D3.2 AI-based farmer's behavioural foundation

agricore

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Executive Summary

AGRICORE is a research project funded by the European Commission under the RUR-04-2018 call, part of the H2020 programme, which proposes an innovative way to apply agent-based modelling to improve the capacity of policymakers to evaluate the impact of agricultural-related measurements under and outside the framework of the Common Agricultural Policy (CAP). As the conclusion of *T3.2. - AI-based farmer's behavioural foundation*, deliverable 3.2. aims to present the mechanisms by which the agents (agricultural holdings) of the AGRICORE ABM make their decisions, both at the long-term structural level and at the short-term agronomic level. To this end, it presents the mathematical tools that make it possible to artificially reproduce the intelligence of the decision-makers (i.e. the human beings who act as managers of the various holdings). Firstly, in order to ease the understanding of the lector, there is explained how the model predictive control approach works, the foundation of the agent's optimisation process. Further on, within the deliverable, there is also detail on how the agents manage risk and uncertainties based on risk aversion and innovativeness indexes. For last, the decision-making must be constrained due to several factors, such as intrinsic, physics or external limitations.

Abbreviations

Abbreviation	Full name
MPC	Model predictive control
RHC	Receding horizon control
ABM	Agent-based model
CR	Current ratio
LR	Liquidity Ratio
D2E	Debt-to-Equity
GFI	Gross Farm Income
FNI	Farm Net Income
PMP	Positive Mathematical Programming
ST	Short-term
LT	Long-term

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1 Introduction

The AGRICORE project aims to provide European, national and regional administrations in charge of the design and implementation of agricultural public policies with a versatile tool to carry out impact assessments on actual finalised policy programmes (ex-post analysis) but also forecasted impact assessments of different alternative policy programmes (ex-ante analysis). These programmes are generally made up of combinations of instruments belonging to pillars I and II of the CAP. In the RUR-04-2018 call under which AGRICORE was granted, the European Commission wanted to improve some features with respect to existing impact assessment models, namely:

- Heterogeneity: models based on computable general equilibrium (CGE) or partial equilibrium (PE) work at an aggregated level (e.g. by sectors corresponding to all farms with the same type of farming throughout each country). Based on the results obtained with these models, it is very difficult to disaggregate (by downscaling) to calculate the different impacts on farms with the same techno-economic orientation but with different sizes or located in different geographical contexts [REF needed]. The commonly used alternative is to generate a series of typology farms, but this solution is still unable to capture the large impact variability of the same policy programme on a completely heterogeneous population of agricultural holdings (from small family farms to large industrially oriented holdings).
- Structural changes: sectoral models compute growth and aggregate variations at the regional or national level but again have problems in translating these aggregate results [REF needed] into variations in the number of active farms, average farm size, resulting labour demand or redistribution of average income.
- Financial viability: with aggregated models, the results are sectoral averages. This can lead to wrong conclusions. For example, a given policy may greatly increase the profitability of a small group of large farms while reducing the profitability of most small farms. In aggregate terms, the policy may appear beneficial to the sector when in fact, it is detrimental to the majority of its constituents.
- Risk and uncertainty: the best way to model uncertainties and the different perceptions of the risk associated with these uncertainties remains an open debate among the bio-economic modelling community [REF needed].
- Inter-farm interactions: it is not straightforward for sectoral models to model the interaction processes by which farms compete (for limited resources such as land) or cooperate (diffusion of more efficient technologies).

Agent-based models (ABMs) have inherent features that allow them to address these needs in a more transparent and understandable way, at the cost of an increase in the complexity of the formulation and the computational power required to solve them [REFs needed]. Obviously, AGRICORE is not the first ABM dedicated to this issue; there is already a long tradition of models using the same approach [REFs]. However, AGRICORE aims to offer significant advances in terms of the heterogeneity of its agents (initialised using synthetic reconstruction techniques to emulate the full population of real farms) and also in terms of its dynamic analysis capabilities (which will allow analysing not only the stationary effects of long-term policies but also their transitory effects during the process of adoption by farms).

The minimum unit of an ABM is the agent. An agent is a software element (a persistent piece of code) that has a set of states that represent characteristics of the real entity represented by the agent that is of interest to the modeller. The agent also has a set of methods defined to emulate its actions and how they are taken, either proactively or in response to an external stimulus (either from the environment or from other agents). The agent's behaviour is computed inside the corresponding method using a set of rules describing how states are translated to actions or new states. These rules can be static or dynamic (in case agents are prone to learning). The observable result of an agent's behaviour is its actions and the actual activities that it performs based on the application of decision rules on its states. There are several types of decision rules [DAM]:

- Programming-based approach
- Learning-based approach
- Model-based approach
- Rule-based
- Multi-criteria decision-making
- Inference engines
- Evolutionary computing
- Machine learning
- Markov Decision Processes

As part of task 3.2 results, the objective of this deliverable is to present how the rationale of a farmer is modelled in a mathematical optimisation problem. Generally, it can be assumed that the farmers act towards maximising their profits while taking some risks, the latter being the key to defining their overall trend and behaviour. In this sense, the first step is to define the main objective of the farmers mathematically as an optimisation problem so that it can be solved by means of solvers. This will settle the core of the agent's rationale, which, as presented in the following sections, has been divided into two parts based on the time framework. Further on, the second step is to shape the core through a parameterisation based on variables that define the agent's behaviour, such as risk aversion. For last, it is important to clarify from the beginning the use of the "*optimisation*" term. In mathematics or control theory, the term "*optimisation*" refers to finding the best set of actions (or control variables) in order to achieve the best solution or reach the objective in the most efficient way. However, in the problem handled within AGRICORE, the objective is not to find the best solution available but to find the best solution according to the agent's criteria and, most importantly, based on the information available to the agent. Consequently, in order to achieve this objective, AGRICORE proposes and model predictive control (MPC) approach.

2 Determination of agents' behaviour

The agent's behaviour aims to replicate the agricultural owner's mind concerning financial and agroeconomical decision-making strategies. Given its complexity, the agent's behaviour has been divided into two interconnected models. The first focuses on long-term optimisation and the second one, constrained by the first, focuses on the short-term. On the one hand, long-term optimisation traduces in financial optimisation of the agricultural holding. Moreover, the strategy reached through the optimisation based on the agent's behavioural parameters settles economic restrictions for the short-term problem. On the other hand, the short-term optimisation at the sight of one year focuses on the agroeconomical strategies for the next agricultural campaign. Both models, as presented in D3.1, are executed sequentially and iteratively. The following sections are detailed both model's mathematical formulation and the optimisation of problem resolution based on the agent's behaviour.

2.1 Long-term model - Financial-based planning of the agricultural holding structure

2.1.1 Model Predictive Control

Predictive Control is a particular strategy in the field of Advanced Control based on the calculation of future actions required to optimize a controlled target. This strategy needs the dynamic model of a plant, known as the predictive model, in order to predict its future behaviour during a time interval, the horizon of prediction. The time interval is assumed to be finite in order to avoid the propagation of errors due to modelling activities. Once applied, the optimum action of control is recalculated, and the predictive horizon is moved in order to adjust the settings to the new initial conditions. This is known as a sliding horizon [1]. In the model, instead of having a sliding horizon, the horizon will be reset after each optimization, as the predictive horizon refers to the years remaining until the agent's retirement. Below, Figure 1 graphically presents the MPC control scheme used in AGRICORE.

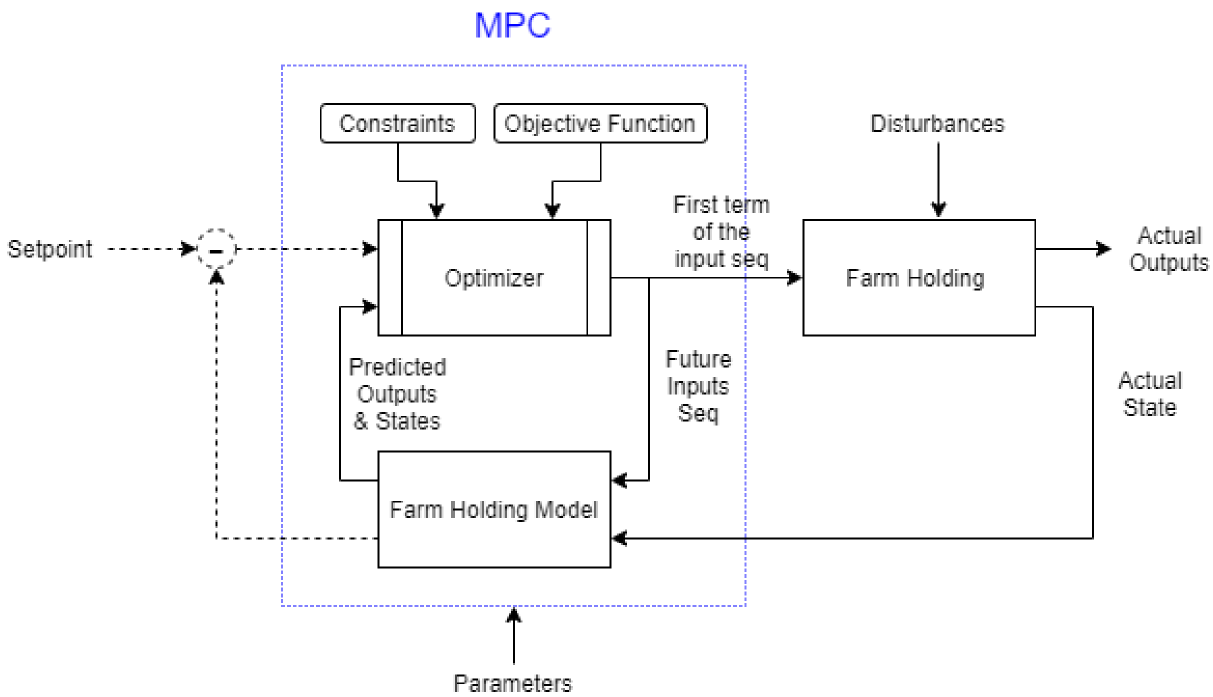

Figure 1 MPC Control Scheme used in AGRICORE to mimic farm agent role

The main aspects related to MPC are listed below and represented graphically in Figure 2 (taken from [2]):

- **Predictive model:** It is a model of the plant/system to be managed that is used to predict the dynamic response based on the action applied during the optimization process.
- **Predictive horizon:** Discrete or continuous time interval during which the operation of the plant/system is predicted by using the predictive model (or a simplified one).
- **Control horizon:** Discrete or continuous time interval, during which the sequence of optimal actions is chosen by means of an optimization problem. It must be less than or equal to the prediction horizon. In the event that it is lower, it is assumed that the rest of the actions are equal to the last one calculated.
- **Restrictions of the model:** A set of restrictions due to saturation of the actuators or dangerous operating conditions of the plant that must be taken into account when designing the optimal control strategy.

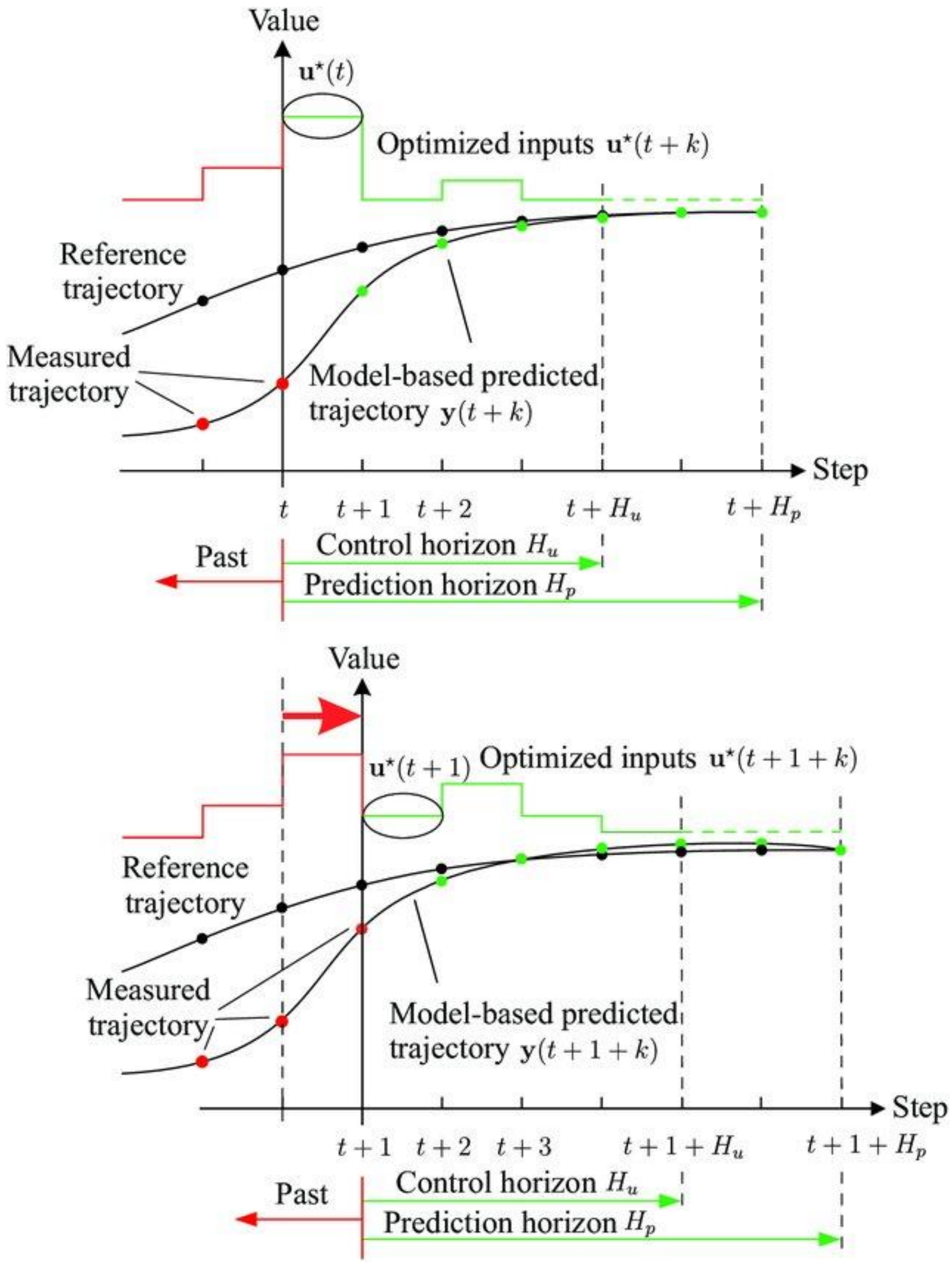

Figure 2 Functionality of the Receding Horizon Control principle of the MPC.

Basically, MPC relies on three main ideas:

1. Explicit use of a model to predict (predictive model) the output of the process (also referred to as the output of the system or the output of the plant) along a future time horizon.
2. Calculation of an optimal control sequence (also referred to as input sequence) based on the optimization of a performance index (also referred to as fitness function, objective function, or optimization function), subject to a set of constraints.
3. A receding horizon control (RHC) strategy, so that at each instant, the horizon is moved towards the future, which involves the application of the first control signal of the sequence calculated at each step. At the next time step, the actual plant states are read (if they're

directly observable) or estimated (if they're not) and the optimal sequence of inputs is recomputed.

Among MPC advantages, the following can be mentioned:

- It handles multivariable control problems naturally.
- It explicitly handles constraints, allowing a closer operation to them.
- It handles structural changes (by modifying the model and/or switching between different branches of the objective function).
- It is an easy-to-tune method through well-understood tuning parameters (prediction horizon and optimization problem setup).

Depending on the choice of the type of model, the objective function type and the mathematical description of constraints, MPC gets different "surnames" (i.e. adjectives that specify the previous three aspects). For example, **the control of AGRICORE agents' operation is intended to become a State-Space based** (defines the type of model) **Non-linear** (defines the form of the objective function) **MPC with non-linear constraints/model** (defines the math form of constraints/model).
In AGRICORE, the 'plant' is the agricultural holding instead, and the model is the set of equations that define the dynamics of the farm (shown in Section 3). It is important here to distinguish between the agent's domain model and the agent's optimisation model. All the elements of the optimization model must be included in the domain model, but not all the elements (attributes) of the domain model are taken into consideration for the optimization model (e.g. the age of the farmer does not explicitly appears in the optimization at a particular step, but might change the optimization parameters between two optimization instants). The next step is the definition of the second one. As mentioned before, AGRICORE is a state-space (SS) based model, which means that the prediction model of the farm will have the following formulation in its most generic version:

$$\begin{aligned} \mathbf{x}[k+1] &= \mathbf{A}[k]\cdot\mathbf{x}[k] + \mathbf{B}[k]\cdot\mathbf{u}[k] + \mathbf{E}[k]\cdot\mathbf{d}[k] \\ \mathbf{y}[k] &= \mathbf{C}[k]\cdot\mathbf{x}[k] + \mathbf{D}[k]\cdot\mathbf{u}[k] + \mathbf{F}[k]\cdot\mathbf{d}[k] \end{aligned} \tag{1}$$

where:

- **States**

  ($\mathbf{x}[k] \in \mathbb{R}^N, N \in \mathbb{N}$): are dependent variables mimicking those attributes of the farm whose value depends on the previous states and on the decisions taken in the prior instant of time.

- **Decisions (Inputs)**

  ($\mathbf{u}[k] \in \mathbb{R}^M, M \in \mathbb{N}$), also referred to as manipulated variables or agro-management controls. They are independent variables that mimic the set of agro-management and financial decisions that a farmer (manager) has to take each season to optimize the holding operation. This includes either purely agricultural decisions (amount of fertilizer used, irrigation plan), or purely financial decisions (new investments). The idea is to first take financial decisions and then make agronomical ones depending on the prior. An example of this is that financial decisions limit land availability, which serves as input in the agronomical module. Finally, the allocation of crops can be optimised.

- **Outputs**

  ($\mathbf{y}[k] \in \mathbb{R}^L, L \in \mathbb{N}$): are the dependent variables to be controlled.

- **Disturbances**

  ($\mathbf{d}[k] \in \mathbb{R}^H, H \in \mathbb{N}$): are independent variables that cannot be adjusted by the controller (they might also include measurement errors).

- **Parameters**

  ($\mathbf{A} \in \mathbb{R}^{N\times N}, \mathbf{B} \in \mathbb{R}^{N\times M}, \mathbf{C} \in \mathbb{R}^{L\times N}, \mathbf{D} \in \mathbb{R}^{L\times M}, \mathbf{E} \in \mathbb{R}^{N\times H}, \mathbf{F} \in \mathbb{R}^{L\times H}$): are model elements considered as "constants" during the optimization, which stand for inherent properties of nature (or of the materials and equipment involved in its transformation).

2.1.2 Financial statements

In this section, the different elements of a balance sheet are presented, taking into consideration the data and rules provided by the FADN, data and rules provided by RECAN and the variables chosen to be modelled as were considered to be the most relevant and defining for an agricultural holding.

2.1.2.1 Balance Sheet

The balance sheet includes asset items on the one hand and liability and equity on the other. Usually, asset accounts are ordered from the highest to the lowest degree of liquidity, while liability accounts are ordered from the highest to the lowest degree of enforceability. The balance sheet accounts are subdivided into several items. These items are described in the following sections, in accordance with the concepts defined in the EU FADN Regulation.

Assets - Final Value (SE436)

The year-end value of total fixed and regular assets. Only assets in ownership are considered.

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Total Assets = Fixed assets + Current assets
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- **Fixed assets - Final value (SE441)** Year-end value of all fixed assets: agricultural land, buildings, machinery and equipment, breeding livestock, intangible assets with no commercial value and other non-regular assets.
- **Land, permanent crops and quotas (SE446)** Year-end value of owned agricultural land, permanent crops, land improvements, quotas and other rights, and forest land.
- **Machinery and equipment (SE455)** Year-end value of the following equipment: machines, tractors, cars and vans, irrigation equipment (except those of low value or with a useful life of less than one year).
- **Current assets - Final value (SE465)** Year-end value of all regular assets: stock of products, non-reproductive livestock and other current assets (cash and cash equivalents, receivables and other current assets).
- **Other working capital (SE480)** Year-end value of cash and other assets that can be readily converted into cash, short-term assets and amounts due to operations. Current assets refer to assets that can be converted into cash in less than 1 year.

Total Liabilities - Final Value (SE485)

The year-end value of the amounts of short-, medium- and long-term loans to be repaid for on-farm purposes.

```
Total Liabilities = Long-term liabilities + Short-term liabilities
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The following kinds of liabilities are assumed to exist in an agricultural holding:

- **Short-term debt (SE495):** Short-term debt, also called current liabilities, is a firm's financial obligations that are expected to be paid off within a year. In particular, this kind of liability will cover operational payments.
- **Long-term debt (SE490):** Long-term debt is debt that matures in more than one year. In particular, this kind of liability will cover structural payments.

Equity - Final value (SE501)

The RECAN names the Equity as Net Worth (SE501) at closing validation and refers to the final value after subtracting to global assets all the liabilities of the farm. Mathematically it can be written as follows:

```
Net Worth (Equity) = Total Assets + Total Liabilities
```

2.1.2.2 Financial Ratios

To determine the economic status of each farm holding, the current ratio is implemented as a measure of liquidity and the Debt to Equity ratio as a measure of solvency.

The current ratio (CR) is a measure of the short-term financial health of an entity. It is also known as the working capital ratio. It will measure the relationship between current assets and current liabilities. It measures the firm's ability to pay for all its current liabilities, due within the next year, by selling off all its current assets [3]. In the AGRICORE Model, the CR is assimilated into the Liquidity Ratio (LR). Its expression may be found below (the text in brackets refers to the code of the corresponding FADN standard variable):

$$LR = \frac{\text{Current Assets (SE465)}}{\text{Current Liabilities (SE495)} + \text{Amortization of LT Liabilities}} \in \mathbb{R}^{+} \qquad (2)$$

Hereby, depending on the value the LR has in each agricultural season, the farm will have or not have the capacity to meet its financial obligations in the short term. Regarding the formula, it is trivial to guess that the higher the ratio, the more liquid the company is. Commonly, the optimal LR value used is 2. However, 1.5 is commonly accepted as a healthy liquidity status for most industrial companies [4]. If the LR is too high (values much greater than 2), then the company may not be using its current assets or its short-term financing facilities efficiently, which may indicate problems in working capital management.

On the other hand, Debt-to-Equity (D2E) ratio is a measure of the degree to which a company is financing its operations through debt versus wholly owned funds. More specifically, it reflects the ability of shareholder equity to cover all outstanding debts in the event of a business downturn. The D2E ratio is a particular type of gearing ratio used as a measure of entity solvency. Therefore, in AGRICORE, it is assimilated into the Solvency Ratio (SR). The SR's expression, coincident with the D2E expression, may be found below:

$$SR = \frac{\text{Farm Liabilities (SE485)}}{\text{Farm Equity (SE501)}} \in \mathbb{R} \tag{3}$$

Given that the SR ratio measures a company's debt relative to the value of its net assets, it is most often used to gauge the extent to which a company is taking on debt to leverage its assets. A high SR is often associated with high risk; it means that a company has been aggressive in financing its growth with debt. If a lot of debt is used to finance growth, a company could potentially generate more earnings than it would have without that financing. If leverage increases earnings by a greater amount than the debt's cost (interest), then shareholders should expect to benefit. However, share values may decline if the cost of debt financing outweighs the increased income generated. The cost of debt can vary with market conditions. Thus, unprofitable borrowing may not be apparent at first. Changes in long-term debt and assets tend to have the greatest impact on the SR because they tend to be larger accounts compared to short-term debt and short-term assets. This is why it has been proposed another ratio for liquidity measuring [5].

As the equation of the SR reveals, $SR \in \mathbb{R}$, and therefore it may be negative. Due to the fact that Farm Liabilities $\in \mathbb{R}^+$, the only way of SR < 0 is having Farm Equity < 0. This happens when the liabilities exceed the assets. This is considered a very risky sign, indicating that the company may be at risk of bankruptcy. According to CSIMarket [6], the closer the SR value to 0 (while positive), the stronger the company's balance sheet. SR > 2 reveals that the entity does not have a healthy solvency status [5]. In the case of agricultural holdings, it will be used as an objective value of 0.2.

According to the model $\mathcal{M}$ presented in deliverable D3.1, the financial ratios that evaluate the financial status of the agricultural holding may be modelled as follows:

$$NP_{t+1} = \frac{FNI_{t+1}}{E_t} \tag{4}$$

$$SR_{t+1} = \frac{TA_{t+1}}{E_{t+1}} = \frac{FA_{t+1} + CA_{t+1}}{FA_{t+1} + CA_{t+1} - LT_{t+1}} \tag{5}$$

2.1.3 Financial optimisation

The assumption is that the Farm Manager makes decisions to maximise profitability and minimise the distance of the solvency ratio to long-term economic viability (solvency). Let $x_t \in \mathbb{R}^N, N \in \mathbb{N}$ be the state vector which will serve as an indicator of the financial health at time t of each farm. In our particular problem $N = 2$ and,

$$x_t \quad = \begin{bmatrix} NP_t \\ SR_t \end{bmatrix} \in \mathbb{R}^2, \tag{6}$$

Where NP_t is a net profitability income ratio and SR_t is the solvency ratio.

On the other hand, the decision vector or output vector $u_t \in \mathbb{R}^K, K \in \mathbb{N}$. In our model, $K = 3$ and,

$$u_t \quad = \begin{bmatrix} B_t^L \\ B_t^M \\ L_t \end{bmatrix} \in \mathbb{R}^3, \tag{7}$$

where $B_t^L \in \mathbb{R}$ and $B_t^M \in \mathbb{R}$ represent, respectively, the desires for buying/selling land and machinery, and $L_t \in \mathbb{R}^+$ represent the acquisition of new long-term liabilities.

It is proposed as a bi-objective problem. On the one hand, the farmer seeks to maximise profitability. On the other, the farmer also looks to keep the solvency close to healthy values.

Let $T \in \mathbb{N} = min\{7, \text{years to retire}\}$ be 7 if the agent has more than 7 years left to retire or the number of years until retirement otherwise. The design of the model, T works as our horizon of prediction. The objective function that mathematically describes the first objective can be expressed as:

$$\mathcal{J}_1(NP, u, t) = -\sum_{s=t}^{T+t} NP_s \tag{8}$$

On the other hand, for any $t \in \{1, \ldots, T\}$ the second objective can be expressed as follows:

$$\mathcal{J}_2(SR, u, t) = \sum_{s=t}^{T+t} |SR_s - S\,\mathrm{R}_{obj}| \tag{9}$$

where SR_{obj} designs the objective value of the solvency ratio.

In addition, it is interesting to mention that a bi-objective problem has a surface of optimal decisions (Paretian efficiency, see [7]). On these surface, there are decisions more effective in one objective than on the other, and otherwise. But there is no optimal solution [7] To that end, by applying the Weighting Method [8], the two objective functions are translated into a single one.

$$\mathcal{J}(x, u, t) = -\sum_{s=t}^{T+t} \beta^{s-t} \cdot \Omega \cdot NP_s - \beta^{s-t} \cdot \Psi \cdot |SR_s - S\,\mathrm{R}_{obj}| \tag{10}$$

where $\Omega > 0$ and $\Psi > 0$ are the weights from combining the objective functions applying the weighting method [8].

Both parameters are used to model the agent's behaviour, as detailed in the section "*Modelling farmers' management of risks and uncertainty*". On the other hand, $\beta \in (0,1]$ refers to the discount factor measuring how much weight an individual attaches to future profitability and solvency. This can also be related to risk aversion, as farmers with low concern for future situations (i.e. lower discount factors) tend to risk more to succeed in current objectives with consequences in the near future [9]. To conclude, the economic optimisation mimics the economic management decisions by means of which Agricultural Holding's manager tries to steer the economic position of Agricultural Holding from its current state towards the ideal or target state. In order to calculate optimal economic control actions, the Farm Manager (and thus the model that represents him/her) has an insight into the dynamics of economic variables. How these economic dynamics are modelled in the AGRICORE model is explained in D3.1. In the following subsections, the restrictions of the optimisation problem are presented, and the final formulation of the financial optimisation problem is presented.

2.1.3.1 Restriction of the optimisation problem

The management of the agricultural holding is subject to a set of restrictions in the control inputs and/or in the agronomic states. These restrictions translate into constraints for the optimisation problem. Some of these restrictions

- Restriction 1: There is a minimum amount of available machinery needed per amount of available area

$$A_t \cdot P_{mach} \leq M \quad (11)$$

where P_{mach} is a ratio of the value of machinery needed per value of land.

- Restriction 2: It is not possible to own negative land

$$A_t \geq 0 \quad (12)$$

- Restriction 3: It is not possible to own negative machinery

$$M_t \geq 0 \quad (13)$$

- Restriction 4: It is not possible to have negative GFI

$$GNI_t \geq 0 \quad (14)$$

- Restriction 5: It is not possible to have negative FNI

$$FNI_t \geq 0 \quad (15)$$

- Restriction 6: It has no sense negative values of Lt, as it represents money lent by a bank in a specific time

$$L_t \geq 0 \quad (16)$$

- Restriction 7: Banks loans are bounded. It is assumed that the maximum loan a bank can offer is c-times the current Equity (E_t), with $c \in \mathbb{R}^+$

$$L_t \leq c \cdot E_t \quad (17)$$

- Restriction 8: If the balance of buying and selling is positive, the farmer must acquire a loan to pay off commitments

$$B_t^L + B_t^M \leq L_t \quad (18)$$

- Restriction 9: It is not possible to sell more land that the owned

$$-A_t \leq B_{t+1}^L \quad (19)$$

- Restriction 10: It is not possible to sell more machinery that the one owned

$$-M_t \leq B_{t+1}^M \quad (20)$$

2.1.3.2 The final formulation of financial optimisation

Let $\mathcal{R}$ be the set of restrictions described by in the previous subsection. Finally, the purpose is to linearize the objective function in the following way.

$$J(x,u,t) = -\sum_{s=t}^{T+t} \beta^{s-t} \cdot \Omega \cdot NP_s - \beta^{s-t} \cdot \Psi \cdot |SR_s - S\,\mathrm{R}_{obj}| \quad (21)$$

The underlying reason for linearising the objective function is that the solvers working with that are not capable of solving the nonlinear problem. For this reason, as a comment, note that a linear problem has been achieved since the denominator of the profitability term is a constant in each implementation since it refers to the value of Equity in the previous optimization step (but not, necessarily to the previous time step). Note also that both problems are equivalent in terms of expected behaviour. Actually, in the implementation, we select Ω with the same order of magnitude as E_{t-1} to simplify the expression.

Finally, the constrained optimization problem can be written as follows:

$$\begin{aligned} u_e^* &= argmin_u\, \mathcal{J}(t,u,x) \\ \text{subject to } &\mathcal{M}[\text{Model Constraint Eqs}] \\ &\mathcal{R}[\text{Input Constraint Eqs}] \end{aligned} \tag{22}$$

where the objective function $\mathcal{J}$ *is given by the equation* (**10**).

The solution to this problem is a sequence of optimal economic decisions

$$u_e^* = \{u_e^*(1), \ldots, u_e^*(T)\} \tag{23}$$

which minimises the objective function by driving the Agricultural Holding (AH) towards SR_{obj} while optimizing its profitability.

2.2 Short-term model - Agroeconomic planning of the agricultural holding operation

2.2.1 PMP approach: cost estimation and calibration phase

The introduction of PMP by Howitt (1995) [10] and Paris and Howitt (1998) [11] was perceived as one of the most important innovations in the field of Mathematical Programming. PMP has provided researchers in the field of agricultural economics with powerful new tools reviving mathematical programming and creating a bridge to econometrics [12]. PMP has opened a new research frontier and has created new opportunities for investigating land allocation under the pressure of new market and policy scenarios.

The seminal works of 1995 and 1998 were criticised and discussed in many aspects, with the main areas of discussion as follows:

- The PMP approach [13];
- The introduction of the positive constraints [14] [12];
- The estimation of the dual value linked to each production activity [15] [16];
- The use of Maximum Entropy and support values for the estimation of the Q matrix [17];
- The characteristics of the Q matrix (Diagonal or full) [18];
- The use of single observations compared with multiple observations [19];
- The possibility of introducing new activities [20].

Literature has two main implications related to the effective implementation of PMP methodology. The first is associated with the objective of PMP methodology. PMP was perceived by many researchers as a good tool to calibrate LP models, especially when dealing with problems of over-specialisation [18] [21] [15] [22](Helming et al., 2001; Heckelei, 2002; Buysse et al., 2007; Kanellopoulos, 2010). A related issue is the "tautology problem" that was perceived as a negative element of the PMP methodology [23].

The second most important implication of the standard PMP approach is the difficulty of estimating the Q matrix that considers all the observed activities when no information is available related to the activity costs, $\boldsymbol{c}$. The problem of implementing the PMP model without knowing $\boldsymbol{c}$ is related to the fact that the imposition of calibration constraints generates at least one associated shadow value equal to zero; otherwise, the shadow price for the structural constraint (land) will be equal to zero [11]and will be missed an observed activity in the Q matrix.

Given the methodological setting of the PMP, an alternative approach is proposed with the objective to use only the endogenous information available for all farms belonging to the FADN database and thus maintain flexibility in terms of creating models able to describe and represent different situations according to the research questions and then consider different farm types at different territorial levels, starting from individual farms. For this reason a "generalised" model is proposed to allow for the new formulation of PMP to be used in a different context (for details on the theoretical formulation, see D5.3 Modelling Supply Chain in the AGRICORE platform).

The model can be presented as follows: assume a sample of farms composed of N farms and consider that information about the production plan, prices and technical coefficients (the quantity of factors used to obtain one unit of each farm product) are known at the farm level. It is also considered only one limiting factor, the land available at the farm level, b_n. The use of this factor per unit output is represented by the technology matrixA_n. The known levels of production for each farm are indicated by the vector $\mathbf{x}_n$, while output market prices are represented by the vector $\mathbf{p}_n$ and exogenous marginal costs related to each activity are represented by the vector$\mathbf{c}_n$. This latter variable can be viewed as the cost originating from the farm accountancy and is observed.

The objective of a PMP model is to recover the part of the information that cannot be directly collected at the farm but contributes to farmers' decision-making process in a more or less conscious way.

Adopting the generalised PMP approach the following problem can be introduced:

$$\mathrm{m}_{\mathbf{u}_n, y_n, \lambda_n, \mathbf{Q}}\{\textstyle\sum_{n=1}^{N}\frac{1}{2}\mathbf{u}'_n\mathbf{u}_n + \sum_{n=1}^{N}(b_n y_n + \lambda'_n\bar{\mathbf{x}}_n + \mathbf{c}'_n\bar{\mathbf{x}}_n) - \mathbf{p}'_n \mathrm{x}_n\} \tag{24}$$

subject to

$$\mathbf{A}'_n\mathbf{y}_n + \lambda_n + \mathbf{c}_n \geq \mathbf{p}_n(\mathbf{w}_n) \tag{25}$$

$$\mathbf{c}_n + \lambda_n = \mathbf{Q}\bar{\mathbf{x}}_n + \mathbf{u}_n(\mathbf{z}_n) \tag{26}$$

Where:

- $y_n \geq 0, \lambda_n \geq 0$
- Q is a symmetric positive semi-definite matrix, as stated by Paris and Howitt (1998) [11] and Paris (2010)[23].
- $\mathbf{w}_n$ and $\mathbf{z}_n$ are the shadow prices associated with equations (25) and (26), respectively
- $\mathbf{u}_n$ is the vector of marginal cost deviations per farm, that is, the distance between the marginal cost $c + \lambda$ and the marginal cost Qx of a non-linear cost function such that:

$$c + \lambda - Qx = u \tag{27}$$

The estimated parameters of Q are part of a quadratic cost function aiming at providing flexibility to model responses towards farm simulations.

The model is optimised by a combined objective function, (24), that considers a **least-squares technique** and minimises the difference between the total revenue, $p'x$, and the total cost, $by + \lambda'\mathbf{x} + \mathbf{c}'\mathbf{x}$. This latter expression identifies the optimal condition for the standard PMP approach, or in general terms, states that under optimal conditions, the primal objective function should be equal to the dual function.

The above model integrates the first and second phases of the standard PMP approach using the PMP dual properties. In this model, there is no explicit trace of both: the calibrating constraints and the epsilon terms that help to break the linear dependence between structural and calibration constraints.

The constraints of the model (25)-(26) concern the equilibrium conditions with marginal costs greater than or equal to marginal revenue and the relationship by which a linear cost function is shifted to a quadratic cost function.

The model does not repeat the tautological procedure of the standard approach of deriving information about the output levels, which were already known before the model was developed, but rather reveals hidden information about the differential marginal costs within the production levels and makes this information available for the simulation phase.

To better understand the significance of this problem and the properties of the solution, the model is transformed in its alternative Lagrangean representation, as follows:

$$L = \sum_{n=1}^{N} \frac{1}{2}\mathbf{u}_n'\mathbf{u}_n + \sum_{n=1}^{N}(b_n y_n + \lambda_n'\bar{\mathbf{x}}_n + \mathbf{c}_n'\bar{\mathbf{x}}_n - \mathbf{p}_n'\bar{\mathbf{x}}_n)$$
$$+\sum_{n=1}^{N} \mathrm{w}_n'(\mathbf{p}_n - A_n' y_n - \boldsymbol{\lambda}_n - \mathbf{c}_n) + \sum_{n=1}^{N} \mathrm{z}_n'(\boldsymbol{\lambda}_n + \mathbf{c}_n - \mathbf{Q}\bar{\mathbf{x}}_n - \mathbf{u}_n) \quad (28)$$

From the Lagrangian function is obtained the following relevant KKT conditions:

$$\frac{\partial L}{\partial y_n} = b_n - A_n\mathbf{w}_n \geq 0 \quad (29)$$

$$\frac{\partial L}{\partial \boldsymbol{\lambda}_n} = \bar{\mathbf{x}}_n - \mathbf{w}_n + \mathbf{z}_n \geq \mathbf{0} \quad (30)$$

$$\frac{\partial L}{\partial y_n} = b_n - A_n\mathbf{w}_n \geq 0 \quad (31)$$

The partial derivatives (29) indicate that the deviation terms, $\mathbf{u}_n$, are equal to the dual values, $\mathbf{z}_n$, linked to the equation (26).

Because the problem attempts to minimise the squares of the farm cost, the deviations$\mathbf{u}_n$ and$\mathbf{z}_n$ should assume very small values close to zero.

The KKT condition (30) can be rewritten as $\mathbf{w}_n - \mathbf{z}_n \leq \bar{\mathbf{x}}_n$, showing that the difference between the two shadow prices associated with equations (25) and (26) should be less than or equal to the realized outputs.

The generalised PMP approach assumes knowledge of information related to the accounting cost c, but it is well known that this information is lacking at the European level. In addition, to properly represent the observed land use for each farm in the sample, the "self selection" problem should be considered (Paris and Arfini, 2000).

According to this objective, models (24) – (26) take the information related to the total variable costs available at the farm level in the European FADN as a guide for the accounting cost estimation and is modified in the following manner:

$$\min_{u} LS = \frac{1}{2}\mathbf{u}'\mathbf{u} \quad \text{subject to} \tag{32}$$

$$\boldsymbol{\alpha} + \boldsymbol{\lambda} = \mathbf{R}'\mathbf{R}\bar{\mathbf{x}} + \mathbf{u} \text{ se } \bar{x} > 0 \tag{33}$$

$$\boldsymbol{\alpha} + \boldsymbol{\lambda} \leq \mathbf{R}'\mathbf{R}\bar{\mathbf{x}} + \mathbf{u} \text{ se } \bar{x} = 0 \tag{34}$$

$$\alpha'\bar{\mathbf{x}} \leq TVC \tag{35}$$

$$\mathbf{u}'\bar{\mathbf{x}} + \frac{1}{2}\bar{\mathbf{x}}'(\mathbf{R}'\mathbf{R})\bar{\mathbf{x}} \geq TVC \tag{36}$$

$$\boldsymbol{\alpha} + \boldsymbol{\lambda} + \mathbf{A}'\mathbf{y} \geq \mathbf{p} \tag{37}$$

$$\mathbf{b}'\mathbf{y} + boldsymbol\lambda'\bar{\mathbf{x}} = (\mathbf{p} - \boldsymbol{\alpha})'\bar{\mathbf{x}} \tag{38}$$

$$\mathbf{R} = \mathbf{L}\mathbf{D}^{1/2} \tag{39}$$

$$\textstyle\sum_{n=1}^{N} u_{n,j} = 0 \tag{40}$$

The objective of models (32)-(40) is to estimate a non-linear cost function, including the unknown accounting variable cost α. The restrictions (33) and (34) define the relationship between marginal costs derived from a linear function and marginal costs derived from a quadratic cost function.

$\alpha + \lambda$ defines the sum of the unknown (or estimated) accounting variable costs and the differential variable marginal costs. The latter is implicit in the decision-making process of the entrepreneur and is not accounted for in the holding's bookkeeping. Both components are endogenous variables within the minimisation problem.

The restrictions (33) and (34) also guarantee that the self-selection rule is followed, enabling farmers to select possible production activities from all activities present in the region (represented by the sample dimension) but restricting activities to those observed in the first phase of the PMP methodology. Moreover, to guarantee consistency between the estimated accounting variable costs and those effectively recorded by the farm accounting system, constraint (35) requires that the total estimated variable cost is not greater than the total variable cost observed in the FADN databank at the farm level. Equation (36) states that the costs estimated by the model by means of a non-linear cost function must be at least equal to the value of the observed total variable cost (TVC). To guarantee consistency between the estimation process and the optimal conditions, restriction (37) introduces the traditional economic equilibrium condition, where total marginal costs must be greater than or equal to marginal revenues. The total marginal costs also consider the use cost of the factors of production defined by the product of the technical coefficients matrix $\mathbf{A}'$ and the shadow price of the restricting factors y; while the marginal revenues are defined by the sum of the products' selling prices, p, and any associated public coupled subsidies. The additional constraint (38) defines the optimal condition where the value of the primal function corresponds exactly to the value of the objective function of the dual problem. To ensure that the matrix of the quadratic cost function is symmetric positive semi-definite, the model adopts Cholesky's decomposition method (39). Finally, restriction (40) establishes that the sum of the errors u must be equivalent to zero.

2.2.2 Agroeconomic optimisation

Once the model is calibrated, the cost function estimated with the model (32)-(40) may be used in a model of maximisation of the farm gross margin, ignoring the calibration restrictions imposed during the first phase of the standard PMP approach. In this case, the dual relations entered in the preceding cost estimation model guarantee the reproduction of the observed situation. The model, therefore, appears as follows:

$$\max_{x\geq 0} ML = \mathbf{p}'\mathbf{x} - \{\frac{1}{2}\mathbf{x}' \hat{Q}\, \mathbf{x} + \hat{\mathbf{u}}'\mathbf{x}\} \tag{41}$$

subject to

$$\mathrm{Ax} \leq \mathrm{b} \tag{42}$$

$$A_j x_j - h_j = 0 \forall j = 1, \dots, J \tag{43}$$

Constraint (23) represents the restriction on the structural capacity of the farm, while relation (24) enables us to obtain information on the hectares of land (or the number of animals) associated with each process j. Once the initial situation has been calibrated through the maximisation of the farm gross margin, it is possible to introduce variations in the public aid mechanisms and/or in the market price levels to evaluate the farm's reactions to various policy conditions. The reaction of the farm production plan will take into account the information used during the estimation phase of the cost function, where it is possible to identify a real, true matrix of firm choices, i.e., Q**.**

The objective function represents the economic part of the model by considering the prices and costs (implicit and explicit) associated with each process as well as any payments (coupled or decoupled) linked to the agricultural policies introduced by CAP through the different intervention measures.

The structure of constraints allows describing the technology used by farmers while taking into account also the rules that define their choice behaviour regarding:

a) the optimal productive combination

$$\begin{aligned} \mathrm{Ax} &\leq \mathrm{b} \\ A_j x_j - h_j &= 0 \forall j = 1, \dots, J \end{aligned} \tag{44}$$

Where **A** is the technical matrix, **x** are the production volumes for each crop and **b** is the vector of land availability.

b) the **possibility of renting land and/or leasing land**, taking into account behavioural rules defined on the basis of socio-economic characteristics of farmers

$$A_{nj} x_n \leq b_n + Z_n - V_n \tag{45}$$

Where the constraint reflects the assumption that each farm can lease (Z) or rent (V) land at the same price. Prices are exogenous to the the short period module, they are calculated in the Land Market Module (D 5.2) and are defined in the objective functions.

c) the **possibility of introducing new activities** into the production plan and in particular the possibility of converting the production plan from conventional to organic farming

$$\begin{gathered}\mathbf{A}_c\mathbf{x}_c + \mathbf{A}_g\mathbf{x}_g \leq \mathbf{b} \\ A_{nc}x_{nc} \cdot A_{ng}x_{ng} = 0\end{gathered} \tag{46}$$

A new crop is considered in the technical matrix with a different yield than the existing crop.

d) the **ability to simulate the financial requirement** for each crop versus the available financial resources.

e) the **ability to simulate the impact** of new environmental constraints introduced within the new CAP

f) the **possibility of monitoring** the use of natural resources and negative externalities to the environment.

Thus this module allows the introduction of variations in the public aid mechanisms and/or in the market price levels to evaluate the farm's reactions to various market and policy conditions.

3 Modelling farmers' management of risks and uncertainty

The management of an agricultural holding directly depends on the decisions made by the farmer. In the decision-making process, the farmer must consider many factors to carry out the most suitable decisions according to her/his objectives because any decision entails outcomes and consequences that are reflected in the farm income. Given that it is impossible to accurately predict a decision's consequences, risk and uncertainty are associated with any agro-management decision. The levels of these parameters vary according to the decision and the context, e.g. for a farmer whose profit from farming in the previous agricultural season was low, buying land to expand her/his farm is riskier than renting it. Despite this, not all farmers have the same attitude towards risk and they usually perceive it differently, which allows for classifying them into three categories: risk-averse, risk-takers and risk-neutral [24]. Therefore, the measurement and modelling of risk are complicated.

As stated in [25], the methods to measure and model individual risk preferences can be divided into two groups according to the available data. On the one side, econometric and mathematical methods can be used to estimate the risk aversion level of farmers based on their economic behaviour. On the other side, multi-item scales and lottery-choices activities can be carried out to collect raw data on the risk preferences of farmers and, based on them, risk aversion can be estimated.

In the initial stages of the project, it was not known whether it would be possible to access economic data resulting from farmers' management in order to estimate risk aversion. Moreover, in recent years, an upward trend of the second group of methods for measuring farmers' risk aversion in Europe was observed [26]. For these reasons, it was decided to collect the data empirically by means of questionnaires including multi-item scales and lottery choice questions. To this end, three survey campaigns have been conducted and the same questions to measure risk aversion were used in order to obtain homogenised results and compare them.

As explained in D3.1, AGRICORE's mathematical model has a bi-objective function that aims to maximise the agent's economic profitability and solvency. These two terms of the function are weighted by two coefficients, Ω and Ψ, which indicate the importance that the agent gives to each of them and guide its decision-making. In this economic context, risk aversion has been defined as the tendency of a farmer to take on debt and invest his money in order to achieve a higher profit from her/his farming activity. This has a direct relationship with the coefficients mentioned above, as a risky farmer will tend to take on more debt in order to make more profit ($\Omega > \Psi$), e.g. increase the size of his farm in order to grow more crops and increase production. From this, it can be deduced that the two coefficients are inversely related and will be complementary, although this is not conclusive as the model has not yet been fully tested. Furthermore, the projection over time of the farmer's management must be considered. That is, the decisions taken by the farmer have both immediate and future consequences. For this purpose, the coefficient β, which multiplies both terms of the objective function, was included to model the importance the farmer attaches to her/his profitability and solvency in the following seasons. This is also related to risk aversion, as a risk-averse farmer tends to be foresighted and consider the future consequences of her/his decisions. For instance, a risk-averse farmer would be less probable to invest more than the profit obtained in her/his last agricultural season to buy land and expand her/his exploitation because s/he would consider the increase in the agricultural costs (machinery, water, etc.) that entails this operation and as a consequence, her/his debt would increase.

Although the role of risk aversion in the optimisation problem is clear, at this point, there are some open issues regarding this. Firstly, as mentioned before, the relation between both coefficients must be determined. Secondly, it is not clear how the data collected through the survey campaigns will be used to estimate these coefficients. A first alternative is to deeply analyse those data in order to extract some correlations between the features of the farmer and her/his farm and the measured risk aversion. This will allow for assigning a risk-aversion ratio to each agent according to its attributes as they are generated by the synthetic population generation module. However, the analysis until now does not reflect a clear and strong correlation, so a deeper analysis will be carried out to accept or reject this approach. As an alternative, a risk aversion distribution could be extracted from the raw data and a risk-aversion rate could be assigned to each agent according to it. For both approaches, some preliminary conclusions of the analysis of the data collected through survey campaigns could be used to determine the coefficients mentioned above:

- In the Andalusian survey campaign, it was detected that most organic olive farmers were high-mid risk-averse (almost 95%) and that the larger the organic olive orchard, the riskier the organic farmer is. Moreover, it was also observed that the farmers maintain their risk-aversion level even though the benefits of the operation are higher.
- In the Polish use case, the survey reflects that no significant differences can be observed between the risk perception of beneficiaries and non-beneficiaries of M6.1 farmers.
- Greek survey campaign shows that gender is an important factor in the level of investment and innovativeness and that a higher education level is positively correlated with the willingness to invest and innovate. In addition, this positive correlation is also observed with the size of the agricultural holding.

Finally, it should be noted that, in addition to assessing the level of risk aversion of the farmers, the propensity to innovate was also measured by employing the same methods. In this case, the innovation ratio is understood as a tendency of farmers to choose cutting-edge technologies and methods, which are understood to improve resource management on the farm, as opposed to traditional technologies and methods. However, the model that has been developed in AGRICORE does not consider this ratio, and a priori, this information will not be used explicitly in the modelling. As a future improvement of the tool, this innovation ratio could be used to determine which technologies the farmer opts for and thus achieve a deeper optimisation. For this, it would be necessary to estimate the effect of each of these technologies on farm income.

4 Types of constraints affecting the optimisation problems

The constraints are physical limitations due to physical or design limitations or external factors, such as the available land for agricultural activities within a geographical region (e.g. NUTS3), or policies. All in all, the restrictions reduce the dimensionality of the optimisation problem, they shape the problem and spotlight the solution to the imposed specifications. That is why their correct handling is essential in all the disciplines involved within the AGRICORE's tool development (e.g. mathematics, control theory). In this sense, as already presented in the MPC presentation, one of the main advantages of the MPC methodology was the explicit management of constraints within its operational framework. Which perfectly couples with the constrained optimisation problems presented for both the ST and LT.

The previous sections have presented the mathematical formulation of the optimisation problem, including all the constraints imposed by different factors. In the following subsections, there will be detailed types of constraints and those factors. Below, in the following subsections, the constraints are in first place divided based on what those restricted in the MPC and modelling framework, the inputs/decisions and the states. In the second place, the constraints will be categorized based on their cause (e.g. structural, market, financial, …). As described below, there is a list of some of the causes of the constraints:

- Agricultural holding constraints are defined by the farm size and economics. Those constraints regulate some financial decisions, such as the acquisition of a loan, land management and crop rotation due to the farm size and available land.
- Strategic constraints are defined by the agent's behaviour and financial state. Those constraints mainly regulate the control actions, such as increasing or decreasing the available land.
- Market constraints are defined by the different markets with which the agents interact, such as the land or product market.
- Technological constraints, which regulate the introduction of new technologies and new activities, such as the transition to organic farming;
- Policy constraints, which regulate how certain agricultural policy actions (such as eco-schemes) are defined at a regional level; There will be a special dedicated section on the policy constraints given AGRICORE's project's main objective.

4.1 Input Constraints

The input constraints limit the decision-making of the agents. Without those constraints, the resolution of the optimisation problem may lead to solutions that are unfeasible in practice. Most of those constraints are imposed by the own agricultural holding states, such as financial status. Moreover, others are imposed by external factors such as the land market or the product market. And last, physical factors, imposed by the own environment and physical limitations such as selling more land than the owned or buying more than the available.

For example, if an agent estimates very high production for the next agricultural campaign, it will try to increase it by buying land through the land market, the available land, and, consequently, the agricultural land utilised. However, the amount of land is restricted by several factors. In the first place, due to the capital available and the maximum loan available. In the second place, due to the land on sale in the land market, an indirect restriction is imposed by the land market resolution. And in the third place, due to the agricultural land available within the geographical region (NUTS3) that the agent belongs, implicit restrictions. Within this example, each restriction is imposed due to a different nature. The first one is imposed by the financial status of the agent.

The second one is imposed by external factors, which in this case is the land market. For last the third one is imposed by physical limitations. All in all, those restrictions limit the decision-making of the agent.

4.2 States Constraints

The state constraints act as bonds for given variables, determined by the nature of the problem and the agents' own attributes. An example of a constraint due to a physical nature is the restriction imposed by eq.*10,* which reflects that an agricultural holding cannot own a negative amount of land. On the other hand, an example of a constraint imposed by the agent's own state, limiting factors such as the structural capacity of the farm (i.e. land available), is imposed by *eq.38,* which reflects that selected any technological alternative (A), the land required to produce x must always be below the land available. In this case, the restriction can be eased by increasing the available land by buying or renting in a new land. Nevertheless, as seen in the previous subsection, these kinds of actions are restricted too, by the financial status of the agricultural holding or by the market.

4.3 Policy Constraints

AGRICORE tool's main objective is to enable the review of different policy strategies simulating their impact on a synthetic population that reflects the real one. In this sense, policy constraints are key. Those restrictions are imposed by the EU and/or local government, so for the agents, they are reflected as external factors. Moreover, those restrictions can adjust both decisions and states of the agents. These kinds of constraints can be imposed on all the agents within the region, or the agent can apply voluntarily to them in order to receive a subsidy in return if the requirements are fulfilled. Those policies are translated to mathematical formulation through the Policy Environment Module (described in detail in D5.7). Further on, these mathematical formulations are integrated as constraints within the agent's optimisation problem previously detailed.

As part of the AGRICORE project, each use case is studied with a different policy; hence all of them have to be considered as constraints for the optimisation problem if the agent applies to the policy in order to receive the subsidy. For example, the Spanish use case focuses on ecological farming and how the subsidies received by following this type of farming impact the agents' decision-making. The ecological farming policy constraints are reflected in the optimisation problem through technological alternatives. In this sense, in order to receive the subsidy, the agent must fulfil several constraints, such as not using fertilizers and biocides and reducing the use of water. Consequently, the production of the farm will probably decrease. Nevertheless, the subsidies should overcome the revenue lost due to lower production.

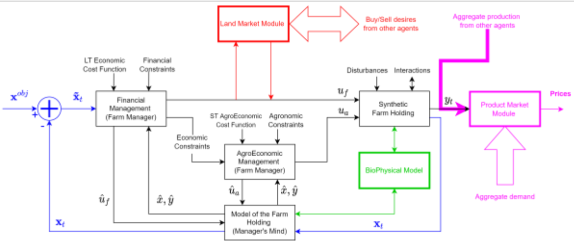
5 Iterative LT-ST optimisation sequence

As described above, the AGRICORE model consists of an interaction between long-term and short-term scenarios through two interlinked modules. With regards to the short-term module, the PMP approach allows taking into account the characteristics of the farm holder from a structural and strategic point of view, by estimating the implicit marginal costs, representing the cost that the farmer may incur by adapting his production plan to the changes imposed by policies or price conditions. The PMP is particularly suited to represent agents, thanks to its capacity to describe farms' behaviour by quantifying the costs incurred, the decision-making process and the relationship between agents.

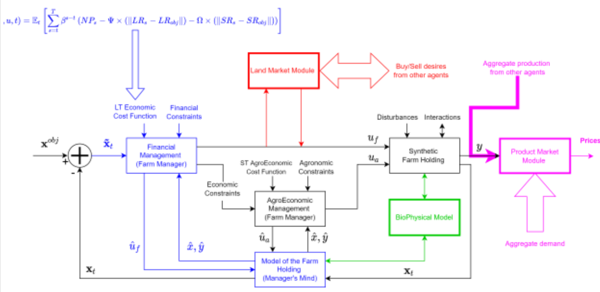
The PMP methodology, theoretically described in "*Short-term model - Agroeconomic planning of the agricultural holding operation*" is implemented in AGRICORE in GAMS (General Algebraic Modeling System, www.gams.com). GAMS is a high-level modelling system for mathematical programming and optimisation for solving linear and non-linear mathematical programming problems, as well as general equilibrium models and stochastic optimization problems. It consists of a language compiler and a range of associated solvers, which was developed by the World Bank in 1976 and became a commercial product in 1987. Using GAMS, the mathematical model has been developed to reproduce farmers' behaviour in the observed situation (represented by the calibration phase of the model) and in the market and agricultural policy scenarios. Those scenarios are defined on an annual basis, and they influence the production choices and agronomic planning of the farm holding.

On the other hand, the financial optimisation has been programmed in Python 3.0. Furthermore, there has been implemented the commercial solver of Gurobi [www.gurobi.com], because it is a state-of-the-art solver for linear programming, quadratic and quadratically constrained programming. In addition, Gurobi can be easily coupled with Python which will highly facilitate the implementation.

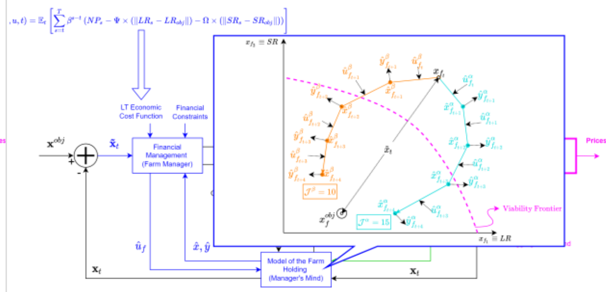
All in all, both sub-modules complement each other through a fluent interaction and following the diagram workflow of the whole presented in D3.1. Below, through several diagram figures, is illustrated and detailed the MPC workflow and its submodules execution and interaction.



(a) Last state read and computation of error between objective state and current state.

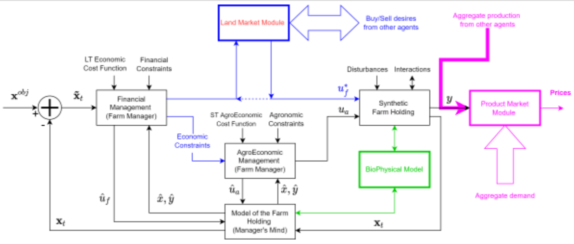


(b1) Financial-based structural planning based on MPC

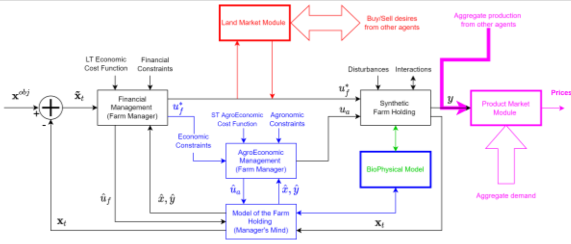


(b2) The EMPC is used to predict alternative financial trajectories of the holding

for different input sequences

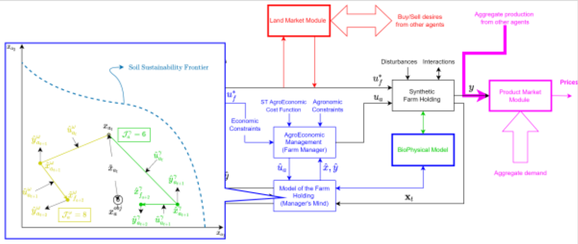


(c) Land trading intentions are introduced in the LMM, which returns the actual achieved land exchanges.



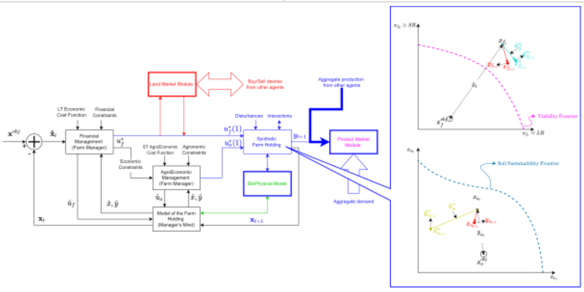
(d1) Once the actual Land and Capital availability (Economic Constraints)

for the current step (campaign) are known, the economic-based activity planning is solved.



(d2) The agroeconomic (and eventually the BioPhysical) model(s) are taken into consideration to

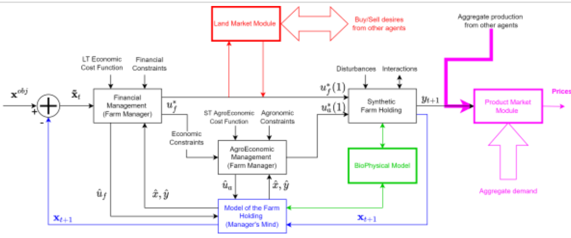
predict the effect of different sequences of activity combos.



(e) The set of Financial and Agronomic management decisions are applied to the Synthetic Agricultural Holding, and simulated using external drivers (climate, policies, interactions, etc...).

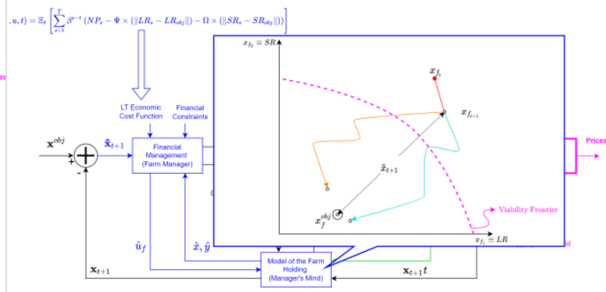
The results are the production outputs (y_{t+1}) and the variation of AH's states (x_{t+1}). Notice that, due to external disturbances and mismatch between the prediction model and the simulation model,

the reached state (x_{t+1}) might differ from the predicted one $\hat{x}_{t+1}$.



(f1) The new states are fed back into the prediction model and the tracking error is recomputed

before the next optimisation-simulation iteration.



(f2) The system tries again to steer the updated current states to the objective state by recomputing a new

optimal trajectory of future inputs.

6 Conclusions

In this deliverable is presented how the rationale of the agricultural holders is modelled mathematically within the agent's optimisation problem. The methodology followed is based on a model predictive control (MPC) approach. This strategy requires a dynamic model in order to predict future behaviours of the system during the horizon of prediction. As already detailed at the beginning of the deliverable, the MPC approach has several advantages, making it the perfect match for the problem handled within AGRICORE and also fits with the ABM approach.

During the development, in order to simplify the problem and achieve better results, there has been decided to separate the optimisation problem into two submodels interconnected. On the one hand, the first submodel focuses on the optimisation done by the agents in the long-term (LT), related to the financial aspects of the agricultural holding. On the other hand, the second submodel focuses on the optimisation done by the agents in the short-term (ST) (1 year), related to the agroeconomical aspects of the agricultural holding. Both submodels include behaviour parameters that shape the optimisation problem to the agent's rationale, such as risk aversion.

7 References

[1]	A. Ferramosca, D. Limon, and E. F. Camacho, "Economic MPC for a Changing Economic Criterion for Linear Systems," IEEE Transactions on Automatic Control, vol. 59, no. 10, pp. 2657–2667, Oct. 2014, doi: 10.1109/TAC.2014.2326013. Referenced at: 1
[2]	B. Alrifaee, "Networked Model Predictive Control for Vehicle Collision Avoidance," phdthesis, RWTH Aachen University, 2017. doi: 10.18154/RWTH-2017-04199. Referenced at: 1
[3]	A. Kantrovich, "Financial Ratios Part 1 of 21: The Current Ratio," Michigan State University Extension, 2005, [Online]. Available: https://www.canr.msu.edu/news/financial_ratios_part_1_of_21_the_current_ratio Referenced at: 1
[4]	ReadyRatios, R.-I. financial reporting and analysis software. Current Ratio. 2013. Accessed: Oct. 04, 2022. [Online]. Available: https://www.readyratios.com/reference/liquidity/current_ratio.html%7D%7BIFRS Referenced at: 1
[5]	Investopedia, Debt-to-Equity (D/E) Ratio Formula and How to Interpret It. 2021. Accessed: Oct. 04, 2022. [Online]. Available: https://www.investopedia.com/terms/d/debtequityratio.asp Referenced at: 1 2
[6]	CSI Market, C. Market. Debt to Equity Ratio. CSI Market - Term Glossary. 2021. Accessed: Oct. 04, 2022. [Online]. Available: https://csimarket.com/glossary/term_Debt_Capital_Ratio.html Referenced at: 1
[7]	B. Enrique and R. Carlos, "Multiple criteria decision making and its applications to economic problems," Springer, 1998, doi: https://doi.org/10.1007/978-1-4757-2827-9. Referenced at: 1 2
[8]	G. O. Odu, "Weighting methods for multi-criteria decision making technique," Journal of Applied Sciences and Environmental Management, 2019, doi: doi: 10.4314/jasem.v23i8.7. Referenced at: 1 2
[9]	J. Rotschedl, "The Subjective Discount Factor and Risk Aversion, Loss Aversion and Uncertainty," 2017. Referenced at: 1
[10]	R. E. Howitt, "Positive Mathematical Programming," American Journal of Agricultural Economics, vol. 77, no. 2, pp. 329–342, May 1995, doi: 10.2307/1243543. Referenced at: 1
[11]	Q. Paris and R. E. Howitt, "An Analysis of Ill-Posed Production Problems Using Maximum Entropy," American Journal of Agricultural Economics, vol. 80, no. 1, pp. 124–138, 1998, doi: 10.2307/3180275. Referenced at: 1 2 3
[12]	T. Heckelei, W. Britz, T. Heckelei, and W. Britz, "Models Based on Positive Mathematical Programming: State of the Art and Further Extensions," 2005, doi: 10.22004/AG.ECON.234607.

	Referenced at: 1 2
[13]	c. Cafiero, “Cafiero, 2004.pdf,” Are mathematical models reliable in agricultural policy analyses?, vol. PAGRI-Po, 2004, [Online]. Available: http://wpage.unina.it/cafiero/pubs/9.pdf Referenced at: 1
[14]	T. Heckelei and H. Wolff, “Estimation of constrained optimisation models for agricultural supply analysis based on generalised maximum entropy,” European Review of Agricultural Economics, vol. 30, no. 1, pp. 27–50, 2003, [Online]. Available: https://econpapers.repec.org/RePEc:oup:erevae:v:30:y:2003:i:1:p:27-50 Referenced at: 1
[15]	T. Heckelei, “CALIBRATION AND ESTIMATION OF PROGRAMMING MODELS FOR AGRIGULTURAL SUPPLY ANALYSIS,” 2002. Referenced at: 1 2
[16]	L. Júdez, C. Chaya, S. Martínez, and A. A. González, “Effects of the measures envisaged in ‘Agenda 2000’ on arable crop producers and beef and veal producers: an application of Positive Mathematical Programming to representative farms of a Spanish region,” Agricultural Systems, vol. 67, no. 2, pp. 121–138, 2001, doi: https://doi.org/10.1016/S0308-521X(00)00051-2. Referenced at: 1
[17]	B. H. de Frahan et al., “Positive mathematical programming for agricultural and environmental policy analysis : review and practice,” in Handbook of operations research in natural resources, Springer, 2007, pp. 129–154. doi: 10.1007/978-0-387-71815-6_8. Referenced at: 1
[18]	A. P. Kanellopoulos, Bio-economic farm modelling for integrated assessment of agricultural and environmental policies: towards re-usability and improved empirical validity. Wageningen: publisher not identified, 2010. Referenced at: 1 2
[19]	T. Heckelei, W. Britz, T. Heckelei, and W. Britz, “Positive Mathematical Programming with Multiple Data Points: A Cross-Sectional Estimation Procedure.,” 2000, doi: 10.22004/AG.ECON.206148. Referenced at: 1
[20]	O. Röhm and S. Dabbert, “Integrating Agri-Environmental Programs into Regional Production Models: An Extension of Positive Mathematical Programming,” American Journal of Agricultural Economics, vol. 85, no. 1, pp. 254–265, 2003, [Online]. Available: http://www.jstor.org/stable/1244941 Referenced at: 1
[21]	J. F. M. Helming, L. Peeters, and P. Veenendaal, “Assessing the consequences of environmental policy scenarios in Flemish agriculture,” In: Agricultural sector modelling and policy information systems : 65th European EAAE Seminar / T. Heckelei, H.P. Witzke, W. Henrichsmeyer. - Kiel : Wissenschaftsverlag Vauk, 2001. ISBN 3-8175-0329-6, 2013. Referenced at: 1
[22]	J. Buysse, G. V. Huylenbroeck, and L. Lauwers, “Normative, positive and econometric mathematical programming as tools for incorporation of multifunctionality in agricultural policy modelling,” Agriculture, Ecosystems & Environment, vol. 120, no. 1, pp. 70–81, 2007, doi: https://doi.org/10.1016/j.agee.2006.03.035. Referenced at: 1

[23] Q. Paris, Economic Foundations of Symmetric Programming, 1st ed. Cambridge University Press, 2010. doi: 10.1017/CBO9780511761782.

Referenced at: 1 2

[24] D. Kahan, Food, and A. O. O. T. U. Nations, Managing risk in farming. Food And Agriculture Organization Of The United Nations, 2013.

Referenced at: 1

[25] P. Sulewski, A. Wąs, P. Kobus, K. Pogodzińska, M. Szymańska, and T. Sosulski, "Farmers' Attitudes towards Risk—An Empirical Study from Poland," Agronomy, vol. 10, no. 10, p. 1555, Oct. 2020, doi: 10.3390/agronomy10101555.

Referenced at: 1

[26] P. Iyer, M. Bozzola, S. Hirsch, M. Meraner, and R. Finger, "Measuring Farmer Risk Preferences in Europe: A Systematic Review," Journal of Agricultural Economics, vol. 71, 2019, doi: 10.1111/1477-9552.12325.

Referenced at: 1

For preparing this report, the following deliverables have been taken into consideration:

Deliverable Number	**Deliverable Title**	**Lead beneficiary**	**Type**	**Dissemination Level**	**Due date**
D3.1.	Non-linear dynamic model of the farm agents	IDE	Report	Public	M37
D3.3.	Model interaction capabilities for the ABM	IDE	Report	Public	M37
D3.4.	Biophysical models linking capabilities for the ABM	IAPAS	Report	Public	M37
D3.5.	Positive-normative	IDE	Report	Public	M37