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Report

Smart Linker for harmonizing trade assumptions between countries' sustainable pathways on the FABLE's Scenathon

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Abstract

In the FABLE scenathons, trade is the element that connects all countries and Rest Of the World (ROW) models. By maintaining consistent national trade assumptions, we can secure that national pathways and global targets are consistent at the global level. This report describes the advances on a method based on Reinforcement Learning (RL) and a set of tools to support collective decision-making during the Scenathon process. The aim is to collectively address four global goals while respecting national priorities and pathways and keeping global consistency. The developed tools are The Smart Linker Tool (SLT), the Scenathon Lab distributed platform and the visualization tool to assess the training and optimization processes of the SLT. within this framework we developed a case of study based on the beef and soybean trade behaviour of the FABLE Scenathon 2019, integrating the FABLE calculators of Argentina, Australia, Brazil, China and the US. The architecture and first results are described.

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1. Introduction

1.1. FABLE Scenathon

Scenathons: Collective Scenario and Development Pathway Planning

Scenathons were conceived at IIASA as participatory decision-making exercises that integrate models, stakeholders, and technology to *collectively* solve complex, large-scale multi-objective problems.

The Food, Agriculture, Biodiversity, Land, and Energy (FABLE) Consortium has applied the Scenathon concept to answer questions concerned with sustainability transformations of food and land use systems. Within this setting, the Scenathon process allows country teams to progressively align national pathways with the global FABLE targets and to balance trade flows (Javalera- Rincon & Sperling, 2021).

Country teams frame their national sustainable development pathways in the land use space, using the FABLE calculator (Mosnier et al, 2020), an Excel-based accounting tool. The FABLE calculator, includes national level data from the Food and Agriculture Organization (FAO) as well as default scenarios. Country teams adapt the FABLE calculator to their national circumstances by refining and validating data input and customizing scenarios.

Customized FABLE calculators from the participating countries are uploaded to a Linker Tool, which is a web-based data platform that extracts, and aggregates reporting variables and assesses performance in relation to global targets. Country teams can view the results in the dashboard of the Linker Tool. To allow for a global aggregation, national FABLE calculators are complemented by regional ones that cover those countries that are not played individually. The regional calculators are played by members of the FABLE Secretariat. Multi-sectoral teams, representing 17 countries and also covering the EU, participated in the first Scenathon. The initial results are presented in the *2019 Report of the FABLE Consortium:* Pathways to Sustainable Land-Use and Food Systems (FABLE, 2019).

While it is currently being applied to the food and land use system, the concept of the Scenathon could be used in a wide variety of contexts and tailored to different scales. In general, the aim is to strengthen the integration of bottom-up perspectives in modeling efforts of complex systems. This will allow a move from homogenous towards more heterogeneous scenarios, which are more cognizant of diverse contexts and allow for a distributed decision-making framework, where each participant makes informed decisions on their discipline, sector, region, or country. Action setting is based on shared predictions and aspirations of future states rather than derived from normative rules such as optimal behavior measured by universal profit maximization.

Stakeholders are brought together by sharing overarching targets, which are of collective relevance. The aim is to progressively converge towards pathways that meet collective and individual aspirations of the stakeholder groups through iterative processes.

While the project team is currently focused on exploring and developing the concept, it is a long-term aspiration to establish an analytical environment that facilitates collaboration and improves decision making on complex development problems, such as the sustainability of our food and land-use systems.

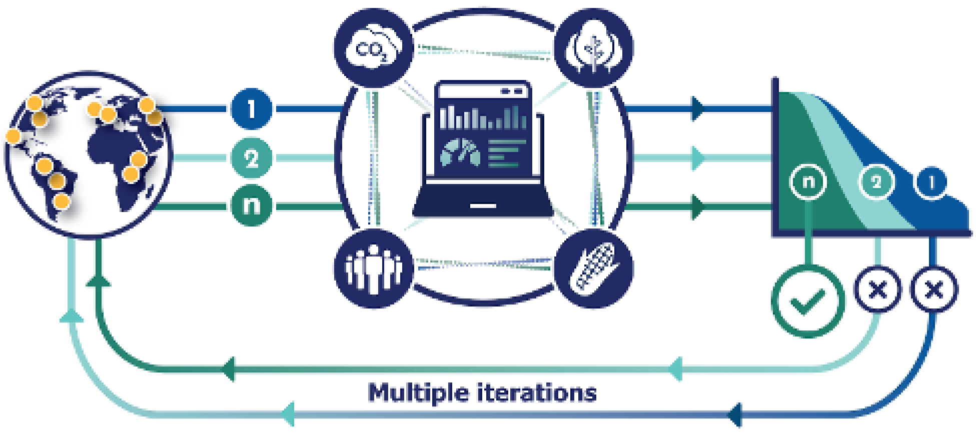

Figure 1.- Schematic of the Scenathon: Multiple stakeholder teams seek to achieve in an iterative process collectively agreed goals, while also realizing individual targets. The FABLE Consortium has applied the Scenathon to food and land-use questions. (Javalera- Rincon & Sperling, 2021)

1.2. Challenges on the FABLE's Scenathon for trade harmonization

Among the many lessons learned on the FABLE Scenathon, our findings of the impact of trade harmonization at the country level stand out. The trade adjustment can have a profound effect on land use planning for some countries. Nevertheless, trade should be harmonized at the global level to establish realistic country pathways. Some of the new challenges on trade harmonization for the FABLE Scenathon are:

1. The effects of the trade adjustment should respect some agreed "safety limits". The trade adjustment should, for instance, not cause the feasible kilo calories per-capita to go below the healthy recommendation for any country; and the physical land and water boundaries for each country should be respected. There are also other country level restrictions to consider, including greenhouse gas (GHG) emissions and economic considerations. It is proposed that the consortium agree on these limits.
2. The trade harmonization should pursue a Pareto solution on common targets, while respecting local restrictions and priorities.

3. To reduce the complexity of these agreed values during the Scenathon process, the linker should automatically advise rather than impose on imports and exports after the closing of an iteration. The participating countries should receive information about the global trade situation if the advice is not accepted.
4. Trade needs to be coordinated, aligned, synergic, and realistic.

1.3. Trade assumptions and their implications on the national pathways

Trade in the FABLE's Scenathon is approached as "a balance of mass". The aim of Scenathon is not the prediction of prices or behavior of markets, but to detect planetary boundaries and physical constraints that will affect sustainable trade and markets in the future. Although international trade is much more complex, and prediction of markets escapes from the limits of these models, hundreds of tradeoffs and synergies' can be explored based on the projected consumption and production plans and capacities from the countries using these powerful learning algorithms.

When net trade is zero at the global level, we say that trade is balanced. When net trade is not balanced, it can be negative (a deficit) or positive (a surplus). Deficits and surpluses tell us that the assumptions for the trade of the countries involved in these unbalances is not aligned. This lack of coordination between countries' pathways makes country-level plans unrealistic. For this reason, it is essential to harmonize countries' trade assumptions.

Trade is important in sustainable land-use planning in many ways. In a perfect world, sustainable trade would involve the materialization of synergies between countries, rather than just being a way of exporting the ecological footprint of rich countries or devising an economic strategy to grow in a new market that may not be that promising in the future.

The figure 1 shows an example of the imbalances of the trade report of the Linker Tool after the first iteration of the FABLE Scenathon 2019. This is the difference (in tons) of the accumulated projected exports minus the projected imports of all the countries by product for 2050. On the righthand side, in blue, we can see that there is a surplus of more than 220.9 thousand million tons for soybeans. The colored chart on the left, shows the countries that where responsible for this huge surplus: Brazil with 133.1 thousand million tons of soybean production, the US with 83.7 thousand million, and Argentina with 54 thousand million tons of soybean production. The negative area of the chart indicates that the largest soybean importer is China, which is planning to import 43.4 thousand million tons. This result was mostly driven by Brazil, Argentina, and the US's internal conditions related to the production of these massive amounts of soybeans and their assumption that there will be a demand for it. On the other hand, as the biggest importer, China is planning to gradually reduce its imports of soybeans (from 67.4 thousand million tons in the year 2010 to 43.4 thousand million tons in 2050).

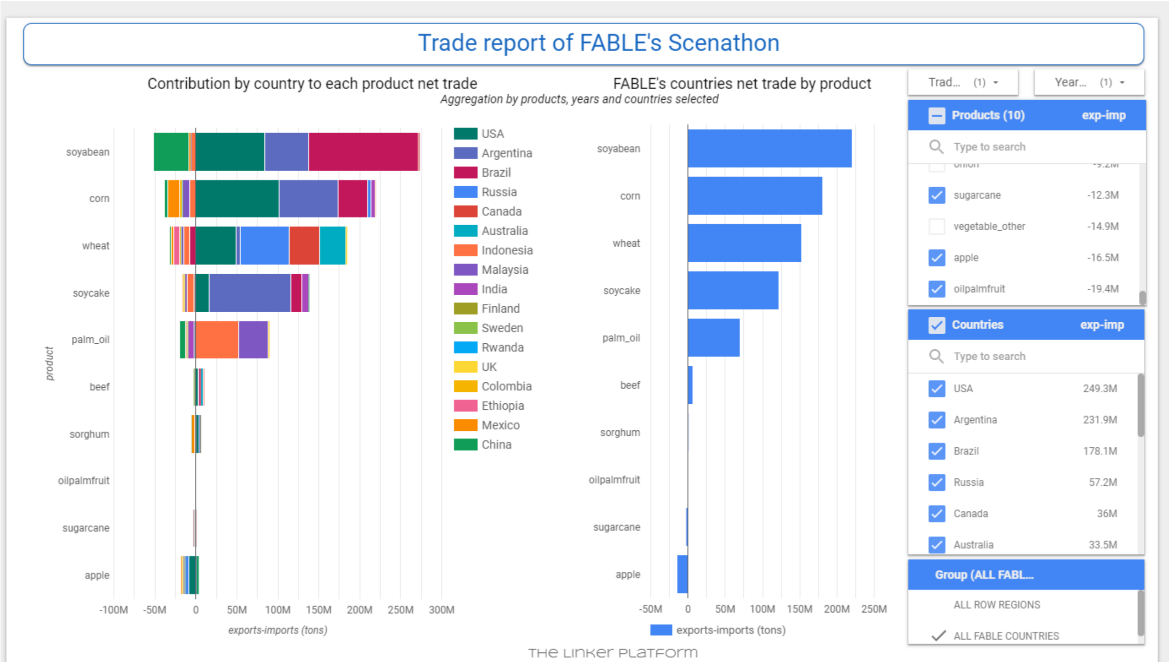

Figure 2.- Trade report of the FABLE's Scenathon 2019 showing the top surpluses of commodities for the year 2050 before the trade adjustment

1.4. Beef case in Scenathon 2019

A similar situation than the one described in the previous section for soybean, can be observed in the case of beef exports involving the same exporting countries during the FABLE Scenathon 2019. It appears in the chart as a smaller surplus (considering the net value in tons at the global level), but the conversion from tons of beef to the necessary land to produce is considerable, which shows that this relatively small global surplus can have an impact on the land use distribution of exporting countries.

In the FABLE's Scenathon, harmonization was applied after the first round of submissions from the participating countries. The harmonization method consisted in fixed adjusted values that each country applied in their calculator before making another submission. The adjusted value was calculated for each product-year and expressed as a percentage. Every country applied the same percentage specific to each commodity to exports. Only net exporter are affected by these changes, increasing their exports if there was a deficit at the global level or reducing exports if it was the other way around. The figure below shows the result of the same products-year after the trade harmonization.

As can be observed in the figure, the surpluses remain but are reduced by about 50% compared to the ones before the previous figure's trade adjustment. There is a tolerance after implementing the proportional adjustment, which is also based on these products' historical trends.

In this example, we can observe a lack of coordination between countries' pathways. While Argentina is planning to continue with a business as usual scenario for soybeans, China plans to reduce imports in the future. In order to move through real transformation, it is therefore crucial for countries to be aligned.

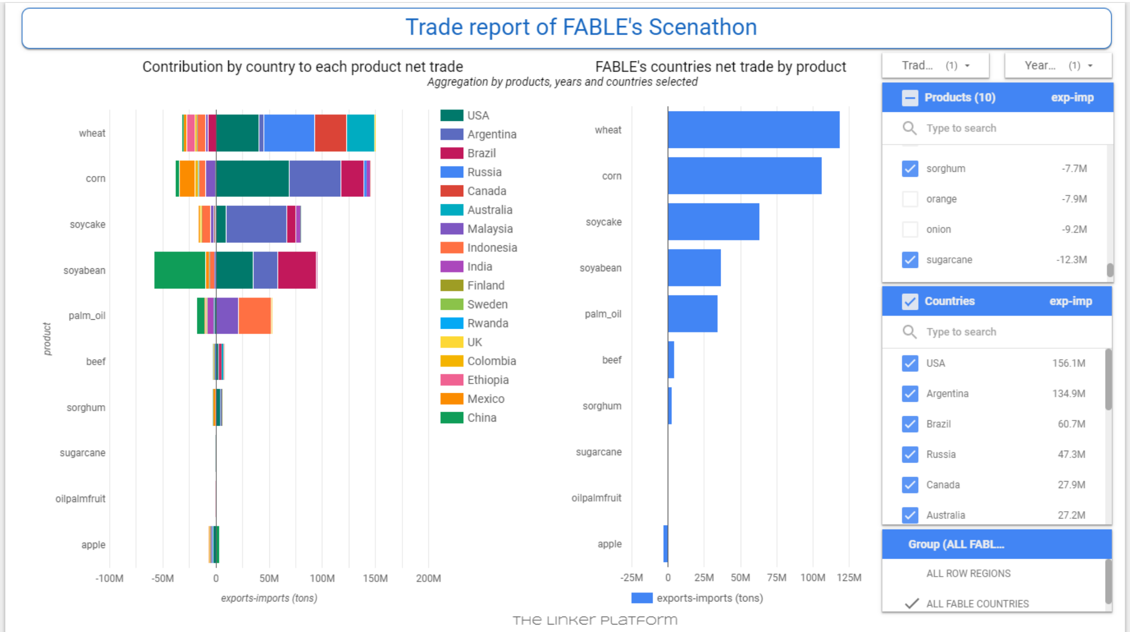

Figure 3- Trade report of the FABLE's Scenathon showing the top surpluses of commodities for the year 2050 after the trade adjustment

Considering the problem above, we have proposed a tool to support an integrated collective decision making during the Scenathon process in a realistic time frame, the Intelligent Linker Tool (ITL).

1.4.1. Countries considered and their models

The considered models (agents) to be integrated are the FABLE calculators of Argentina, Australia, Brazil, China and the US. The Smart Linker algorithm objective is to find the optimal trade volumes of beef and soybean for all years between these countries that best contributes to the four global targets of the Scenathon 2019:

Box 1: Global targets Scenathon 2019

1. Net forest cover change > zero from 2030 onwards.
2. Biodiversity; the share of land that can support biodiversity > 50 % by 2050.
3. Greenhouse Gas (GHG) emissions; from Agriculture < 3.0 Gt CO2 Eq, from Land-use change < zero by 2050.
4. Food security; Kcal feasible > MDER by 2050.

Within this approach, the country pathways and selected scenarios during the Scenathon 2019 will be respected. In (FABLE, 2019) the reader can find a complete chapter for each of these countries where a comprehensive explanation of the scenario selection is done. The solution we are looking for in this work is such that we are able to align the pathways globally for beef and soybean trade, respecting the pathways presented by the country teams and advancing through the targets complying with a Pareto efficiency.

1.4.2. The Pareto efficiency for our problem

The result of the learning algorithm will be a new trade "adjustment table". The new table to be applied should be such that:

1. Pathways are consistent for both products', so, net trade should be zero; this means that the trade volumes should be balanced (as explained in section 1.3).
2. No other changes are implemented in the models, other than the new trade adjustment table. The selection of scenarios made by the country teams in their models during the Scenathon 2019 remains the same.
3. The resulting trade adjustment table should be Pareto efficient

Box 2: Pareto efficiency for trade volumes for the Scenathon 2019

We are looking for consistent trade volumes for the selected commodities such that; maximizing global targets I, 2 and 3; there is no violation of the "food security constraint" for any country.

To improve the trade harmonization results for soybean and beef surpluses of the FABLE's Scenathon we designed a learning algorithm to calculate a new trade adjustment for the top importer/exporter's countries of soybean and beef: Argentina, Australia, Brazil, China, and the US. Since the calculator is not an optimizer and doesn't provide a total cost for a selected scenario, a reward is calculated constructing a function from weighted and normalized values of the FABLE targets. A penalization is applied to actions that violate established limits and constraints from the involved countries. Once this new trade adjustment is applied, the new results of this countries/products are substituted on the global database to obtain a new dashboard and trade report to be compared against the result using just the proportional adjustment.

1.5. The price of button-up globally consistent country pathways

There has been some discussion about opening a negotiation space on the Scenathon website to support communication in the collective decision making of the Scenathon. Still, the complexity and time needed to coordinate all these interactions are huge, considering the number of countries participating, the resulting unbalance found in so many commodities and years projected. This is a problem of Large-scale distributed decision Making and it has many dimensions.

Box 3: Complexity dimensions of a Large Scale participatory decision-making exercise

- Multiple actors/ decision-makers. The decision-makers have partial knowledge of the global problem. There is a need for a systemic view.
- Multi-objective. Also, with conflicting objectives, the need for a Pareto solution.
- local (individual) goals Vs. global (collective) goals
- Dynamic. The environment is changing, so the solution should adapt to these changes.
- Distributed. The decisions are taken and implemented in specific regions/ countries.
- Multiple scenarios and possible actions
- A high number of linkage variables

When the factors listed above increases, the communication and coordination needed from the actors is affected in such a way, that is not possible to assure consistency of the linkage variables and converge to a joint solution.

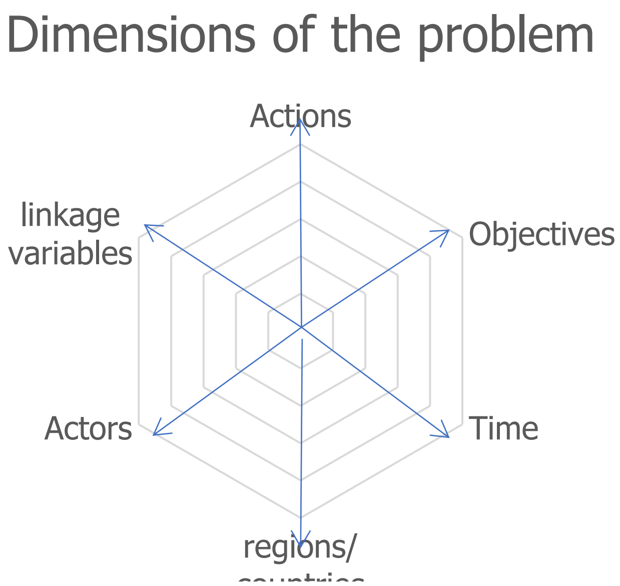

Figure 4. Dimensions of the problem.

1.5.1. Some parameters to consider in the formalization of the learning process of the Smart Linker.

The general goal is to make the process described above to include all the participating countries in future Scenathons. For this, it will be necessary to put some boundaries (max and min values) to some parameters to ensure consistency on the results and to assign a meaningful reward (or penalization) during the future learning process of the Smart Linker. These should be in the report tab of the calculators, to be extracted and validated by the (SLT). The learning algorithm will consider all these restrictions to find the Pareto area for sustainable trade volumes.

Some of these maximum and minimum parameters values by country are: Yields, total land cover, forest area, productive land (irrigated, not irrigated), land that could support biodiversity, total GHG emissions, recommended kilocalories per capita (or the chosen healthy recommendation for the food security target). A parameter that could represent the production capacity for the specific commodities that could restrict the production like water availability (e.g., China assigns limits for production based on GHG emissions). This list could be expanded to include those elements that limit the production capacity of a country for a specific commodity and the calculated demands.

With the consideration of these limits (or constraints), the Linker will be able to explore millions of pathways and identify the ones that respect the established boundaries of all the countries. Once a knowledge base is constructed with this information. The linker will be able to find pathways that maximize the accumulated reward from all these evaluated futures in advance. With this, we are aiming to provide automatic advice of solutions inside of the Pareto frontier during the Scenathon that will simplify decisions and negotiations between the countries' teams.

We can establish boundaries on trade volumes calculated considering other analysis or socio/economic models

2. The Linker platform

The Linker platform is a tool to integrate independent assessment models and a tool to communicate and coordinate teams of modelers and decision-makers from different regions, sectors, or even countries. The Linker platform provides a communication infrastructure for stackholders and experts during the Scenathon.

The Linker platform implements a distributed architecture that allows to:

- Integrate knowledge and models assets
- Get more realistic scenarios from a button-up approach
- Support governance and respectful collaboration
- Define the information/ data to be shared
- Define common goals
- Find synergies and trade-offs to reach the common goal while defining feasible local pathways
- Agile development
- Rapid learning curve
- Flexibility

The Linker platform helps to integrate the local pathways with the global context. It also provides a measure of the advance towards the global targets through a Global dashboard (Annex 1), while ensuring consistency on shared variables, biophysical boundaries, and countries' different priorities. The Linker platform connects each country to a worldwide integrated plan, and each country provides a part of this integrated plan by sharing some agreed indicators.

Shared variables are those elements that connect all the country models. These variables are exogenous to the country models and have an impact on their internal variables.

2.1. Smart Linker Architecture

Figure 5.- Smart Linker architecture used to run the model designed to improve the Beef trade between Argentina, Australia, Brasil, the USA and China.

The figure depicts the Smart Linker architecture used to run the model designed to improve the Beef trade between Argentina, Australia, Brasil, the USA and China. The architecture includes the use of a virtual computer for each country. A virtual computer to display the iterative and real-time charts. A virtual computer to run the manager Agent in charge of coordinating the trade operations between the countries. And a Virtual computer to set up the Smart Linker environment and to program the trade iterations. The Smart Linker technology is coded using Java and the implementation of Distributed Intelligent Agents and the use of the FABLE calculator for each country as the I/O model.

3. Reinforcement learning algorithm of the Smart Linker

In this work we use, what is knows in RL as model free algorithm. Model free algorithms learns pairs state-action Q(s,a) by accumulating rewards assigned depending on how good is the state resulting from the last action.

Reinforcement learning operates with actions, states and rewards. In the training phase, a learning agent experiments with the environment by sequentially taking various 'actions' (typically denoted as a in the reinforcement learning literature, but we will denote it by a' to deferientiate from the agents), collecting corresponding 'states' (a state is a response of the environment to an action; due to stochasticity, the environment can respond with different states to the same action in different experiments; (typically denoted as s), and evaluating these states by 'rewards' (denoted by r). It is assumed that admissible actions and corresponding states are elements of finite sets. Usually, rewards are real numbers; the learning agent computes reward values based on the goal that is defined for it.

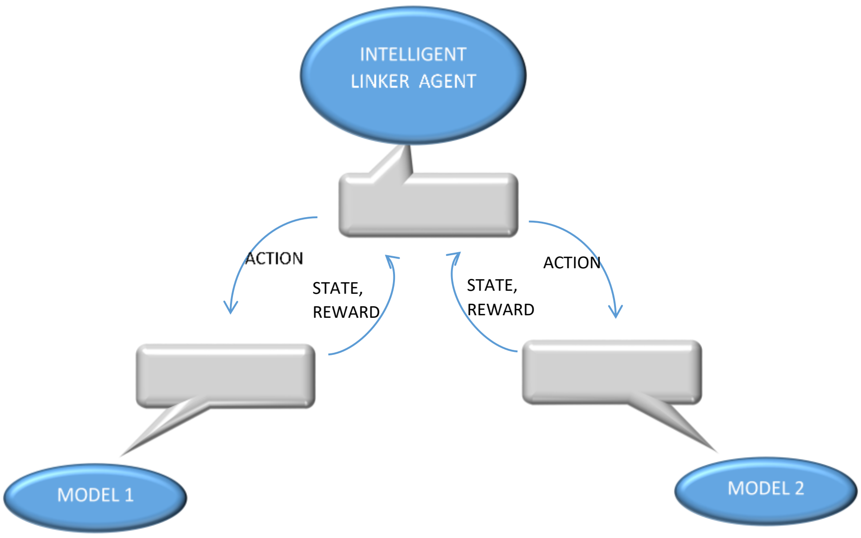

Figure 6.- Actions, states and rewards for the Multiagent approach of the Smart Linker

The applied learning technique is based on a reinforcement learning approach for cooperative multi-objective optimization of Multi-Agent Systems (Javalera-Rincon et al. 2019b) and applied in a large-scale water distribution network (Javalera-Rincon et al. 2019a).

The dynamic running over the the Scenathon Lab distributed platform is the same in planning and optimization behaviours. The difference is that in planning we construct a value function and on optimization we obtain optimal actions from the obtained function. The policy to choose actions and states is different on each case.

During the learning process, hundreds of actions are sent to the local models. An action (c) gets a reward (r) depending on how good or bad this action was for each agent (a). The rewards are accumulated in a knowledge base Q, one for each commodity to be solved.

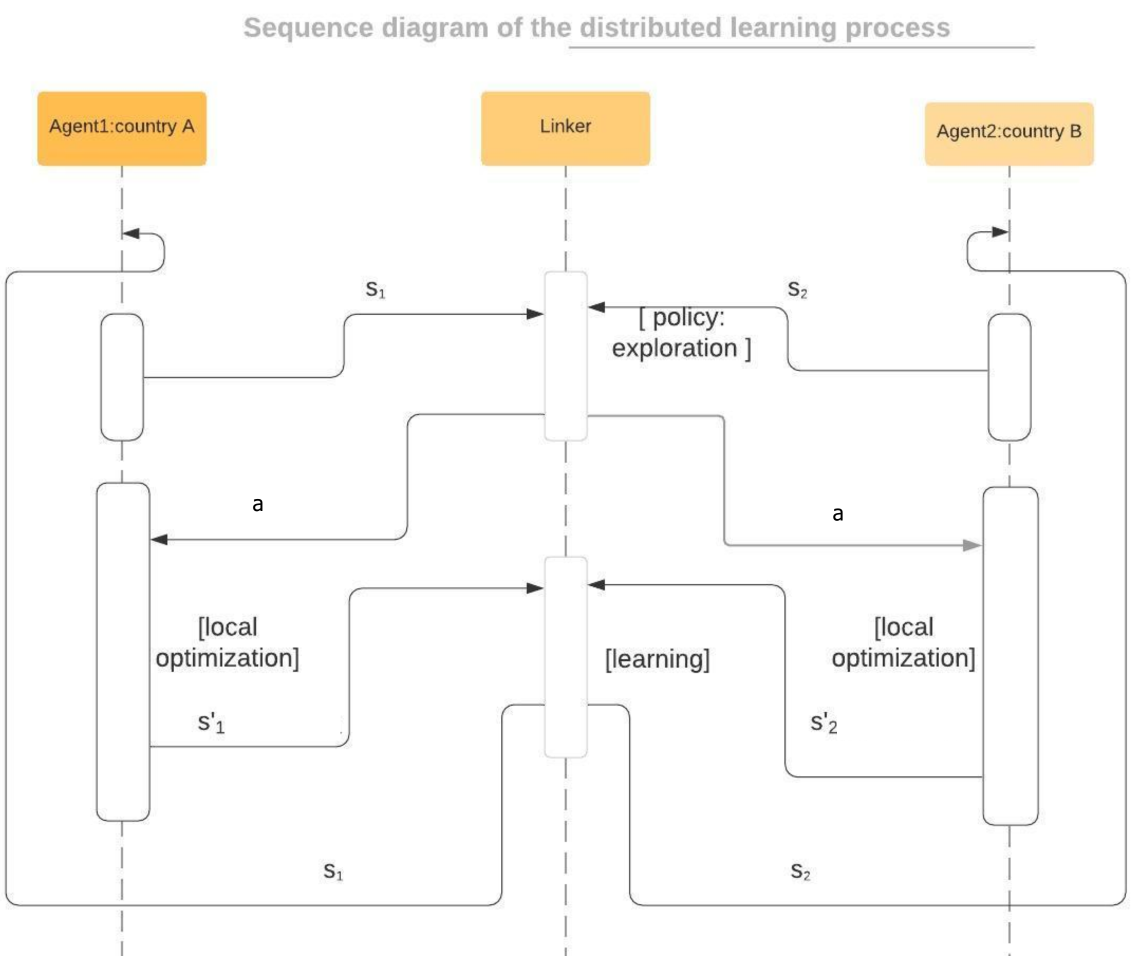

Figure 7.- The sequence diagram exemplifies the messages of two agents during the learning process

4. Formulation of the Smart Linker problem

The Linker algorithm has its basis in reinforcement learning. As such, the main elements that we need to define for this problem are States, Actions and Rewards.

4.1. Multi parametric state

Each model reside in one virtual computer of our distributed architecture, we will call each of these models agents

State

For the Linker algorithm, the state is a representation of the agent at a specific instant of time. Since we have four global goals (Box 1) we defined a composed state with one parameter by target as:

$$s_{a.y} = NFC_{a.y} + Bio_{a.y} + (1 - GHG_{a.y}) + FS_{.a.y} \qquad \text{Eq. (1)}$$

where,

$NFC_{a.y}$ $is\ the\ normalized\ value\ of\ agent\ a\ for\ the\ indicator\ related\ to\ the\ Global\ goal\ 1$, *NetForestCoverchange for agent a on year y.*

$Bio_{a.y}$ $is\ the\ normalized\ value\ of\ agent\ a\ for\ the\ indicator\ related\ to\ the\ Global\ goal\ 2$, *Bioshareland on the year y.*

$GHG_{a.y}$ $is\ the\ normalized\ value\ of\ agent\ a\ for\ the\ indicator\ related\ to\ the\ Global\ goal\ 3$, *TotalGHGland of agent a on year y.*

$FS\ is\ the\ normalized\ value\ of\ agent\ a\ for\ the\ indicator\ related\ to\ the\ Global\ goal\ 4$, *FoodSecurity of agent a on year y.*

FoodSecurity

We measure food security using two indicators from the agents, the kilocalories target and the kilocalories feasible; both are percapita. For a specific year for the agent, food security is calculated as

$$FS_{a.y= Kcf_{a.y}-Kct_{a.y}} \quad \text{Eq. (2)}$$

Initial state

The starting point for our optimization for each model was the last pathway submission made by each country team for the Scenathon 2019. Their selection of the scenarios is in Annex 2.

Preparing the models for the initial state. All trade volumes for all years for beef are initialized to 1 ton; this is done by selecting ¨YES¨ in each FABLE calculator's trade adjustment scenario and then modifying the volumes directly in the trade adjustment table.

Box 4: Observation

The initial idea was to start with no trade at all but we observed that by putting zero in the trade adjustment table, default values for trade are assigned internally in the FABLE calculators.

4.2. Multiparametric reward function and penalty

Opposite also to most RL algorithms that use scalar rewards, we use a function that evaluates the aggregated reward obtained for each common goal by each agent. Each goal is adjusted by an exogenous determinate weight and the reward will aggregate all the parameters in a single value.

$$r = \sum_a (w_1.NFC_{a.y} + w_2.Bio_{a.y} + w_3.\left(1 - GHG_{a.y}\right) + w_4.FS_{.a.y}) \quad \text{Eq. (3)}$$

To ensure that the Smart Linker's learning drives to a Pareto efficiency, we validate that the FS parameter is always positive before we accumulate r in the knowledge base Q. If FS is negative we will use a penalty instead, after a calibration process penalty was assigned in -10.

4.3. Actions

As mentioned in section 4.1, our initial state is calculated considering trade equal to zero for all countries. We will define two importers for this example, China and the US; the exporters countries will be Argentina, Australia, Brazil and also the US. Actions were modelled as transactions; there is a seller and a buyer, the possible actions are in the next table

Importer	Exporter	Quantity (in 1000 tons)				
		a1	a2	a3	a4	a5
China	Argentina	1	10	20	50	100
China	Australia	1	10	20	50	100
China	Brazil	1	10	20	50	100
China	US	1	10	20	50	100
US	Argentina	1	10	20	50	100
US	Australia	1	10	20	50	100
US	Brazil	1	10	20	50	100

On each iteration of the learning algorithm, the new trade adjustment table for these products is constructed increasing imports or exports by the quantity according to the selected action. Actions are selected following two different policies.

Exploration policy-> A random action is selected.

Greedy policy-> The action that maximizes the accumulated reward for a particular pair of agents on their current state is selected.

4.4. Multiagent learning function of the Smart Linker

We already established that the states and reward are multiparametric, but the Linker needs to learn from the accumulated experience of agents. Figure 7 describes the interactions between two agents in a given iteration, but during the learning process hundreds of these interactions are happening, even simultaneously, with different pair of agents. Our approach considers bilateral trade flows (seller-buyer) this is why we believe it is essential to consider the state of both agents that participate in a transaction. We do this in two different ways one is using a static structure and the second a dynamic tree. In this report, we will describe the first one. Similar to (Javalera-Rincon et al, 2019) where a multi-dimensional Q matrix was introduced, we use a Q matrix with the form

$$Q\ (s_1', s_2', s_3', s_4', s_5', a') \leftarrow r+\gamma\ Q\ (s_1, s_2, s_3, s_4, s_5, a') \qquad \text{Eq.(3)}$$

Where γ weigh experience and $s_1', s_2', s_3', s_4', s_5'$ are the next states.

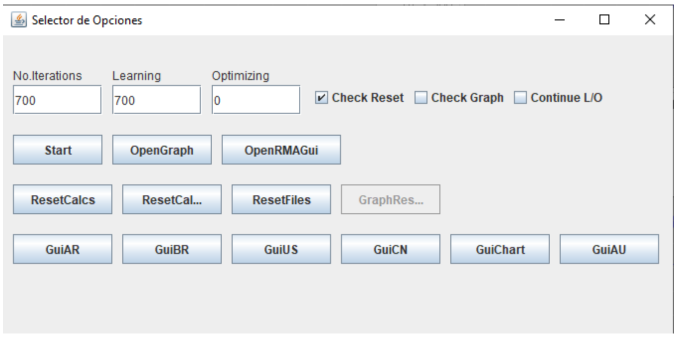

Figure 8.- Main user interface.

5. The learning process on the distributed infrastructure

Currently, the Smart Linker application includes options for Learning and Optimization. The possibilities include the option to specify the number of iterations to execute. It also provides opportunities to continue previous learning or previous optimizing. Another option given is to reset the countries calculators; this is a commonly used option when a new cycle for learning/optimizing will start.

One primary option is OpenRMAGui. This option allows starting the Agents environment. Without this option, the country Agents, won't find the Coordinator, and trade won't be possible. To run the dynamic and real-time charts it is required to select the GuiChart option. The country's Agents can start choosing GuiAR, GuiBR, GuiAU, GuiUS, GuiCN. When one country Agent is chosen, we select if we want to run the Agent for learning or optimization, as depicted in the next image.

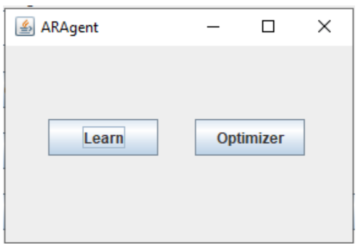

Figure 9.- Interface to run the Argentina Agent.

To load the real-time charts, we select the option GuiChart; after the selection, the charts will be displayed according to the country agents' behaviours. The following image shows the graphs for TotalGHG, food security, NetForestchange, and BioShareLand.

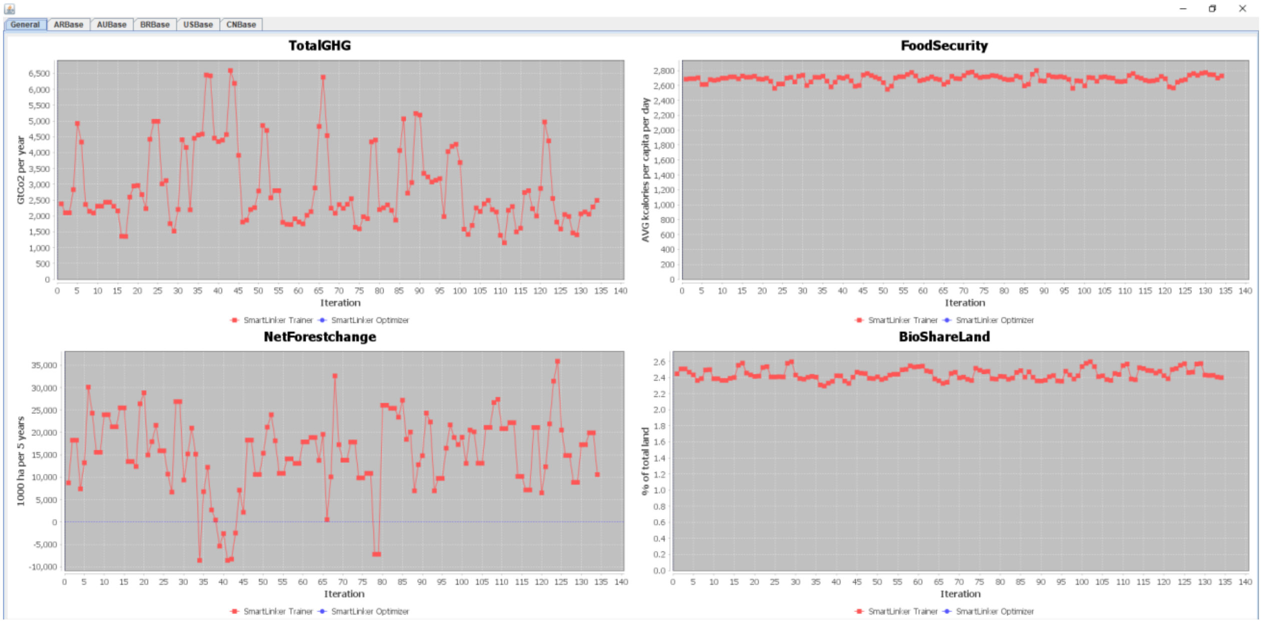

Figure 10.- Learning process by iteration for each global target.

Figure 10 depicts an option group for general charts and country charts. We have one for learning and one for optimizing according to the selection done.

The following images show an example of running learning graphs with Argentina data.

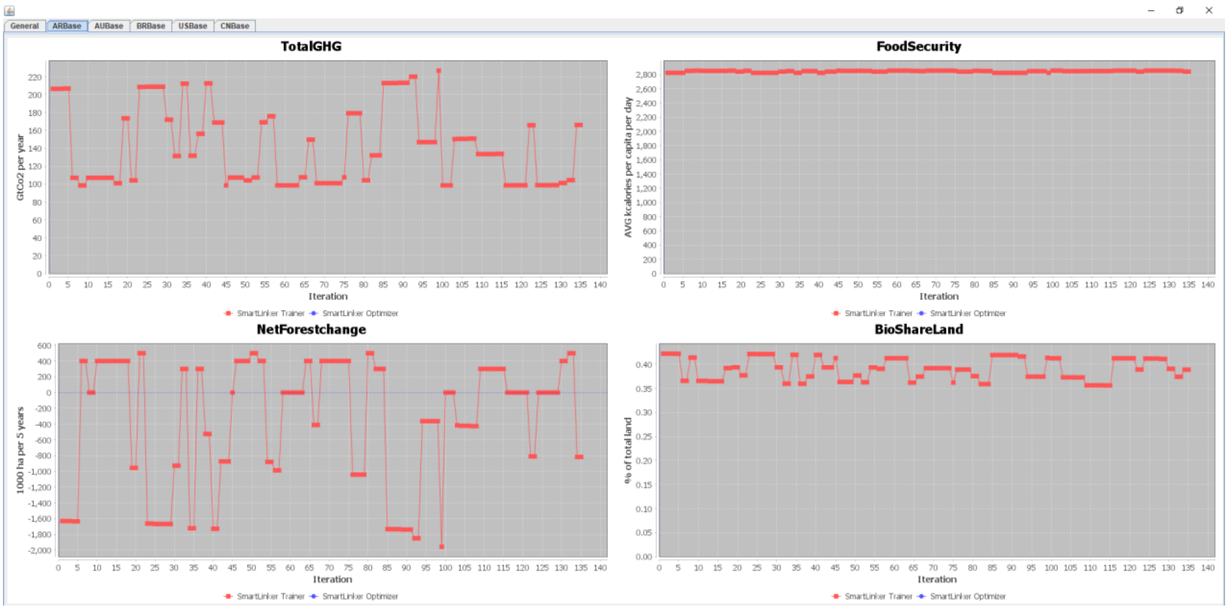

Figure 11.- Graphs showing the learning behavior of the 4 Targets (TotalGHG, FoodSecurity, NetForestChange, BioShareLand).

The following images show an example of running optimized graphs with Argentina data.

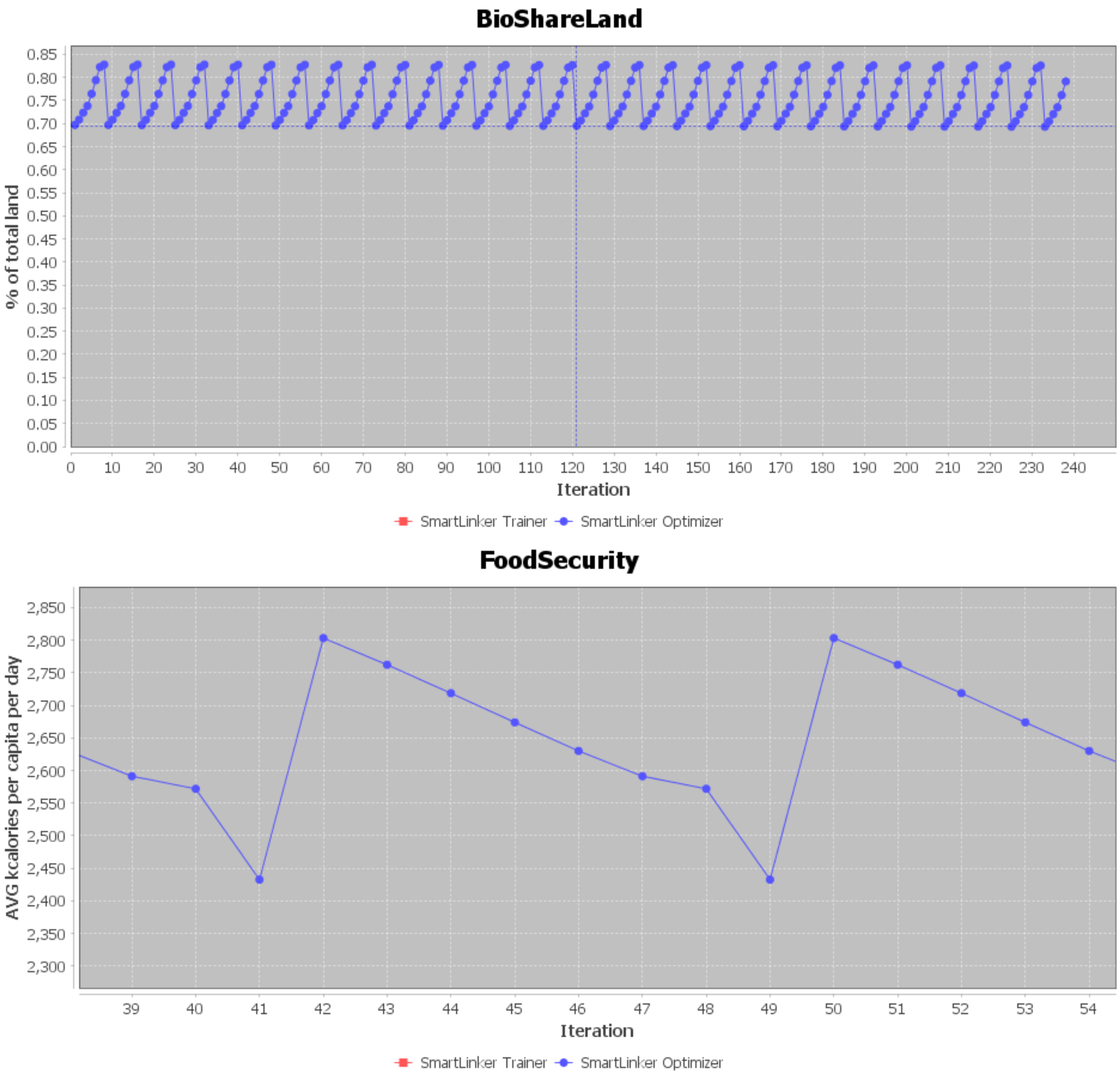

Figure 12.- Graph showing the optimization of BioShareland and FoodSecurity.

Previous charts depict the target status of each country calculator and the iteration number.

5.1. The Smart Linker Dynamic algorithms

The following image describes the iteration between all the Agents living in the Scenathon Lab distributed platform.

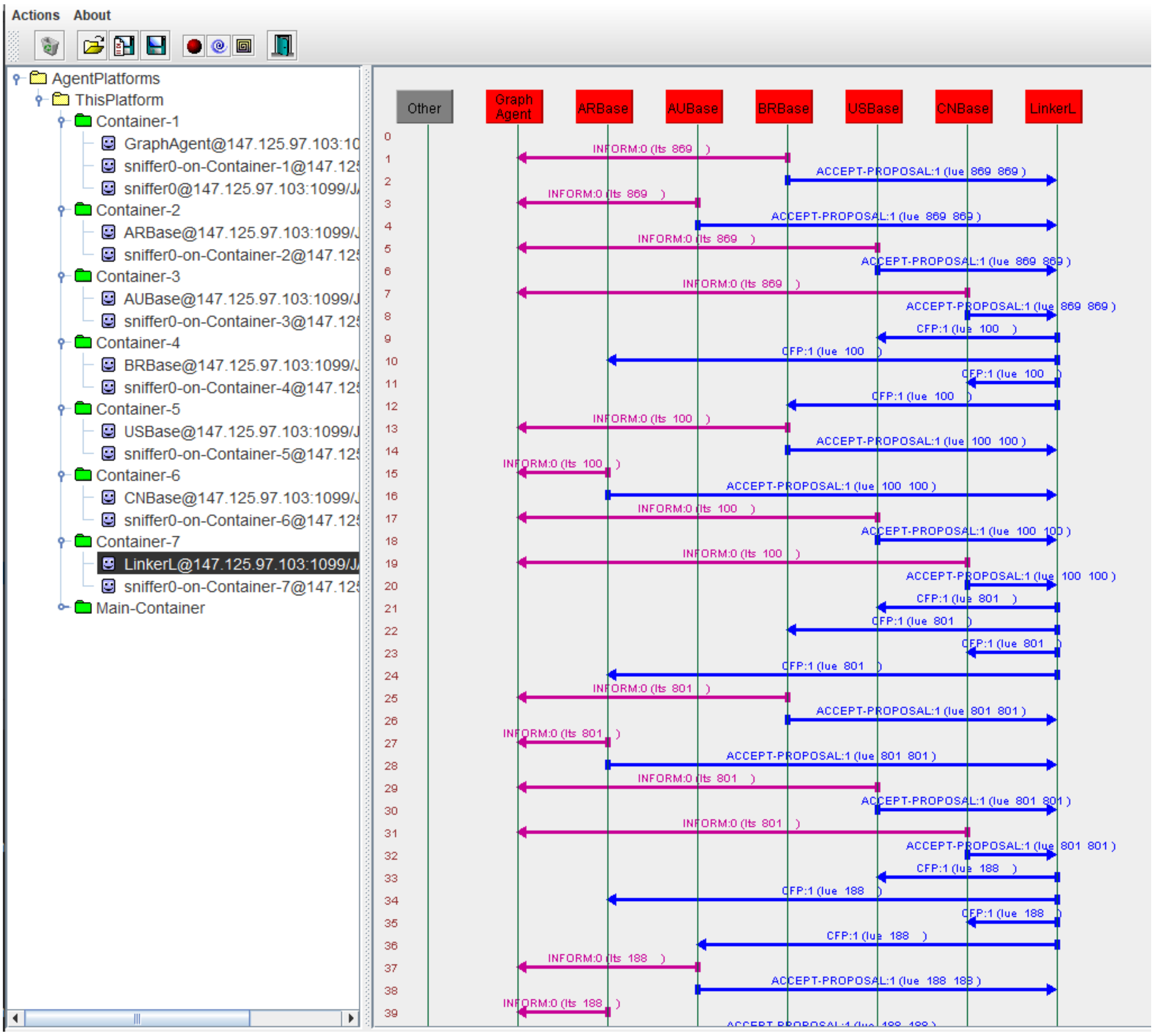

Figure 13.- Graphical interface showing communication between intelligent agents.

All the agents have direct communication with the Smart Linker; this communication follows the standard FIPA message protocols. The communication protocol for learning dynamic follows the steps:

1. Once the agents main container is running, the Charts Agent starts.
2. The Country agents start; the first task of a country agent is to get the current calculator state (s_x, Eq.(3) and send it to the chart Agent as an initial message.
3. The Smart Linker (LinkerL in Figure 13) begins with the initial configuration, considering the given iteration number and whether it continues learning or starting new learning. The agent coordinates the designation of four tasks to be done in parallel by the countries agents. The jobs details are sent in the message to the agents. A job consists of the importer and exporter assignment, the total amount for the trade and the operation year.

1. The Country Agent applies the action sent by the Linker Agent the instruction message to know his role following take the actions in the calculator. The update in the calculator produces a change in the calculator status. A FIPA message to both Agents Charts and Linker Agent is sent, including the new calculator position.

4. The Chart Agent gets the status messages and updates the general charts and country charts.

5. The Linker Agent receives the new status, computes the reward for the action done, and updates the Q-learning Tree for the next task.
6. Once the Linker Agent receives the country Agents' updates, then a new job assignation is done.
7. The task assignation will continue until it achieves the total iteration number.

When the learning cycle ends, then the optimizing process starts following the next steps:

2. Once the Agents main container is running, the first agent to start is the Charts Agent.
3. The country agent should start. The first task is to get the current calculator status and send it to the Chart Agent as an initial message, including an optimizing instruction.
4. The Linker Agent begins with the initial configuration, considering the given iteration number for optimizing and continuing or starting new learning. The Agent coordinates the designation of two tasks to be done in parallel by the countries Agents.
5. The Linker Agent looks for the current states of the country Agents and searches in the Q-Learning Tree for the best job; the best job contains the best reward. It also includes the importer and exporter assignment, the total amount for the trade. A message to the agents is sent, including the jobs.
6. The Country Agent analyze the instruction message to know his role following take the actions in the calculator. The update in the calculator produces a change in the calculator status. A FIPA message to both Agents Charts and Linker Agent is sent.
7. The Chart Agent gets the status messages and updates the general charts and country charts.
8. Once the Linker Agent receives the country Agents' updates, then a new job assignation is done.
9. The task assignation will continue until it achieves the total iteration number.

Discussion

Many advances have been made regarding the Smart Linker. First of all, the construction of the distributed infrastructure allows us to test and processes in parallel, which is very useful not just for the research activities but also for automatic processes during the Scenathons.

Good progress has been made regarding the new methodology to calculate the trade adjustment table using the Smart Linker. Special tools were developed to monitor and evaluate both the processes and the results. We have observed that the system is sensitive to the variations of trade volumes, even without any change on the country scenario definition.

We have also developed a tool to find the minimum and maximum values for each state's parameter and reward function for calculating the normalization effectively.

A new approach to accumulate and organized the knowledge obtained during training was developed and is been tested.

The current work was mostly invested in programming and developing and also in the calibration of the learning parameters. Still pendent a detailed analysis of the results compared without trade adjutant and with the proportional trade adjustment used in the Scenathon 2019.

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Annex 1: FABLE Scenathon 2019 global resuts

Figure 14.- Global results after trade adjustment FABLE Scenathon 2019

Annex 2: Countries' scenarios selection

Tables for scenario definition in the FABLE calculator

S.1	Alternative GDP projections
S.2	Alternative population projections
S.3	Alternative diets
S.4.	Share of food consumption which is wasted
S.5	Share of consumption which is imported
S.6	Evolution of exports
S.7	Alternative scenarios on livestock productivity
S.8	Alternative scenarios on crop productivity
S.9	Alternative scenarios on land available for agricultural expansion
S.10	Alternative scenarios on afforestation/reforestation
S.11	Alternative scenarios on ruminant density per ha of pasture
S.12	Fix Trade Scenario
S.13	Choose the level of activity of the population
S.14	WATER USE Scenario

Scenario definition made by the country teams during the FABLE Scenathon 2019.

Scenario selection of Argentina

S.1	S.2	S.3	S.4	S.5	S.6	S.7
SSP3	SSP3	SSP1	Current	I3	E1	HighGrowth

S.8	S.9	S.10	S.11	S.12	S.13	S.14
HighGrowth	NoDefor2030	BonnChallenge	NoGrowth	Yes	Middle	NoChange

Scenario selection of Australia.

S.1	S.2	S.3	S.4	S.5	S.6	S.7
ANO2_GG	ANO2_GG	HealthyDiet	Current	I1	Trade_Shift	ANO2_TA_GG

S.8	S.9	S.10	S.11	S.12	S.13	S.14
ANO2_TA_GG	FreeExpansion	ANO2_GG_2050	MidHighGrowth	Yes		Middle

Scenario selection of Brazil.

S.1	S.2	S.3	S.4	S.5	S.6	S.7
SSP2	SSP2	SSP2	Reduced	I2	TestExports	HighGrowth

S.8	S.9	S.10	S.11	S.12	S.13	S.14
BAUGrowth	NoDefor2030	BonnChallenge	HighGrowth	Yes		Middle

Scenario selection of U.S.

S.1	S.2	S.3	S.4	S.5	S.6	S.7	S.8
SSP2	**SSP2**	**HealthyDietUS_USDA**	Current	I1	E2	HighGrowth	HighGrowth

S.9	0	S.11	S.12	S.13	S.14
FreeExpansion	**HalfEarth**	**Mid-century strategy report - Otherland**	**Yes**		**Middle**

Scenario selection of China.

S.1	S.2	S.3	S.4	S.5	S.6	S.7
SSP1	familyplanning	ChineseHealthyDiet	ChineseReduce	ChineseImports	E4	NoGrowth

S.8	S.9	S.10	S.11	S.12	S.13
LowGrowth	FreeExpMinCropland	territorial_planning		Yes	Middle