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# Energy-Optimized Edge-Computing Framework for the Sustainable Development of Modern Agriculture †

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**Abstract:** The implementation of smart agriculture is confronted with various challenges, such as a lack of infrastructure and isolation from networking facilities that are required for the smooth operation of the Wireless Sensor Network established. The sensors and imaging systems present in the cropland generate large amounts of data that need to be processed in an affordable and scalable manner, even with a limited internet connection. This paper proposes the use of agricultural waste to power edge devices being deployed in a given cropland. In order to ensure efficient energy usage and processing, we implement the K-Means clustering algorithm integrated with the FPKM algorithm to efficiently denoise the collected data and an offloading mechanism that ensures efficient usage of computational resources by enabling parallel computation to minimize errors and delays in actuator instructions that could increase crop productivity and significantly diminish the possibility of crop loss.

**Keywords:** edge computing; sustainable development; smart agriculture; internet of things; FPKM algorithm; clustering algorithms; microgrids



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## 1. Introduction

In order to successfully incorporate Wireless Sensor Networks (WSN) in agriculture and to fully utilize its benefits, it is crucial to take into account certain features of the environment in which the nodes will be placed. Factors like crops, machinery, temperature, humidity, rainfall, high solar radiation, and shading by plant leaves can interfere between the nodes and can lead to discrepancies and errors in the data transferred. As the nodes are battery-operated and are placed in croplands where finding a suitable power supply replacement is difficult, ensuring an efficient power supply lifetime is a challenge. In using a wireless network, it is difficult to safeguard the deployed nodes from interference from devices operating and communicating in the neighborhood. This could lead to tremendous inconsistencies and unreliability of the inferred data and control signals. Ensuring interoperability among the multiple technologies and standards implemented can be a grueling task due to the number of devices used and the wide range in the variety of technologies applied. Although cloud computing was introduced to tackle the "Big" data problem by handling large amounts of edge network data, maintaining an optimal balance between the storage and processing of this acquired data can be cumbersome. Furthermore, it is vital to ensure a good trade-off between the computational workload and the high costs and latency that accompany it. Wireless communication can cause inconsistencies in sensed data due to the unavoidable presence of noisy data. This adds more pressure on the preprocessing processes implemented in the service layer to clean the data and offer more reliable inferences. The FPKM algorithm, conventionally used in the quantification of gene expression levels in RNA sequencing data analysis, can be applied to agricultural data due to its similarity. It is essential to ensure data integrity, outlier removal, and normalization of data to accommodate variations in the experimental environment. Deploying agricultural sensors, robots, drones, and other tools and technologies requires significant investment, high-skilled manpower, and heavy maintenance costs. High-bandwidth continuous internet connectivity, HD cameras for crop satellite imagery via sensors and drones, and a huge capacity server are also necessary to store regular logs related to crops and other activities [1]. Creating a consistent and energy-efficient environment is critical for secure information transmission to stakeholders. As per a study, cloud data centers make up 2.4 percent of global electricity consumption, and this is estimated to increase. Authors in [2] have suggested reducing the data to be sent to the data centers for processing to minimize energy consumption. As given in the proposed architecture, integration of microgrid with edge computing improves the efficacy of using renewable energy effectively to meet the IoT energy requirements.

## 2. Methods

Our proposed architecture utilizes microgrids as a way to reuse agricultural waste so as to enable an independent power grid capable of safeguarding the edge devices from power shortages/disruptions, even when the cropland is located off-grid.

### *2.1. Valorization of Agricultural Waste Using Microgrids*

The Indian Council of Agricultural Research conducted a study wherein they examined the agricultural waste produced after every harvest cycle. On average, about 350 million tons of waste is produced, which includes crop residues that have a rich bioactive compound content. This waste can be revalued to harness renewable energy in order to power edge devices. This can be achieved in various ways, including biogas generation using anaerobic digestion and biomass energy to produce heat and electricity that can power edge devices through electrical generators, biofuel production, thermal energy, microgrids, etc.

Microgrids are systems that can incorporate several renewable energy sources and efficiently distribute the power generated to edge devices in a WSN. They are small-scale and localized in the sense that they are capable of generating, storing, and distributing energy only to a fixed area or a group of edge devices. They play a major role in the valorization of agricultural waste, as shown in Table 1.

**Table 1.** Microgrid applications in waste-to-energy processes.

| Method | Role of Microgrid | Benefit | Reference |
| --- | --- | --- | --- |
| Energy Generation from Waste | Host biogas digesters, gasification units, or boilers | Converts agricultural waste into heat, electricity, and energy | [3] |
| On-site Energy Production | Process the waste on-site instead of a distant facility | Reduces transportation costs and loss in energy due to transport of waste to and from processing facility | [3] |
| Energy Efficiency | Optimize processes involving energy conversion using CCHP systems | Captures heat generated while using CCHP systems | [4] |
| Energy Storage | Store renewable energy when the power demand is low | Utilizes the stored energy cuts down on the process of regenerating brown energy in the power grid | [2] |
| Independence ofzhongguorenthe Grid | Allow the grid to work independently of the main power supply | Supports agricultural practices in off-the-grid areas or more remote areas while securing continuous and reliable energy | [5] |
| Excess Energy Utilization | The excess energy generated at low-peak hours can be fed back to charge batteries or monetized by selling it at high cost | Contributes to energy supply and acts as a potentially revenue-generating activity | [2] |

### *2.2. Integrating Microgrid and Edge Computing*

Our proposed work as seen in Figure 1 integrates microgrids with edge computing [6] so as to establish an environment that supports the management of energy, decision making, and processing of data. The biggest advantage of this integration is the enhancement of energy, computing efficiency, and reliability. Furthermore, this results in an energy infrastructure that is more responsive, efficient, and secure. When we deploy edge-computing devices within a microgrid infrastructure, such as a renewable energy site, they act as computing nodes in the microgrid. They can be used to dynamically monitor the energy generation, consumption, and distribution in a real-time agricultural environment.

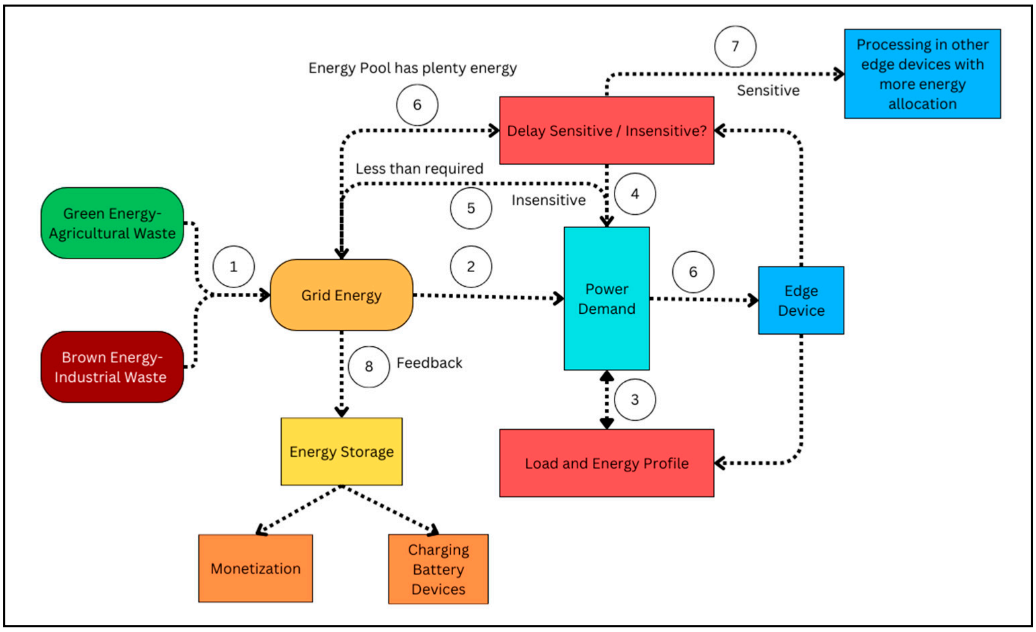


**Figure 1.** Integration of microgrid with edge computing.

Within a microgrid infrastructure, we can deploy energy-aware nodes like substations or distributed energy resources (DERs), which can host edge servers and process sensed data while being powered by the microgrid itself. These nodes can manage, monitor, and optimize their own energy usage and track their consumption pattern. The principle behind the architecture of these nodes is to bring down the overall energy consumption per processing task, which will, in turn, reflect in the extended lifetime of these devices. These energy-aware nodes possess the capability of dynamically adjusting operating parameters such as voltage and clock cycle depending on the energy available and the work demand. In the low-demand periods, they adopt power-management techniques like sleep modes, dynamic voltage modification, and power gating to restrict energy usage.

Smart agriculture involves smart irrigation, smart fertigation, and pest control systems that utilize sensors to measure temperature, humidity, NPK content, and intrusion detection systems based on imaging systems that use deep neural networks to detect pests. Several technologically advanced farms have hundreds or thousands of sensors deployed to collect these data. Keeping in mind the amount of energy that is required to power these devices, for various processing tasks, we list the advantages of integrating microgrids with edge-computing devices.

The evaluation of irrigation, fertigation, etc., requirements is achieved by sending the sensed data to a centralized cloud data center, followed by sending all actuator instructions from the data centers to the actuators deployed. This requires a tremendous amount of energy and can lead to latency due to the time taken to transmit the data to and from the IOT devices and analyze it. Further, due to limited network connection and bandwidth in these lands, the data are vulnerable to external forces that may produce erroneous or corrupt results. The concept of edge computing can be implemented to minimize the risk associated with wireless data transmission. With the help of microgrids, all computation and processing are performed locally on the designated edge devices for a set of WSN nodes, thus diminishing the possibility of latency and improving the response time.

In some cases, edge analytics can be implemented to establish patterns in energy usage, irrigation, fertigation, and intrusion to reduce the energy used in computing the requirements for every unit of sensed data.

### *2.3. Clustering Using FPKM and K-Means*

In modern agriculture, an abundance of data is collected from the sensors deployed on agricultural lands. This type of data is shown in Figure 2.

| | |
|---|---|
| **WEATHER**<br>• Temperature<br>• Precipitation<br>• Humidity<br>• Wind speed and direction<br>• Solar radiation<br>• Evapotranspiration | **SOIL**<br>• Soil moisture content<br>• Soil temperature<br>• Soil pH levels<br>• Soil nutrient levels (e.g., nitrogen, phosphorus, potassium)<br>• Soil texture and composition |
| **CROP**<br>• Crop growth stages<br>• Crop health and vigor<br>• Crop yield data<br>• Crop pest and disease data | **IRRIGATION**<br>• Irrigation scheduling and timing<br>• Water usage and application rates<br>• Soil moisture levels before and after irrigation |
| **REMOTE SENSING**<br>• Satellite imagery<br>• Aerial imagery (drones or UAVs)<br>• Spectral data (e.g., NDVI for vegetation health)<br>• Infrared imagery for temperature monitoring | **ENVIRONMENTAL**<br>• Air quality data (relevant for livestock farming)<br>• Water quality data (relevant for aquaculture and irrigation)<br>Crop Management<br>• Planting dates and methods<br>• Fertilizer and pesticide application rates and timing<br>• Harvesting dates and yield per acre |
| **FARM INFRASTRUCTURE**<br>• Information on farm buildings and structures<br>• Storage capacities for crops and livestock products<br>• Energy consumption data | |

**Figure 2.** Type of agricultural data collected by IoT sensors.

Due to the wireless transmission of data to and from the edge devices and sensors/actuators, the presence of redundant data, inconsistent data, as well as null value-rich data are familiar issues with original and raw data, and thus data preprocessing is an essential phase in the data-mining procedure. Extracting accurate data from all the sensed data improves the accuracy of the system in determining irrigation, fertigation, and pest-control requirements. We propose a denoising methodology used in RNA sequencing to detect anomalies in the collected data, isolate them, and then dump them. FPKM and K-means clustering, as determined by authors in [7], is suited to data that has varying sizes and randomness.

Apart from denoising the data, clustering [8,9] plays a crucial part in ensuring efficient energy consumption by utilizing optimization techniques to distribute computing tasks and processing resources amongst the edge devices.

Consider a single cluster of devices in an agricultural area; in order to determine the irrigation and fertigation requirements, we must read at least 15 parameters [10] for every single crop in the area, access the water and NPK requirements from the database, compare it with the read values, and utilize a series of IF-THEN rules to initiate the process. With the help of clustering, these tasks can be distributed amongst the edge devices in a single cluster; this reduces instances of overburdening and idle devices, which can lead to excessive energy consumption and resource wastage at the same time.

Due to the variety of processing tasks involved with varying resource requirements, for example, NPK requirements tasks, these tasks can be offloaded to those edge devices that are equipped enough and have the appropriate resource allocation to perform them.

Further, in order to reduce the distance of data transmission, clustering ensures that the data are processed at the closest edge device.

Other benefits include dynamic resource allocation, energy-aware scheduling, and predictive analysis to determine resource allocation during predicted peak workload hours e.g., irrigation time and monitoring energy usage.

## 3. Experimental Setup

Our system architecture shown in Figure 3 is a small-scale prototype consisting of DHT11 sensors to monitor the temperature and humidity of the soil, ZigBee Communication Protocol, a Dell 1U server equipped with a 3.3 GHz Intel Xeon CPU, 8 GB RAM, and a 1 TB SATA hard drive, having per server maximum and static power consumption of 260 W and 120 W, respectively. The edge-computing platform is the eclipse ioFog paired with kubernetes as the cloud service provider. As the source of renewable energy, we have chosen two solar photovoltaic cells having a peak output of 65 W. We use a DC-DC converter, and we include a battery to store excess energy produced.

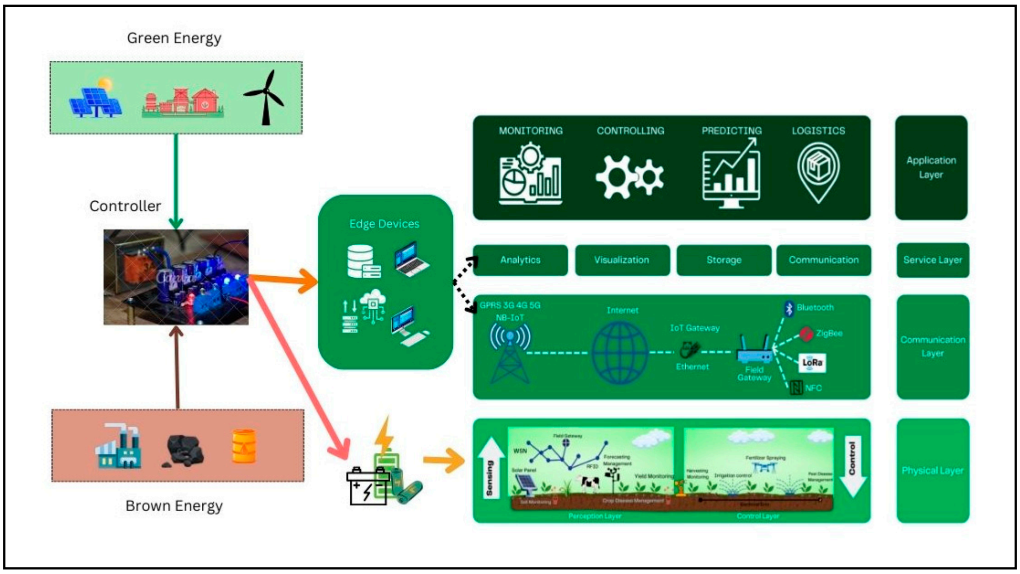


**Figure 3.** Experimental setup.

## 4. Results and Discussions

When we integrate microgrids with edge computing in an agricultural wireless sensor network, we obtain an energy-secure infrastructure that combines task-handling capabilities such as energy management, renewable energy production, and monitoring the energy usage of deployed IoT and edge devices. The energy storage component of the proposed architecture serves as a sustainable way to efficiently utilize the produced energy, securing future resource requirements and a way to monetize and use the energy produced in cases where it exceeds the edge device requirements. The energy-aware nodes deployed at essential points of the microgrid possess the capability of energy monitoring, dynamic load balancing, and energy distribution for real-time and continuous data. Enhanced energy management and real-time decision making contribute to sustainable and robust farming practices. The use of the FPKM algorithm integrated with the K-means clustering algorithm ensures robust preprocessing to minimize the latency and discrepancy in actuator instructions, thereby minimizing the risk of improper irrigation and fertigation that could lead to widespread crop failure. Clustering in edge computing optimizes task distribution, allocation of resources, and efficient device utilization to enable offloading mechanisms and parallel computation. The renewable energy generation for solar and wind was obtained from statewide energy consumption as shown in Figure 4.

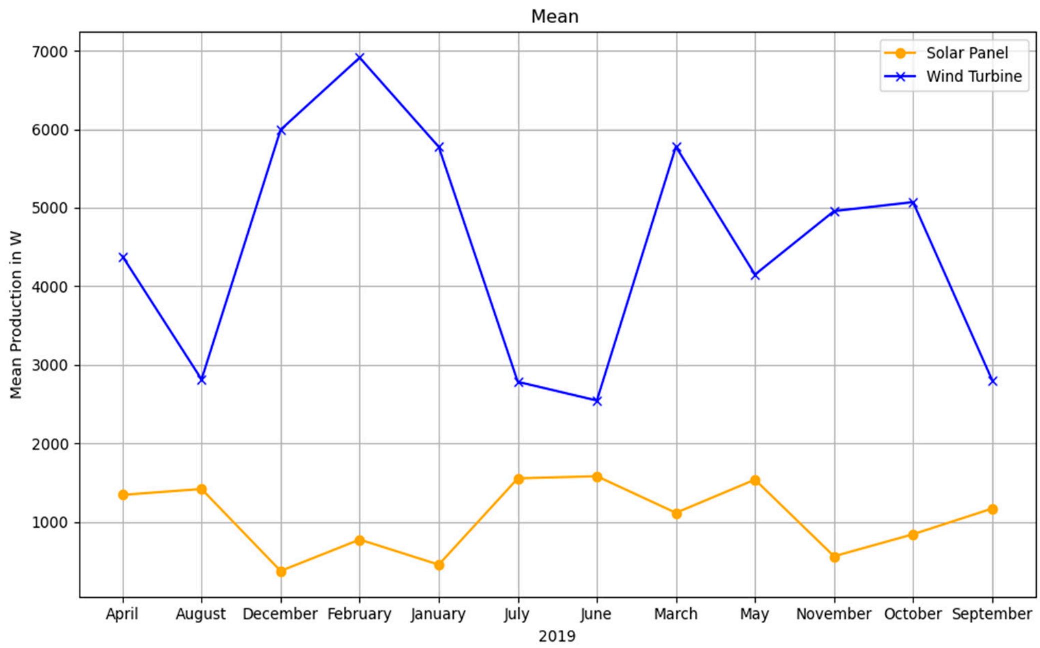


**Figure 4.** Renewable energy generation [11].

The energy consumption of edge devices and the IOT sensors was monitored, collecting two sets of data: with a microgrid integrated, and without a microgrid integrated. The results, along with the load of the network, were plotted on a graph using MATPLOTLIB libraries on Jupyter Notebook. The graph shown in Figure 5 significantly reduced energy consumption when using microgrid infrastructure to power the devices. Additionally, it shows minimal difference in the energy required and energy consumed compared to a traditional system, thus ensuring minimal energy wastage through heat dissipation.

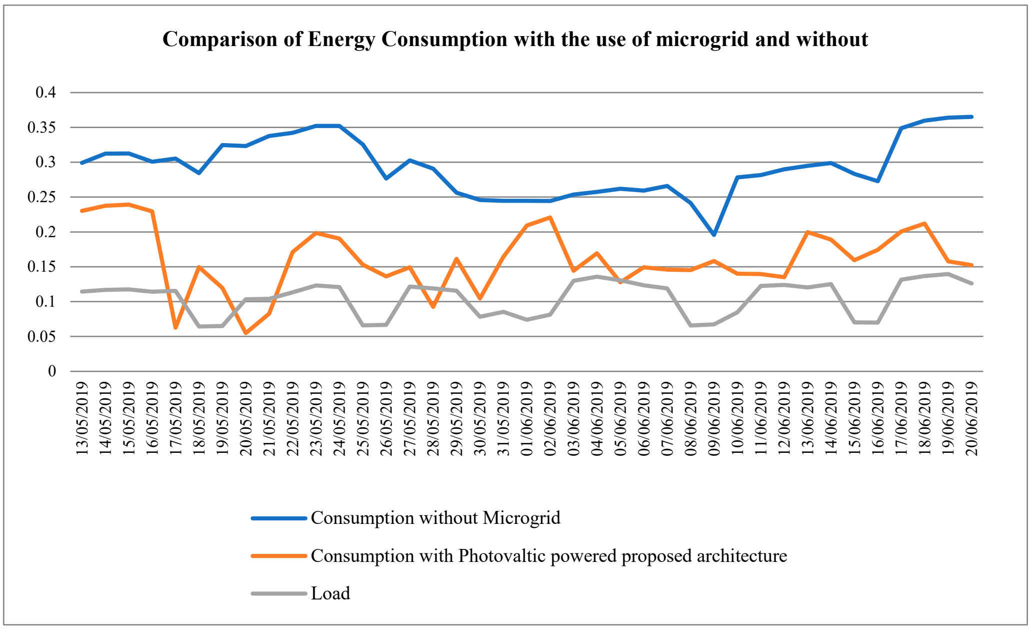


**Figure 5.** Comparison of energy consumption with the use of microgrid and without [12–14].

## 5. Conclusions

Thus, we have proposed an edge computing framework that addresses the issue of efficient energy usage by integrating it with a microgrid infrastructure that produces renewable energy from agricultural (green energy) waste and industrial waste (brown energy).

Our work plays an important role in the sustainable development of the agricultural sector by providing solutions to limited network connectivity, off-the-grid croplands, and an abundance of noise that affects the actuator instructions. Furthermore, we highlight the importance of the FPKM algorithm in the preprocessing stage and the essential role of the K-Means clustering algorithm in edge computing to support data analysis, the management of resources, offloading, and load balancing to develop an optimized computing environment safeguarded from latency and excess traffic issues, all while utilizing resources efficiently. Performing further research in the field of smart agriculture to ensure efficient energy usage and securing maximized crop yields to provide food security must be achieved for an ever-increasing population like ours. Future work entails incorporating edge-caching mechanisms to further improve the spectral efficiency of the architecture.

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**Conflicts of Interest:** The authors declare no conflicts of interest.

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