Decentralized Intelligence for Smart Agriculture

Pascal Francois Faye[1] [a], Jeanne Ana Awa Faye[2] and Mariane Senghor[1]

[1] *Université du Sine Saloum El Hadj Ibrahima NIASS (USSEIN), Sing Sing, Kaolack, Senegal*

[2] *Universite Aix-Marseille, Institut de Management Public et Gouvernance Territoriale, Aix-Marseille, France*

Keywords: Conceptualization, Internet of Things Network, Data analysis, Artificial Intelligence, Multi-Agent System, Crop Yield.

Abstract: This work proposes a model called AIMS (Agricultural Information and Management System) based on some Machine Learning Algorithm (ML) as CART (Classification And Regression Trees), KNN(K-nearest neighbors) and SVM(Support Vector Machine). It describes both a multi-agent system and Internet Of Things device that ensures data collection and control as well as a data monitoring system via our web platform for decision-making support in a real-world agricultural environments. This for a prompt, effective and sustainable agricultural development. We refer to cases in which agent collaboration is needed for efficient task execution (e. g. data processing and decision making). In our context, dynamics and uncertainty prohibit computation strategies ahead of task execution. Combining methods from Machine Learning (ML), Markov decision processes (MDP) and probability, we introduce an auto-stabilizing coordination mechanism.

1 INTRODUCTION

Nowadays, technical developments are very active in the collection and data processing even in the agricultural sector. This raises the question: What the future of our countries' agricultural sector will look like in terms of sustainable production if information on agricultural parameters and management, as well as fluctuations in climatic factors, are observed and instantly controlled. In an agricultural environment, an example may be to have tools to predict and improve the crop yield by taking into account, global population growth, climate change, available resources and land degradation. There, agents are deployed on various platforms such as smart farming IOT, autonomous robots, personal devices and smart sensors. The agents of these platforms, aim to reduce the arduousness of the work. Many of these tasks require coordination as a suitable solution approach. However, the platforms and the agents, have resource constraints (e.g., energy), unstable communication, dynamically changing, various availability and stochastic tasks. An example of a stochastic task in a farm may be the scheduling of the irrigation and the temperature in order to avoid fluctuations. Some challenges discussed above are addressed, in the literature (Shehory and Kraus, 1998) and (Faye et al., 2015) and (Faye et al., 2014). However, a coordination solution that addresses well both the dynamism and the uncertainty in environments as in the example above is lacking. Our main contribution is a coordination mechanism that enables autostabilizing collaboration in dynamic, uncertain contexts. We propose an adaptive, decentralized and asynchronous mechanism denoted AIMS (Agricultural Information and Management System). The AIMS mechanism introduces a novel combination of disparate techniques. In particular, it combines:

1. laws of probability to model the dynamics of tasks' events and agents' availability;
2. Machine learning algorithm (ML) to find the better coordination, taking advantage of agent dependencies and network structure;
3. *MDP (Markov decision processes)* formalism to dynamically examine and adapt the agent's behaviour.

This combination delivers a new solution that addresses well the dynamism and uncertainty challenges targeted in this work. In the rest of the paper, Section II we discuss related works. Section III presents some preliminaries. Section IV highlight the AIMS mechanism, followed by performance evaluation in Section V. Section VI concludes.

[a] https://orcid.org/0000-0002-2078-5891

Faye, P., Faye, J. and Senghor, M.
Decentralized Intelligence for Smart Agriculture.
DOI: 10.5220/0012342100003636

In *Proceedings of the 16th International Conference on Agents and Artificial Intelligence (ICAART 2024) - Volume 1*, pages 240-247
ISBN: 978-989-758-680-4; ISSN: 2184-433X

2 RELATED WORK

In (Sellam and Poovammal, 2010), the authors persist to research the environmental parameters that affect the crop yield and related parameters. Here a multivariate Regression Analysis is applied for the same. A sample of environmental factors considers a period of 10 years. The System is applied to find the relationship between explanatory variables like AR,AUC, FPI and hence the crop yield as a response variable and R2 value clearly shows that, the yield is especiallyhooked into AR,AUC and FPI are the opposite two factors that are influencing the crop yield. This research is often enhanced by considering other factors like MSP, CPI, WPI so on. And their relationship with crop yield. In (Sellam and Poovammal, 2010), the authors focus on the users and expert reviews across three product categories that are sellers, products and experimental products were conducted. Here the bulk of research cited attempted to finalize the consequences of a user reviews on a product cost and the probability of a purchage.The results of this work help illuminate the contradictory findings across the discrete research study. In paper (Paswan and Begum, 2013), the authors have compared feed forward neural networks with traditional statistical methods through linear regression. This work presents the capability of neural networks and their statistical counterparts used in the world of crop yield prediction. In (Zhang et al., 2010), the authors have done the comparison between OLS regression model and special autoregressive model for crop yield prediction in Iowa. The special autoregressive model has shown enormous enhancement in the model performance over the OLS model. The model can provide better prediction than the OLS model and has capability of adjust with the special autocorrelation, which is not considered by the OLS model. This work has shown that NDVI and precipitation are the most important predictors for corn yield in Iowa. In (Zingade et al., 2018), the authors have presented an android based application and an internet site that uses Machine learning methods to predict the foremost profitable crop in the current weather and soil conditions and with current environmental conditions. This system helps the former with a sort of option for the crops that will be cultivated, which will be helping them over the long run.

3 PRELIMINARIES

Many active populations around the world have taken agriculture as a main occupation. Day by day for a particular crop; the farmers are not getting good yield due to environmental conditions like soil quality, weather, rainfall, drought, seed damages, fertilizers, pesticides, ... However, it rests traditional in several Africans countries (lack of information, poor time management, no forecast,...). This notwithstanding, taking the historical agricultural (Faye et al., 2022) data records we can predict the crop yield using machine learning techniques in order to achieve the high accuracy and model performance. To create - a network's agents, a set of controllers agents, a monitoring platform, a dynamic digital model for efficient and sustainable agriculture, and set up distributed decision making. In our context, an agent is an equipment more or less autonomous, connected and able to perform tasks. An equipment can be any IOT component like an Arduino UNO WIFI, an ESP8266 or ESP32-CAM, a Humidity and temperature sensors (DHT-11, capacitive soil, soil sensor, moisture sensor, ...), a Raspberry Pi 4 model B or an Agricultural irrigation electric Pump DC 12V,3.5L.

As mentioned in figure 1 the digital platforms access - Anacim : https://www.anacim.sn/spip.php?article67 - ANSD : https://www.ansd.sn/enquete - FAO : https://www.fao.org/aquacrop/software/fr/ - PowerLarc : https://power.larc.nasa.gov/data-access-viewer/ - Kaggle : https://www.kaggle.com/datasets.

Thus, we define a set of concepts to highlight our coordination model. Let A=$\{a_1,...,a_n\}$ be a set of agents and C a coordination schema, C=$\{A_C,G_C,T_C,V_C\}$. $A_C \subset A$ and $G_C \subseteq \{G_{a_i} : a_i \in A_C\}$ a set of agents' goals (e.g., reliability, power supply, ...). T_C is the set of unpredictable evolving tasks and V_C is the expected payoff after execution. An unpredictable evolving task is a set of actions, possibly changing over time (e.g. prevent drought or rainfall damage). Coordination schema C receives a payoff V_C such as an agent a_i gets v_{a_i} and V_C=$\sum_{a_i \in A_C} v_{a_i}$. Each agent aims to maximize its payoff during coordination.

Each agent a_i is constrained by the parameters: $\{R_{a_i},E^t_{a_i},Hs_{a_i},\vartheta^t_{a_i},U_{a_i},L^{Net}_{a_i}\}$. R_{a_i} is its resource(s) and $E^t_{a_i}$ is its energy at time t. We dissociate R_{a_i} from $E^t_{a_i}$ because we assume energy is not shareable, unlike other resources (bandwidth, computation, ...). Hs_{a_i} is its *history set* which consists of a set of *alliances*, probable stability and reliability of a set of ally agents. A *view* $\vartheta^t_{a_i}$ of a_i is the set of agents in its neighborhood with whom it can directly communicate at time t. U_{a_i} is its private utility function. $L^{Net}_{a_i}$ defines its dependence level in a given network (Net).

Definition 1. Al_{a_i,a_j}=$(\{R_{a_i},R_{a_j}\}, \{T^{a_i}_{help},T^{a_j}_{help}\})$ *is an alliance* ($Al_{a_i,a_j} \in Hs_{a_i}$)*, i.e., a persistent agreement between agents* a_i*,* a_j *in which they establish mutual commitment to provide one another with resources*

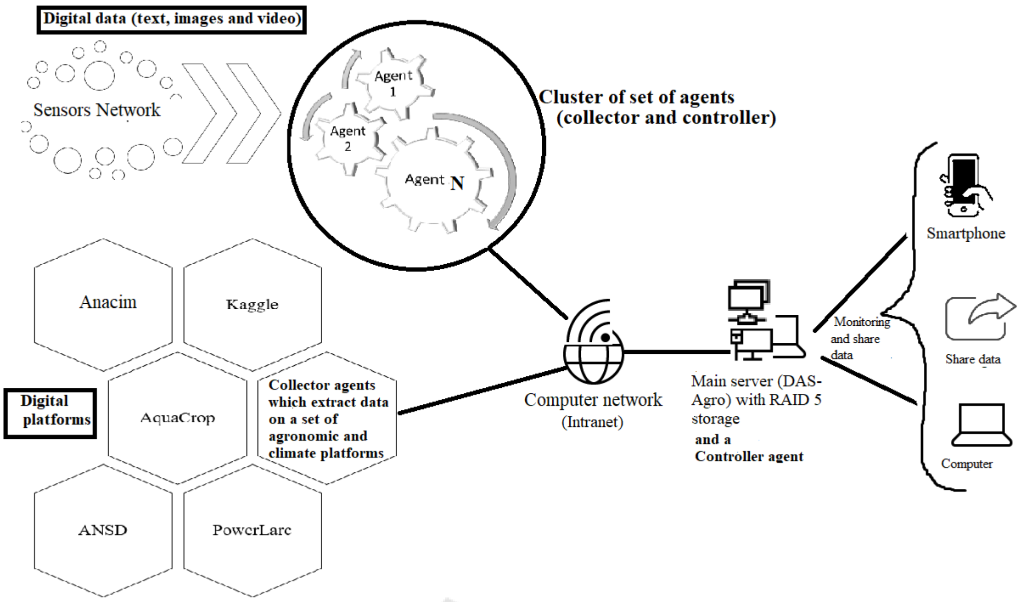

Figure 1: The main component for data collection, decisions and outputs results.

and information during a specific time period. The alliance above specifies that a_i (respectively a_j) commits to provide its resource R_{a_i} (respectively R_{a_j}) during a time period $T^{a_i}_{help}$ (respectively $T^{a_j}_{help}$) within a coordination schema of a_j (respectively a_i).□

Alliances aim to simplify agent coordination. We give the explanations and the enlightenment on this matter further. An *alliance* is canceled by an agent if the *reliability* of its ally is below some threshold. The *reliability* of a_j is computed by a_i using the *Poisson law* (Yates and Goodman, 2005). The *Poisson law* expresses the prior probability of random events over a time interval t. The random events are the number k of times that an agent does not respect an established *alliance*.

Definition 2. *The reliability of an agent a_j equals*

$$\rho_{a_j} = (\frac{(\lambda_{a_j})^k}{k!})e^{(-\lambda_{a_j})} \tag{1}$$

where λ_{a_j} is the withdrawal rate of a_j from Al_{a_i,a_j} over a time interval t.□

To enhance or conserve its *reliability*, $a_j \in A$, it is in its interest to join and respect its commitments.

Definition 3. *The probable stability $P^{a_j}_s$ of an agent a_j equals*

$$P^{a_j}_s = 1 - Q^{a_j}_s \tag{2}$$

where $Q^{a_j}_s$ is the probable disconnection of its hosting device. $Q^{a_j}_s$ is computed by using the modified geometric distribution (Yates and Goodman, 2005) which is the prior probability distribution when we are interested in the probability of the first withdrawal due to some failure. $Q^{a_j}_s = (q^{a_j}_s)^k(1 - q^{a_j}_s)$ where $q^{a_j}_s = \frac{(\lambda_{a_j})^k}{k!} e^{-\lambda_{a_j}}$. λ_{a_j} is the arrival rate of disconnections of the device j, k the number of its disconnections since its first starting.□

A larger $P^{a_j}_s$ entails that, the device is more preferred.

Definition 4. *The utility function U_{a_i} of an agent a_i is*

$$U_{a_i} = \sum_{C=1}^{\infty} u^{a_i}_C \tag{3}$$

where $u^{a_i}_C$ is its utility in the coordination schema C. Knowing that, U_{a_i} is the value of this utility function at time t.□

Agents use the message sharing process in their *view* $\vartheta^t_{a_i} \subseteq Net$ for the coordination that maximize their utility in each of their coordination schema despite the uncertainties and the dynamics of the deployment environment.

Definition 5. *The utility in the coordination schema C is for an agent a_i as follows:*

$$u^{a_i}_C = v_{a_i} - Cost^{a_i}_C \tag{4}$$

The cost function $Cost^{a_i}_C$ is a private knowledge and depends on the messages cost (i.e., messages sent until the establishment of C), energy and resources used, ...□

When involved in coordination, each agent $a_i \in Net$ has also to consider its level of dependence $L^{Net}_{a_i}$ on other agents in its *view* $\vartheta^t_{a_i} \subseteq Net$.

Definition 6. *$\forall a_i \in Net, \exists\, L_{a_i}^{Net}$ such that $L_{a_i}^{Net} = \{\gamma_{a_i}^{Net}, H_{a_i}^{Net}, S_{a_i}^{Net}\}$ where $\gamma_{a_i}^{Net}$ is the set of controllers to a_i, $S_{a_i}^{Net}$ is the set of agents lead by a_i and $H_{a_i}^{Net} = (\vartheta_{a_i}^{t} \setminus \gamma_{a_i}^{Net}) \setminus S_{a_i}^{Net}$ (homologous agents).*□

For example, in a farm environment a set of collector agents may be under the command of a controller agent, independent or allies in order to reach a goal (data analysis, intrusion detection, irrigation start, ...). The agents must also consider these dependencies to determine their preferences and priorities or prohibited interactions when seeking to maximize their utility. In the following, we present our coordination schema for such contexts.

4 COORDINATION SCHEMA

Our Agricultural Information and Management System (AIMS) describes an automated farm management model that starts from data collection and uses these data obtained through our monitoring platform (MP-Agro) and different platforms as shown in Figure 1. Our monitoring platform receives data through a set of smart farming IOT, autonomous robots, personal devices and smart sensors. AIMS acts with two systems.

1. A multi-agent system that has a reactive agent set. Among them are:
   - The collector agents that collect agroclimatic data and send them to the agents that implement the machine learning algorithms (ML) and also to our monitoring platform (MP-Agro).
   - Controllers agents that are programmed to control a set of agricultural equipment such as irrigation and a set of spraying based on information obtained through the collector agents.
2. A management system that has the ability to interact with the multi-agent system (data collector and equipment controller) of our AIMS. It is an IoT web platform that allows us to aggregate, visualize, and analyse real-time data stream from collector agents.

In the next section we highlight our architecture.

4.1 Architecture Details

The physical topology of our deployment environment is shown in Figure 1.

- Agronomic and climatic data collector agents :
  1. Send information to agent 2 after collecting and processing the data.
  2. Sends the data to our platform called MP-agro
- Equipment controller agents:
  1. Switch on or not the irrigation systems or the motion detection systems located where the collector agents are. This depends on the message received and ML decision result.
  2. Sends a response message to the collector agent whether or not the task is completed. For example, if the phytosanitary treatments are carried out.
- MP-agro
  1. Distributes data in table or graph format.
  2. Displays statistics of different information sent to the platform by the collector sensors.
  3. Manages crops by allowing to save information about the date of sowing, the likely date of harvest, etc.
  4. Manages human resources by offering the opportunity to add employees to dashboard and have an overview of employees.
  5. Locates all collector agents, controllers agents and displays their positions on a map.
  6. Offers the possibility to download the data stored in the platform as a CSV file for future data analysis.
  7. Offers the possibility to download crop calendars of some speculations as a PDF file.

The interactions between the set of component can be summarised by the flowchart above (cf. Figure 2 and Figure 3).

To find the better machine learning model in order to face with data collected can be summarised by the flowchart above (cf. Figure 4).

We add a set of definition in order to highlight analytically our coordination mechanism (AIMS).
We define $O_C^{a_i}$ as a message sharing of an agent a_i which aims to form a coordination schema C.

Definition 7. *A message sharing $O_C^{a_i}$=$\{\{B_i, B_j, B_k, ...\}, \{pl_{a_i}\}\}$ is such as B_i=$(Ri, \Delta i, Ui)$. B_i is a goal to reach with the offer which specifies a resource Ri needed by T_C, the constraints Δi of B_i and the expected pay-off Ui. pl_{a_i}=$\{a_i, a_j, a_k, ...\}$ is a probe list which gives at each time the set of agents which have agreed to participate to message sharing.*□

During message sharing a set of agent may have conflicting goals. This, because an agent have to save energy, forward its own payload, etc.

Some Notations
$\equiv$ equivalence between two parameters.
$\not\equiv$ non equivalence between two parameters.

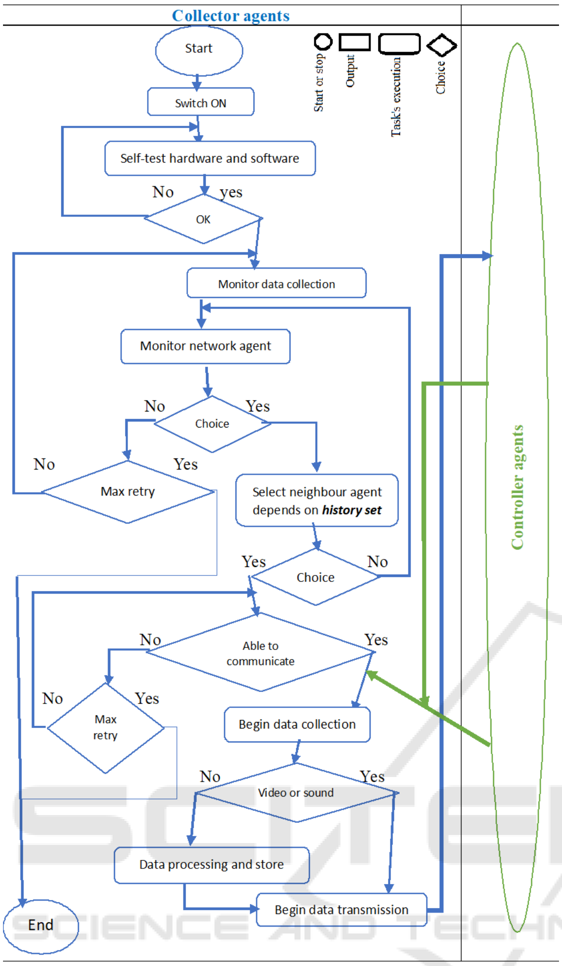

Figure 2: collectors agent's interactions.

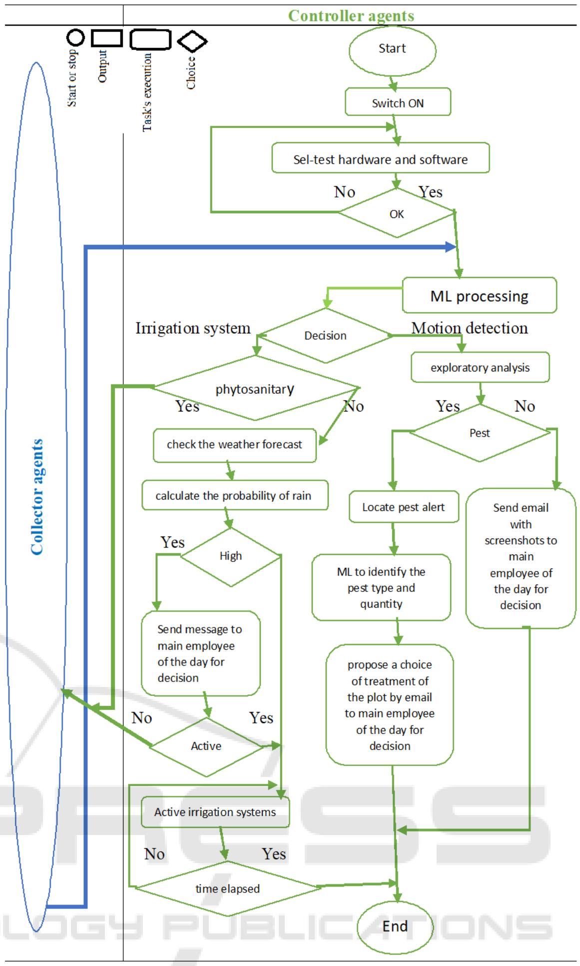

Figure 3: controllers agent's interactions.

$Card(A_C)$ measure the cardinality of a set A_C.
$\succ_{a_i}$ depicts the strict preference of a_i between two outcomes.

4.2 The AIMS Mechanism

The main steps of AIMS are detailed below:
Step 1: *Concurrent message sharing propagation and decision making.* A message sharing is propagated across agents in a noreply mode (cf. rule 3), along with a TTL (Time To Live) and a hop counter Hop. Initially $Hop = 1$ and each agent increments it by 1 before forwarding the message sharing. TTL defines the maximum hops allowed. The *range* of an agent is 0 or 1, expressed by:

$$range = Hop \text{ modulo } 2 \tag{5}$$

This is used for distributing the control of AIMS.

Step 2: *Sampling next hop.* When *range*=1, an agent samples the agents in its next hop by using a message $probe(O_C^{a_i})$.

Step 3: *Managing conflicts before a reject or a weak-accept.* Conflicts arise when a set of agents has incompatible preferences, goals and/or dependencies. Such conflicts are handled via agent weights, as:
- A reject means that no agent has agreed to the message sharing.
- A weak-accept means that a set of agents denoted *W-Set* has agreed to the message sharing and to participate in C if their utility is enhanced and their goals are not in conflict. Formally, a weak-accept of *W-Set*$=\{a_j, a_k, \ldots\}$ of a message sharing implies that: $\exists\, \{(G_{a_j}, a_j), (G_{a_k}, a_k), \ldots\} : \forall\, a_x \in$ *W-Set*, $G_{a_x} \in O_C^{a_i}$.
We distinguish two types of weights based on :
- *view*, alliances and dependency;
- preferences of the agents in the message sharing.
Formally, the weight of agent a_i is:

$$W_{a_i} = \begin{cases} \frac{Card(Hs_{a_i} \cap \vartheta^t_{a_i})}{Card(\vartheta^t_{a_i})} & \text{if } \gamma^{Net}_{a_i} = \emptyset : \gamma^{Net}_{a_i} \subset L^{Net}_{a_i} \\ W^{Net}_{\gamma_{a_i}} & \text{if } \gamma^{Net}_{a_i} \neq \emptyset : \gamma^{Net}_{a_i} \subset L^{Net}_{a_i} \end{cases} \tag{6}$$

when agents are in conflict, the agent with the high-

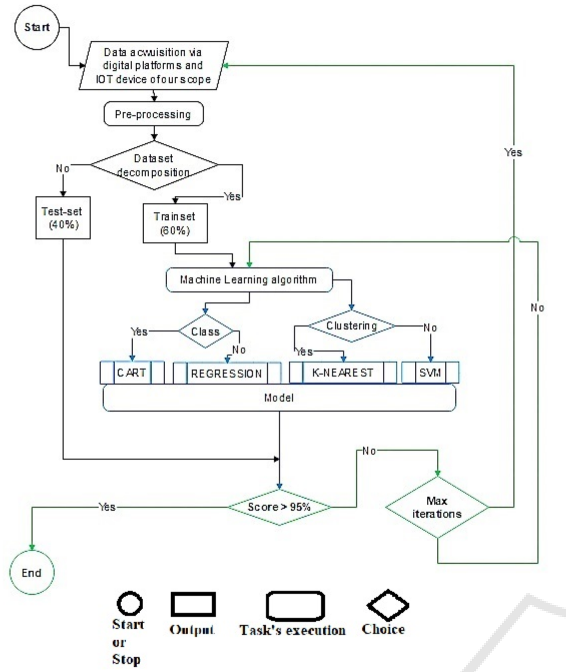

Figure 4: Machine learning to find the better data processing way for useful decision making.

est weight and reliability is selected. If this does not solve the conflict, the agent with the highest probable stability is selected.

Note that, agents weights and reliabilities can be computed by others.

The assessment of this weight is as follows:

- Each agent assesses its preference model regarding its utility and the following 3 criteria: 1- reliability, 2- stability and 3 weight. In our context, the agents are self-interested and have an unpredictable availability, the preference of a_i for a_j depends on the reliability ρ_{a_j} and on the probable stability $P_s^{a_j}$ of a_j and the difference between the weight W_{a_j} of a_j and W_{a_i} of a_i. Due to uncertainties, agents have to dynamically compute their preferences. $Y^x_{a_i,a_j}$ is the preference of agent a_i for the agent a_j regarding criterion x. Thus,

$Y^1_{a_i,a_j} = \rho_{a_j} - \frac{\sum_{a_k \in A'} \rho_{a_k}}{Card(A')}$ if $Y^1_{a_i,a_j} > 0$;
$Y^1_{a_i,a_j} = 0$ if $Y^1_{a_i,a_j} \leq 0$.
$Y^2_{a_i,a_j} = P_s^{a_j} - \frac{\sum_{a_k \in A'} P_s^{a_k}}{Card(A')}$ if $Y^2_{a_i,a_j} > 0$;
$Y^2_{a_i,a_j} = 0$ if $Y^2_{a_i,a_j} \leq 0$.
$Y^3_{a_i,a_j} = W_{a_j} - W_{a_i}$ if $Y^3_{a_i,a_j} > 0$;
$Y^3_{a_i,a_j} = 0$ if $Y^3_{a_i,a_j} \leq 0$.

- Each a_i computes its preference vector $\prod_{a_i}$ over agents in *W-Set*.

$$\prod_{a_i} = (X_{a_i,a_j}, X_{a_i,a_k}, \ldots) \tag{7}$$

Prior to computing its preference for each a_j in *W-Set*, a_i uses the *Choquet integral* to aggregate its preferences for the agents on the three criteria.

$$X_{a_i,a_j} = \sum_{k \in [1,3]} (Y^k_{a_i,a_j} - Y^{k+1}_{a_i,a_j})\mu(p) \tag{8}$$

$\mu(p)$ is the weight of a subset of criteria. $p = 1, 2$, or 3, refers respectively to reliability, probable stability or weight. Thence, $\mu(1)$=ρ_{a_i}, $\mu(2)$=$P_s^{a_i}$, $\mu(3)$=W_{a_i}. Due to the uncertain context, we consider reliability as the most important criterion. Thus, $\mu(1,2)$=$\mu(1,3)$=$\frac{1-\rho_{a_i}}{2}$, $\mu(2,3)$=$1 - \rho_{a_i}$ and $\mu(1,2,3)$=1. -The weight equals:

$$\overline{\prod} = \frac{\sum_{a_i \in A' \subset A} \prod_{a_i}}{Card(A')} \tag{9}$$

where A'=*W-Set* is the set of agents which respond with a weak-accept. The agents that maximize $\overline{\prod}$ are always preferred (see lines 5, 6 in algorithm 1).

Step 4: *Message sharing and decision making* (see algorithm 1). In this step, message sharing is done between the agents which have the highest weight. When conflicts arise, the agents solve them by preferring agents with the highest weight. MDP (Faye et al., 2015) and (Faye et al., 2022) is used to compute the stability of the coordination (see next step).

Step 5: *Commitment or rejection of a coordination.* This stage requires no synchronization between the agents. The decisions will be known by each agent after the computation of the invariant vector of the MDP.

5 PERFORMANCE EVALUATION OF AIMS MECHANISM

5.1 Analytical Evaluation

Lemma 1. *Message sharing terminates without deadlock, regardless of the existence of a coordination.*

Proof. $\forall Probe(O_C^{a_i})$ an agent forwards this message sharing if $\vartheta^t_{a_i} \neq \emptyset$ by respecting the noreply message principle to avoid message loop back. Each conflict between a_i and a_j is managed by the rest of the agents of their *message sharing* by selecting the agent

Data: *W-Set=X1* and *W-Set=X2*: $X1, X2 \subset A$
Result: $commit(X1 \cup X2) : X1 \cap X2 = \emptyset$
initialization;
while $a_j \in X1 : range{=}{=}0$ *and* $(X1 \setminus a_j)=\{a_k, a_l, ...\}$: $W_{a_j}=Max(W_{a_k}, W_{a_l}, ...)$ **do**
  if $\nexists\ a_j \in X1$ *and* $a_x \in X2$: $G_{a_j} \equiv G_{a_x} \in O_C^{a_i}$ **then**
    $commit(X1 \cup X2) : X1 \cap X2 = \emptyset$;
  end
  if $\exists\ a_j \in X1$ *and* $a_x \in X2$: $G_{a_j} \equiv G_{a_x} \in O_C^{a_i}$ **then**
    if $W_{a_j} > W_{a_x}$ *and* $\overline{\prod}$ *of* a_j *is maximal* **then**
      Select a_j and $commit(X1 \cup X2) : X1 \cap X2 = \emptyset$;
    else
      Compute the MDP for each configuration in order to predict the stability if a coordination is committed;
    end
  end
end

Algorithm 1: MergeD() (Merging decision).

which provides a larger weight to its *message sharing*. This avoids the case where a_i and a_j are in an impasse without awareness by the agents which are awaiting a commitment. Note that, the conflict resolution is decentralized and depends on the *message sharing(s)* concerned by the conflict. Thus, deadlocks are avoided in the coordination. This proves our lemma. □

Definition 8. *A set of agents A form a Nash equilibria partition P, if none of the agents in A is motivated to leave other agents in order to join another partition P′ of another set of agents, i.e,* $\neg(\exists\ a_i \in A : a_i \in P, \exists P' : P' \cup \{a_i\} \succ_{a_i} P)$.□

Theorem 1. *A weak-accept entails that there exists a set of agents W-Set of a message sharing which guarantees a Nash equilibria partition in C.*

Proof. Consider *W-Set* as the set of agents which responded with a weak-accept in a *message sharing*. Consider that, $U_{a_x}^t$ is the outcome of the utility function U_{a_x} of a_x at time t.
(1) $\forall a_j$, *W-Set=W-Set* $\cup\ a_j$ if and only if $G_{a_j} \in O_C^{a_i}$ and $U_{a_j}^{t-1} \leqslant U_{a_j}^t$ and $E_{a_j}^t \neq 0$. This means $\forall a_j \in$ *W-Set* it has agreed to join coordination C in offer $O_C^{a_i}$.
(2) $\forall a_i, a_j \in$ *W-Set*, $G_{a_i} \not\equiv G_{a_j}$ and $U_{a_i}^{t-1} \leqslant U_{a_i}^t$, $U_{a_j}^{t-1} \leqslant U_{a_j}^t$. This means that, there is no conflict between the agents in *W-Set* and each utility is maximized.
(3) $\forall\ W_{a_i}$ of $a_i \in$ *W-Set*, W_{a_i} depends on its alliances of its view $\vartheta_{a_i}^t$. In addition, a_i aims to maximize its weight and reliability because if it withdraws from *W-Set* its weight and reliability will decrease. (1), (2) and (3) above mean that, $\forall a_i \in$ *W-Set* is not motivated to deviate from *W-Set* and has agreed to join C with each agent in *W-Set*. Thus, *W-Set* $\subseteq C$ is Nash equilibria. This proves our lemma. □

Lemma 2. *The merging of two W-Set gives also a set of agents which is a Nash equilibria partition in C.*

Proof. Consider $X1$ and $X2$ two sets of agents involved in two different *message sharing* which responded with a weak-accept. By theorem 1, $X1$ and $X2$ are both Nash equilibria. $X1 \cup X2$ is such that $X1 \cap X2 = \emptyset$. By algorithm 1, $X1 \cup X2$ is such that $\forall a_i \in X1 \cup X2$, W_{a_i} and $\overline{\prod}$ are maximized. Thus, if the merging is a success, each agent maintains its agreement to join coordination C with each agent in $X1 \cup X2$. This proves our theorem. □

Theorem 2. *message sharing convergences toward a coordination.*

Proof. Lemma 1 proves that, if a weak-accept exist for a *message sharing*, it will be without deadlock. In addition, AIMS works even if some agents are unavailable, the termination is always guaranteed and each agent has control over the outcome regardless the state of other agents. Theorem 1 implies that, the outcome of AIMS is always a stable coordination. By lemma 2, if a weak-accept comes from a *message sharing* or from the merging of a set of *message sharing* then, no agent is motivated to deviate from the outcome. In addition, the utility, the reliability, the probable stability and the utilitarian social welfare of the set of agents are maximized because the *message sharing* which provides a larger weight is always preferred. Thus, for each agent's, the outcome of message sharing leads to a coordination where no agent is motivated to deviate and where the utilitarian social welfare is maximized. □

5.2 Data Analysis

We show after 2 years experiments, different correlation between maximum wind speed (Vent2M_Max), maximum ground temperature (Temp2M_Max), maximum soil moisture (Hum2M), the day (JOUR) and the year (YEAR).

The figure 6 highlight the dependences of a set of variables of our context. This heat map is a two-dimensional representation of data in which values are represented by colors. Each square shows the correlation (a measure of dependence) between variables on each axis represented by colors. Correlation ranges from -1 to +1. Values closer to zero means there is no linear trend between the two variables. The close to 1 the correlation is the more positively correlated they are; that is as one increases so does the other and the closer to 1 the stronger this relationship is. A

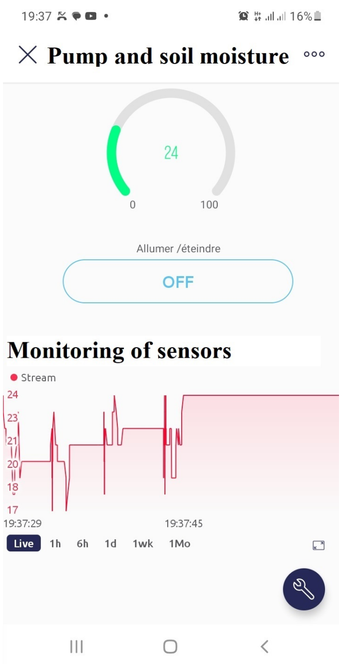

Figure 5: An example of a real time monitoring (live, hourly, daily Weekly, Monthly) of the irrigation system through a smart-phone.

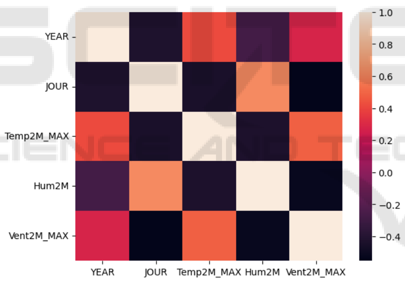

Figure 6: Data correlation of the agents data.

correlation closer to -1 is similar, but instead of both increasing one variable will decrease as the other increases. The diagonals are all 1 because those squares are correlating each variable to itself (so it's a perfect correlation). The larger the number and the lighter the color the higher the correlation between the two variables. The figure 5 show an example of data display of the sensors on our web application for a real time decision making.

6 CONCLUSION AND PERSPECTIVES

Based on climate input and agroecological input parameters, this experiment provided a demonstration of the use of Machine Learning algorithms (K-MN, SVM and CART) and Markov Decision Process (MDP) to provide a good decision making. In addition, in the agricultural sector our AIMS model wants to open up to other areas of IoT that it has already explored in theory and evaluated its feasibility. Indeed, the model does not seek to minimize agricultural practices but rather seeks to perfect them by relying on the analysis of agroclimatic data and their management over time. Future work will include examining large datasets from different area to predict crop yields in advance, detecting plant diseases and predicting yields quality.

REFERENCES

Faye, P. F., Aknine, S., Sene, M., and Shehory, O. (2015). Dynamic coalitions formation in dynamic uncertain environments. *International Conference on Web Intelligence and Intelligent Agent Technology (WI-IAT)*, page 273-276.

Faye, P. F., Aknine, S., Sene, M., and Sheory, O. (2014). Stabilizing agent's interactions in dynamic contexts. *28th International Conference on Advanced Information Networking and Applications*, page 925-932.

Faye, P. F., Senghor, M., and Ndione, G. A. (2022). Stable trade coordinations in smart agriculture. *International Joint Conference on Web Intelligence and Intelligent Agent Technology (WI-IAT)*, pages 215–222.

Paswan, R. P. and Begum, S. A. (2013). Regression and neural networks models for prediction of crop production. *International Journal of Scientific and Engineering Research*, pages Volume 4, Issue 9,ISSN 2229–5518.

Sellam, V. and Poovammal, E. (2010). Prediction of crop yield using regression analysis. *IEEE Trans. Knowl. Data Eng.*, pages vol.23, no. 10, pp. 1498–1512.

Shehory, O. and Kraus, S. (1998). Methods for task allocation via agent coalitions formation. *AIJ*, pages 165–200.

Yates, R. D. and Goodman, D. J. (2005). *Probability and Stochastic Processes: A Friendly Introduction for Electrical and Computer Engineers*. John Wiley and Sons, INC, Rutgers, The State University of New Jersey.

Zhang, L., Lei, L., and Yan, D. (2010). Comparison of two regression models for predicting crop yield. *IEEE International Symposium on Geoscience and Remote Sensing (IGARSS)*.

Zingade, P. D., Buchade, O., Mehta, N., Ghodekar, S., and Mehta, C. (2018). Machine learning-based crop prediction system using multi-linear regression. *International Journal of Emerging Technology and Computer Science(IJETCS)*, pages Vol 3, Issue 2.