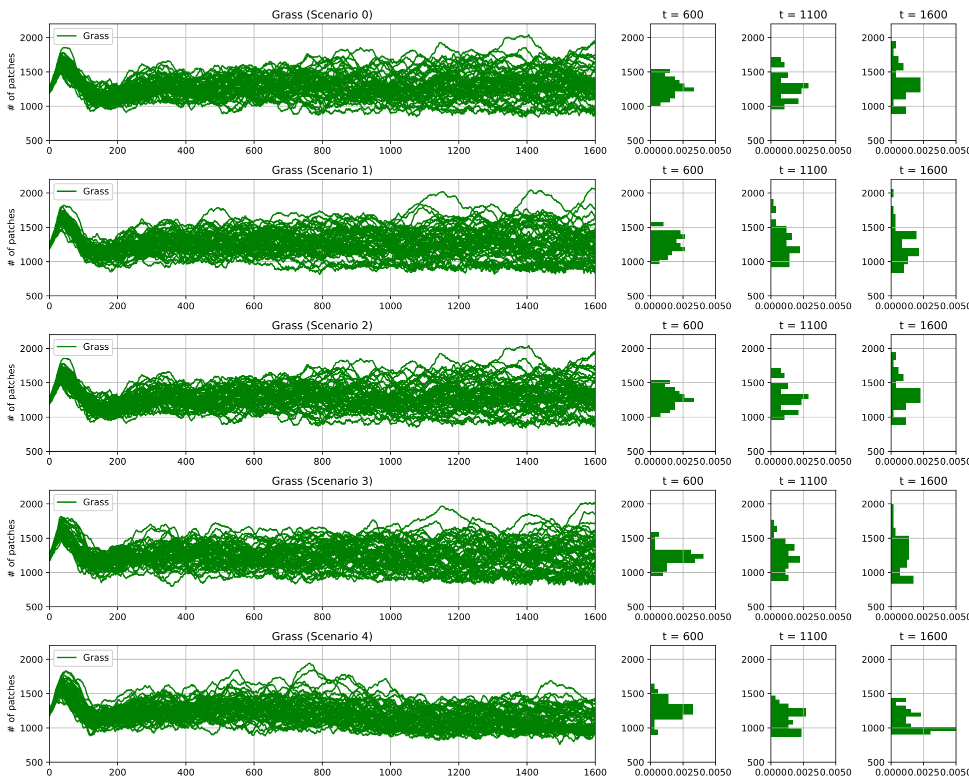

Figure 7: Predation model results - grass.

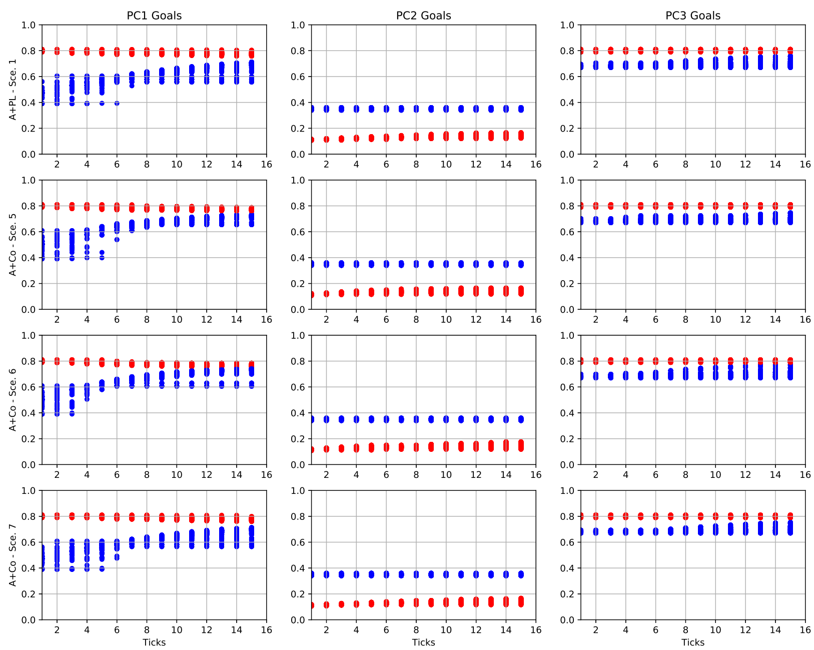

Figure 8: Policy core issue goals.

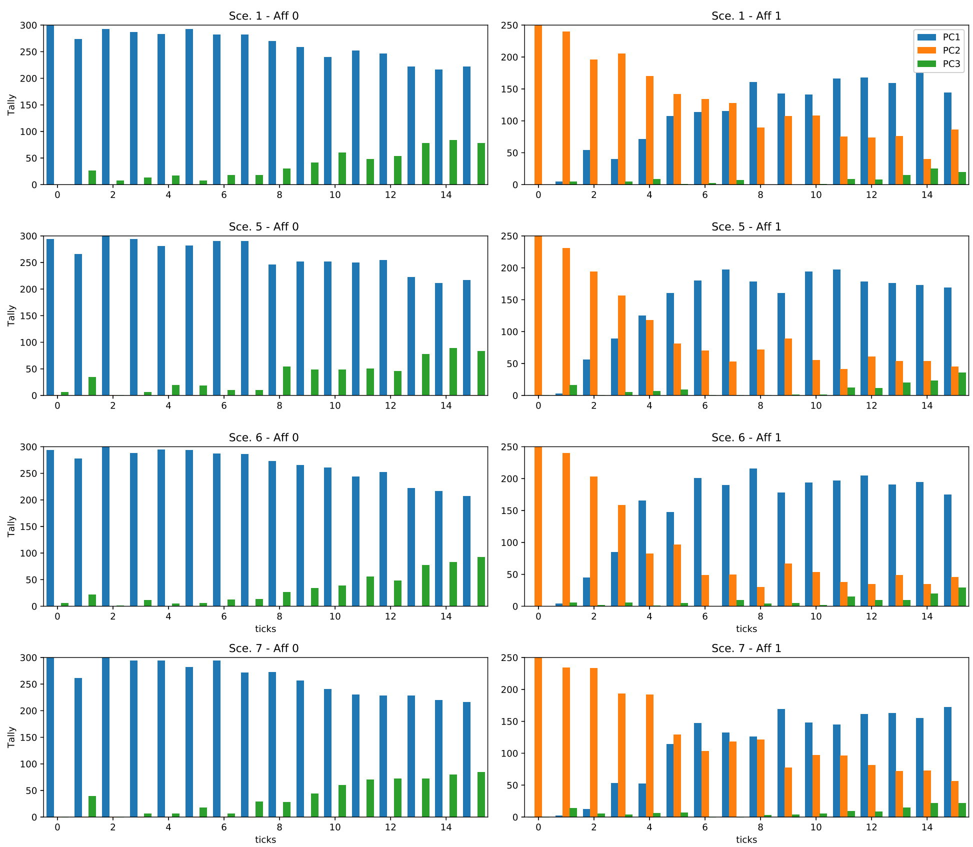

Figure 9: Policy core issues selected.

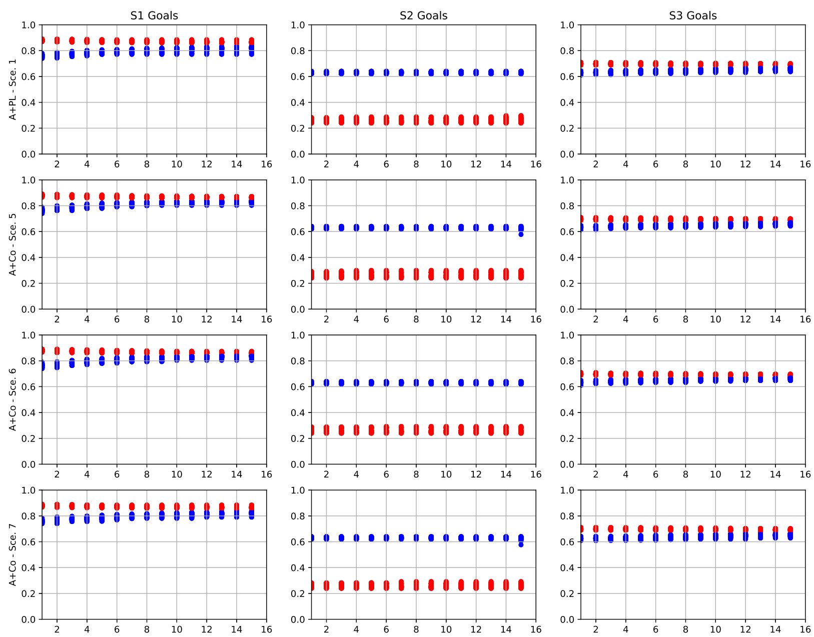

Figure 10: Secondary issue goals.

Figure 11: Secondary issue selected.

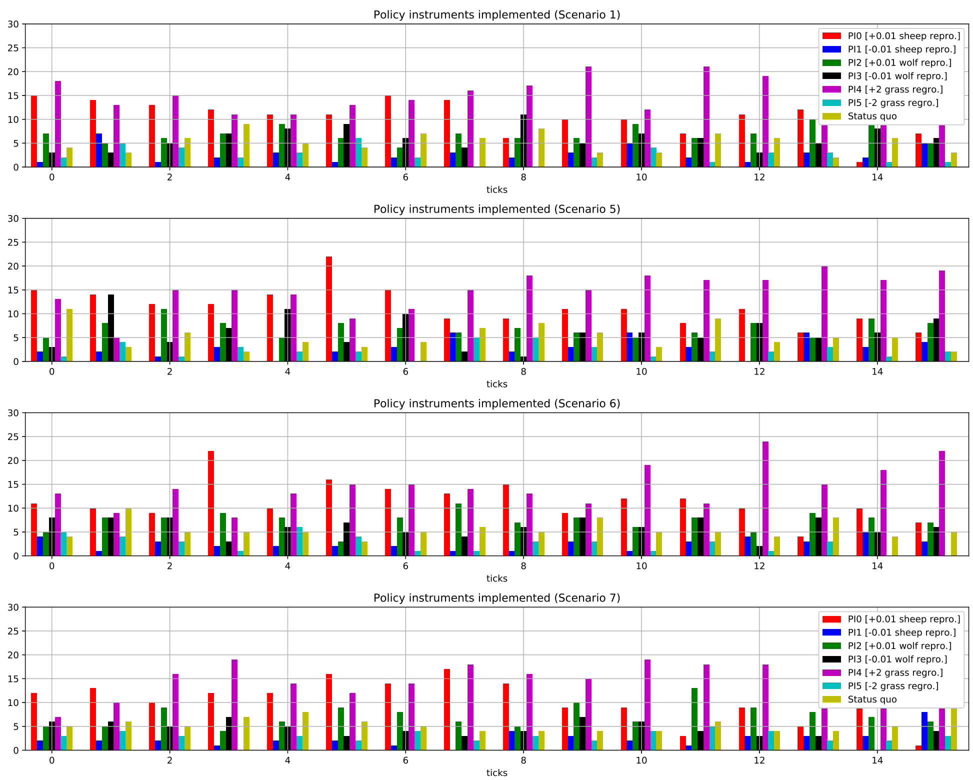

Figure 12: Policy instruments selected.

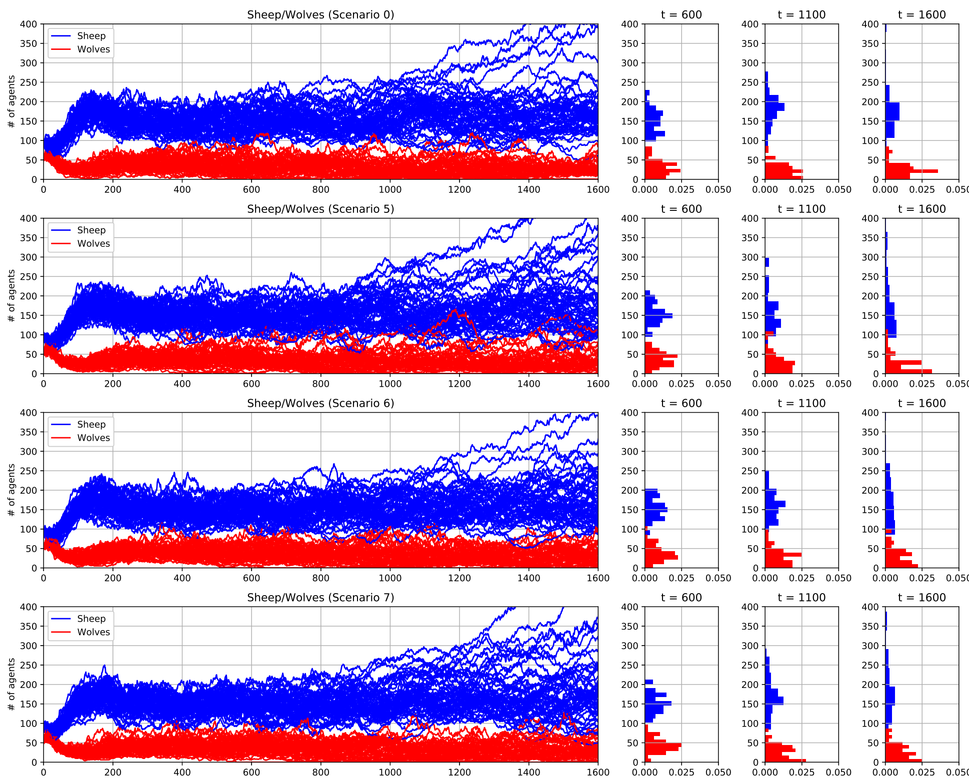

Figure 13: Predation model results - wolf and sheep.

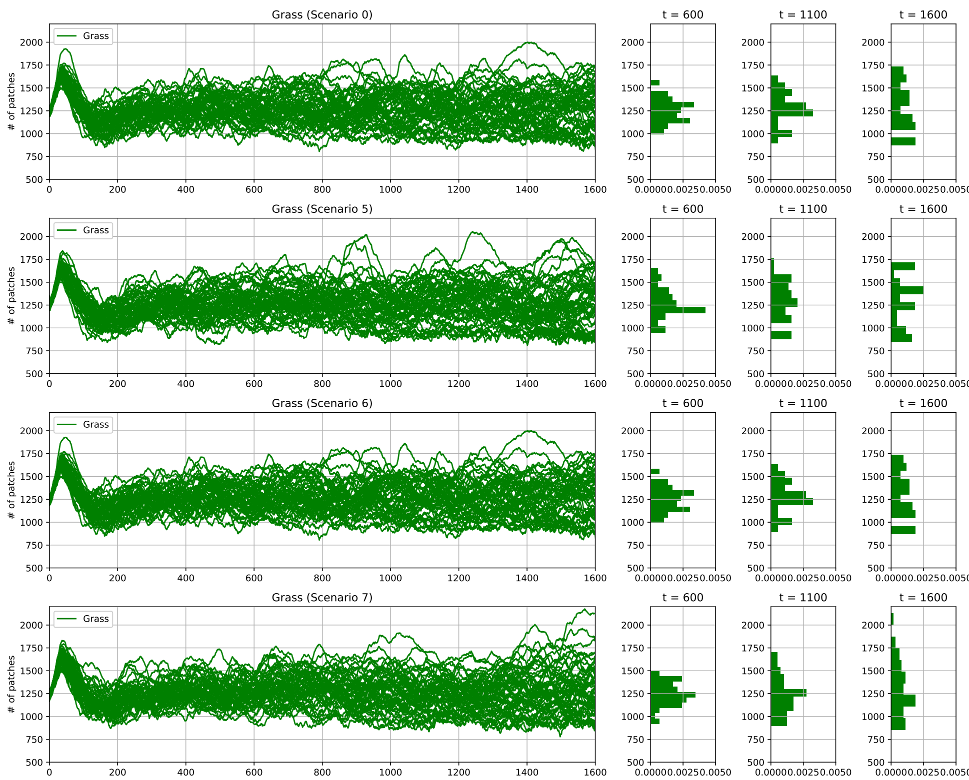

Figure 14: Predation model results - grass.