Enabling AI in Agriculture 4.0: A Blockchain-Based Mobile CrowdSensing Architecture

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Summary. Agriculture 4.0 relies on extensive data for predictive services, necessitating effective data collection. Mobile CrowdSensing (MCS), with its cost-effectiveness and scalability, addresses this need but faces centralization limitations. Blockchain-based frameworks have been proposed to mitigate these issues but often focus solely on data collection, lacking a comprehensive end-to-end architecture for smart agriculture. Recent literature has explored the integration of the Internet of Things (IoT), edge computing, fog computing, and cloud computing capabilities to establish centralized end-to-end architectures. Nonetheless, these architectures come with their own set of centralized limitations. In the context of contemporary technologies, the integration of blockchain and digital twin (DT) holds the potential to revolutionize the field of smart agriculture. This paper introduces a holistic end-to-end, layered, and service-oriented architecture for Agriculture 4.0, integrating mobile crowdsensing, blockchain, and DT. Unlike existing architectures, this approach aims to overcome centralization limitations, leveraging the strengths of emerging technologies. The proposed architecture extends current capabilities for more efficient and secure Agriculture 4.0 practices. We deploy the suggested architecture onto the Ethereum blockchain, demonstrating its practicality through the obtained results.

1 Introduction

The continuous evolution of technologies transformed the industrial revolutions from Industry 1.0 to Industry 4.0, which is expected to transform the agricultural industry revolutions towards Agriculture 4.0. The technologies characterizing Industry 4.0 include IoT, big data, cloud computing, AI, 5G, and Blockchain, enabling the agricultural ecosystem to be more intelligent, secure, advancing towards high automation and decision making capabilities [1]. Agriculture 4.0 utilizes IoT technology to collect a large amount of Spatio-temporal data in real-time. The realm of big data science often integrates various technologies such as machine learning (ML), artificial intelligence (AI), cloud computing, and others to perform analytics on the collected data, enabling decision-making capabilities. On the other hand, Blockchain technology maintains data integrity and enhances trust among the system entities. In addition, the DT concept plays a crucial role in Agriculture 4.0 by offering a virtual representation of physical agricultural assets, processes, and systems [2]. This innovative approach brings numerous benefits, including enhanced precision farming, optimized resource efficiency, and informed decision-making through real-time monitoring and predictive analytics. DTs empower farmers with a comprehensive toolset to drive sustainability, productivity, and resilience in modern agriculture practices.

Besides the benefits of using AI in Agriculture 4.0, there are certain challenges of using AI technology. To harvest the full potential of AI in Agriculture 4.0, the AI models should be fed with real-time data for making timely predictions and to rewire themselves as per the "concept drift [3]." Another critical issue is the scalability requirement for data collection. The volume and diversity of input data measure the strength of an AI system. Artificial neural networks, fuzzy control systems, and other forms of AI engines require massive amounts of data for proper training before they can be successfully applied in the agricultural sector to guide farmers toward precision agriculture. However, data collection becomes a hurdle for such a large amount of data.

Deploying sensing infrastructure to collect the data across many farm fields in the country and providing its maintenance is neither feasible nor economically viable for any third-party service provider, including the government. Agricultural Mobile crowdsensing (AMCS) is considered a cost-effective and scalable solution to solve this issue [4]. The existing AMCS systems are centralized and have their own limitations, such as being less secure due to a single point of failure, the threat of data modification, being vulnerable to attacks, and having trust deficit issues due to lack of transparency. Most importantly, such systems do not allow data sharing among multiple stakeholders, especially farmers. Moreover, two critical issues in the data collection process through mobile crowdsensing demand attention: data ownership and transfer and lack of motivation among farmers to actively participate in the data collection process.

Numerous blockchain-based MCS frameworks, [5], [6], have been proposed to address centralization issues. However, these frameworks primarily focus on raw data collection based on requester specifications, neglecting the crucial aspect of providing services based on the acquired data. An essential service of an MCS system involves delivering validated data to the requester. Existing frameworks often rely on common methods like finding data similarity and truth discovery to validate data over the blockchain. Nevertheless, these approaches face challenges when applied to agricultural data due to the dynamic nature of field properties. Addressing this issue requires an additional implementation of ML/AI methods, which is currently lacking in established blockchain-based MCS systems due to the impracticality of integrating such methods directly into the blockchain. Consequently, an opportunity exists to create an environment that facilitates the seamless integration of ML/AI into existing blockchain-based MCS systems. Beyond these frameworks, the literature also presents layered IoT architectures discussed in section 2 that explore integrating advanced technologies, including IoT, edge computing, fog computing, Cloud computing, DT, and blockchain, to enhance service capabilities. However, there is a notable absence of architectures that comprehensively integrate all these technologies to harness their collective advantages.

To remove these obstacles in enabling Agriculture 4.0, we propose an end-to-end, layered, and service-oriented architecture, integrating advanced technologies like IoT, DT, mobile crowdsensing, blockchain, and AI. The proposed architecture enables real-time, scalable, cost-effective agricultural data collection using blockchain-based mobile crowdsensing that caters to centralization problems, data ownership, and incentivization. Also, it enables AI to provide services from the collected data.

2 Related Work

This section discusses a succinct overview of smart agriculture architectures, primarily centered on sensor/things, edge, fog, and cloud computing paradigms. A recent survey [7] on smart agriculture has discussed the role of these computing paradigms in detail. The IoT ecosystem comprises three key components: Perception, Communication, and Intelligence/Control Layers [8]. Numerous proposed architectures address challenges related to data traffic, communication reliability, and efficient resource utilization. Examples include layered architectures [7], [9], [10], [11].

Authors in [12] proposed an extended layered centralized architecture encompassing the security and privacy requirements, such as authentication, access control, authorization, integrity, availability, entity, data, and location privacy. However, the application of traditional centralized security measures faces constraints related to a singular point of failure, traceability, verifiability, and scalability. The authors in [13] proposed a blockchain-IoT layered architecture. The additional blockchain layer is responsible for the storage and security of data. However, storing data in the blockchain may create storage scalability issues. The authors in [14] integrate blockchain technology into the existing layered architecture to identify the anomalies through the smart contract. However, the data collection is solely done in a centralized environment. The authors in [15] proposed a blockchain-assisted architecture for smart agriculture to maintain communication among the stakeholders securely. The proposed architecture utilized a private blockchain explicitly designed to secure supply chain processes and forecast commodity prices.

A few articles incorporate the concept of DTs in the existing centralized layered architecture. For instance, [16] proposed a novel architecture by integrating the concept of DTs into an existing layered architecture to address resource scheduling, resource allocation, and task scheduling challenges in smart agriculture. Note that the discussed architectures are not designed explicitly for mobile crowdsensing. On the contrary, our proposed architecture presents a core layer that seamlessly integrates DT and Blockchain, amplifying the capabilities of the existing architecture. This integration establishes an environment capable of providing secure and privacy-preserving data collection and AI-enabled agricultural services and opens a new window to generate frameworks on top of the proposed architecture.

3 Proposed Architecture

This section discusses the proposed end-to-end layered and service-oriented architecture for mobile crowdsensing, enabling AI to perform data analysis and predictions. The layers include the physical sensing layer, virtual sensing layer, DT layer, and application layer. The DT layer is a core layer in the architecture and comprises the storage, blockchain, and AI/ML/Cloud layers. Each layer provides different services and has different responsibilities and purposes, as shown in Figure 1. The primary services of the proposed architecture include data services and agricultural services. These services span data collection, local and persistent data storage, data delivery, and data analysis and/or prediction, all carefully designed to prioritize the security and privacy of both the data and the users.

3.1 Physical Sensing Layer

This layer outlines the methodology for collecting data from farmers' fields. The physical sensing layer is responsible for interacting with the physical environment and employs IoT

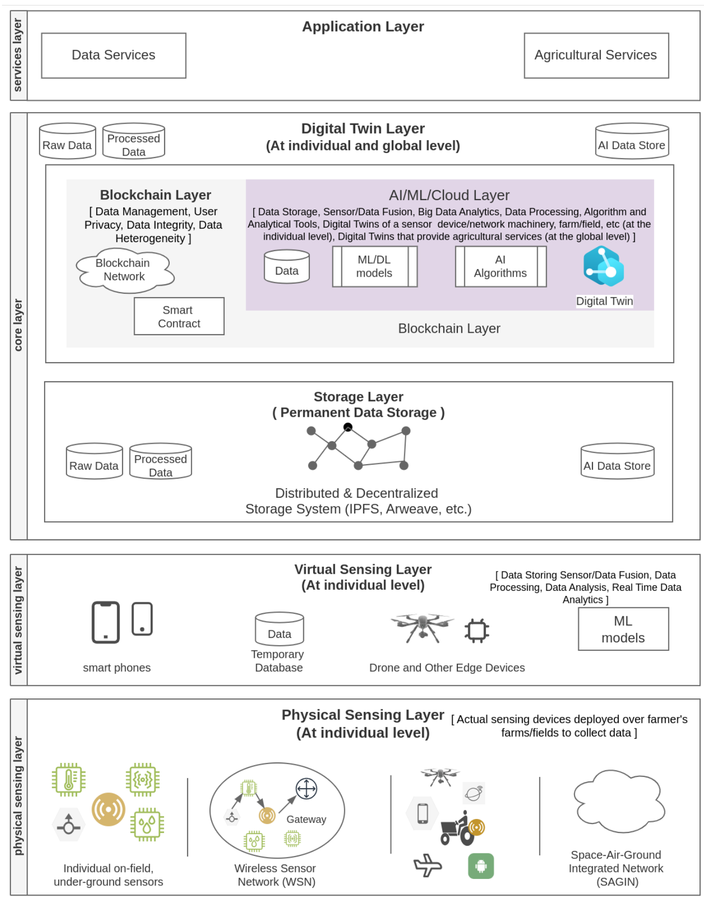


Fig. 1: Proposed End-to-End Service-Oriented Architecture for Agriculture 4.0

sensing devices for data collection. Various sensing technologies play a pivotal role in this process, encompassing individual or networked on-ground and underground sensors, as well as remote sensing technologies like drones, aircraft, and satellites. Farmers or service providers can deploy sensors in fields, on agricultural machinery, vehicles, or robots, forming wireless sensor networks, or utilizing remote sensing technologies for comprehensive data collection. Remote sensing technologies are particularly effective for gathering imagery data. The collected data from these physical IoT devices can be transmitted to the owner's smartphone using wireless technologies such as Wi-Fi, ZigBee, 5G, etc.

3.2 Virtual Sensing Layer

This layer is termed the virtual sensing layer because physical sensing devices do not directly engage with remote devices or third-party applications, mitigating the impact of cybersecurity attacks. High-end devices like smartphones and drones play a crucial role in collecting data from physical sensing devices. Subsequently, these devices validate and analyze the collected data using ML models through mobile or standalone applications. Such advanced devices possess the capability to process raw discrete and imagery data, extracting valuable information. Moreover, they facilitate edge computing capabilities in agriculture. In the contemporary landscape, smartphones are considered IoT sensing devices, leveraging their embedded sensors to sense the environment and collect data. Another reason for labeling this layer as the virtual sensing layer is that high-end devices conceal the actual sensing devices, responsibly interacting with and sending data in a privacy-preserving manner using blockchain identities to the upper layer.

3.3 Digital Twin (DT) Layer

The DT layer assumes a pivotal role in various domains, particularly in Agriculture 4.0, owing to the versatile services it offers. Functioning at individual and global levels, the DT layer entails the creation of virtual counterparts corresponding to physical entities within a farmer's domain, be they living, non-living, process, or system. Living entities encompass animals, plants, and more, while non-living entities include agricultural vehicles, machinery, robots, fields, and farms. Farmers or service providers can fashion the DT for living and non-living entities, delivering services such as real-time monitoring, system failure analysis, optimization and updates, technology integration, and energy consumption analysis at an individual level. The article [17] describes the utilization of DTs in different applications of smart agriculture.

The service providers can also harness DTs of processes or systems to deliver agricultural services globally to the application layer. For such global services, a DT needs robust data storage, the capability to handle big data, and an infrastructure for implementing ML, DL, or AI over big data to analyze data and offer predictions, all while ensuring security, privacy, and trust. The DT layer is structured into three components to fulfill these requisites: storage, blockchain, and AI/ML/Cloud. It's important to highlight that the development of DTs in the context of smart agriculture is predominantly in its conceptual stages. Creating a DT is an optional feature in the proposed architecture, allowing service providers to leverage the DT layer for services without necessarily creating a DT.

Storage Layer

The gathered data is initially stored locally for individual-level data cleaning, processing, and analysis. However, opting for local storage on personal devices or local servers introduces potential drawbacks, including data loss, security vulnerabilities, scalability issues, and maintenance overhead. Although local storage may appear cost-effective in the short term, it is crucial to consider the long-term expenses associated with hardware maintenance, upgrades, and the potential costs linked to data loss. Therefore, there is a need for persistent data storage for extended usability. In contemporary times, numerous distributed and decentralized storage systems like InterPlanetary File System (IPFS), Arweave, etc., are accessible, providing enduring data storage solutions. These external storage systems offer various advantages, including decentralization, censorship resistance, data immutability, content addressing, and enhanced security. Often, these systems incorporate built-in security features, such as encryption, ensuring data protection during storage and transmission. Users at an individual level can trust the integrity and confidentiality of their stored information, while additional security measures can be implemented to safeguard data security and privacy when utilizing external storage systems.

Blockchain Layer

The blockchain layer assumes a pivotal role in the proposed architecture, facilitating the implementation of a blockchain-based mobile crowdsensing system for data acquisition. It serves as an intermediary between data producers and consumers, with the specifics of the data acquisition process discussed in section 4.1. Leveraging blockchain for data acquisition provides inherent advantages in managing data and handling heterogeneity. The technology ensures data immutability and user privacy, facilitates the use of smart contracts, and significantly establishes trust. Users interacting with the blockchain employ a pseudonymous identity, preserving privacy as personal information is not linked to this pseudonym. It's worth noting that while blockchain can be used for data storage, the potential scalability issues associated with massive data sizes led us to consider an external storage system in the proposed architecture. Additionally, it is crucial to highlight that implementing ML, DL models, or AI algorithms directly over the blockchain is not deemed feasible.

AI/ML/Cloud layer

The Cloud Layer, a pivotal component in our architecture, is dedicated to leveraging AI/ML technologies to extract valuable insights from the data collected in the proposed agriculture. This layer serves as the powerhouse for performing big data analytics, ML/DL models, and AI algorithms over the collected agricultural data. It leverages big data analytics tools to process and analyze large datasets efficiently. This includes trend analysis, predictive modeling, recommendations, and identifying patterns to support data-driven decision-making, empowering stakeholders with actionable insights from historical and real-time data.

The Cloud Layer caters to individual and global needs within the agriculture domain. It provides scalable and flexible AI-as-a-services tailored to stakeholders' unique needs. These services encompass infrastructure for creating DTs, big data storage, data validation, and a suite of other services that can be seamlessly integrated into the overall agriculture ecosystem. Stakeholders, from individual farmers to agricultural service providers, can harness the cloud infrastructure for various purposes. For instance, in Empowering individual farmers, the cloud infrastructure allows them to create and manage DTs for their specific agricultural plots. Through the analysis of DTs, farmers can gain insights into crop health, soil conditions, and optimal resource utilization, enhancing their decision-making capabilities. Agricultural service providers can leverage cloud services to deliver innovative solutions to consumers globally. This includes precision farming services, crop monitoring, disease prediction, and customized recommendations based on data-driven insights.

3.4 Application Layer

This layer serves as the user interface, where stakeholders can interact with the agricultural data, analytics, and AI-driven functionalities. This layer describes various software applications and services directly interacting with users tailored to their specific needs within the agriculture domain. The software applications may include desktop or mobile, primarily web3 applications.

This layer's key features and capabilities may include: 1) Tailored for farmers and landowners, precision agriculture applications empower users to monitor and manage their agricultural operations with precision. Features may include real-time crop health monitoring, weather forecasting, and automated recommendations for optimal resource utilization. 2)

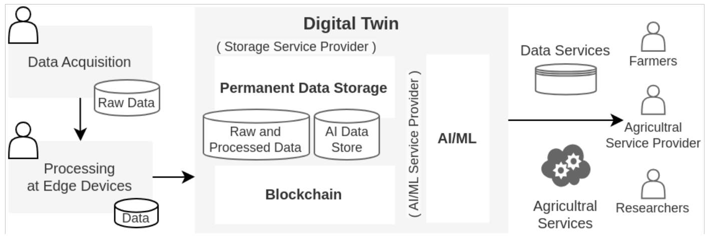


Fig. 2: Data flow for the proposed architecture

Users can visualize and interact with DTs created in the cloud layer. The application layer enables a graphical representation of agricultural plots, presenting data on soil conditions, crop growth, and other relevant parameters. 3) Decision support systems within this layer provide stakeholders with actionable insights derived from big data analytics, ML models, and AI algorithms.

4 Working flow of the proposed architecture: An Implementation Perspective

The proposed architecture aims to achieve key objectives centered around providing data and agricultural services. The data services may include the raw data or processed data. Agricultural services can encompass a wide range of offerings that contribute to various aspects of farming, land management, and agricultural productivity. Here are some possible agricultural services: Crop Monitoring Services, Weather Forecasting Services, Precision Farming Services, Soil Health Assessment Services, Pest and Disease Management Services, Smart Irrigation Services, and others. This architecture has two distinct user entities: producers and consumers. Producers are the entities responsible for offering services, while consumers are those who utilize these services. The specific identity of producers and consumers varies based on the nature of services the proposed architecture facilitates. To illustrate, for data services, producers may include farmers, agricultural industry farms, and other relevant entities, whereas consumers could comprise researchers, agricultural service providers, government agencies, and others. Similarly, producers might be agricultural service providers and government bodies in the context of agricultural services, while consumers could be farmers, agricultural industry farms, and additional stakeholders. This dynamic interplay between producers and consumers forms a pivotal aspect of the architecture's functionality, ensuring a tailored and effective service delivery system.

The working flow of the proposed architecture is visually represented in Figure 2, outlining the processes related to data and agricultural services. Focusing on data services, the architecture's physical and virtual sensing layers are crucial for data collection. The physical sensing layer initiates the data acquisition process by utilizing actual physical sensors owned by data producers. Subsequently, the acquired raw data is transmitted to the virtual sensing layer, which incorporates edge computing capabilities to process the raw data from the physical layer, if necessary. Following data collection based on the specific requirements of data consumers, the data producers leverage the DT layer to securely deliver the data to the consumers while upholding privacy standards. The DT layer encompasses various functionalities within the proposed architecture for data services, including storage services offered by external storage service providers, facilitating interaction or communication between data producers and consumers through blockchain, enabling AI/ML service providers to generate synthetic data for data producers, and providing an infrastructure for data producers to create the DTs. The section 4.1 further explains the collaborative process between producers and consumers in the data collection phase through the utilization of a blockchain-based Mobile Crowdsensing (MCS) system.

In the context of agricultural services, the DT layer assumes a pivotal role in facilitating interactions between producers and consumers through blockchain technology. In addition to the functionalities outlined for the DT layer in the preceding description, it holds the responsibility of delivering global services derived from the aggregated agricultural data to the consumers. This layer serves as a valuable resource for service providers to generate DTs corresponding to various processes, services, and systems. It is noteworthy that the creation of DTs is an optional step for service providers, and they retain the capability to offer services without necessarily generating DTs. This flexibility caters to diverse preferences within the architecture's framework.

4.1 Data Service: Data Collection Using Blockchain-based Mobile Crowdsensing System

The data acquisition involves collecting data from the farmers utilizing blockchain technology to ensure transparency, security, and trustworthiness. Since agricultural needs can be region-specific, they are often influenced by various factors that vary from one region to another. Agriculture is deeply connected to the local climate, soil conditions, water availability, pests and diseases, and other environmental factors. Thus, we assume that the world map is divided into multiple zones, and each zone is uniquely identified using a zone ID. Moreover, diverse agricultural applications may necessitate distinct types of data. The data requirements depend on each application's goals, objectives, and processes. However, there are common types of data that can be relevant across various agricultural applications. In response, a smart contract has been devised to oversee sensing tasks, with each task aligned to a specific region and a singular sensor type, effectively managing data heterogeneity [5]. Dividing a complex task into subtasks corresponding to each sensor type and zone allows sharing among multiple subscribers. The data shared by multiple subtasks is transmitted only once, leading to optimizing the use of available sensing and blockchain resources. Each instance of the smart contract handles a particular sensing task that can be defined using the following parameters: zone ID, sensor type, sampling interval (SI) list of a day, frequency in each SI, task duration in number of days, number of required data collectors, and the data submission frequency, and others.

The system comprises three entities: the data producer, the consumer, and the blockchain-assisted MCS system, as shown in Figure 3. The data producer gathers data according to the consumer's specifications. The blockchain acts as a decentralized and trusted third-party intermediary between the data producer and consumer. Smart contracts are employed to implement and manage the system's various phases, including user registration, task creation, task subscription, reservations, selection of data producers, data submission, and reward distribution. While data validation is a crucial aspect of the MCS system, employing similarity matching techniques becomes challenging due to variations in the values of similar or different crop parameters managed by individual data producers. Implementing ML-based validation techniques directly over the blockchain is impractical. Therefore, data validation can be conducted individually on the virtual sensing layer by utilizing edge computing capabilities or globally on the cloud layer of the proposed architecture.

Two smart contracts are used to execute these phases and to maintain the data ownership. The first smart contract encompasses user registration and task creation phases, while the sec-

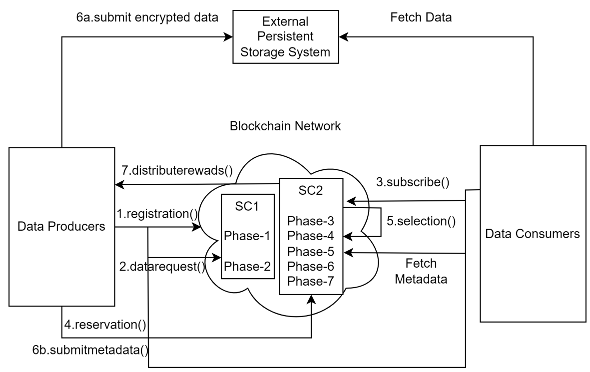


Fig. 3: Data Acquisition Process using blockchain-based MCS system

ond smart contract handles the functions for the remaining phases. In the system's initial steps, users are required to register. Each user interacts with the system using their blockchain address as an identity. Upon calling the *"registration"* function specified in the smart contract, the blockchain initially validates the identity's authenticity by verifying the signature attached to the transaction. Following the confirmation of authenticity, the smart contract stores the blockchain address and other relevant parameters, including reputation, among others. The data consumer initiates another function, *"datarequest"*, wherein they provide updated requirements for the previously discussed parameters. This function leads to creating an instance of the second smart contract. Alternatively, the data consumer can invoke the "subscribe" function to subscribe to another ongoing sensing task that aligns with their sensing requirements. This design permits multiple data consumers to subscribe to the same sensing task, addressing the issue of data redundancy and data sharing.

After the creation of a new sensing task, data producers can express their interest in providing the required data by invoking the *"reservation"* function of the second smart contract. This smart contract incorporates a *"selection"* function that considers factors such as reputation to determine the necessary number of data producers. Subsequently, the selected producers utilize their sensing technologies to collect and validate the data on the second layer of the proposed architecture using the application provided by the data consumer. Upon successful validation, each producer submits the encrypted data to the external storage system, such as IPFS, and the respective data fetching addresses are submitted to the smart contract by calling *"submitmetadata"* function. The data submission is done after considering the data submission frequency parameter set by the data consumer based on the need, enabling real-time data collection. To ensure authorized access, each producer encrypts the key used for data encryption with the consumer's public key and submits the encrypted key(s) to the smart contract. Following the submission of keys, the smart contract has a *"distributerewards"* function used to distribute the rewards to the producers, which can be utilized to obtain agricultural services from service providers. Now, the data consumer can retrieve metadata (data fetching address and key) from the smart contract, use the data fetching address to obtain encrypted data from an external storage system, and use the key to decrypt the data.

4.2 Agricultural services

The envisioned architecture expands upon the depicted data acquisition process outlined in Figure 3 to encompass the provision of agricultural services. Within this framework, ser-

Table 1: Smart contracts deployment cost (in gas)

Smart Contracts	Deployment Cost
BRSCAgri	1579620
TSSCAgri	1246499

vice consumers, primarily farmers, have the capability to request various agriculture services through the blockchain-assisted MCS system. To facilitate this, service providers can leverage the cloud sublayer embedded in the core architecture, employing the collected data to generate the requested services. Subsequently, these generated services are delivered to the service consumers, thus completing the service cycle within the proposed system. This integration offers a seamless and efficient exchange, where farmers utilize the rewards acquired from the initial data collection process to compensate service providers through the blockchain-assisted MCS system. This comprehensive approach not only enriches the system's functionalities but also establishes a sustainable ecosystem that encourages continued data participation and service utilization.

5 Result

We instantiate the proposed architecture on the Ethereum blockchain, employing Solidity as the programming language. Leveraging the brownie framework, we develop, test, and deploy smart contracts on Ganache. Utilizing Python scripts, we deploy the smart contracts on Ganache, an invaluable tool for establishing a decentralized Ethereum network locally featuring multiple accounts. The implementation encapsulates the MCS system phases (1. Registration, 2. Task Creation, 3. Task Subscription, 4. Reservation, 5. Selection, 6. Data Submission, 7. Reward Distribution) within two smart contracts. These contracts interact seamlessly to ensure the system's coherent functionality. To assess the smart contracts' performance, we scrutinize two Ethereum blockchain-related metrics: gas consumption and latency. ”gas” denotes a unit measuring resource consumption, encompassing computation and storage necessities for specific operations. Conversely, latency refers to the block generation time on Ganache, encompassing a transaction's time to execute and successfully validate.

Table 1 provides insights into gas consumption during the deployment of smart contracts. Each MCS phase is represented by a dedicated function in the smart contracts, complemented by two additional functions (8. adding service providers with services and 9. service subscriptions by service consumers) related to the services offered by the proposed architecture. In the assessment of these phases, the considered metrics hinge on various factors, such as the number of reservations & selections and the number of sensor values submitted. In our experimental setup, five data producers initiate reservations, three are subsequently selected, and each chosen data producer submits 12 sensing values. Figure 4 depicts each function's total gas and time consumption.

The factors influencing gas and time consumption in the selection phase encompass the number of reservations (NR) and the required number of data producers required (NP). To comprehend the impact of these parameters, we explore three scenarios. In the first scenario, we maintain a constant number of reservations and manipulate the number of selections. Figure 6a illustrates the effects of this scenario on gas and time consumption. Similarly, in the second scenario, we fix NP (with 70% selections) and vary NR, with Figure 6b depicting the consequences on Gas and Time consumption. In the third scenario, we vary both NR and NP,

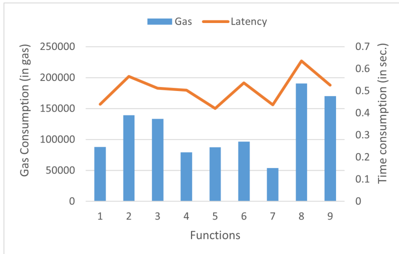


Fig. 4: Total gas and time consumption of each function

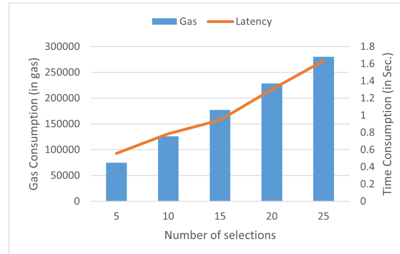
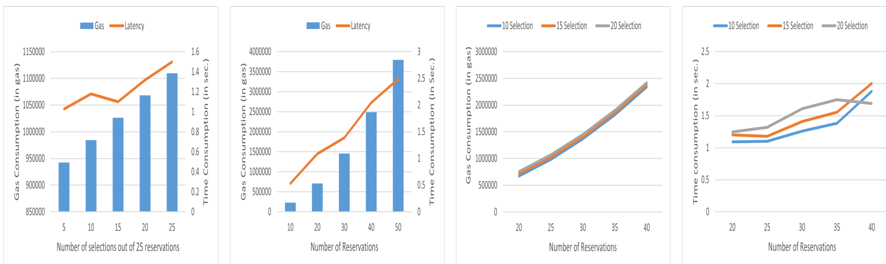


Fig. 5: Effect of number of selections on reward distribution



(a) Effects of scenario 1 on gas and time consumption

(b) Effect of scenario 2 on gas and time consumption

(c) Effects of scenario 3 on gas consumption

(d) Effects of scenario 3 on time consumption

Fig. 6: Effect of parameters on the selection phase

and Figures 6c and 6d showcase the effects of this scenario on gas and time consumption, respectively. Notably, the reward distribution function is contingent on the number of selections. Thus, Figure 5 elucidates the impact of the number of selections on gas and time consumption during the reward distribution process.

6 Conclusion

This paper introduces a comprehensive and service-oriented architecture tailored for Agriculture 4.0. By integrating cutting-edge technologies, the architecture enhances the capabilities of existing architectures. Our proposal incorporates a blockchain-enabled mobile crowdsensing system, presenting a cost-effective and scalable solution for real-time data collection while enabling data ownership and sharing. The blockchain also enables the integration of incentivization mechanisms to motivate the data producers to participate in the data collection. Integrating DT technology within our architecture transforms individual-level data collection and global agricultural services. In conjunction with blockchain technology, the DT layer establishes a robust foundation for secure interactions between providers and consumers, facilitating the seamless exchange of data and agricultural services. Blockchain's inherent features, including transparency, traceability, and trust, strengthen the integrity of these exchanges within the agricultural ecosystem.

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