Smart Agriculture: An Open Field For Smart Contracts

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***Abstract*—Smart agriculture is increasingly becoming a paramount financial sector with important implications on a global scale. The real time weather and soil status monitoring as well as the desired higher food quality are major drivers behind this technological, ecological, and financial trend. This work explores the enticing prospect of combining IoT and smart contract technologies with smart agriculture in order to deliver not only higher quality agricultural products, but also improving the associated supply chain and agricultural logistics, thus resulting in multiple benefits for all the parties involved. Emphasis is placed on deriving similarity metrics for tuples describing soil and climate conditions based on numerical and possibly categorical data. Moreover, a sample implementation of one such metric is given in Solidity, a high level language for formulating smart contracts designed for the Ethereum Virtual Machine is also provided as a concrete example. Finally, aspects of agricultural asset digitization, a crucial step for smart contracts relying on physical objects are also discussed.**

***Index Terms*—smart agriculture, smart farming, soil factors, crop quality, weather monitoring, supply chains, blockchains, smart contracts, solidity, Ethereum Virtual Machine (EVM), IoT**

I. Introduction

With the advent of IoT a number of technological fields, as well as economy sectors, have received a considerable boost bringing different outcomes on environmental monitoring applications that use sensors to support the assessment of air, water and soil quality. Additionally, The physical devices connected to the internet (namely IoT devices) bare the potential of improving agricultural machinery and building smart infrastructure for remotely managing and controlling water pumps, atomizers and other agricultural apparatus. These integrated systems are not yet considered to be widely used in agriculture, although pivotal for the current development of farming techniques. Intelligent methods of agriculture involve incorporation of computer science and information technologies into the traditional notion of farming [1].

The large volumes agricultural data, created by most IoT monitoring and controlling applications, demand distributed storage for dynamic data enrichment, trackability, ownership, and scalability. Given the fact that oT smart capabilities also include integrated information processing, agricultural related data are produced by electronic identities that can be queried remotely that are equipped with sensors for detecting physical changes around them, even particles as small as dust might be tagged and networked. Such characteristics transform merely static objects of agricultural practice into newly dynamic things, embedding intelligence in the environment, and stimulating the creation of innovative products and entirely new services. These things themselves are capable of distributing processing power with embedded intelligence to the edges of each network structure that offer further possibilities for greater data processing and the resilience the interconnected apparatus [2].

These procedures require the development of well defined, meaningful, measurable, motivational, and self-explanatory metrics based on a set of indicators providing broad and general information [3]. The vast amounts of data collected shape an optimally designed and managed monitoring network to track, anticipate, and manage changes related to the biophysical components of agricultural filed applied to. This allows scientists and farmers to find solutions to pressing problems, such as allow for aspects of agriculture and food systems to be quantified and compared across time and space. In other words the scope of an monitoring system is to produce quantifiable information about environmental conditions in agriculture [3].

Agriculture as a practice is established across different ecological and climatic zones, so an IoT system focuses on gathering data on a set of common metrics for each application. However, the produced indices cannot be dictated by a generic framework for application in all jurisdictions. Contrariwise, the researcher/farmer should assess spatial, temporal, and spatio-temporal transferability of such metrics [4] on a regional level. This approach understands the variability of ecological and agricultural conditions that bare different biotic taxonomies. Furthermore, in association of their spatial, temporal, and spatio-temporal transferability these subsets are subject of the scientific and managerial scope the particular cropland is monitored. In conclusion, an IoT system for agricultural monitoring should reflect well designed, optimally conceptualized, customized model of entities that represent the physical parameters under question as shown in figure 1.

The primary research objective of this conference paper is the exploration of the applications of IoT and smart contracts technologies to smart agriculture. Moreover, as a secondary

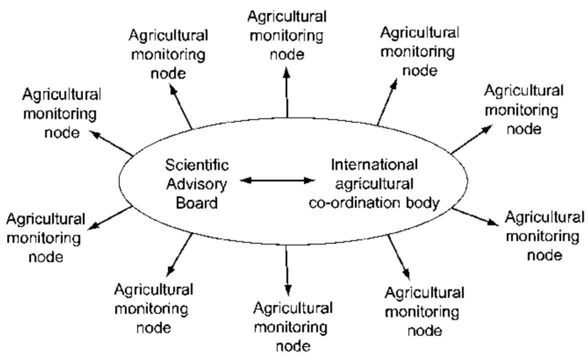

Fig. 1. Agricultural monitoring framework (source: [4])

TABLE I
NOTATION OF THIS CONFERENCE PAPER.

Symbol	Meaning
$\triangleq$	Definition or equality by definition
$\{s_1, \ldots, s_n\}$	Set with elements $s_1, \ldots, s_n$
$(t_1, \ldots, t_n)$	Tuple with elements $t_1, \ldots, t_n$
$\|S\|$ or $\|T\|$	Set or tuple cardinality
$\rho(T_1, T_2)$	Cosine tuple similarity coefficient
τ_{S_1,S_2}	Tanimoto set similarity coeffcient

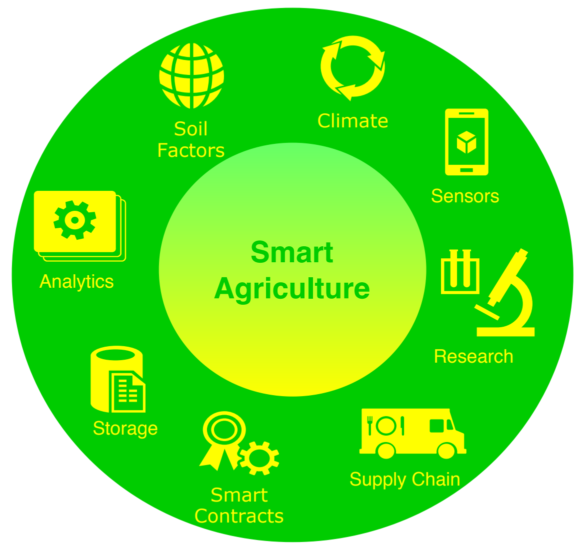

Fig. 2. Factors of smart agriculture (source: authors).

objective, a similarity metric quantifying tuples representing soil surface factors is presented in Solidity, a high level language for formulating smart contracts in the Ethereum digital ecosystem.

The remaining of this conference paper is structured as follows. In section II the recent scientific literature regarding smart agriculture and the relevant applications of IoT to it are briefly summarized. Section III examines smart agriculture from an abstract standpoint and enumerates the basic ecological and farming factors involved. The applications of IoT and smart contracts to smart agriculture are analyzed in section IV. Section V outlines possible future research directions. Finally, table I summarizes the notation of this work.

II. PREVIOUS WORK

Smart agriculture is treated in a number of scientific publications. One of the early adopters where Zhao et al.[5], which introduced a platform for real-time data monitoring in agricultural related applications based on wireless sensors through M2M. The system takes into consideration data collection, management, and distribution under the scope of greenhouse control. The platform was able to operate online while producing reliable humidity and temperature measurements. Smart agriculture based on patterns discovered through thermal imaging systems mounted on drones is discussed in [6]. Finally, for a survey between the connection of smart agriculture and climatic change see [7]. In [8] a data architecture for smart insular viticultures is proposed, whereas in the follow-up work [9] a collaborative platform for data annotation based on said architecture is presented. Multifactor ontologies for smart agriculture can be constructed following design principles such as the ones stated in [10].

Regarding the deployment of IoT networks such as smart sensors a number of factors must be also considered. Besides energy consumption and heat dissipation, reconfiguration capabilities, and area coverage patterns, robust architectures based on structural resilience should also be taken into account [11]. IoT devices including sensors and drones can provide ultra high resolution multispectral images describing crop status [12]. Multispectral images consist of images of the same physical object in various spectra, typically including near infrared (NIR) and various components of the visible (VIS) spectrum [13][14], with each such spectrum contributing different image features. The fundamentals of multispectral images including lighting conditions, angle of acquisition, and synthesis of the available spectra are described in [15]. Such images are typically handled with tensor based techniques, a generalization of linear algebra to more than two dimensions. For a review of tensor analytics, or equivalently of multilayer graphs, see [16], [17], or [18]. Multispectral imaging techniques are gradually becoming pivotal in DNA analysis [19].

The connection between the emerging technology of blockchains, and smart contracts by extension, and IoT is thoroughly examined in [20]. The various cost aspects incurred by the lack of clause negotiations in traditional contracts is studied in [21]. The high disruptive potential of smart contracts and the underlying blockchain infrastructure are discussed in [22]. Finally, insight on certain legal perspectives about smart contracts can be found in [23].

III. SMART AGRICULTURE

There is a plethora of technological, ecological and farming, and financial factors shaping smart agriculture. The most important of them are shown in figure 2. Ecological and farming factors such as surface conditions are presented in this section, whereas the section IV deals with smart contracts and logistics.

The set of factors influencing the crop quality depends heavily on the latter, climatic, and soil factors influence the optimal growth and production rate of each yield type. Each of the sensing devices, namely IoT Weather Stations, must ensure reliable wireless data transfer and provide logging capability such as that proposed in [24] as a common set of atmospheric factors found in the literature is the following:

- Wind speed and direction
- Prevailing temperature
- Barometric pressure
- Precipitation volume and rate
- Relative humidity
- Leaf humidity
- Solar irradiance
- Ultra-violet (UV) irradiation

In addition to surface conditions, a set of chemical and physiological parameters are considered decisive for the assessment of each monitoring model. Particularly, the basic parameters, namely the soil nutrients, of the crop are:

- pH
- Nitrogen (N)
- Calcium (Ca)
- Zinc (Zn)
- Potassium (K)
- Phosphorus (P)

It should be noted that the importance of each of the above factors depends heavily on the type of agriculture, as each plant type thrives under a specific range of requirements.

Among the traditional farming equipment which can significantly upgraded to contribute to smart farming are the following [25]:

- Tractors
- Trucks
- Seeds
- Fertilizers

Recently, high tech equipment has been added to the inventory of smart farms. These include the following [26]:

- Telemetry drones
- Robot workers
- Knowledge mining techniques for plant DNA
- Life cycle simulation for new seed variants
- Ground on-the-spot sensors
- Remote imaging systems
- Spaceborne ultrahigh resolution monitoring systems

IV. Applications

A. IoT Applications

Smart agriculture can benefit from IoT powered technology in multiple ways. First and foremost, smart sensors are instrumental in determining whether a specific location is appropriate for a given type of agriculture [27]. These recommendations can be useful in answering important questions not only in local but also in nation-wide agriculture strategies such as [28]:

- Which variants of the seeds available are suitable for a given area.
- How much water and other resources would these variants require.
- How sustainable these variants are.
- How resistant these variants are to threats like disease or insects.
- What effects will a cultivation shift cause to local climate change.
- Conversely, whether more resistant variants should be selected to counter effects from any local climate change in the near future.

IoT technology is pivotal in quickly evaluating the crop status after a potentially disastrous event such as excessive drought or rainfall, an aggressive locust raid, or environmental pollution [29][30]. Especially the topic of pollution plays an instrumental role in crop planning, since accidents leading to it cannot be predicted beforehand. To this end specialized IoT-powered specialized sensor networks [31], usually in conjunction with drones [32]. Note that for remote and inaccessible areas, crop status can be evaluated from space using ultrahigh resolution imaging systems [33].

Last but not least comes the topic of agriculture logistics, both inbound and outbound. *Inbound logistics* cover the supply chain aspects necessary to procure smart agriculture units with the appropriate equipment (e.g. tractors, drones, or seeds) and information (e.g. weather conditions, local disease outbreaks, or long term regional climate predictions). On the contrary, *outbound logistics* deal with the distribution of high quality agricultural products, ensuring that the latter abide by the standards set by all the parties involved, for instance resellers, local government, agricultural units, and consumer unions. Both forms of logistics involve IoT for quality monitoring (e.g. product temperature and humidity variation while in storage) as well as for automated inventory controls (e.g. how many trucks were needed in order to move a given amount of commodity across country and how much time did that take) [34][35].

B. Smart Contracts: Parameters

Smart contracts rely on dynamic clauses which in turn are formulated based on the negotiations between the parties involved as well as on data fed from a smart agriculture IoT infrastructure. Recall that both negotiations regarding any smart contract and the various versions thereof are appended to the original contract in a blockchain environment per the requirements set forth in [36]. At any rate, when formulating agricultural smart contracts care must be exercised because of the sensitive nature of agricultural products. In [37], [38], and [39] security guidelines are provided from a systems perspective in order to thwart malevolent software agents. Moreover, as is the case in any field physical field involving smart contracts, asset digitization is an important issue, as stated among others in [40]. Study of smart contracts with formal methods is the focus of [41].

In order for digital contract clauses to change, hard data must be obtained as stated earlier. In the case of soil or climate factors, they can be represented as tuples which can contain either numerical or categorical data. Depending on how factors change over, certain similarity metrics can be built so that they can serve as the basis for negotiation in smart contracts.

Let p and q be two tuples of the same cardinality, namely $|p| = |q| = n$.

$$
\begin{aligned}
p &\triangleq (p_1, \dots, p_n) \\
q &\triangleq (q_1, \dots, q_n)
\end{aligned} \tag{1}
$$

When p and q contain only numerical data, then the absolute value of the cosine similarity suffices and additionally, it is computationally effective:

$$
\rho(p, q) \triangleq \frac{\left|\sum_{i=1}^{n} p_i q_i\right|}{\sqrt{\sum_{i=1}^{n} p_i^2 \sum_{i=1}^{n} q_i^2}} \tag{2}
$$

When the factor tuples contain also categorical data, then the similarity metric in equation 2 must be modified. One way to achieve that is to first separate the numerical from the categorical data. Assume that there are m categorical entries with $1 \leq m \leq n-1$. Then, the categorical data from p and q are placed in sets S and T respectively with $|S| = |T| = m$. Thus, they have the form:

$$
\begin{aligned}
S &\triangleq \{s_1, \dots, s_m\} \\
T &\triangleq \{t_1, \dots, t_m\}
\end{aligned} \tag{3}
$$

In order to compare any two non-empty sets S_1 and S_2, the Tanimoto coefficient can be used. The latter is defined as follows:

$$
\tau_{S_1,S_2} \triangleq \frac{|S_1 \cap S_2|}{|S_1 \cup S_2|} = \frac{|S_1 \cap S_2|}{|S_1| + |S_2| - |S_1 \cap S_2|} \tag{4}
$$

Notice that the second form of equation 4 is preferable in terms of performance for large sets since the intersection can be efficiently computed. Moreover, the intersection size cannot exceed by definition the smallest cardinality of the two sets involved.

Now let us call p' and q' the parts of p and q which contain only numerical data and are also tuples themselves with cardinality $n - m$. Since they are tuples, the cosine similarity as defined earlier can be clearly applied to p' and q'.

Given that both $0 \leq \rho(\cdot, \cdot) \leq 1$ and $0 \leq \tau_{\cdot,\cdot} \leq 1$, then two similarity metrics for tuples with numerical and categorical data can be defined. The first is the geometric mean of the cosine and the Tanimoto similarity coefficients:

$$
g \triangleq \sqrt{\rho(p', q') \cdot \tau_{S,T}} \tag{5}
$$

The geometric mean is known to be the strictest among the three classical means (i.e. arithmetic, harmonic, geometric) in the sense that it is systematically closer to the lowest of the two factors.

Alternatively, the harmonic mean of the two similarity coefficients when $\rho(p', q') \neq 0$ and $\tau_{S,T} \neq 0$ can be computed as:

$$
\begin{aligned}
h &\triangleq \frac{2}{\rho(p', q')^{-1} + \tau_{S,T}^{-1}} \\
&= 2\frac{\rho(p', q') \cdot \tau_{S,T}}{\rho(p', q') + \tau_{S,T}}
\end{aligned} \tag{6}
$$

However, neither equation 5 nor equation 6 take into account the number of categorical tuples entries to the total number of entries, which may be desirable in certain cases. To this end, a weighted version of equation 6 can be derived as follows:

$$
\begin{aligned}
h' &\triangleq \frac{n}{(n-m)\,\rho(p', q')^{-1} + m\tau_{S,T}^{-1}} \\
&= n\frac{\rho(p', q') \cdot \tau_{S,T}}{(n-m)\,\tau_{S,T} + m\rho(p', q')}
\end{aligned} \tag{7}
$$

C. Smart Contracts: Scripting

How are smart contracts scripted? One answer is Solidity, namely a high level, object-oriented, statically-typed language based on C++, Python, and Javascript intended to develop smart contracts for the Ethereum Virtual Machine (EVM). At this point it should be highlighted that, contrary to popular belief, Ethereum is not a cryptocurrency. Instead, it is the name of the blockchain infrastructure designed to implement and support the functionality of the Ether cryptocurrency. It is noteworthy that contracts support inheritance.

In order to implement the cosine similarity metric of equation (2) in Solidity, the source code (excluding array initialization) could be like the following. Notice that mathematical libraries for square root and absolute value are not yet implemented. Although it is easy to implement the absolute value, the square root needs some work. In this case, we implement the well known Babylonian numerical algorithm in an auxiliary method.

```
pragma solidity ^0.5.0;

contract MyContract {

 function SR(uint x) returns (uint y) {

  uint a = (x + 1) / 2;
  y = x;
  while (a < y) {
   y = a;
   a = (x / a + a) / 2;
   }
  }

 function CS(uint n) returns (uint cs) {

  uint[] memory p = new uint(n);
  uint[] memory q = new uint(n);
  uint num, denomp, denomq;
```

```
  for (uint i=0; i<n; i++) {
   num += p[i]*q[i];
  }

  for (uint i=0; i<n; i++) {
   denomp += p[i]*p[i];
   denomq += q[i]*q[i];
  }

  cs = num / SR(denomp*denomq);
  if (cs < 0)
   cs = -cs;
  return cs
 }
}
```

V. Conclusions And Future Work

This conference paper focuses on the potential applications of smart contracts and IoT technologies to the growing field of smart agriculture. In particular, smart contracts can be useful in logistics, inventory, and the mass negotiations associated with moving large food quantities. As a concrete example, the cosine similarity metric has been implemented in Solidity, a high level language for scripting smart contracts in the Ethereum Virtual Machine (EVM) which is a popular platform. This similarity metric allows checking whether some of the factors involved in crop quality has been changed and, if desired, be the basis for a new digital negotiation.

Regarding future work directions, more smart contracts covering the entire spectrum of agricultural supply chain in order for quality constraints set by all the parties involved be met. For instance, monitoring the quantity, size, and texture of fruits through the appropriate combination of sensors may well be of interest for high end, luxury food trading routes.

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