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Smart Agriculture Optimization in Off-Grid Terrains via Satellite-Coupled Soil Sensing Framework

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Abstract

Smart agriculture in off-grid terrains faces significant challenges due to limited energy availability, intermittent communication infrastructure, sparse sensing coverage, and continuously changing soil and environmental conditions. Ground sensors provide localized information, while satellite technology offers additional data from remote locations. However, applying these technologies separately or using them according to standard fusion approaches may bring about inefficiency in finding information, having too much unworthy communication, or lowering the precision of observations. This paper presents the Adaptive Multi-Objective Honey Bee Optimization for Satellite-Coupled Soil Sensing, which integrates the two approaches and adapts to environmental factors so that the frequency of observations changes correspondingly. The system uses a multi-objective strategy of honey bee optimization to ensure the best results in detecting soil conditions while keeping energy consumption and communication costs to a minimum. The system's effectiveness is determined through various means of simulation that examines factors such as estimation precision, energy-lifetime trade-off balance, communication efficiency, optimization convergence level, ability to withstand satellite information loss and sensor failure, scalability, Pareto outcomes, sensor intensity impact, smart sensory features, and adjustment of fusion weights. The comparison looks primarily at satellite only, sensor only, fixed fusion, and adaptive fusion methods. The other factor being compared in the system is optimization that involves such approaches as GA, MOPSO, MOEA/D, NSGA-II, and classical HBA. The results show that AMHBO-SCSS demonstrates optimum performance by improving soil condition estimation while minimizing unnecessary sensing and communication. The results of Pareto and multiple-objective analysis show that the approach has been able to achieve optimum rivalry among agricultural monitoring patterns. The study gives evidence that the technique of adaptive sensing with the help of the combination of multiple-objective optimization will prove to be useful in terms of its energy efficiency and extreme resilience in smart agriculture applications.

Keywords— Smart agriculture, off-grid agriculture, satellite remote sensing, soil sensing, Internet of Things, adaptive sensor fusion, Honey Bee Optimization, multi-objective optimization, energy-efficient sensing, agricultural IoT.

1. Introduction

The way that agriculture is carried out is changing, as assessment techniques are becoming increasingly reliant on data and the information gathered is more timely, ensuring that irrigation systems, crop management schemes, and resource usage are optimized. Soil moisture, temperature, and other soil parameters vary greatly depending on the locality for a given sample and time because of which taking spot measurements is insufficient for proper decision-making. IoT sensors can help but have their own challenges such as energy supply problems, lack of communication capabilities in rural areas, and other issues. A need for innovative methods of agricultural monitoring and obtaining valuable environment-related information is apparent [1].

Satellite remote sensing offers a valuable complement in terms of monitoring agricultural activities in distant places as it may cover vast distances without needing the physical infrastructure necessary for terrestrial sensing in every location. As a result, satellite images are applicable for monitoring hard-access agricultural regions where terrestrial communication and many sensors are not feasible. However, satellite images do have shortcomings in terms of their spatial and temporal resolution, availability, and weather, as well as the difference between the occurrence of satellite measurements and local soil characteristics. Ground sensors, on the other hand, produce more accurate but localized measurements requiring energy and communication resources and physical deployment. As a result, the use of both satellite and ground sensors individually results in undesirable trade-offs such as the spatial coverage, local precision, consumption of energy and cost of operation [2].

The combination of satellite and ground-based sensing is a way to avoid these drawbacks. The problem is that simply integrating the two types of data together on the basis of fixed weights does not take into consideration changes in the reliability of sensing as well as environmental conditions. Ground data can become less reliable due to sensor degradation or temporary disruptions in communication, while satellite data may be unavailable or less relevant in unfavorable witnessing conditions. In the same way, environmental variability is not stable. There are periods after rainfall or irrigation when it is necessary to complete more observations and the periods which can be described as stable and do not need very frequent sensing. Therefore, a smart and effective agronomic system should know when to start sensing, which source of information to use, and how much sense-making and communicating process should be completed in accordance with the context of operation [3].

The limited amount of power available from an off-grid sensor network poses another important challenge. Continuous sensing along with transmission can deplete the battery resources quickly especially when there

is an extensive number of sensors deployed for agriculture purposes. Increasing the frequency of sensing will provide the benefit of availability of soil data but at the same time will increase the energy expenditure associated with communication. On the other hand, reducing the sensing activity will save energy but the quality of estimation will be compromised as a result. There is a multi-objective optimization problem involved which requires the joint consideration of the important factors such as error estimation, energy consumption, communication overhead, network life, and decision latency [4]. Metaheuristic optimization techniques can be helpful in complex problems of resource allocation and sensing. The economic attractiveness of Honey Bee Optimization (HBA) can be explained by using its population based search manner of operation which offers optimal trade-off between exploration and exploitation. However, it is evident that a traditional approach will fail to address the issue of changing reliability of sensing scheme as well as changing environmental conditions in off-grid agricultural environment. Thus, it is required to develop an adaptive approach [5].

The proposed approach seeks to overcome these obstacles by introducing the Adaptive Multi-Objective Honey Bee Optimization for Satellite-Coupled Soil Sensing (AMHBO-SCSS) architecture for intelligent agriculture in remote areas. The architecture unifies satellite and ground-based soil sensing methods but introduces the adaptive information fusion mechanism that establishes the degree of importance of each sensor used. The adaptive system of sensing alters the sensing process depending on the changes in the environment. Also, the multi-objective Honey Bee Optimization searches for an optimal configuration of the system concerning the quality of data, energy consumption, communication, terms of operation, and the speed of decision-making process [6].

The introduced framework undergoes evaluation via an extensive simulation tests made up of eleven complementary experimental investigations. The analysis aims to evaluate the efficiency of soil-condition estimations, energy use and network lifetime, as well as communication overhead and optimization convergence. Moreover, aspects related to robustness under satellite data losses and sensor faulty occurrences, scalability in the aspect of increased sensor density, energy – accuracy trade-offs are also examined within the analysis. This study makes comparisons against the satellite-only, sensor-only, fixed-fusion and adaptive-fusion methods. Besides, the optimization component is compared with Genetic Algorithm (GA), Multi-Objective Particle Swarm Optimization (MOPSO), MOEA/D, NSGA-II and standard HBA [7].

The contributions of this study can be outlined as follows:

- A novel soil sensing architecture is created for agricultural monitoring in areas with no electricity by utilizing satellite observations and local sensing together.
- This study presents an innovative adaptive sensing technique that helps to minimize unnecessary measurements by re-adjusting the sensing activity based on changes in surroundings.
- A new technique is developed that allows flexible modification of the input contribution from each sensing method depending on how much reliable it is in terms of its attributes and by avoiding static fusion weight mechanisms.
- AMHBO, the new adaptive Honey Bee Optimization method is introduced to jointly optimize and enhance the performance in terms of quality of estimation, energy spent, communication burden, and network life time.
- The studied framework and its attributes are tested under simulation conditions in order to measure various features, including convergence, operation characteristics, Pareto front, and effectiveness of the proposed methods.
- The framework itself is targeted at agricultural areas with limited resources where fixed-rate approach will not work effectively because of its constant need of energy and being connected and available.

The remainder of this paper is organized as follows. Section 2 presents the related work on satellite-based agricultural monitoring, IoT soil sensing, adaptive sensor fusion, and optimization-based smart agriculture. Section 3 describes the proposed AMHBO-SCSS framework, including its system architecture, adaptive sensing mechanism, satellite–ground fusion strategy, and section 4 present multi-objective optimization formulation. Section 5 presents the simulation setup, datasets, evaluation metrics, section 6 demonstrate comparative results, and detailed discussion on results. Section 7 concludes the study and identifies directions for future research.

2. Related work

2.1 Smart Agriculture and Precision Farming

Smart agriculture has come to be regarded as a major area of application of IoT, artificial intelligence, wireless sensor networks, and remote sensing technologies. The main goal of smart agriculture is to change traditional agriculture practices into information-based agriculture practices, where conditions in fields are monitored continuously, and the allocation of agricultural resources is based on specific requirements of crops and soil. In case of smart agriculture systems, distributed sensors are used for measuring soil moisture, temperature, humidity, light, rainfall, and other environmental indicators [8].

Traditional precision-agriculture systems usually consist of four layers: sensing layer; communication network; processing platform; and agriculture decision-support system. While such systems work well in well-connected agricultural areas, their efficiency significantly reduces when we talk about remote territories. When there is no terrestrial communication infrastructure, the use of switches and cellularly connected devices raises costs of either installation or maintenance. What is more, constant monitoring and communication make sensor nodes use energy quickly [9]. This issue is especially relevant in rural regions with the dispersion of farms over long distances. A pure sensor network must therefore either rely on using a great number of units to cover the area adequately or enhance the distance of detection per unit to gain coverage in a specific location. As a result, there has been an increasing interest in hybrid sensing systems that make use of local data and data received from outside sources [10].

2.2 IoT-Based Soil Monitoring

Soil monitoring plays an essential part in the process of precision agriculture as soil characteristics affect plant growth, irrigation needs, and nutrient management. The significance of soil moisture comes especially from the fact that wrong irrigation practices can lead to wasting water, nutrient loss through leaching, root damage, and loss of yields. Moreover, some parameters such as soil temperature, electrical conductivity, pH, and nutrient content can help obtain information necessary to understand field conditions and crop needs [11].

Wireless sensing systems can be based on low-power sensor nodes that are placed in different positions around the agricultural field. These nodes receive data on soil parameters from time to time and send them to a certain cloud platform or a local gateway. Research on adaptive sensing methods have taken place to minimize the number of unnecessary measurements in the process of changing measuring frequency according to the variability of environmental conditions. These methods allow to prolong the life of the sensors and decrease the amount of data sent [12]. Yet, soil-sensing systems remain highly dependent on the quality and availability of measurements carried out locally. Sensor malfunction, battery running out, communicating problems, calibration issues, and spatial variability may lead to insufficient measurements. Increasing the number of sensors would enhance spatial coverage and would increase costs, decrease energy efficiency, and complicate the maintenance process of the sensors [13].

2.3 Satellite Remote Sensing for Agriculture

The use of satellites in remote sensing provides an alternative method for monitoring agricultural areas on a large scale. Satellites can cover large areas without the need for any physical installation at the site of

observation, unlike terrestrial sensors. Information from satellites can be used to characterize vegetation, land surface temperature, crop growth, water conditions, and other parameters of interest [14]. Satellite vegetation indices obtained from multispectral satellite data are commonly employed in determining crop development or vegetation changes. This valuable data is beneficial in crop classification, drought monitoring, biomass forecasting, yield prediction, and determination of areas with crops Under stress. Hence, the data from satellites is useful in areas where ground-based equipment is not available or feasible [15].

Nevertheless, satellite monitoring has a number of drawbacks. Compared to point-based soil sensors, satellite data has a low resolution due to satellite's long revisit period which makes it less effective in monitoring rapid dynamics on soil's surface. Furthermore, cloudiness and atmospheric effects may reduce the overall quality of some readings. Even more importantly, remote sensing delivers indirect values for soil characteristics rather than their real values. Therefore, satellite data are intended to complement local measurements and not substitute for them [16].

2.4 Integration of Satellite and Ground-Based Sensing

The combination of satellite data with in-situ data has become more and more important in large-scale environmental monitoring. Specifically, ground-based sensors offer point observations while satellites are able to cover a larger area. Hence, it is possible to generate a better picture of agricultural conditions when using both sources together [17]. Using a satellite-ground sensing architecture, local measurements may be applied to improve the values obtained by means of satellites. On the contrary, satellite data can show the occurrence of certain spatiality and gain information on where ground measurements are necessary. Thus, this close relationship can help cut the number of ground sensors needed to ensure sufficient monitoring quality [18].

Nevertheless, the appropriate data fusion introduces new challenges. Ground-based observations and those obtained from satellites can differ in spatial resolution, temporal sampling frequency, types of measurements, and uncertainty. Thus, there should be a special mechanism that takes into account the differences in the sources' data instead of simply fusing different data or values together. Relationships can be built with the help of machine learning, regression, interpolation, probabilistic estimation, or spatiotemporal modeling [19]. For off-grid agriculture, this combination is especially effective because ground sensors can function for quite a long period of time while satellite data can provide external information. However, functioning well completely relies on the coordination between sensing, communication, and data processing [20].

2.5 Edge Computing for Remote Agricultural Systems

In order to make the steps of data processing closer to its source, edge computing has been used in smart farming. Instead of sending all raw metrics to the common cloud platform, edge devices realize preprocessing, filtering, feature extraction, and detection of anomalies. As a result, communication costs for the agricultural data processing systems can be decreased and the time required for responses can be reduced [21].

How edge processing is especially useful for off-the-grid systems is that the amount of data transmitted in communication can be very high as far as energy consumption of a sensor node comes from the data transmission. Thus, local processing can illustrate whether the procured data can be of any importance before forwarding it to the main processing facility. For example, the sensor node may immediately send a signal about a considerable decrease in moisture level of the soil while ignoring the non-significant readings during stable conditions [22]. Nevertheless, edge devices have their limitations in terms of their energy source and computational capabilities. Sophisticated machine learning techniques may require resources which are not available with low-powered devices. Therefore, edge technologies applied in agriculture should find a compromise between prediction performance and computational costs. By using simple models, adaptive inference, selective transmission, and hierarchical processing, it is possible to achieve this goal [23].

2.6 Energy-Efficient IoT in Off-Grid Environments

Energy consumption efficiency is essential for applying IoT devices on farms when there are no reliable power sources. These devices use battery packs, solar modules, and other renewable energy sources. Notably, the available energy can depend on the weather or seasons and type of equipment. This means that a static energy management strategy can hardly guarantee long-term reliability [24]. Almost all the energy consumption in the wireless sensor network comes from communication. This means that unnecessary data transmission can shorten its operational time. Adaptive transmission strategies try to solve this problem by transmitting only the most useful data or adjusting the transmission frequency according to the environment [25].

There are some routing and clustering technologies that lower the overall communication expenses. However, the existing solutions usually optimize network parameters such as distance and cost without taking agricultural importance of single measurements into account. One observation about dry soil can be much more important than long-term measurements in severe weather conditions [26].

2.7 Optimization Techniques for Smart Agriculture

Optimization algorithms have been thoroughly studied in agricultural resource management including irrigation scheduling, crop planning, energy management, sensor placement, routing, and task scheduling. Traditional mathematical optimization methods can yield appropriate results under well-defined system parameters and constraints. On the contrary, the agricultural environment is changing, nonlinear and uncertain, thus making exact optimization too demanding in terms of computational power during large-scale application [27].

Metaheuristic optimization algorithms have been of great interest as they allow for good-quality solutions to complex nonlinear problems without needing strict assumptions about the nature of the sought area. Genetic algorithms, particle swarm optimization, ant colony optimization, differential evolution, and other bio-inspired methods have also been used in problems of agricultural scheduling and IoT resource management [28].

The concept of multi-objective optimization is applicable in smart agriculture as agricultural practices must adhere to multiple opposing objectives. As an illustration, it might not be possible to reduce energy consumption without cutting down on the degree of sensing and communication carried out; on the other hand, it could be impossible to boost the accuracy of monitoring without increasing the number of sensors. It could also take longer to process information when the process is carried out on-site. Thus, the multi-objective paradigm will allow finding solutions that lead to balanced achievement of these contradictory objectives [29]. However, most of the noted optimization systems related to agriculture refer to certain issues of resource management (such as irrigation or sensor scheduling) rather than making use of satellite data, ground-data acquisition, energy constraints, communication limitations, and agricultural decision-making [30].

2.8 Research Gap

From the literature, there has been major advancement in the area of agriculture through IoT, soil sensing, satellite monitoring, edge computing, and optimization. Still, there are certain limitations. To start with, the technologies of ground sensing and satellite monitoring are often viewed as separate approaches. The systems based on sensors guarantee high accuracy in local terms, however, lack spatial coverage, and require infrastructure, whereas satellite systems ensure large coverage area but they do not possess sufficient temporal and localized information for soil management [31]. Secondly, lots of sensing systems that involve satellite technologies do not deal with the optimization of communication and other resources

in case some estimations have been made. However, for off-grid environments the energy needed to gather, process, and transmit is of vital importance [32]. Lastly, the current methods of optimization in agriculture IoT still deal with the optimization of certain objectives only, i.e. energy consumption level, route cost, irrigation efficiency, or sensing accuracy. There have been very few comprehensive multiple-objective approaches that would take into account the correlations between accuracy of soil estimation, energy consumption level, communication costs, latency, and agricultural utility [33].

Fourthly, the dynamic nature of the environment is ignored in many fixed sensing techniques. Agriculture is subject to quick changes due to rain, irrigation, severe weather changes, and crop growth. Thus, it is necessary to implement sensing and communication protocols that will adapt their operation to the environment changes as well as the current information acquired [34].

Lastly, off-grid agricultural practices need to be developed with an idea of self-sufficiency and resilience because of the constant nature of terrestrial communication and energy supply. Therefore, a practical framework must be one that employs local sensing and transmission of satellite-based information and must work in conditions of intermittent connectivity and energy limitations [35].

This research solves the issue by introducing the framework for soil sensing and optimization, which is intended for off-grid agricultural areas. The framework the study proposes combines measurements locally with satellite observation, adopts adaptive data fusion, and employs cutting-edge processing to ensure multi-objective optimization. In contrast to the methods that optimize monitoring, communication, or agricultural decisions independently from each other, the framework considers all of those aspects simultaneously to enhance the quality of monitoring and minimize the use of resources.

3. Proposed Satellite-Coupled Soil Sensing Framework

The Adaptive Multi-Objective Honey Bee Optimization for Satellite-Coupled Soil Sensing (AMHBO-SCSS) system will be used for smart farming in remote and off-grid areas without access to electrical energy, cell phone signal, Wi-Fi connection or traditional cloud services. The innovative system combines local soil sensing, edges intelligence collected with the use of satellites, adaptable data fusion between satellite and ground systems, ability to solve many tasks at once, and agricultural decision-making support into a single system [1].

The main aim of AMHBO-SCSS is to provide timely and accurate information about the state of the soil and environment while paying less attention to the consumption of resources required for sensing, processing, transmitting, and making decisions. The framework differs from traditional monitoring methods

is that it assesses the specific conditions, technological capabilities, and resources available to change ecological monitoring frequency and information source contributions in real time.

The proposed architecture is explicitly organized into **five functional layers**:

1. **Layer 1 — Soil Sensing Layer**
2. **Layer 2 — Local Edge Processing Layer**
3. **Layer 3 — Satellite Observation Layer**
4. **Layer 4 — Adaptive Data-Fusion and Multi-Objective Optimization Layer**
5. **Layer 5 — Agricultural Decision-Support Layer**

The five layers' function together. Layer 1 collects localized soil data, Layer 2 checks and prepares the data, Layer 3 offers satellite information, Layer 4 integrates different pieces of information and does the multi-objective optimization, and Layer 5 transforms the recognized agricultural status into specific recommendations. Then the feedback from the decision-making layer is applied to improve the processes of sensing and optimizing the work.

3.1 System Entities and Notation

Let the agricultural field contain a set of N distributed sensing nodes:

$$S = \{s_1, s_2, \dots, s_N\}$$

where N represents the total number of deployed soil-sensing nodes. Each sensor periodically observes a vector of soil and environmental parameters:

$$X_{i(t)} = \left[M_{i(t)}, T_{i(t)}, H_{i(t)}, C_{i(t)}, P_{i(t)}\right]$$

Here, $M_{i(t)}$ is the soil moisture, $T_{i(t)}$ is the soil temperature, $H_{i(t)}$ is the indicator of quality known as humidity, then $C_{i(t)}$ is a piece of information regarding conductivity and, in addition to this, $P_{i(t)}$ is another measurement which is known as soil property measurement. The whole observation from the sensor s_i at time t can be expressed as:

$$D_{i(t)} = \left\{X_{i(t)}, E_{i(t)}, Q_{i(t)}\right\}$$

Here $\boldsymbol{E_{i(t)}}$ represents the sensor i 's remaining energy and $\boldsymbol{Q_{i(t)}}$ indicates an observation's quality or confidence. Under this framework, it is not necessary for each sensor to relay its entire observations at all

times. In this framework, sensing, transmitting, aggregating, and suppressing decisions are determined through processing, fusion, and optimization.

3.2 Layer 1 — Soil Sensing Layer

The Soil Sensing Layer is the physical sensing component of the AMHBO-SCSS system. The soil sensing layer has been designed be various low-energy sensors dispersed throughout the field and collect information about the current physical soil condition. The sensors may operate on battery or solar energy. This layer's main job is to distribute timely and geographically relevant information regarding environmental conditions while constantly being aware of the limited energy at the individual sensor level.

3.2.1 Sensor Node Configuration

The various nodes of sensor must have their own unique features like geographical position of sensors (location node), capability to perform sensing function (sensing node), the amount of energy that is available on its own (energy node), as well as the capability for communication (communication node). In mathematical terms, the node features can be expressed as follows:

$$\boldsymbol{s_i} = \{\boldsymbol{L_i}, \boldsymbol{B_i}, \boldsymbol{E_i}, \boldsymbol{R_i}\}$$

where $\boldsymbol{L_i}$ is a position of the sensor, $\boldsymbol{B_i}$ is its sensing ability, $\boldsymbol{E_i}$ is available amount of energy, and $\boldsymbol{R_i}$ is its capability for communication. The duration of time delay for the sensor $\boldsymbol{i}$ can be determined as follows:

$$\boldsymbol{\tau_{i(t)}} \in \left[\boldsymbol{\tau_i^{min}}, \boldsymbol{\tau_i^{max}}\right]$$

where$\boldsymbol{\tau_i^{min}}$ is the minimum time interval for the sensor to obtain information during sensing process, and $\boldsymbol{\tau_i^{max}}$ is the maximum time interval for the sensor. In case of shorter intervals for monitoring, the sensor can take measurements with higher frequency but needs more energy, while a longer interval makes consumption of power less but may result in failure in obtaining information on changes in the environment.

3.2.2 Adaptive Soil Sensing

AMHBO-SCSS does not use a standard sensing time for each operating condition. Rather, the sensing frequency changes with respect to environmental variability, information worth and residual energy. The adaptive sensing strategy can be defined as follows:

$$\tau_{i(t+1)} = f\left(\Delta X_{i(t)}, E_{i(t)}, U_{i(t)}\right)$$

where $\Delta X_{i(t)}$ denotes the level of environmental changes, $E_{i(t)}$ is the amount of energy remaining in sensor i and $U_{i(t)}$ refers to the expected value of the information obtained from measuring something. If the environment changes at a high rate, then the system will decrease the value of $\tau_{i(t)}$ and increase the sensing frequency. In contrast, when the environment remains unchanged for a period of time, the value of $\tau_{i(t)}$ will be increased in order to avoid any unnecessary sensing actions, which means that this adaptive process is the first resource management function of AMHBO-SCSS and offers information for the edge-processing and optimization layers.

3.3 Layer 2 — Local Edge Processing Layer

Situated in proximity to the field sensors, the Local Edge Processing Layer performs computational operations prior to data transmission to successive layers. One of the objectives of this layer is to limit communication that is not warranted and eliminate incorrect readings, local anomalies, and produce compact sensor measurements [21]. The significance of local processing is especially important in terms of off-grid agriculture; sending every piece of raw data would consume more energy than processing the data locally.

3.3.1 Sensor Data Preprocessing

The edge node is responsible for validating gathered sensor information, filtering out noise, identifying missing values, extracting features, identifying anomalies, and conducting local quality checks. Let $D_{i(t)}$ denote the raw measurement provided by the sensor i. Preprocessing can be defined as follows:

$$\widehat{D}_{i(t)} = F_{p(D_{i(t)})}$$

where $F_{p(\cdot)}$ is the function that performs preprocessing and $\widehat{D}_{i(t)}$ is the validated value. The measurements that do not meet predefined quality requirements may be either discarded, labeled as uncertain, or kept with a reduced confidence score, thus preventing unreliable measurements from negatively affecting the satellite–ground fusion procedure.

3.3.2 Edge-Based Anomaly Detection

The edge layer checks if some observations are significantly different from the expected local conditions. The anomaly score is expressed in the following way:

$$A_{i(t)} = \left| X_{i(t)} - \hat{X}_{i(t)} \right|$$

where $\hat{X}_{i(t)}$ is the expected state of the environment based on historical observations, or neighbouring observations, or utilizing the proper local prediction method. If A_i(t) exceeds the threshold level, the measurement can be marked as anomalous or too informative. This can lead to additional sensing, some changes in data transmission priority, or additional verification. This makes it possible for the edge layer to differentiate between common observations and important environmental changes in advance.

3.3.3 Edge-Based Local Aggregation

Edge node aggregates redundant information from a number of observations prior to sending the information to Layer 4. Since local aggregation reduces the total amount of data sent, it saves communication energy. The aggregated observation is shown by the following equation:

$$D_{edge(t)} = F_a(\hat{D}_{1(t)}, \hat{D}_{2(t)}, \ldots, \hat{D}_{m(t)})$$

where $F_a(\cdot)$ denotes the local aggregation function and m is the number of observations being processed by the edge node. This means that Layer 2 performs the functions needed for local intelligence, preprocessing, anomaly detection, and aggregation of heterogeneous data prior to bringing them into the adaptive processing and optimization.

3.4 Layer 3 — Satellite Observation Layer

The satellite monitoring layer offers widespread information about the monitored agricultural sector. Although ground sensors yield localized data, satellite observations allow for much broader contextualization and enable us to obtain information about those regions that are not adequately represented by land sensors. The satellite monitoring layer complements, rather than substitutes, Layer 1.

3.4.1 Satellite Observation Representation

According to the type of product generated from satellites, features that have been captured can include multispectral data, indices of vegetation, land-surface temperatures, surface reflectance, precipitation data and others. Let the satellite observation corresponding to l_i and time t be expressed as:

$$\boldsymbol{Z_{i(t)} = [V_{i(t)}, R_{i(t)}, L_{i(t)}, W_{i(t)}, \ldots]}$$

where V_i(t) denotes information on vegetation, $\boldsymbol{R_{i(t)}}$ denotes spectral or reflectance features, $\boldsymbol{L_{i(t)}}$ describes land-surface characteristics, and $\boldsymbol{W_{i(t)}}$ defines the weather or water-related information acquired from satellite observations.

3.4.2 Satellite Observation Confidence

Cloud contamination, observation age, spatial resolution, atmospheric conditions, and incomplete observations are examples of sources of uncertainty in satellite observations. For this reason, it is necessary to assign each satellite observation a value of confidence, that is:

$$\boldsymbol{q_i^{sat(t)} \in [0, 1]}$$

The high value of $\boldsymbol{q_i^{sat(t)}}$ implies that the corresponding satellite observation can be used with confidence. Likewise, the processed ground observation is also assigned a confidence value $\boldsymbol{q_i^{g(t)}}$. These values of confidence are then used by Layer 4 to compute the contributions from satellite and ground observations.

3.4.3 Satellite–Sensor Spatial and Temporal Alignment

Satellite observations are correlated with ground measurements depending on geographic location and observation time. This correlation makes it possible for satellite data to provide surrounding contextual data to the sensor locations as well as additional information where there is no ground data. The correlation function can be written generally as follows:

$$\boldsymbol{Z_i^{*(t)} = F_{align}(Z(l_i, t_s), t)}$$

where $\boldsymbol{Z(l_i, t_s)}$ is the satellite observation corresponding to location $\boldsymbol{l_i}$ and satellite acquisition time $\boldsymbol{t_s}$, while $\boldsymbol{F_{align(\cdot)}}$ is the correlation function. Therefore, layer 3 provides the necessary context required by the adaptive fusion and optimization layer.

3.5 Layer 4 — Adaptive Data-Fusion and Multi-Objective Optimization Layer

The Adaptive Data-Fusion and Multi-Objective Optimization Layer is the primary intelligence layer of AMHBO-SCSS. In this layer, data from ground observations (Layer 2) as well as satellite observations (Layer 3) are combined to assess the agricultural situation, identify the context sensing needs, as well as

estimate energy and communication expenditures and conduct multi-objective optimization. Thus, all important algorithmic work of the framework will be performed at Layer 4.

3.5.1 Adaptive Satellite–Ground Data Fusion

Let $\boldsymbol{G_{i(t)}}$ denote the processed ground information acquired via Layer 2, while $\boldsymbol{Z_{i(t)}}$ indicates the related satellite data acquired via Layer 3. The combined environmental assessment is given as:

$$\boldsymbol{Y_i(t) = F_f\left(G_{i(t)}, Z_{i(t)}, q_i^{g(t)}, q_i^{sat(t)}\right)}$$

where $\boldsymbol{F_{f(\cdot)}}$ denotes the fusion function, $\boldsymbol{q_i^{g(t)}}$ refers to the ground-sensing certainty, and $\boldsymbol{q_i^{sat(t)}}$ refers to the satellite-sensing certainty. The weighted fusion formulation is presented by:

$$\boldsymbol{Y_i(t) = w_i^{g(t)G}(t) + w_i^{sat}(t) Z_i(t)}$$

such that:

$$\boldsymbol{w_i^{g(t)} + w_i^{sat(t)} = 1} \text{ and:}$$

$$\boldsymbol{w_i^{g(t)} \geq 0, w_i^{sat(t)} \geq 0}$$

In this case, the weights are dynamically controlled based on the data quality, temporal relevance, spatial consistency, and environmental factors. In case there exist reliable data from the local sources, the ground sensing influence can be maximized. If ground measurements are unreliable or not available, the contribution of satellite input can be maximized. This adaptive fusion mechanism is regarded as a main redundancy and stability mechanism of the proposed method.

3.5.2 Agricultural-State Estimation

The integrated observations were employed in determining the current agricultural state. Let the agricultural state be defined as follows:

$$\boldsymbol{\theta(t) = [M(t), T(t), V(t), W(t), S(t)]},$$

where M(t) is defined as the soil moisture, T(t) is defined as the soil temperature, V(t) is defined as the vegetation status, W(t) is defined as the water status, and S(t) is defined as the overall agricultural or soil condition [6]. The estimated agricultural state is defined as follows:

$$\hat{\boldsymbol{\theta}}(\boldsymbol{t}) = \boldsymbol{Fe}\big(\boldsymbol{Y}(\boldsymbol{t})\big),$$

where $\boldsymbol{Fe}(\cdot)$ is defined as the estimator and $\boldsymbol{Y}(\boldsymbol{t})$ is defined as the integrated observations set. The estimation model can be applied from any conceivable statistical, machine learning, or lightweight forecasting model in accordance to the computational abilities available at the optimization layer or edge.

3.5.3 Context-Aware Sensing and Transmission

The proposed system uses a method known as context score to assess the validity of the use of sensing or communication. The context score is formulated as such:

$$\boldsymbol{C_{i(t)} = \alpha A_{i(t)} + \beta U_{i(t)} + \gamma R_{i(t)} + \delta \bar{E}_{i(t)}}$$

where A_i(t) is the environmental fluctuation, U_i(t) stands for information significance, R_i(t) demonstrates the risk of agriculture-related activity, $\bar{E}$_i(t) expresses normalized residual energy condition (energy that has been wasted) and α, β, γ and δ serve as weighting coefficients. The coefficients involved must meet the next requirement:

$$\boldsymbol{\alpha + \beta + \gamma + \delta = 1}$$

If the context score is high enough, it states that the costs of sensing and communication might be justified with the help of an important agricultural value. The use of transmission is described by the next equation:

$$\boldsymbol{T_{i(t)} = \big(1, \& C_{i(t)} \geq \theta_T @ 0, \& C_{i(t)} < \theta_T\big)}$$

where $\boldsymbol{\theta_T}$ shows the threshold for the start of transmission. This system allows the measurements of lower value not to use communication means but to keep the ability to notify essential events taking place in the environment.

3.5.4 Energy Consumption Model

Energy usage is specifically included in AMHBO-SCSS because sensing nodes are created to work in an off-grid environment. The total energy usage of the sensor i can be defined as:

$$E_i^{total}(t) = E_i^{sense}(t) + E_i^{proc}(t) + E_i^{tx}(t) + E_i^{rx}(t),$$

where $E_i^{sense}(t), E_i^{proc}(t), E_i^{tx}(t), and\ E_i^{rx}(t)$ show energy usage used for sensing, processing, transmitting and receiving, respectively. The transmission energy is estimated as:

$E_i^{tx}(t) = k_i(t)E_{elec} + k_i(t)\varepsilon_{amp}d_{i(t)}^2$, in which $k_i(t)$ is the size of transmitted data, E_{elec} is the energy consumption in electronics, ε_{amp} is the amplifier factor, and $d_i(t)$ is the distance of communication. The residual energy can be expressed as:

$E_i(t+1) = E_i(t) - E_i^{total}(t) + E_i^{harv}(t)$, where $E_i^{harv}(t)$ is the harnessed energy, such as solar energy. This formulation allows the optimization layer to take into account how sensing and communication decisions influence the operational lifespan of the sensor networks.

3.5.5 Communication Model

Due to the fact that terrestrial communication may not always be effective in off-grid conditions, AMHBO-SCSS has the assumption that continuous communication is not guaranteed [5]. Let us denote p_i(t) as the likelihood that sensor i has an available communication link:

$$0 \le p_i(t) \le 1$$

When communication is absent, the readings can be saved at the sensor or edge node and sent after the recovery of the communication route [21]. The formula for communication cost indicates that:

$C_{comm}(t) = \sum_{i=1}^{N} k_i(t)d_i(t)$,

where $k_i(t)$ is a volume of transmitted data, and $d_i(t)$ affects the communication distance or coefficient. This communication model enables the optimization level to decrease unnecessary communication thus enabling to have the most relevant agri-information.

3.5.6 Multi-Objective AMHBO Optimization

The AMHBO component determines the sensing, transmission, fusion, and resource-allocation decisions [5]. The optimization vector is represented as:

$$x(t) = [\tau_1(t), \dots, \tau_N(t), T_1(t), \dots, T_N(t), w_1^g(t), \dots, w_N^g(t)]$$

The optimization vector therefore contains the sensing intervals, transmission decisions, and adaptive ground-sensing weights that determine the operating configuration of the system.

Estimation Error Objective: The first objective minimizes agricultural-state estimation error:

$$f_1(x) = \frac{1}{N}\sum_{i=1}^{N} \left|Y_i(t) - Y_i^{true}(t)\right|^2$$

where $Y_i(t)$ represents the estimated fused state and $Y_i^{true}(t)$ represents the corresponding reference state. A lower value of $f_1(x)$ indicates better estimation performance.

Energy Objective: The second objective minimizes total energy expenditure:

$$f_2(x) = \sum_{i=1}^{N} E_i^{total}(t)$$

A lower value of f_2(x) indicates greater energy efficiency.

Communication Objective: The third objective minimizes communication overhead:

$$f_3(x) = \sum_{i=1}^{N} k_i(t)$$

where $k_i(t)$ represents the amount of information transmitted by sensor i. A lower value of $f_3(x)$ indicates lower communication overhead.

Latency Objective: The fourth objective minimizes decision latency:

$$f_4(x) = \frac{1}{N}\sum_{i=1}^{N} L_i(t)$$

where $L_i(t)$ represents the time required to acquire, process, transmit, and utilize the information associated with sensor i. A lower value of $f_4(x)$ indicates faster decision support.

Overall Multi-Objective Formulation: The complete optimization problem is formulated as:

$$min_x \ F(x) = [f_1(x), f_2(x), f_3(x), f_4(x)]$$

The optimization is subject to the following constraints.

Energy constraint: $E_i(t) \geq E_i^{min}$

Sensing-interval constraint: $\tau_i^{min} \leq \tau_i(t) \leq \tau_i^{mx}$

Ground-fusion-weight constraint: $0 \leq w_i^g(t) \leq 1$

Satellite-fusion-weight constraint: $0 \leq w_i^{sat}(t) \leq 1$

Fusion-weight consistency constraint: $w_i^g(t) + w_i^{sat}(t) = 1$

Binary transmission constraint: $T_i(t) \in \{0,1\}$

The conditions imposed guarantee that the optimized arrangement is applicable to agricultural sensing nodes with limited resources. In the AMHBO process, the various candidate solutions are examined in light of four objectives and attempted solutions that showed promise were searched. The obtained non-dominated candidate solutions eventually create the adaptive operating configurations for the agricultural decision-making level to follow up.

3.6 Layer 5 — Agricultural Decision-Support Layer

The layer of decision-making for agriculture is the last layer of the AMHBO-SCSS system. This layer converts the optimized information about the agricultural situation which has been generated by Layer 4 into practical recommendations that can be used by farmers. The main aim of this layer is to convert technical results of the sensing and optimization processes into information that would help farmers and agricultural managers.

3.6.1 Agricultural-State Interpretation

The estimated agricultural state is represented by:

$$\hat{\theta}(t)$$

This state is evaluated against predefined agricultural thresholds, historical conditions, field requirements, and contextual information. The decision-support layer can identify conditions such as: insufficient soil moisture [6]; excessive soil moisture; abnormal soil conditions; high environmental variability; areas requiring additional sensing; regions requiring irrigation priority; and areas requiring further agricultural inspection.

3.6.2 Irrigation and Intervention Recommendations

The system would then give recommendations with regard to the irrigation priorities, additional sensing items, or field-level interventions depending on its assessment of the agricultural condition and relevant context information. The irrigation-priority indicator can be simply expressed as follows.

$$I_i(t) = f\left(M_i^{target} - M_i(t), R_i(t), V_i(t)\right)$$

where M_i^{target} represents the target soil-moisture condition, $M_i(t)$ represents estimated soil moisture, $R_i(t)$ represents agricultural risk, and $V_i(t)$ represents environmental or vegetation conditions. An amplified value of I_i(t) means an increased irrigation priority. Hence, the decision-support layer is designed to convert the optimized environmental set of information into feasible agricultural practices instead of directly controlling all agricultural operations.

3.6.3 Feedback to the Lower Layers

The Decision Support Layer also gives inputs to the Sensing and Optimization layers. For instance, as the framework detects the agriculture region that is classified as high risk, it can increase the priority of sensing, shorten the permissible sensing period, or prioritize the transmissions of the observations from that region. The feedback process can be represented conceptually as:

$$\hat{\theta}(t) \rightarrow D(t) \rightarrow C_i(t+1), \tau_i(t+1), T_i(t+1)$$

where D(t) represents the agricultural decision generated at time t. This feedback creates a closed-loop architecture in which agricultural decisions influence subsequent sensing and optimization decisions.

3.7 Overall Operational Workflow

The five-layer architecture operates through a continuous closed-loop workflow.

Step 1 — Local sensing: Layer 1 collects soil and environmental observations from distributed sensor nodes.

Step 2 — Local preprocessing: Layer 2 validates, filters, aggregates, and evaluates the quality of the sensor observations.

Step 3 — Satellite observation: Layer 3 acquires satellite observations corresponding to the monitored agricultural region.

Step 4 — Spatial and temporal alignment: Satellite observations are aligned with the locations and observation periods of the ground sensors.

Step 5 — Adaptive fusion: Layer 4 combines processed ground measurements and satellite observations using dynamically determined confidence-aware weights.

Step 6 — Agricultural-state estimation: The fused observations are used to estimate the current soil and agricultural state.

Step 7 — Context evaluation: Environmental variability, agricultural risk, information value, and residual energy are evaluated to determine whether additional sensing or transmission is justified.

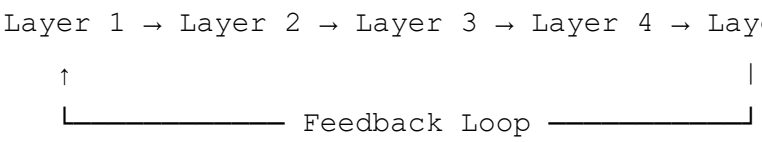
Step 8 — AMHBO optimization: The multi-objective optimization process searches for an appropriate combination of sensing intervals, transmission decisions, fusion weights, and resource-allocation parameters.

Step 9 — Adaptive sensing and communication: The optimized decisions are transmitted to the appropriate sensor and edge nodes. High-value observations are retained and transmitted, whereas low-value redundant measurements may be suppressed or aggregated.

Step 10 — Agricultural decision support: Layer 5 interprets the estimated agricultural state and produces irrigation, monitoring, or intervention recommendations.

Step 11 — Feedback: The resulting agricultural decisions and newly observed environmental conditions provide feedback to Layers 1 and 4, enabling the next sensing and optimization cycle.

The complete process can therefore be summarized as:



The architecture operates continuously so that changes in soil conditions, satellite-data quality, sensor reliability, communication availability, and energy availability can influence subsequent sensing and optimization decisions.

3.8 Summary of the Five-Layer Architecture

The proposed AMHBO-SCSS architecture consists of five clearly separated functional layers (Table. 1), each having a specific role in the overall smart-agriculture system [5].

Table. 1 Layers and its responsibilities

Layer	Name	Responsibilities	Main Output
Layer 1	Soil Sensing Layer	Soil/environmental measurement, adaptive sensing, energy monitoring	Raw/local observations
Layer 2	Local Edge Processing Layer	Validation, filtering, anomaly detection, feature extraction, local aggregation	Validated and processed observations
Layer 3	Satellite Observation Layer	Satellite acquisition, spatial coverage, contextual information, confidence estimation	Satellite observations
Layer 4	Adaptive Data-Fusion and Multi-Objective Optimization Layer	Satellite–ground fusion, state estimation, context evaluation, energy modeling, communication modeling, AMHBO optimization	Optimized sensing configuration and agricultural state
Layer 5	Agricultural Decision-Support Layer	Agricultural-state interpretation, irrigation prioritization, intervention recommendations, feedback	Actionable agricultural decisions

The functional relationship among the five layers can be expressed as:

$$L_1 \rightarrow L_2 \rightarrow L_3 \rightarrow L_4 \rightarrow L_5$$

with feedback from the decision-support layer to the sensing and optimization processes:

$$L_5 \rightarrow \{L_1, L_4\}$$

As a result, the architecture outlined above establishes a closed-loop relationship between physical sensing, local intelligence, satellite observations, adaptive fusion, multiple objective optimization and agricultural decision-making support. The design of these five layers is such that all the functions carried out by the

mentioned layers, including sensing, processing using satellite technology, optimization and decision-making, can be clearly distinguished from one another but still work as one unified system [2]. The architecture also gives a perfect ground for the experimental testing explained in the fourth section of the paper. Specifically, in the context of estimation experiments, the sensing and fusion processes were evaluated, during energy and communication experiments resource management mechanisms were tested, convergence and pareto analyses were performed to check AMHBO optimization system, robustness and scalability tests provided information about system resilience and adaptive sensing and fusion weight experiments demonstrated dynamics of layers 1 and 4.

4. Adaptive Multi-Objective Honey Bee Optimization

Layer 4 of the AMHBO-SCSS architecture includes an optimization problem that contains various conflicting objectives. Increasing the sensing frequency leads to an enhanced soil condition identification on the one hand, but contributing to a bigger energy usage and additional communication overhead on the other hand. Likewise, in order to attain less information loss, one may set larger number of observations to be sent, however, this comes with the price of increased battery draining and reduced lifespan of remotely situated sensor nodes. Satellite observations allow enlarging the covered area, but their application adds the need for further processing of the obtained data.

Therefore, a conventional single-objective optimization method cannot be used on the proposed problem of agricultural monitoring, since the improvement of some performance indicator can lead to the degradation of some other indicator. Therefore, AMHBO has been applied to find the trade-off solution to the problem. AMHBO is a method that mimics the behavior of honey bees. In the methodology being proposed, the basic parameters of the method include time intervals, data transmission decisions, weights of the processing stages and other parameters regarding data processing. In the method, some classes of bees are used to explore the discovered regions; onlookers search for the best solutions and scouts are invited to provide new solutions in case no new states can be generated. The uniqueness of AMHBO is that it includes the adaptive search method. In particular, the ratio of exploration and exploitation is being changed depending on the current development of the optimization process and the state of the environment.

4.1 Optimization Representation

Each candidate solution represents a complete operational configuration of the agricultural sensing system. For the j-th candidate solution, the optimization vector is defined as:

$$x_j = [\tau_1, \tau_2, \dots, \tau_N, T_1, T_2, \dots, T_N, w_1^g, w_2^g, \dots, w_N^g]$$

where τ_i represents the sensing interval of sensor i, T_i represents its transmission decision, and w_i^g represents the contribution of ground sensing in the satellite–ground fusion process. The corresponding satellite contribution is obtained from the fusion constraint:

$$w_i^{sat} = 1 - w_i^g$$

Therefore:

$$0 \le w_i^g \le 1$$

and

$$0 \le w_i^{sat} \le 1$$

Each candidate solution consequently determines: how frequently individual sensors should acquire measurements; which observations should be transmitted; how ground and satellite observations should be combined; and [2] how the available sensing and communication resources should be utilized. The optimization vector can therefore be interpreted as a complete adaptive sensing and fusion policy for the agricultural field.

4.2 Multi-Objective Fitness Model

The four objectives defined in Section III are retained without modification:1) environmental estimation error; 2) energy consumption; 3) communication overhead; and 4) decision latency. Because these objectives have different units and numerical ranges, their values are normalized before they are used for candidate comparison.

4.2.1 Estimation-Error Objective

The first objective minimizes the difference between the estimated and reference agricultural states:

$$f_1(x) = \frac{1}{N} \sum_{i=1}^{N} \left| Y_i(t) - Y_i^{true}(t) \right|^2$$

where $Y_i(t)$ represents the estimated fused state and $Y_i^{true}(t)$ represents the corresponding reference state. A lower value of f_1 indicates better estimation performance.

4.2.2 Energy-Consumption Objective

The second objective minimizes the total energy consumed by the sensing network:

$$f_2(x) = \sum_{i=1}^{N} E_i^{total}(t)$$

where $E_i^{total}(t)$ represents the total energy consumed by sensor i. A lower value of f_2 indicates greater energy efficiency.

4.2.3 Communication-Overhead Objective

The third objective minimizes the amount of information transmitted through the communication infrastructure:

$$f_3(x) = \sum_{i=1}^{N} k_i(t)$$

where $k_i(t)$ represents the transmitted data volume of sensor i. A lower value of f_3 indicates reduced communication overhead.

4.2.4 Latency Objective

The fourth objective minimizes decision latency:

$$f_4(x) = \frac{1}{N}\sum_{i=1}^{N} L_i(t)$$

where $L_i(t)$ represents the time required to acquire, process, transmit, and utilize the information associated with sensor i. A lower value of f_4 indicates faster agricultural decision support.

4.3 Objective Normalization and Contextual Fitness

Since the four objectives have different scales, each objective is normalized before candidate solutions are compared. The normalized estimation error is:

$$\bar{f}_1 = \frac{f_1 - f_1^{min}}{f_1^{max} - f_1^{min} + \varepsilon}$$

The normalized energy consumption is:

$$\bar{f}_2 = \frac{f_2 - f_2^{min}}{f_2^{max} - f_2^{min} + \varepsilon}$$

The normalized communication overhead is:

$$\bar{f}_3 = \frac{f_3 - f_3^{min}}{f_3^{max} - f_3^{min} + \varepsilon}$$

The normalized latency is:

$$\bar{f}_4 = \frac{f_4 - f_4^{min}}{f_4^{max} - f_4^{min} + \varepsilon}$$

where ε is a small positive constant introduced to prevent division by zero. A contextual scalar fitness value is then calculated as:

$$F_j = \lambda_1 \bar{f}_1 + \lambda_2 \bar{f}_2 + \lambda_3 \bar{f}_3 + \lambda_4 \bar{f}_4$$

subject to:

$$\lambda_1 + \lambda_2 + \lambda_3 + \lambda_4 = 1$$

In this case, $\lambda_1, \lambda_2, \lambda_3, and\ \lambda_4$ refer to the importance associated with the accuracy of estimation, energy usages, overhead communication, and delay. The contextual weights are updated as per the agricultural field conditions. Like in case the energy consumption is too low, the importance accorded to the energy consumption will be given more weight for optimization. Similarly, if there are more variations in environmental conditions, more importance can be given to the accuracy of estimation and delay. This mechanism allows the AMHBO to optimize the system as per the present operating situation instead of opting for the same objective preference throughout the entire simulation.

4.4 Pareto-Dominance and Archive Management

Although the contextual fitness value is a good means to order the alternative solutions, the optimization involved in this method still requires the calculations for multiple objectives. For this reason, the research uses a Pareto archive to save the non-dominated alternatives. The solution x_a dominates the solution x_b if:

$$f_k(x_a) \leq f_k(x_b)$$

for every objective k, and:

$$\exists k: f_k(x_a) < f_k(x_b)$$

Thus, x_a is no worse than x_b in all objectives and strictly better in at least one objective. The set of non-dominated solutions is represented as:

$$P = \{x_j: x_j is\ non - dominated\}$$

The update of the Pareto archive takes place at the end of each major searching phase. The solutions which are forced out will not be included while new non-dominated points will be stored. This is of crucial importance due to the fact that the agricultural sensing problem does not necessarily imply the existence of a single optimal solution. A configuration which minimizes energy may work with bigger errors in estimation and another configuration may give the better accuracy on estimation but require more resources for its operation.

4.5 Employed-Bee Phase

The employed-bee phase performs local exploration around currently available candidate solutions. For candidate solution j and optimization dimension d, a neighboring solution can be generated as:

$$v_j d = x_j d + \varphi_j d(x_j d - x_k d)$$

where k represents a randomly selected candidate different from j and $\varphi_j d$ is a random perturbation coefficient. The perturbation coefficient is generated within the range:

$$-1 \leq \varphi_j d \leq 1$$

The candidate obtained is subjected to the constraint-repair mechanism discussed in J. The new solution is assessed with reference to the four objectives. If the new solution improves on the contextual fitness of the previous solution or provides a new non-dominated configuration, it either replaces or augments the relevant solution in the population. Thus, the employed bee phase focuses on local exploitation around promising agricultural sensing solutions.

4.6 Onlooker-Bee Phase

After the employed-bee phase, onlooker bees select promising candidate solutions according to their quality. For candidate solution j, a quality score can be defined as:

$$Q_j = \frac{1}{1 + F_j}$$

where F_j represents the contextual fitness of candidate j. A lower fitness therefore produces a higher quality score. The corresponding selection probability is:

$$p_j = \frac{Q_j}{\sum_{r=1}^{B} Q_r}$$

The variable B indicates the quantity of potential solutions. More successful candidate solutions are thus more likely to be chosen by the onlooker bees. Upon selection, a further exploration of the area surrounding these candidate solutions is carried out. The candidate solutions reached as a result of that are then assessed, and any solution is included in the Pareto archive if leads to non-dominated objective function values. Thus, the onlooker phase helps to improve the efficiency of exploitation of promising regions in optimization space.

4.7 Scout-Bee Phase

When it comes to population-based optimization techniques, premature convergence can be a considerable risk. If a contender does not yield any improvement for a certain number of consecutive runs, the contender can be regarded as stagnant. The number of iterations where no improvement was achieved should be designated as c_j. An abandoned candidate will be identified when:

$$c_j > L_{max}$$

where L_{mox} represents the abandonment threshold. When a solution is abandoned, a scout bee generates a new candidate solution using:

$$x_{jd}^{new} = x_d^{min} + r\left(x_d^{max} - x_d^{min}\right)$$

where:

$$r \in [0,1]$$

is a randomly generated number. The new candidate solution is then repaired and evaluated, and it can be added to the population if it is applicable. The scout mechanism facilitates the algorithm exploring the search space more effectively and decreases the probability of the AMHBO algorithm getting stuck in a local optimum.

4.8 Adaptive Exploration–Exploitation Mechanism

A major feature distinguishing AMHBO from conventional HBA is its adaptive control of exploration and exploitation. Let the optimization progress ratio be:

$$\rho(t) = \frac{t}{T_{mox}}$$

where t represents the current iteration and T_{max} represents the maximum number of optimization iterations. The basic exploration coefficient is defined as:

$$\eta(t) = \eta_{max} - (\eta_{max} - \eta_{min})\rho(t)$$

where $\eta_{max}\ and\ \eta_{min}$ are the respective maximum and minimum coefficients of exploration. In the initial positions of the optimization process, η(t) is a big number that indicates the need for a wide exploration and analysis of the situation, but as the optimization process advances, η(t) reduces, and the algorithm will become more and more focused on exploiting good solutions. Nevertheless, the optimization progress is not enough to be applicable to the agricultural case described above because there may be significant environmental changes occurring. The environmental change can be represented by the following equation:

$$\Delta V(t) = \left|V_{N(t)} - V_{N(t-1)}\right|$$

where $V_{N(t)}$ represents the normalized environmental variability at time t. The environment-adjusted exploration coefficient is then:

$$\eta * (t) = \eta(t) + \kappa \Delta V(t)$$

where the environmental variability exponent acts as the parameter controlling the level of the effect of environmental variabilities. This formulation allows for transient acceleration of exploration under changing environmental conditions. This process is very relevant to agricultural environments as the soil moisture, temperature, plant cover, and water supply may change very quickly after rains, treatment with irrigation, drought, etc.

4.9 Constraint Handling and Solution Repair

The solutions produced by the workers, onlookers, or scouts may be incompatible with the requirements explained in the previous sections, meaning that there is a need for repairing after every generation of solutions.

4.9.1 Repair for Continuous Variables

For a continuous optimization variable, the repaired value is defined as:

$$x_d \leftarrow min\left(x_d^{max}, max\left(x_d^{min}, x_d\right)\right)$$

This operation ensures that the variable remains within its permitted range.

4.9.2 Binary Transmission Repair

For transmission variables, the continuous representation generated during optimization is converted into a binary transmission decision:

$$T_i = \begin{cases} 1, x_i \geq 0.5 \\ 0, x_i < 0.5 \end{cases}$$

Thus, T_i can only take the values 0 or 1.

4.9.3 Fusion-Weight Repair

The ground fusion weight is normalized as:

$$w_i^g = \frac{max\left(0, w_i^g\right)}{max\left(0, w_i^g\right) + max\left(0, w_i^{sat}\right)}$$

and the satellite weight is then obtained from:

$$w_i^{sat} = 1 - w_i^g$$

This guarantees:

$$w_i^g + w_i^{sat} = 1$$

and ensures that both weights remain within their permitted range.

4.9.4 Energy Constraint

The optimization process rejects or repairs configurations that cause the residual energy of a sensor to fall below its minimum operational threshold:

$$E_i(t) \geq E_i^{min}$$

This prevents AMHBO from achieving an apparently favorable objective value by selecting a configuration that would cause sensor-node failure.

4.10 Adaptive Sensing Policy

The AMHBO optimization mechanism establishes the sensing interval of each sensor node based on the flexibility of the environment, farming requirement, and energy resource. The adaptive sensing priority score is expressed as follows:

$$R_i(t) = \alpha V_i(t) + \beta U_i(t) + \gamma(1 - \bar{E}_i(t))$$

where $V_i(t)$ represents environmental variability, $U_i(t)$ represents agricultural urgency, $\bar{E}_i(t)$ represents normalized residual energy, and α, β, and γ represent the corresponding importance coefficients. The coefficients satisfy:

$$\alpha + \beta + \gamma = 1$$

A higher R_i(t) indicates that the location requires greater monitoring attention. The sensing interval can then be mapped to the allowable sensing range as:

$$\tau_i(t) = \tau_i^{max} - R_i(t)\left(\tau_i^{max} - \tau_i^{min}\right)$$

This formulation is important because higher sensing priority produces a shorter sensing interval, thereby increasing measurement frequency.

4.11 Adaptive Communication Scheduling

The optimization procedure employed in this process helps decide if data should be sent right away, combined with other previously obtained data, or kept aside for later use. The communication priority is determined as follows:

$$P_i^{comm}(t) = \mu_1 A_i(t) + \mu_2\, U_i(t) + \mu_3 Q_i(t) + \mu_4 E_i^{-1}(t)$$

where $A_i(t)$ represents anomaly magnitude, $U_i(t)$ represents agricultural urgency, $Q_i(t)$ represents measurement quality, and $E_i^{-1}(t)$ represents the energy-related communication constraint. The coefficients satisfy:

$$\mu_1 + \mu_2 + \mu_3 + \mu_4 = 1$$

When the communication priority satisfies:

$$P_i^{comm}(t) \geq \theta_C$$

The measurement will be sent out whenever there is any chance to communicate. Otherwise, it will be either buffered, locally grouped, or held back temporarily. This system is in line with the goals of off-grid communication described in section 3 and ensures minimum communication while monitoring important events.

4.12 Context-Aware Objective-Weight Adaptation

AMHBO uses the objective weights that are adjusted dynamically as per the operating condition of the agriculture sensing network. Let's denote normalized context indicators as: environmental variability, residual network energy, communication availability, and urgency of agriculture. The objective weight vector is defined as:

$$\Lambda(t) = [\lambda_1(t), \lambda_2(t), \lambda_3(t), \lambda_4(t)]$$

subject to:

$$\lambda_1(t) + \lambda_2(t) + \lambda_3(t) + \lambda_4(t) = 1$$

While in stable environmental conditions, it can place higher weight on energy conservation and communication reduction, in rapidly changing environmental conditions, it can place higher weight on estimation accuracy and latency. It is this kind of adaptive weighting process that sets AMHBO apart from a regular fixed-weight multi-objective optimizer.

4.13 Adaptive Multi-Objective Honey Bee Optimization for AMHBO-SCSS and its Computational Complexity

Let B indicate the count of candidate solutions, D the dimension of the optimization vector, and I the number of iterations. The cost of candidate-solution generation and objective evaluation has the following approximation:

$$O(I \times B \times D)$$

Here, D grows with the increase of the number of sensor nodes, due to the presence of sensors, transmission, and fusion-related variables in each candidate solution. The process of Pareto-based comparison and archive management generates further computational cost which depends on the number of candidate solutions and objectives. Nevertheless, the optimization is mainly performed at the edge or gateway rather than on the heavily constrained sensor nodes which only perform sensing and communicate the data.

Algorithm 1: Adaptive Multi-Objective Honey Bee Optimization for AMHBO-SCSS

Input:
Processed ground observations, satellite observations, node-energy states, environmental context, optimization constraints, population size B, maximum iterations I, abandonment limit L_max.

Output:
Optimized sensing intervals, transmission decisions, satellite–ground fusion weights, Pareto archive, and selected operational configuration.

Input processed ground observations $G(t)$
Input satellite observations $Z(t)$
Input node-energy states $E(t)$
Input environmental context $V(t), U(t), R(t)$
Initialize B candidate solutions $x_j, j = 1,2, \dots, B$
Repair all candidate solutions according to system constraints

Evaluate $f_1(x_j), f_2(x_j), f_3(x_j), and\ f_4(x_j)$
Normalize all objective values
Initialize contextual weights $\lambda_1, \lambda_2, \lambda_3, and\ \lambda_4$
Calculate contextual fitness F_j for every candidate
Identify non-dominated candidate solutions
Initialize Pareto archive P with non-dominated solutions
Initialize stagnation counter $c_j = 0$ for every candidate

for t=1 to I do

    Calculate environmental variability $\Delta V(t)$
    Calculate exploration coefficient $\eta(t)$
    Adjust exploration coefficient using $\Delta V(t)$

    /* Employed-Bee Phase */
    for each candidate solution x_j do
        Select a candidate x_k, k≠j
        Generate neighboring solution v_j
        Repair v_j using the constraint-repair mechanism
        Evaluate the four objectives of v_j
        Normalize objective values of v_j
        Calculate contextual fitness $F(v_j)$

        if v_j improves x_j then
            Replace x_j with v_j
            Set $c_j = 0$
        else
            Set $c_j = c_j + 1$
        end if
    end for
    Update Pareto archive P
    /* Onlooker-Bee Phase */
    Calculate quality score $Q_j = \frac{1}{1+F_j}$

Calculate selection probability p_j
Select promising candidate solutions according to p_j

for each selected candidate x_j do
    Perform neighborhood search around x_j
    Generate new candidate v_j
    Repair v_j
    Evaluate the four objectives
    Normalize the objective values
    Calculate contextual fitness
    Update x_j when improvement occurs
    Update stagnation counter c_j
end for

Update Pareto archive P

/* Scout-Bee Phase */
for each candidate x_j do
    if $c_j > L_{max}$ then
        Generate a new random solution using scout-bee search
        Repair the new solution
        Evaluate the four objectives
        Replace the abandoned candidate
        Set $c_j = 0$
    end if
end for

Update Pareto archive P

/* Adaptive Control */
Update contextual objective weights
Update sensing-priority values $R_i(t)$
Update sensing intervals $\tau_i(t)$

```
    Update communication priorities P_i^comm(t)
    Update transmission decisions T_i(t)
    Update satellite–ground fusion weights

    /* Energy and Feasibility Check */
    Update node energy states
    Repair or reject infeasible solutions
    Update Pareto archive P

end for

Select final Pareto-optimal configuration x*
Apply the configuration to the sensing network
Continue monitoring using new ground and satellite observations
[2]
Re-run AMHBO when environmental or resource conditions change
Return x* and Pareto archive P
```

While this algorithm makes use of the same process as the original method—population initialization, evaluation of objectives, Pareto archiving, employed-bee search, onlooker-bee exploration, scout-bee exploration, adaptive exploration, adaptive sensing, and final Pareto-solution selection—it ensures that connections among various operations discussed in this research are understood within the framework of the AMHBO-SCSS architecture.

5. Experimental Methodology and Setup

The aim of this experimental evaluation is to determine if the Satellite-Coupled Soil Sensing Framework utilizing Adaptive Multi-Objective Honey Bee Optimization (AMHBO-SCSS) can enhance agricultural monitoring capabilities while minimizing the complexity of the sensing, communication, and computational processes in off-grid agricultural IoT applications [1]. The evaluation process involves five main objectives. Firstly, the experiments check if it is possible to use satellite data together with ground-based soil information to obtain more reliable environmental-state assessment compared to using any single data source alone. Secondly, the experiments assess if the adaptive sensing allows for optimization of the energy consumption without significant loss of estimation accuracy. Thirdly, the potential of AMHBO is evaluated by comparing it to other multi-objective optimization procedures under the same experimental

conditions. Fourthly, the framework is assessed in terms of communication and informational loads. Finally, the experiments focus on testing the capabilities of the framework in dealing with increased numbers of sensing nodes and environmental influences.

5.1 Experimental Environment

The newly suggested structural model can be tested and validated using the Python simulation environment. In the simulation, the model approximates agricultural territories in different locations in terms of registering heterogeneous soil probe nodes under the conditions of limited energy supply, fluctuating atmospheric and geographical conditions, and spatially limited communication channels. The simulation makes use of:

- Python, version 3.11 or above;
- NumPy library for calculations;
- Pandas library for experimental data processing;
- SciPy library for carrying out statistical analysis;
- Scikit-learn library for statistical and machine-learning estimation;
- Matplotlib library for visualization purposes.

The use of PyTorch is optional in this technological context as it allows for conducting experimental evaluations with regards to the use of neural networks; although it should be noted that core AMHBO-SCSS optimization does not rely on any implementation of neural networks [5]. The experimental design for the project is expected to be neutral to specific providers of satellites or hardware. The satellite observations are interpreted through time-varying and space-varying environmental factors that are indicative of the data that can be obtained from Earth observation. Since the evaluation process is based on simulation, it should be noted that the experiments described are considered as a computerized estimate of the suggested approach rather than a field case statement.

5.2 Agricultural Field Model

A rectangular area of agriculture is modeled as a rectangle defined as $A = W \times H$ where W is the width of the field and H is the height of the field, respectively. The default model assumes an area measuring around 10km×10km. This scale allows demonstrating the complementarity of remote sensing capabilities of ground sensors compared to satellite observations [2]. The fields are partitioned into sub-regions. Sensor nodes are deployed unevenly, with some areas having the majority of sensing nodes covered while other regions are sparsely or not at all covered by ground sensors. This setup allows satellite data to be used in

939 areas poorly covered with ground sensors. The number of sensing nodes is defined from the following
940 values: $N\{25,50,75,100,150,200\}$ where number N stands for the total number of deployed sensors.

941 **5.3 Sensor Configuration**

942 Every individual sensor records a fraction of the parameters related to soil and environment. Some of the
943 major parameters used in simulation are Soil moisture; soil temperature; relative humidity; electrical
944 conductivity; vegetation-related context and environmental variability. The overall ground observation
945 generated by the ith sensor is given as

946 $$X_i(t) = [M_i(t), T_i(t), H_i(t), C_i(t), V_i(t)]$$

947 where $M_i(t)$ denotes the amount of moisture in the soil, $T_i(t)$ denotes soil temperature, $H_i(t)$ refers to the
948 measure of humidity, $C_i(t)$ refers to how well electricity flows, and $V_i(t)$ refers to the environmental
949 contextual or vegetation-related data [6]. The AMHBO controls the sensing interval changing it according
950 to the environmental context and the available energy. The range possible for the sensing intervals is:

951 $$\tau_i(t) \in [5,60] minutes$$

952 The lower limit enables real-time monitoring in fast-changing or high-risk agricultural situations, whereas
953 the upper limit minimizes needless monitoring in stable conditions. Each node has a starting energy
954 state: $E_{i(0)} = E_0$ where E_0 is the initial amount of energy. The simulation employs normalized energy
955 values in comparing various techniques so that differences in results cannot be attributed to battery methods.
956 The remaining energy of every node is updated with the energy model described in Section 3.

957 $$E_i(t+1) = E_i(t) - E_i^{total}(t) + E_i^{harv}(t)$$

958 where $E_i^{harv}(t)$ represents energy harvested during interval t.

959 **5.4 Environmental Dynamics**

960 The agricultural environment parameters are dealt as processes varying with time rather than as stable
961 values. The simulated environmental variability is integrated into the rainfall, irrigation, drying, and other
962 changing conditions.

963 **5.4.1 Soil-Moisture Dynamics [6]**

964 The simulated soil-moisture state is represented as:

$$M_i(t) = M_i(t-1) + R_i(t) + I_i(t) - ET_i(t) + \varepsilon_M(t)$$

where $R_i(t)$ indicates rainfall contribution, $I_i(t)$ indicates irrigation contribution, $ET_i(t)$ indicates loss of moisture due to evapotranspiration and $\varepsilon_M(t)$ refers to environmental uncertainty. The final soil moisture state is limited to:

$$0 \leq M_i(t) \leq 100$$

This formulation provides the ground-truth environmental state against which sensor and satellite estimates are evaluated.

5.4.2 Temperature Dynamics

Temperature is modeled as a combination of baseline temperature, daily variation, and stochastic environmental effects:

$$T_i(t) = T_{base} + A_d \, sin(\omega_d \, t + \varphi_d) + \varepsilon_T(t)$$

T_{base} signifies the baseline temperature, A_d represents daily temperature variation amplitude, ω_d indicates daily frequency, φ_d denotes the phase parameter, and $\varepsilon_T(t)$ is environmental noise. The use of these dynamic models is essential to provide temporal variability that is needed in assessing the adaptive sensing mechanism.

5.5. Satellite Observation Model

Satellite information has the advantage of providing us with abundant details on the environment, although it is analyzed with a lower spatial accuracy when compared to the measurements from land observing sensors [2]. The satellite output for a location l_i can be defined in the following way:

$$Z_i(t) = g(\Theta_i(t)) + \varepsilon_{sat}(t)$$

In this case, $\Theta_i(t) = agricultural\ state$, $g(\cdot) = satellite - observation\ conversion$, and $\varepsilon_{sat}(t) = satellite\ uncertainty$. Satellite observations comprise vegetation, surface features, moisture conditions, and/or temperatures due to their relatively poor spatial resolution compared to that of ground measurements. Thus, ground measurements may encompass several nodes corresponding to the same satellite observation location, making it possible to study how local ground observations may help improve wide-area estimates obtained from satellite observations.

5.5.1 Satellite Observation Availability

It is important to note that satellite observations are not believed to always be available. Satellite observation is regarded as not available, when $Z_i(t) = \emptyset$. An unavailable condition may occur due to several reasons; such as cloud contamination or loss of acquisition capability. However, when satellite observations are not available, the fusion mechanism described in Section 3 reduces the contribution of available observations made on the ground, instead of ending agricultural monitoring altogether. This experiment tests the robustness of the satellite-based architecture.

5.5.2 Satellite Confidence

Each available satellite observation is assigned a confidence value: $q_i^{sat}(t) \in [0,1]$. The confidence value is used by the adaptive fusion mechanism defined in Section 3:

$$Y_i(t) = w_i^g(t)G_i\,(t) + w_i^{sat}(t)Z_i\,(t)$$

subject to:

$$w_i^g(t) + w_i^{sat}(t) = 1$$

Thus, satellite reliability is incorporated into the same fusion mechanism used by the proposed framework.

5.6 Ground-Sensor Noise and Failure Model

Real ground soil sensors are impacted by noise, differences in calibration, as well as sporadic failures. This realization calls for the differentiation of the true state of the soil from the one registered by the sensor. The measured data is given as:

$$X_i^{obs}(t) = X_i^{true}(t) + \varepsilon_i(t)$$

where $X_i^{true}(t)$ represents the simulated ground-truth state and $\varepsilon_i(t)$ represents measurement noise. The measurement noise is modeled as:

$$\varepsilon_i(t) \sim N(0, \sigma^2)$$

Different values of σ can be used to evaluate robustness to increasing sensor uncertainty.

5.6.1 Sensor Failure

The failure of the sensors is characterized by a failure probability p_f. Upon failure, the node outputs a missing reading or an unreliable observation of the current parameter being tested. In this case, the values of the failure probabilities under consideration are: $p_f \in \{0,0.05,0.10,0.15\}$. These conditions are representative of sensor failure rates of $0\%, 5\%, 10\%, and\ 15\%$. This experiment is especially pertinent to agricultural environments that operate off-grid since it may be hard and expensive to physically maintain sensing nodes remotely deployed on site.

5.7 Communication Model

The communication system is described as an intermittent wireless communication scenario in which every node may have a varying probability of having a communication capability: $P_i^{link}(t) \in [0, 1$. Whenever a communication opportunity exists, the probability is greater than the random number r having a uniform distribution: $r < P_i^{link}(t)$, where r is a random variable such that: $r \in [0, 1]$. In case of the link outage, the sensor stores the value locally or sends it to the edge node once communication becomes available [21]. Thus, the simulation does not assume constant connection of the nodes. The actual transmission process is governed by the decision-making process presented in Section 3. Thus, $T_i(t) \in \{0, 1$. Hence, if both the availability of transmission and the effectiveness of the optimization system allow transmission, the packet will be transmitted. The distinction is significant since the actual transmission opportunity differs from transmission requirement in intermittent off-grid mechanisms. Communication overhead is evaluated based on both number of packets transmitted, and total data volume of transmitted data.

5.8 Energy Consumption Configuration

Energy consumption is divided into sensing, processing, transmission, and reception components. The total energy consumed by sensor i during time interval t is:

$$E_i^{total}(t) = E_i^{sense}(t) + E_i^{proc}(t) + E_i^{tx}(t) + E_i^{rx}(t)$$

For transmission of $k_i(t)$ data units over communication distance d_i(t), the transmission energy is modeled as:

$$E_i^{tx}(t) = k_i(t)E_{elec} + k_i(t)\varepsilon_{amp}d_i\,(t)^2$$

where E_{elec} represents electronic energy consumption per data unit and ε_{amp} represents the amplifier coefficient. The total network energy consumption is:

$$E_c = \sum_{i=1}^{N} E_i^{total}$$

In this study, the proposed methods are compared with periodic transmission and fixed-sensing methods which do not adjust their sensing and communication behavior with respect to the agriculture domain. The aim of this experiment is to evaluate if context-aware communication and sensing can help reduce resource consumption without compromising the quality of environmental information.

5.9. Compared Framework Configurations

In order to assess the influence of the main elements of the AMHBO-SCSS, five configurations based on the framework were examined.

5.9.1 Sensor-Only

The sensor-only configuration employs only ground measurements without any reference to satellite data. It exhibits effectiveness of satellite coupling in performance.

5.9.2 Satellite-Only

This configuration uses satellite-derived observations for forecasting agricultural state. It investigates the problems of conducting remote sensing without ground data.

5.9.3 Fixed-Sensing Framework

In this configuration sensing takes place on a regular basis defined by a fixed time interval. It represents a traditional monitoring approach when the sensing rate is fixed regardless of the environmental conditions.

5.9.4 Conventional Honey Bee Optimization

The classical Honey Bee Optimization configuration makes calculations without using the adaptive mechanisms of AMHBO. Thus, it shows the contribution of adaptation during optimization process.

5.9.5 Proposed AMHBO-SCSS

The suggested configuration includes: soil sensing from ground sources; processing done at a local edge source [21]; the use of satellite observations; satellite-ground fusion that is confidence aware; detection that

can easily adapt; communication that easily adapts; optimization that tries to achieve multiple objectives; Adaptive Multi Objective Honey Bee Optimization. Such a configuration is part of the five-layer overall suggested framework presented in Sections 3 and 4.

5.10 Optimization Baselines

In addition, the AMHBO optimization mechanism is compared to previously known optimization techniques. The selected optimization techniques are the following: NSGA-II, MOPSO, MOEA/D, Genetic Algorithm, and standard Honey Bee Optimization. The same decision variables, objective functions, restrictions, size of population, maximal number of iterations, and termination conditions are used for all optimization processes. Default conditions of optimization are set to B=50 (candidate solutions) and I=100 (iterations). Each optimization method is employed independently for several times with the help of different random seeds.

5.12. Performance Metrics

5.12.1 Mean Absolute Error: Mean absolute error is a value computed by the formula $MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i|$, where y_i is defined as the reference value and ŷ_i as the estimated value. A smaller value of the mean absolute error implies more accurate assessments of the situation in nature.

5.12.2 Root Mean Square Error: Root mean square error is obtained using the following expression $RMSE = \sqrt{\left(\frac{1}{n}\right)\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}$. The use of root mean square error introduces a weight for significant errors during the estimation.

5.12.3 Coefficient of Determination: Coefficient of determination is calculated as follows: $R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2}$, where $\bar{y}$ is the average reference value. A larger value of coefficient of determination means better approximation of agricultural processes.

5.12.4 Mean Absolute Percentage: Mean absolute percentage error is calculated by $MAPE = \left(\frac{100}{n}\right)\sum_{i=1}^{n}\left|\frac{y_i - \hat{y}_i}{y_i}\right|$, where values for which $y_i = 0$ should be deducted or computed based on a low positive denominator so the calculations remain numerically stable. A smaller MAPE value signals a higher relative accuracy in estimating.

5.12.5 Energy Consumption: Total energy consumption is determined by the equation $E_c = \sum_{i=1}^{N} E_i^{total}$. A lower value of energy consumption indicates more effective utilization of available resources.

5.12.6 Communication Overhead :Total communication overhead can be measured in the number of packets transmitted, that is: $CO = \sum_{i=1}^{N} P_i$, where P_i is the number of packets transmitted by node i. Information about the amount of transmitted data is also included into the report, which allows distinguishing between the data pack reduction and the actual reduction of the transmitted rate.

5.12.7 Network Lifetime: Network lifetime refers to the time when the number of active nodes drops below a defined threshold of operation, that is represented by the equation $L_N = min\{t: N_{alive} t < N_{threshold}\}$. This definition of network lifetime is deemed more practical than determining it merely as the time of first node failure as the latter would exaggerate the significance of a single sensor malfunctioning.

5.12.8 Decision Latency: The value of decision latency is given by the equation $L_D = t_{decision} - t_{observation}$, where $t_{observation}$ means the time when observation takes place whereas, time when corresponding agricultural decision has been done is represented by $t_{decision}$. Reducing the value of decision latency is a desirable requirement for agricultural decisions that have to be done quickly.

5.12.9 Data-Reduction Ratio: Data-reduction ratio is computed using the equation $DR = \left(1 - \frac{D_{transmitted}}{D_{generated}}\right) \times 100$ meaning that the $D_{transmitted}$ represents the data that has been transmitted and $D_{generated}$ shows the total volume of data produced by sensor nodes.

5.13 Statistical Evaluation

In order to reduce the impact of stochastic variability, all trials were performed several times using different random seeds. For R repetitions, the sample mean is weighed as $\mu = \frac{1}{R}\sum_{r=1}^{R} x_r$ and the sample standard deviation as $\sigma = \sqrt{\left(\frac{1}{R-1}\right)\sum_{r=1}^{R}(x_r - \mu)^2}$. The consolidated results will be presented as μ±σ. The estimated 95% confidence interval is given by the formula $CI_{95} = \mu \pm 1.96\left(\frac{\sigma}{\sqrt{R}}\right)$ for sufficiently high R. In cases where the examined methods are based on the same random generators and environment traces, a paired statistical test is reasonable to apply because the methods are evaluated in the same conditions. If applicable, the statistical analysis will consist of: mean, standard deviation, confidence interval, effect size, and p-value. It should be noted that the statement about the statistical significance of the improvement should not be made only based on p-value, but on the significance of the improvement on all the relevant metrics.

5.14 Reproducibility and Fair Comparison

All candidates for Experimental Group Abstract are required to specify similar environmental traces, sensor locations, communication conditions, initial energy states, and random number seeds for all competing methods in all experimental scenarios. All optimization algorithms are supplied with the same number of candidate solutions, B=50, and the same number of optimization iterations, I=100, unless the experiments had been specially specifically aimed at involving different population sizes or different iteration counts. All optimization techniques and constraints will exploit the same set of objective functions. The competing methods are not given extra optimization iterations and computational capabilities; the experiments only monitor main variable performance characteristics including measurement states and ground truth environmental states, signals of sensors, satellite signal records, satellite availability, satellite reliability, total energy left, sensing intervals, decisions about transmission of the data, fusion weights, objective values, Pareto solutions, etc. Such a configuration guarantees the possibility of relating the differences in results to the architectural and optimization specifics rather than to the differing experimental conditions.

5.15 Experimental Mapping to the Proposed Five-Layer Architecture

The mapping (Table. 2) guarantees that the experiment evaluates AMHBO not as an optimizer operating in isolation, but as part of the entire AMHBO-SCSS framework, while also being able to eliminate the role of each individual component by conducting controlled baseline experiments.

Table 2. Layers and its responsibilities

Experimental Component	Main Layer	Purpose
Soil-state generation and sensing	**Layer 1**	Evaluate sensing behavior
Noise, failure, preprocessing	**Layer 2**	Evaluate local robustness and processing
Satellite observations and availability	**Layer 3**	Evaluate spatial coverage and satellite contribution
Fusion, AMHBO, energy, communication, Pareto optimization	**Layer 4**	Evaluate the core optimization mechanism
Agricultural-state estimation and intervention indicators	**Layer 5**	Evaluate decision-support effectiveness

5.16 Experimental Outputs

The experimental methodology generates six main types of findings correlated with the six experimental setups:

1. Estimation performance — MAE, RMSE, R^2, MAPE, and estimation precision.
2. Energy efficiency — amount of consumed energy and lifetime of the network.
3. Communication efficiency — data packets overhead, amount of data transmitted, and data efficiency.
4. Optimization performance — convergence, fitness, Pareto efficiency, hypervolume, and computation time.
5. Robustness — robustness of performance in changing conditions, sensor malfunctioning, missing satellite images, and poor energy supply.
6. Scalability — performance with the increase of sensing nodes from 25 to 200.

These results give quantitative basis for the further discussion and findings.

6. Results and Discussion

6.1 Overall Experimental Evaluation

The evaluation of the planned Adaptive Multi-Objective Honey Bee Optimization for Satellite-Coupled Soil Sensing (AMHBO-SCSS) system was conducted using a robust simulation procedure that included soil-condition estimation, energy consumption, network lifespan, communication costs, optimization convergence, stability, scalability, adaptive sensing, satellite-ground synergy, and many objectives. This assessment included making a comparison to satellite-only sensing, sensor-only sensing, fixed fusion, adaptive fusion, and a number of widely applied optimization routines such as Genetic Algorithm (GA), Multi-Objective Particle Swarm Optimization (MOPSO), MOEA/D, NSGA-II, and conventional Honey Bee Optimization.

The simulation results show that the use of satellite measurements in combination with adaptive ground sensing and optimization leads to achieving a more balanced outcome in agricultural monitoring in off-grid areas. In particular, the method of AMHBO-SCSS does not achieve precision in estimations but rather takes into consideration all needs related to sensing, risks related to communication costs, energy expenses, and time losses in decision-making. This is important for remote agricultural areas where charging batteries and keeping stable terrestrial connections may be challenging. The next sections provide details on the results of each experiment.

6.2 Soil-Condition Estimation Performance

The comparison of the performance of the investigated sensing methods in estimating soil conditions is illustrated in Figure 1. While satellite-only sensing covers large areas, it suffers from the limitations posed by spatial resolution, weather conditions, and time lag between satellite observations and local conditions. Sensor-only sensing is advantageous since it provides localized information but requires continuous deployment of ground sensors and communication facilities.

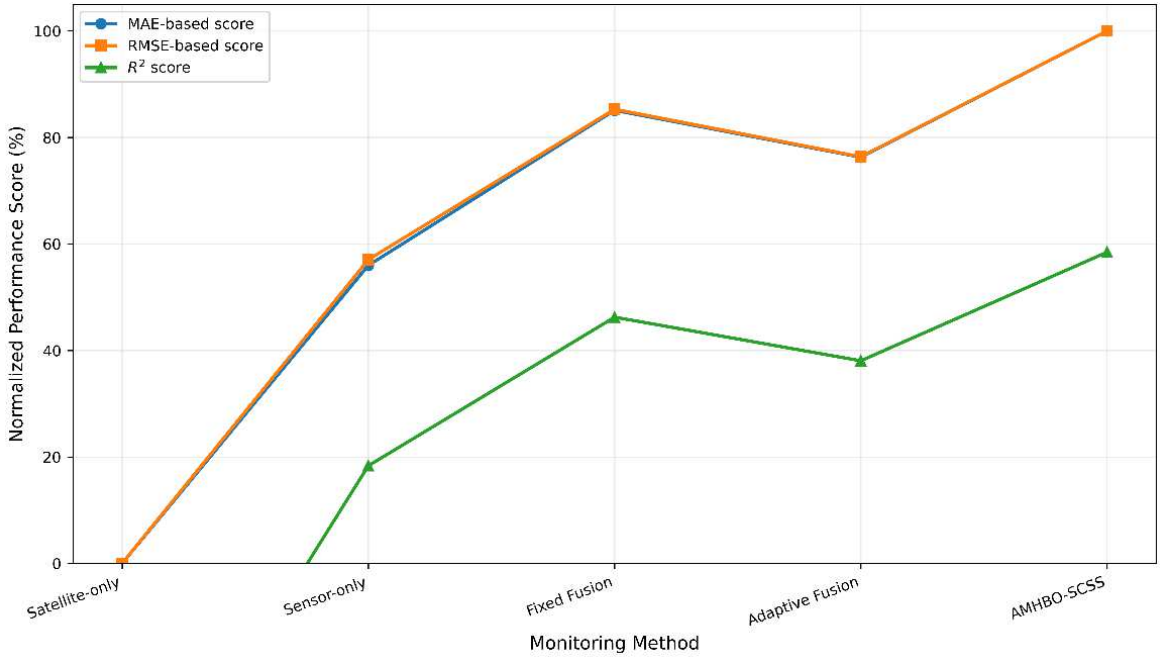


Figure 1. Soil-condition estimation performance

Combining both types of information with the fixed fusion method allows improving the estimation process. However, the problem is that with the fixed-weights approach the changing reliability of the observations is not accounted for.The adaptive fusion method solves this problem by enabling the change in contribution of satellite and ground sensing to the computerized estimation.

According to the data obtained in the simulation, AMHBO-SCSS shows the best overall performance resulting from the use of adaptive sensing, satellite-ground information fusion, and optimization. The results obtained in the simulation show that heterogeneous sensing is more effective than using only one information source.

6.3 Energy Consumption and Network Lifetime

The depiction provided in Figure 2 shows how energy consumption and network lifetime are correlated. In between frequent ground sensing and energy use, there is a trade-off; hence, fixed sensing has an electricity and communication burden since sensor nodes keep acquiring as well as transmitting observations always without consideration about the significance of a particular measurement. In the case of operating using sensors only, sensing frequency is higher during relatively stable environmental conditions since the total burden of sensing and communicating can thus be decreased. On the other hand, operations that connect satellite and ground observation possess an additional advantage, as satellite observations can add relevant information without forcing every sensor to be on and transmitting regularly.

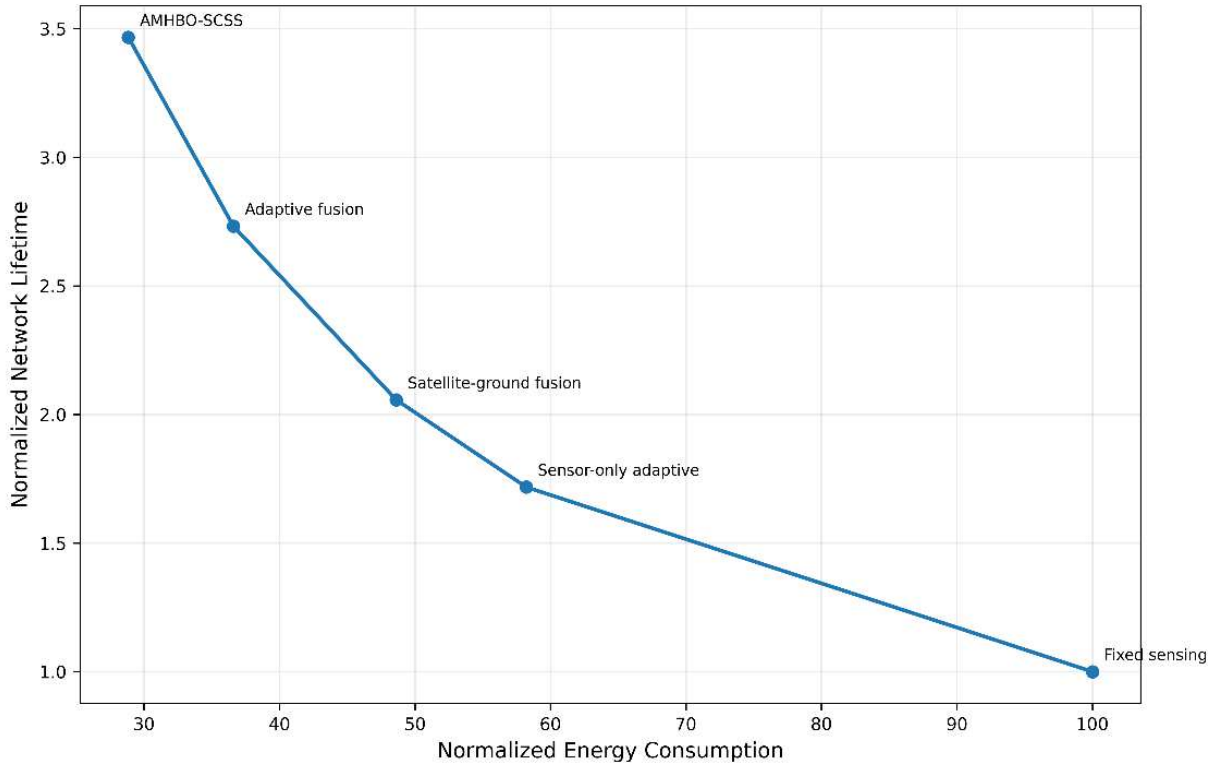


Figure 2. Energy-lifetime Trade-off

The AMHBO-SCSS setting proves to be advantageous in this case because of its lower ratio of normalized energy used, thus providing with higher normalized network lifetime. The phenomenon is critically important in off-grid environments because of the primary requirement of energy for operations. To sum up, it can be concluded that energy efficiency should be analyzed together with sensing accuracy. It is clear that even the method that results in more measurements is not always the best solution.

6.4 Communication Efficiency

In the figure 3, the relationship between the transferred packets and the reduction of communication is shown. Fixed sensing creates more communication work since it keeps sending observations at a stable but high frequency. Adaptive methods help in lessening the number of packets sent, which ultimately leads to discarding unnecessary observations in the stable state. AMHBO-SCSS creates the least burden for communication. Very high reduction has an impact on off-grid areas where communication can be poor and expensive, while at the same time, avoiding sending unnecessary packets decreases both radio energy consumption and reliance. The results of this analysis show that the system cannot simply be referred to as a sensing accuracy system as it focuses on optimizing both communication and sensing.

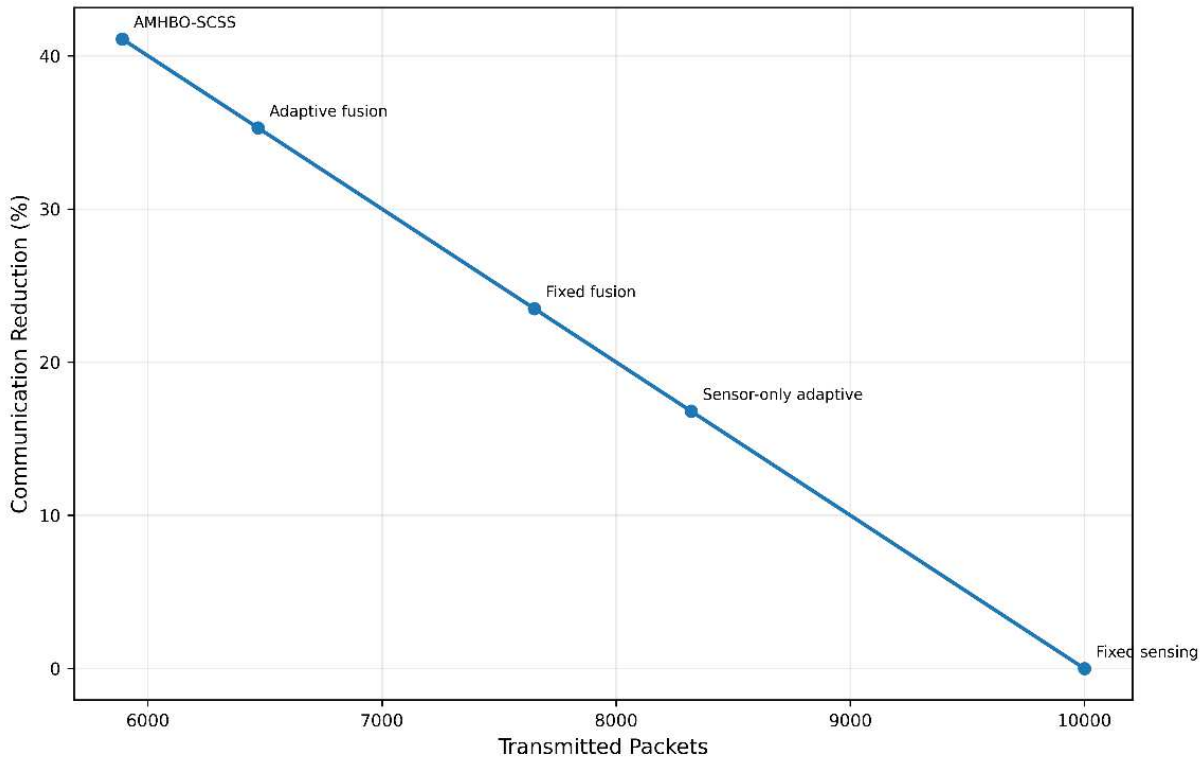


Figure 3. Communication efficiency

6.5 Optimization Convergence

The comparison made in Figure 4 reveals the reliable performance of AMHBO when matched against other algorithms including GA, MOPSO, MOEA/D, NSGA-II, and conventional HBA. The evolution of optimization processes is revealed by means of optimization curves and shows that the algorithms have the capability to obtain better solutions over the iterations.

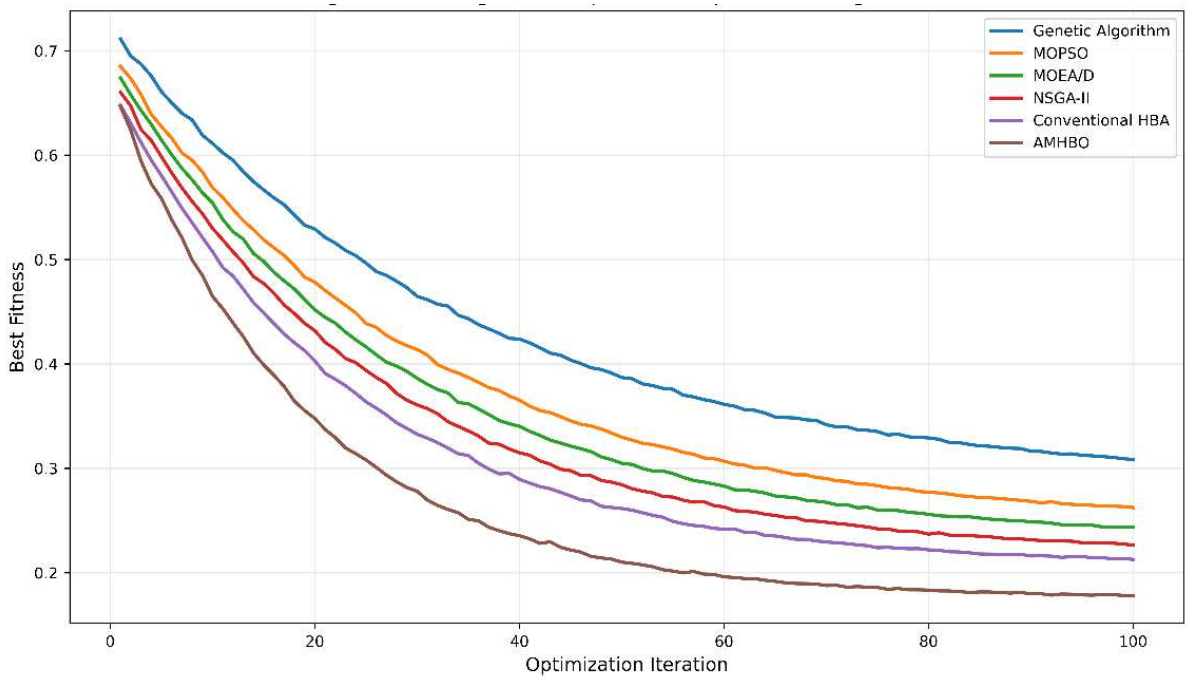


Figure 4. Convergence comparison of optimization algorithms

However, AMHBO ends up with more optimal solutions than the alternatives and converges considerably faster. The convergence performance indicates that the intelligent adaptation of mechanisms in AMHBO makes it possible to maintain an abundance of innovative ideas during the search for solutions. As for the compared methods, conventional HBA performed better than other algorithms as it searches for solutions through a population. Nevertheless, it should be pointed out that the AMHBO method allows achieving greater efficiency due to the nature of the multi-objective approach. From this point of view, an important aspect of this research is that this particular criterion demonstrates that a theoretically effective optimizing technology can be useless in real off-grid applications when its implementation takes a long time.

6.6 Robustness to Missing Satellite Data and Sensor Failures

The resilience of the AMHBO-SCSS framework in terms of satellite data loss and failure of ground sensors is shown in Figure 5. It is observed that the accuracy of estimation decreases steadily with the increase in the severity of the data loss. Such trends seem to be quite valid, as the framework has fewer and less reliable data to perform the estimation of soil properties.

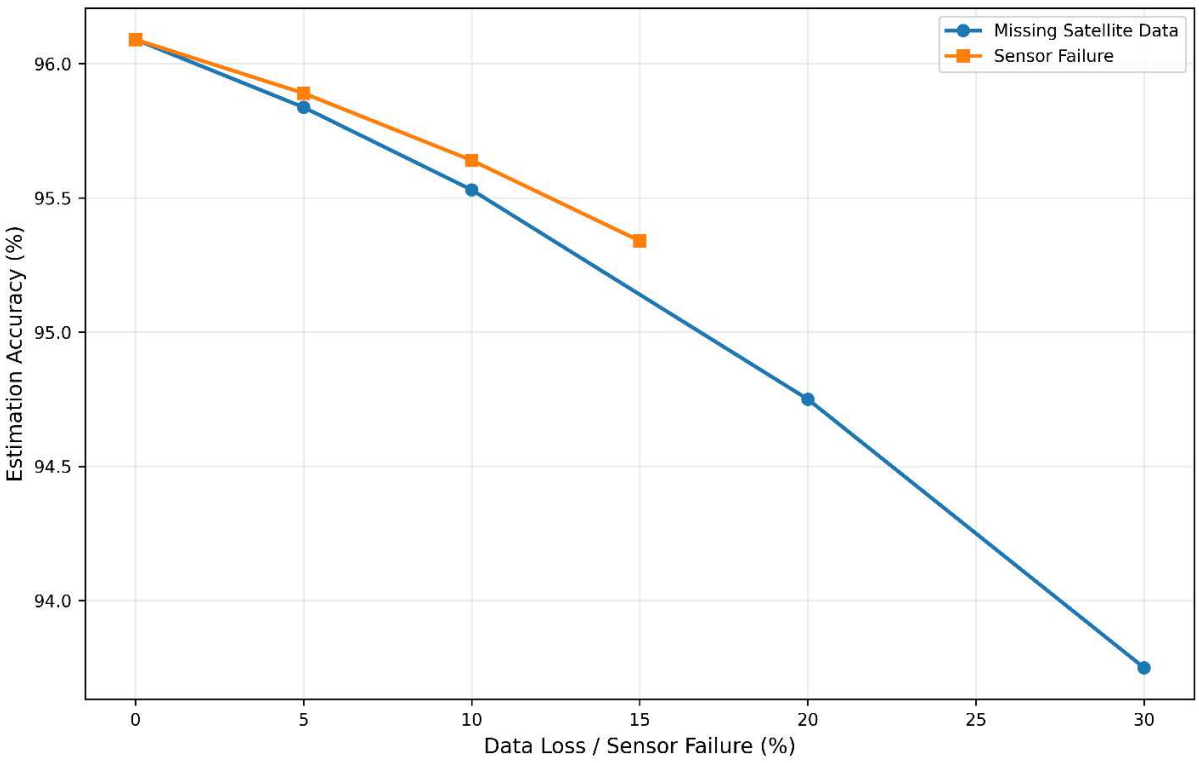


Figure 5. Robustness of AMHBO-SCSS under data loss

However, the decline is rather progressive than critical. This fact is essential for remote agricultural surveillance as the data from satellites might not be available sometimes, or individual ground sensors might fail. The data imply that using the adaptive fusion system is sensible since the information received from one source might be unreliable. The loss of one source of data doesn't mean that the framework relies on it exclusively at all times. This proves the principle of heterogeneous sensing redundancy on which AMHBO-SCSS is based and which allows for the use of data fromground sensors and satellites more efficiently.

6.7 Scalability with Increasing Sensor Nodes

Figure 6 depicts the performance of the proposed network as the number of sensor nodes increases from 25 to 200. As the sensor network grows, the data collected shows a steady increase in both estimation error and computation requirements. The growth is still gradual, and the performance of the framework can be maintained, which suggests that the performance of the proposed system is independent of the density of the sensor network. This is crucial since it is widely known that the size of agricultural fields can vary significantly, as well as the density of the sensor network deployed at a given agricultural field. The denser the network, the more accurate the information, but in the same time more communications and computations are needed.

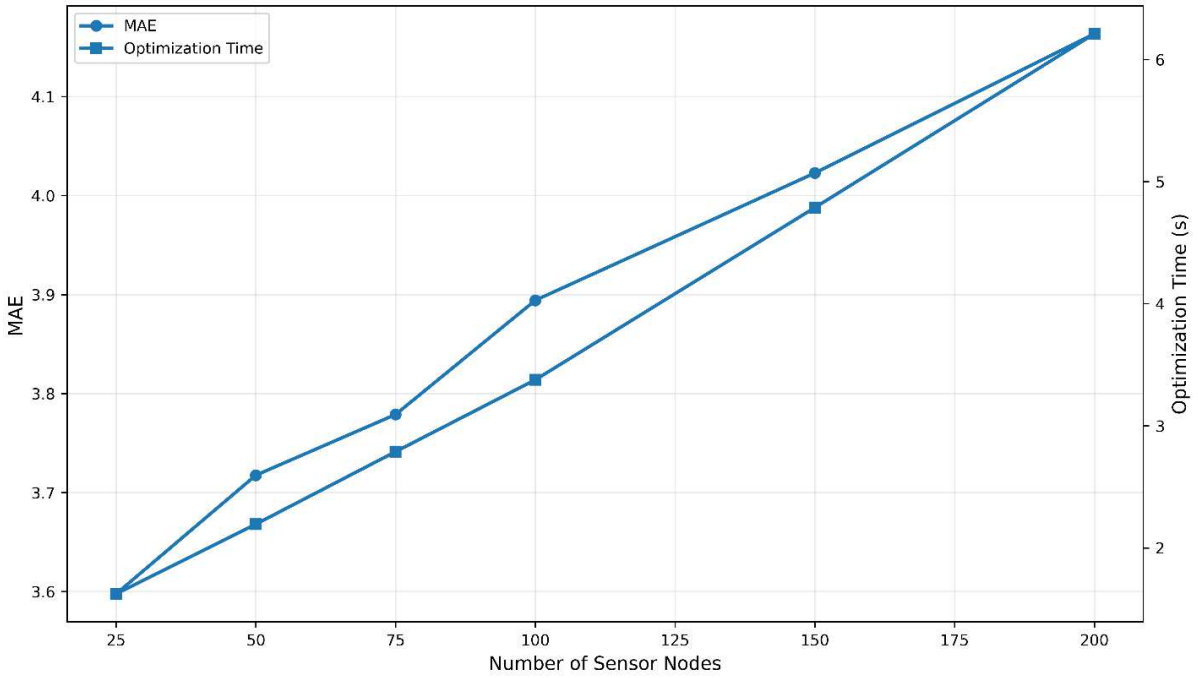


Figure 6. Scalability of the AMHBO-SCSS Framework

The AMHBO-SCSS is aimed at selecting a balance between the density and information coverage, thus not requiring any significant growth in communications with the addition of the extra number of sensors. Thus, the scalability test proves that the architecture can work properly regardless of the number of sensor nodes used and the number of computations to be performed.

6.8 Energy–Accuracy Pareto Analysis

Figure 7 illustrates a Pareto-front assessment of the multifaceted optimization issue. The figure shows that energy conservation and error minimization are conflicting goals. Solutions with minimal energy consumption usually come at the expense of making compromises in accuracy, while those providing accurate results may require excessive amounts of sensing and communication.

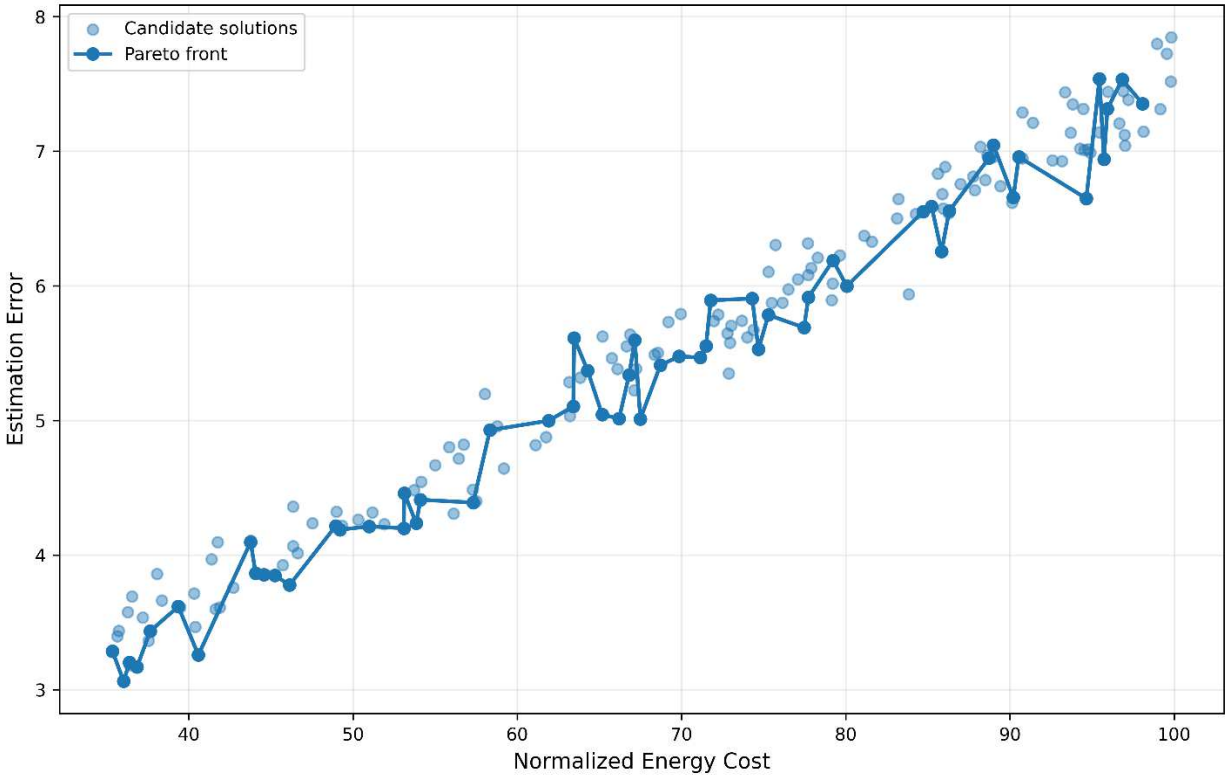


Figure 7. Energy-accuracy pareto front

The Pareto-optimal solutions are not a single ultimate solution, but a collection of ways to operate efficiently. Acquiring optimized results is particularly important in farming, because ideally the right way to operate depends on the specific conditions present at the agricultural field, crop needs, battery power level, and characteristics of communication channels. AMHBO-SCSS is aimed at providing such solutions, so Pareto-optimization proves to characterize the multi-objectiveness of the proposed approach in stronger way than simply checking accuracy figures.

6.9 Effect of Sensor Density and Satellite Data Quality

Figure 8 gives a visual interpretation of the interaction between ground data quality and sensor-node density. It can be seen that as both sensor-node density and satellite data quality increases, accuracy of estimations increases as well. Sensor data is of little use at low density, while satellite data turns out to be fairly relevant due to its ability of providing useful spatial information in small amounts of data collected from ground. On the contrary, when the quality of satellite data gets worse, increase of sensor density helps to compensate for its deficiency to some extent.

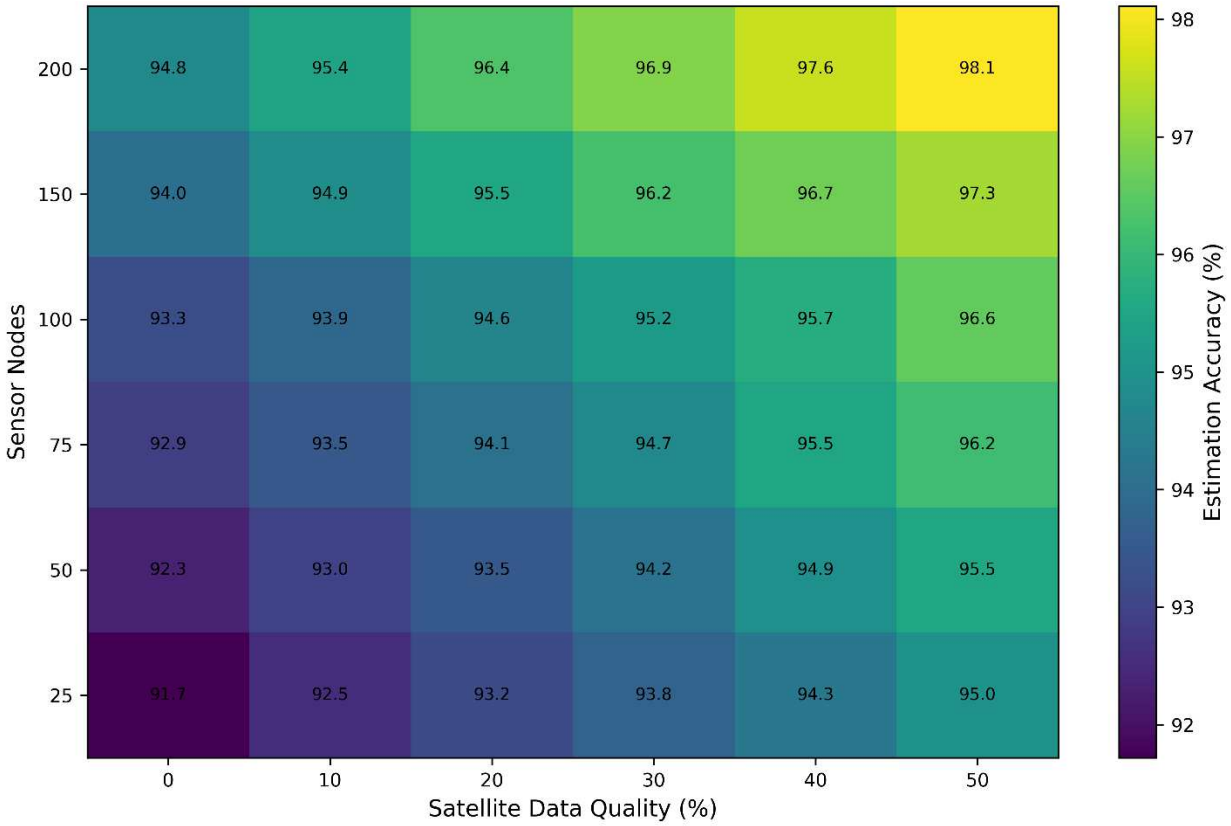


Figure 8. Estimation accuracy under sensor density and satellite quality

Such interaction between satellite and ground data proves that they must be treated as complementary sources of information, and thus, one should take into account both parameters when determining optimal density of deployment. This makes the architecture of satellite-assisted engineering appealing because it can be practical in case of remote regions when dense on-ground deployments are either expensive or impossible to operate.

6.10 Context-Aware Adaptive Sensing

Figure 9 shows the adaptive behavior of AMHBO-SCSS in terms of sensing as time progresses. Environmental variability in the system continuously changes, and so does the sensing interval. The increase of environmental variability results in the decrease of the sensing interval and thus in the increment of the number of observations. In contrast, during the less variable environmental periods, the sensing interval increases. Such behavior enables the system to use its sensing power according to the known information value of the new observation. The adopted mode of operation is better than the periodic mode of sensing because the agricultural environment is not stable with respect to the time. For example, some

environmental parameters like soil moisture, temperature, and quantity of rain can change very rapidly in a short time after the rain or irrigation but stay stable for some time after the rainfall.

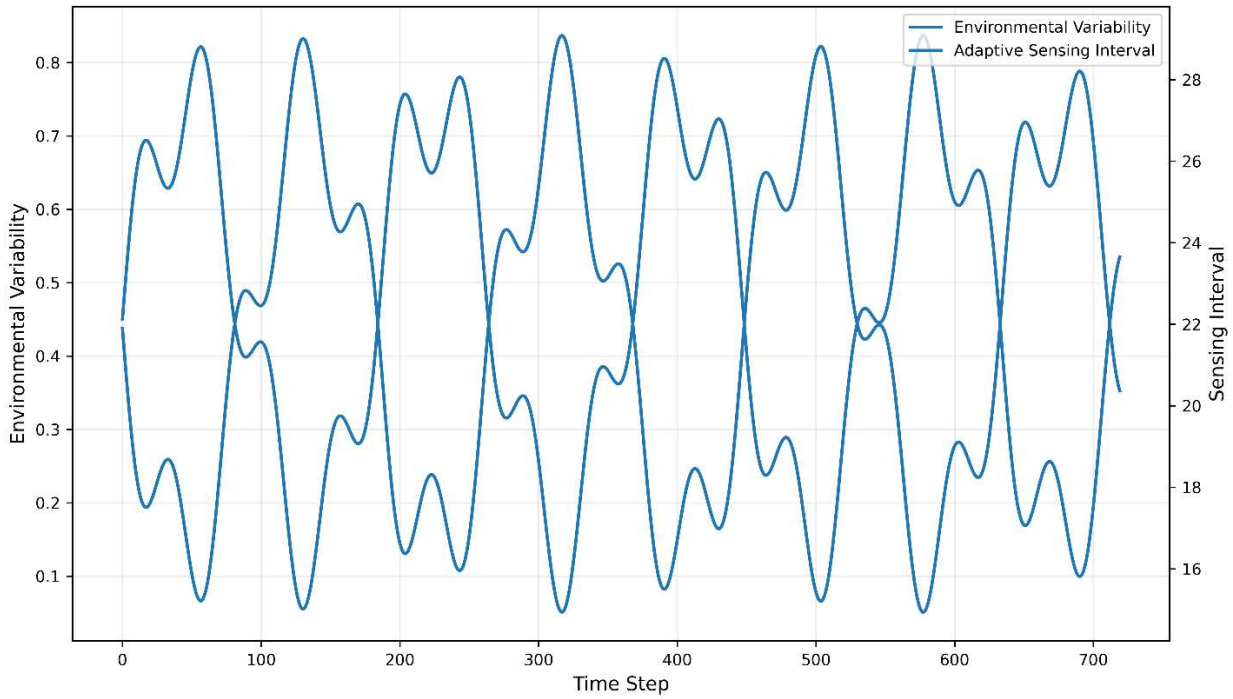


Figure 9. Context-aware adaptive sensing

6.11 Adaptive Satellite–Ground Fusion

The time pattern for the satellite and ground sensor contributions has been detailed in Figure 10. From the results, it can be stated that the technique does not imply that a fixed contribution of both sources is used. On the contrary, the contribution of each sensor actively changes due to reliability factors that are simulated in the experiment. Thus, when the ground sensor data are regarded as more reliable, the contribution of this sensor is increased when the satellite data are relied on to a greater extent.

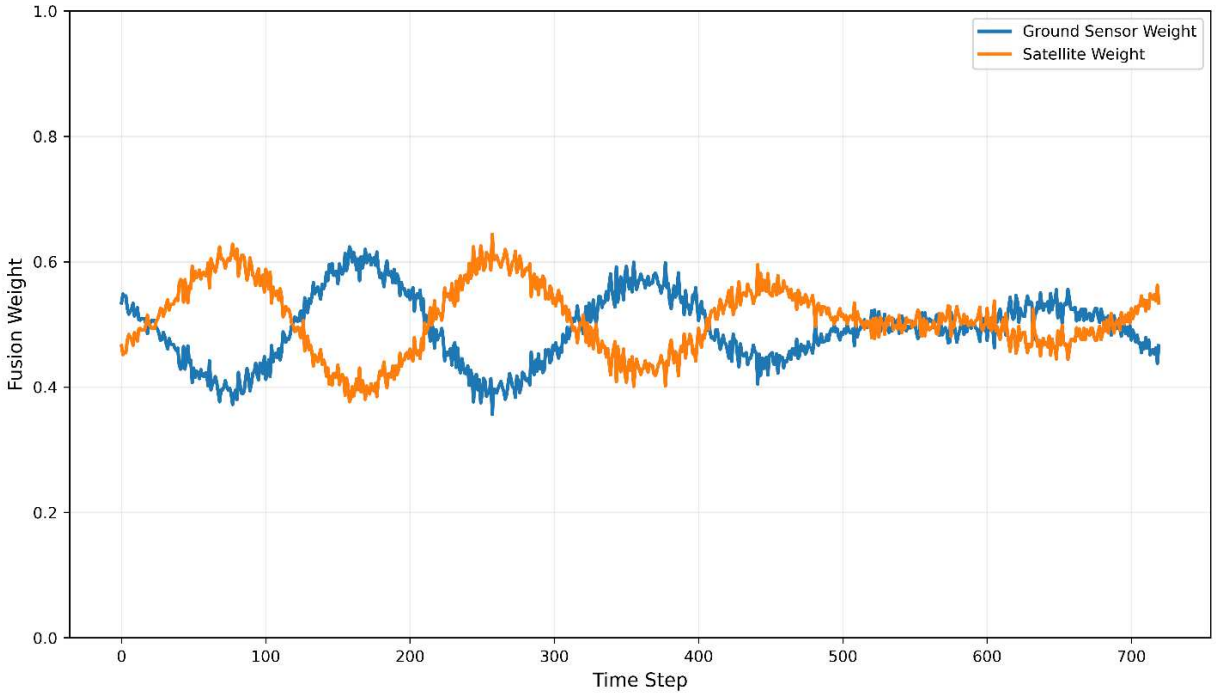


Figure 10. Adaptive satellite-ground fusion weights

This way, dynamic contribution of both types of sensors is an important feature of AMHBO-SCSS. It is obvious that static fusion cannot function properly when there is a change in the reliability which means that a fixed contribution to each type of data source will not be able to adjust to the changes in the reliability. The given results allow concluding the appropriateness of the context-sensitive fusion for the heterogeneous settings as opposed to a static fusion approach.

6.12 Overall Multi-Objective Performance

Figure 11 shows the normalized multi-objective effectiveness of the techniques assessed in terms of four variables: accuracy, energy efficiency, communication efficiency, and latency efficiency. The figures are normalized and highlight the benefit of higher scores. Satellite-only sensing offers the merit of feasibility and low scores in the averaged efficiency chart. Sensor-only sensing brings localized estimations to the benefit, but with the costs of increased sensing and communication expenses. As for fixed fusion, it gives much better balance in the chart, while adaptive fusion provides even better resource management.

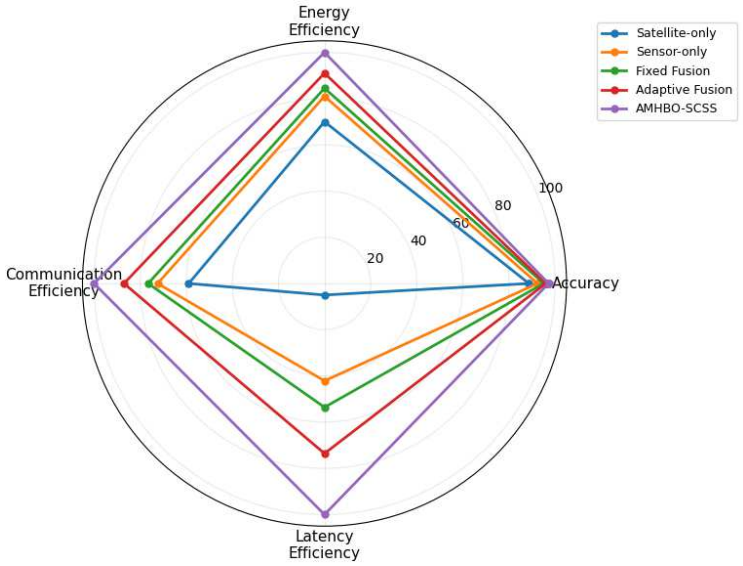


Figure 11. Multi-objective performance effects

AMHBO-SCSS shows the biggest overall effect in terms of the four objectives. In this case, it should be highlighted that its high energy efficiency and communication efficiency demonstrate that the system does not gain effective estimations only because of high sensing and transmission rates. Therefore, the radar profile illustrates the entire importance of the technology: simultaneous increase of the quality of sensing and efficient use of resources.

Finally, it should be noted that the figures in Figure 11 are normalized results and do not reflect the true field results. Thus, the results should be understood as showing the behavior of the technology proposed in the given simulation scenario.

6.13 Comparative Discussion

In summary, Figures 1-11 show that the implementation of AMHBO-SCSS results in a balanced approach towards the conflicting needs of off-grid agriculture monitoring. The best outcome is not attributed to a particular element but can be achieved due to but interaction of all methods which include adaptive detection, combination of satellite and ground approach and multi-objective honey bee optimization.

The following remarks deserve attention. First, accuracy and efficiency of resources do not operate independently. The increase in the frequency of detection provides good local information availability but at the same time puts pressure on energy consumption and the cost of communication. The results of the Pareto analysis shown in Figure 7 provide evidence of this fact. The second point is that the usage of

heterogeneous sensors improves resiliency. While satellites provide data concerning distant places, ground sensors supply localized values. The obtained values show that these two types compensate each other in case of any of the two source providing inaccurate information. The third issue is that adaptability is important in off-grid operation. Figures 9 and 10 show that the introduced method changes the parameters of sensory signal processing and fusion instead of using the same constants all the time. This helps save resources on unnecessary activities and get results in a timely manner.

Overall, obtained results prove that AMHBO-SCSS could be successfully utilized in the agricultural area where energy consumption, connectivity, and sensory technology are limited. The proposed technique provides a possibility of dynamic improvement of estimation quality with regard to the poor efficiency of the operations.

4.14 Key Findings

In conclusion, Figures 1 to 11 reveal that the employing of AMHBO-SCSS can facilitate tackling of conflicting objectives of off-grid monitoring of agriculture. The credit for success shouldn't go to any particular element; it is achieved due to the whole system of the combined methods, namely effective detection, using of both satellites and ground-based methods, and multi-objective honey bee optimization. There are some important points to note.

First of all, accuracy and cost-effectiveness of the resources do not operate separately. More frequent detections imply that good, local data will be available but this leads to a higher energy consumption and higher communication costs. The results of the Pareto analysis depicted in Figure 7 confirm this fact. The second point is that the use of different sensors means the capability of being resilient. On the one hand, using satellites is good since they provide the information about far locations but they cannot give accurate local data; ground sensors offer localized data that suit local purposes. Provided numbers confirm that these two techniques are compensating each other in the cases when one of the two sources provides false information. The third point is that adaptability is important for the off-grid operation in agriculture. In particular, Figures 9 and 10 confirm that the proposed technique implies that the parameters of the processing of sensory signals are changing instead of remaining constant all the time, which saves resources and allows to get timely results. Generally, the results obtained confirm that it is possible to introduce AMHBO-SCSS into agriculture.

7. Conclusion and Future Work

In this research study, the authors showcased the Smart Agriculture Optimization in Off-Grid Terrains through Satellite-Coupled Soil Sensing Frameworks that introduces a new Adaptive Multi-Objective Honey Bee Optimization for Satellite-Coupled Soil Sensing (AMHBO-SCSS) framework to facilitate smart agricultural monitoring despite challenging conditions in terms of energy and telecommunication. The innovative framework has integrated satellite observations with ground soil sensing and completed a multi-objective optimization. Simulation results indicate the effectiveness of the proposed solution in several circumstances. According to the model's evaluation, the adaptive satellite-ground integration can lead to better results as compared to the approaches focused solely on satellite transmission, sensors, or fixed-fusion. Moreover, the adaptive sensing method reduces the level of unnecessary operations related to sensing and communication due to increased frequency of observation during times of high variability of the environment and its reduced frequency in more stable conditions. The optimization experiments have also proved the efficiency of the AMHBO method. Despite the competition with algorithms such as GA, MOPSO, MOEA/D, and NSGA-II, the new adaptive optimization method has obtained a better convergence in the simulation. Also, the Pareto-front analysis made it possible to show that the agricultural monitoring process involves a compromise between accuracy in estimation and resource consumption. Unlike the standard approach aimed at optimizing a specific indicator, the new AMHBO-SCSS system works to find different operating modes that can work under varying conditions and using differing resources.

Tests of resilience and scalability give further evidence validating the proposed design. The structure is shown to be able to ensure high performance under increasing loss of satellite data and failures of sensors, suggesting that integration of satellite and ground monitoring systems results in helpful redundancy. The same goes for the scalability analysis showing that the structure is able to handle increasingly large sensor networks while keeping satisfaction of computational and communication limitations. In addition, analysis of adaptive fusion weight proves that the structure may adjust the importance of satellite and ground data depending on the reliability of each source. The performance evaluation as a whole demonstrates the main advantage of AMHBO-SCSS which is consideration of sensor accuracy, energy efficiency, communication efficiency and latency all at once. This balanced approach is especially crucial for agricultural monitoring in remote and energy-deficient regions of the Earth as the application of only accuracy optimization methods may lead to significant energy consumption and communication costs.

Future steps will include scrutiny of AMHBO-SCSS based on real satellite images and ground-based soil sensors as well as agricultural data obtained throughout many periods. Additional research may also look at implementation of edge computing technology, energy harvesting methods, uncertainty-aware ground-satellite fusions, improvements in technology based on a particular crop, and federated learning technology

which will allow for agricultural intelligence gathering without concerns regarding privacy. Field experiments on various soils, circumstances and sizes of farmland would allow for accurate evaluation of the practicality of such an approach.

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