UNIVERSITY OF RWANDA,

COLLEGE OF SCIENCE AND TECHNOLOGY,

AFRICAN CENTER OF EXCELLENCE IN INTERNET OF THINGS (ACEIoT)

A MACHINE LEARNING SYSTEM FOR IOT CONTROL OF IRRIGATION AND FERTILIZATION TO OPTIMIZE RICE YIELD IN RWANDA

PhD. Thesis submitted in the fulfilment of requirements of award of PhD Degree in Internet of Things – Embedded Computing Systems.

Submitted by

Peace Bamurigire

(218014358)

28thJune 2022

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Main Supervisor: Prof. Anthony Vodacek

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28^{th} June 2022

DECLARATION

I hereby declare that the dissertation entitled "A Machine Learning System for IoT Control of Irrigation and Fertilization to Optimize Rice Yield in Rwanda" to be submitted for the Degree of Doctor of Philosophy is my original work and the dissertation has not formed the basis for the award of any degree, diploma, associate ship or fellowship of similar other titles. It has not been submitted to any other university or institution for the award of any degree or diploma.

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Date: 11^{th} August 2022

Peace Bamurigire, a Ph.D. student of UR-ACEIoT student ID 218014358, successfully defended the thesis/dissertation entitled "A MACHINE LEARNING SYSTEM FOR IOT CONTROL OF IRRIGATION AND FERTILIZATION TO OPTIMIZE RICE YIELD IN RWANDA", which we prepared after fulfilling the requirements specified in the associated legislations, before the thesis examination members whose signatures are below

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FORWARD

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CONTENTS

LIST OF ABBREVIATIONS

UR:	University of Rwanda
ACEIOT:	African Center of Excellence in Internet of Things
MCP:	Markov Chain Process
SARSA:	State–Action–Reward–State–Action
IoT:	Internet of Things
SMS:	Short Message Service
GSM:	Global System for Mobile
APP:	Application
NPK:	Nitrogen, Phosphorus, and Potassium
ha:	Hectare
W_{ad}:	Water Added
W_{ex}:	Water Extracted
ΔW:	Soil Water Content
GIS:	Geographic Information System
RFID:	Radio Frequency Identification
WSN:	Wireless Sensor Network
LoRa:	Long Range
GPRS:	General Packet Radio Service
MLmodel:	Machine Learning Model
NISR:	National Institute of Statistics of Rwanda
TSW:	Cumulative Total Soil Water
CNW:	Calculated Needed Water
ET:	Crop Evapotranspiration

ERF:	Effective Rainfall
K_c:	Rice Coefficient
FAO:	Food and Agriculture Organization
S:	State
A:	Action
i:	Time Step
C:	Cumulative
J:	Days
SP:	Seepage and Percolation
FeP:	Iron Phosphate
Al-P:	Aluminum Phosphate
Ca-P:	Calcium Phosphate
O-P:	Occluded P
Sl-P:	Soluble Orthophosphate
O_2:	Oxygen
NH_{4^+}:	Ammonium Cation
NO_{3^-} :	Nitrate
ARE:	Agronomic Efficiency
PE:	Physiological Efficiency
APE:	Agrophysiological Efficiency
ARE:	Apparent Recovery Efficiency
UE:	Utilization Efficiency

LIST OF SYMBOLS

Δ: Delta

γ: Gamma

α: Alpha

λ: Lambda

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SUMMARY

Water and fertilization are widely recognized as essentials for optimal rice plant growth. Efficient use of water and fertilization for agriculture are critical to ensure high yields and maximize economic benefits.

The central role of water access for agriculture is a clear challenge everywhere in Rwanda, especially in areas with significant seasonal variation in rainfall such as Muvumba Northeast Rwanda. it fails to increase the resilience of agricultural systems in the face of complex demands for water use in rice due to each stage needs its amount of water independent to previous one.

In Muvumba, where the farmers have a low level of economic development are facing the problem of infrastructure, lack of irrigation control for individual farmers, lack of access to equipment, and low reliability of power and Internet access.

Applying IoT technology will solve the problem that is why in our thesis explores algorithms using Markov chain process that automatically provide irrigation control according to the stage of rice, when the system are operating correctly. In cases of system component failure, the system switches to an alternative prediction mode called SARSA. The SARSA algorithm outputs realistic irrigation options depending on previous data from Markov chain process algorithm until the failure is corrected. Farmers can receive information about the faults and suggested actions via SMS. Both algorithms are examined using simulations to assess how the system might respond to growth stage, effective rainfall, and evapotranspiration for both correct operation and failure scenarios.

Regarding fertilization, Muvumba plantation suffers from poor fertilization management due to only one laboratory for testing soil nutrients which causing delays in soil testing and information dissemination. Here, two algorithms based on fuzzy logic were designed

with input from well-known best practices for local conditions. The first is a nutrient balance method for automatic decision making and the second is dissimilar subtraction for the case of system fault. The fuzzy algorithms have a linguistic rule base of 183 IF THEN statements linking measurable field conditions to crop yield. These rules were designed using input from interviews with Government of Rwanda (GoR) agricultural experts and published knowledge of site conditions. The rules incorporate the known nutrient requirements of the different growth stages of rice. To validate the algorithms, historical weather and field data are used to drive simulations of yield for different plots during the season A(September-march) of 2020 at sites in Northeast Rwanda. Predicted yields are compared to measured yields for scenarios with different irrigation levels and fertilization amounts and with and without full Internet connectivity.In case of fault tolerance in the commonly occurring case of network communications failure, an dissimilar subtraction algorithm where the farmer is informed on the system status and recommended actions via SMS through a GSM.

The novelty of our work lies on designing low-cost IoT algorithms system would automatically provide irrigation and fertilization control according to seasonal and daily irrigation or fertilization needs when the system sensors and communications are operating correctly. In cases of system component failure, the system switches to an alternative prediction mode and messages farmers with information about the faults and realistic irrigation or fertilization options until the failure is corrected controls water and fertilizer on each stage of rice more efficiently with fault tolerance to optimize yields.

CHAPTER 1

INTRODUCTION

Rice is a staple food which has been cultivated for at least 8,000 years around the world. More than 3.5 billion people depend on rice for more than 20% of their daily calories [1]. In Asia, rice is important as a source of income to a millions of rice farmers and different workers[2]. In the other countries 123,250 square kilometres of land is planted with wetland and upland rice, and total of rice production is 19000 million kg[3, 4]. The population of the African continent consumes 11,600 million kg of milled rice per year[5] of which 3,300 million kg (33.6%) is imported. African rice farmers tend to cultivate rice below the yield potential and cannot produce enough to account for rapid population growth. Furthermore, the quality of the rice they harvest cannot compete with that of imported rice[6]. Thus, most African countries are far from self-sufficient in meeting their rice consumption and with population increasing, diet change, and stagnant yields on existing land, countries will not become fully self-sufficient in rice[7].

In Rwanda agriculture plays a crucial role for economic growth and reduction of poverty. As the backbone of the economy, agriculture accounts for 39 percent of gross domestic product (GDP), 80% of employment, 63% of foreign exchange earnings, and 90% of the country's food needs. Among other crops, rice has been identified and promoted as one of the priority food crops for both rural and urban households because rice is not only a rich source of carbohydrate and proteins but also provides nutrients, minerals and fibre. However, 76% of the rice purchased is imported from other countries in order to meet the demands of consumers [8]. According to the National Rice Program of the GoR [9, 10], past predictions for the national demand for rice were underestimated, where the national institute of statistics of Rwanda [11] indicates that production of 2018 was only about one third of demand, thus leading to negative economy [12] where the local production in Rwanda lags behind the consumption needs of national market. It is estimated that Rwanda's annual requirement stands at 73 million kg of milled rice in 2012 [13] meaning that at least 5.4kg for person per year. Lagging production is caused by poor water management, lack of public and private capacity, poor fertilization management, and limited commercialization constrained by poor access to output and financial markets[10]. Rice in Rwanda is cultivated mainly in marshlands over an area of approximately 16,302 hectares[14].

The rice plantation in Muvumba Valley where this research was conducted is about 10.6% of the land in Rwanda that is cultivated for rice. Muvumba Valley is located in north-eastern Rwanda in one of the nation's trans-boundary catchments. With high mountains in the west and lower and flatter conditions in the east, almost all-economic growth in the catchment is linked to irrigation for rice agriculture[15]. The plantation was established by the GoR to provide irrigation for the flat land of the valley bottom to support rice farming. This project supports more than 1,750 farmers with field sizes of about 1 ha. Rice is grown in two seasons per year and each season starts as a rainy season and ends in a dry season which requires irrigation (Season A is March to August and Season B is September to January). Unfortunately, while farmers at the Muvumba Valley plantation have adequate access to water, they rely on traditional methods of irrigation control with a lack of field-by-field control of irrigation. This causes conflict and irrigation inefficiency. Further, lack of adequate soil testing leads them to apply more fertilizer than necessary, where they apply 200kg/ha of NPK, and 100kg/ha of urea in the course of a growing season [9]. Fertilizer is administered at time of the plantation and weeding to save labor cost rather than when maximum rice plant uptake occurs, in many cases leading to over-fertilization and soil degradation. The result of these inefficiencies are lower yields of about 2000kg/ha than should be possible for rice. A few individual farmers at Muvumba Valley who are very efficient can produce more than 6000 kg/ha, indicating the potential productivity of the site. In rice agriculture, measuring the soil water level, pH, clay-soil, temperature, water level in tanks/dams, and fertilizer levels is important as it helps farmers manage their rice farming more efficiently. Efficient farmers can use less water and fertilizer while increase yields and the quality of the rice production.

1.1 Problem Statement

The current irrigation system at Muvumba Valley is manual, where farmers observe the water depth and when the water is reduced to a certain level they contact the authorities to divert water to the canals so they can irrigate. However, conflicts arise in this system. First, there has to be a collective request of the farmers to achieve maximum consumption. As a result, the farmers are obliged to plant at the same time. Second, water control structures are minimal, causing further conflicts among farmers when inadequate control of water creates flooding of plots when it is not needed. Finer control of water would decrease conflicts and provide the farmers more choice in planting and harvest. Considering fertilizer, Rwanda has only one soil testing laboratory for testing soil nutrients, causing delays in soil testing and information dissemination. As a result, farmers in Rwanda lack knowledge about soil nutrient status for their plots and consequently often make large errors in fertilization actions. When farmers add fertilizer without knowing the soil nutrient status, their actions can negatively impact soil pH and nutrient availability. In Rwanda, improper timing and amounts of fertilizers result in rice yields that generally fail to rise above an average of about 4000kg/ha per season while at Muvumba Valley the average yield is even lower at about 2000kg/ha.

1.2 Research Objectives

The overall objective of this project was to improve rice production by providing farmers with a low cost and robust means for monitoring farm conditions through the design, develop machine learning algorithm IoT powered irrigation and fertilization support system for rice farmers so as to increase yields. This objective is based on the hypothesis that there are fertilizer and water wastage on farms, which can be analyzed to determine nominal conditions versus problem conditions using a fuzzy algorithm, Markov Chain process and SARSA to provide rice farmers information that will allow them to reduce the amount of fertilizer and water from current practice while increasing yield.

1.2.1 Specific Objective

- To design machine learning algorithm for appropriate automatic control of irrigation and fault tolerance.
- To design machine learning algorithm for appropriate automatic control of fertilization and fault tolerance.
- System which integrates both irrigation and fertilization with fault tolerance in order to increase rice yield.

1.3 Overview of the Study Approach

The research carried out in this work takes a modeling and technology integration approach to propose solutions for IoT farming systems to optimize rice production using machine Learning techniques. Specifically, the focus of the research is the improvement of yield production of rice crop while simultaneously reducing inputs. The solutions proposed in this work are relevant and timely for the Rwanda agriculture system. However, for any such solutions, it is important that the beneficiaries of the solution should be involved during the development of the solution. This is because, although people may not know what the solution is, they have firsthand experience with the problems. To fully achieve the objectives of this work, we took a combined approach of both a qualitative and quantitative research methodologies. These two approaches complement each other in that, with quantitative methods one can able test the assumptions, while with qualitative approaches one can easily find out the unknown. Where possible, to test the ideas and models, experiments were carried out.

1.3.1 Sensor System

The system envisioned Wireless sensor nodes capture and transmit data on water level, pH, fertilizer, and other parameters. When these sensor systems are combined with a service-oriented business model, the gains that may be realized and assessed through an integrated system can be amplified. After data analysis the result could be sent to farmers via SMS or smartphone application to help him/her make precise decisions.

1.3.2 Surveys of Farmers and Agricultural Development Experts

The survey utilized questionnaires, documentation, and interviews with farmers, agricultural scientists, and agricultural experts to understand the actual needs and problems. These experts on Rwandan rice production included personnel at the Rwanda Agriculture Board and government agronomists working at Muvumba Valley. The interview questions were designed to elicit responses on practices and knowledge related to irrigation,irrigation required amount at each stage, fertilizer application, fertilizer requirements for the stages of rice growth, and appropriate quantity and quality of fertilizer for different soil conditions.

1.3.3 System Framework

Figure1.1 shows a notional system architecture. The architecture has components for field sensors and Web data, actuators, the system state modeling, fertilizer store and the user interface. The system will either take action depending on the information from the state modeling system to fertigate (when the fertilization is delivered with the irrigation system), irrigate, not irrigate, or extract water from the field. The display system used to communicate the rice field status to the farmer through the smartphone app or short message service (SMS) using GSM protocols. The weather station provides daily rainfall and evaporation and other weather variables and sends them to the cloud database, while the weather forecast can be obtained from the Web. Hardware such as the Raspberry Pi 3 or 4 can be used as the controller and processing unit. Water level sensors in the field help monitor irrigation needs and solenoid valves and pumps will allow water to flow from storage tanks to the rice field under control of the Raspberry Pi. The farmer can check the irrigation status of the field using a smartphone app. If the farmer does not have a smartphone, their phone number can be registered to receive the notification for changes made to their field via SMS. The flow meter sensor will measure the volume of water used for irrigation at every irrigation time step and all the sensed data will be collected to take action based on the decision algorithms embedded on the Raspberry Pi. When a sensor indicates that a certain amount of fertilizer is needed within soil, the store releases that amount to the mixer tank, then the pump turns on, then fertilizer will flow to the field where its needed.

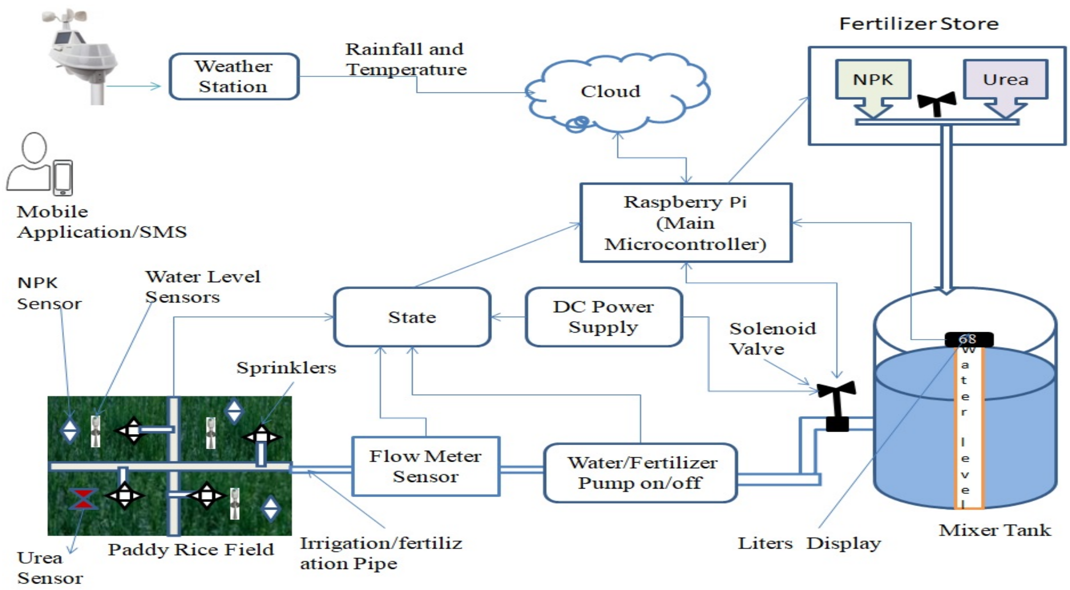


Figure 1.1: System Architecture

1.4 Work Done

This section describes the overview of the accomplishments achieved toward improving rice yield in Muvumba Valley. This research identifies efficient fertilization and irrigation as key for rice agriculture solutions that can lead to increased yield. The solutions proposed in this work aim to address the problems are summarized from items 1 to 5 below:

1. A simulation procedure was formed to demonstrate the key components of the appropriate automatic control of irrigation using a Markov chain process, and SARSA

for fault tolerance. The applied Markov chain process algorithms for automatic irrigation decision-making that were sensitive to growth stage to use water for the irrigation more efficiently. When the water level was below a threshold, the system would irrigate, send field sensor data to a cloud network, and then send system status updates by smartphone, or short message service (SMS) to those farmers without a smartphone. In the case of system failure in the field, the system would switch to a SARSA algorithm, where farmers will receive an alert and an irrigation recommendation depending on data from previous algorithm (Markov chain process) so the farmer can manually intervene. The system will react automatically to water level through an algorithm that adjusts irrigation needs according to growth stage, evapotranspiration, and rainfall. In this study, the core algorithms for water control for normal operation and for failure mode operation were tested through simulation.

2. Intelligent Irrigation, Fertilization, Post-Harvest Management with IoT Technology: Challenges and Setbacks.This research provides an in-depth review of the employment of good technologies in agriculture and elaborates the progressive technologies for good agriculture together with, the Web of Things, cloud computing, machine learning, and computer science.

3. The effects of NPK fertilizer on rice yield and soil condition for irrigated land in Muvumba Valley rice plantation were examined. To cultivate rice, fertilizer is the most important input that supports rice growth and increases yields. Nitrogen (N), phosphorus (P), and potassium (K) are fertilizers which are necessary for rice growth. To improve NPK efficiency, timing and amount are crucial for higher yields and to reduce environmental pollution. This study identified amounts of NPK to be applied at the appropriate time to increase rice production and reduce soil degradation. The recommendation was formed to suggested the minimum and maximum rate of NPK are from 90 to 140 kg/ha to produce rice yields of 6500 to 7000 kg/ha per season. The recommended timing should be at seedling, tillering, and flowering, with the amount of fertilizer determined by the results of the system monitoring.

4. Simulations were done for a system which uses IoT to control both irrigation and fertilization, with fault tolerance, to increase rice yield. The concept is to improve farm production by providing farmers with a low cost and robust means for monitoring farm conditions through the IoT system powered by algorithms for both irrigation and fertilization. This support system for rice farmers was demonstrated to increase yields using these two parameters only. This research was based on the hypothesis that there is fertilizer and water wastage on farms, which can be analyzed using modeling methods such as Markov chain process and SARSA. The method can determine nominal conditions versus problem conditions and thus provide rice farmers information that will allow them to reduce the amount of fertilizer and water from current practice while increasing yield. Simulations using data of parameters from Muvumba Valley rice project in northeast Rwanda demonstrate validity. This method used independently addressed single agricultural production variables, i.e., irrigation or fertilization.

5. Finally, this work expands on prior work by adapting fuzzy logic as a means to account for multiple interacting variables (pH, clay soil content, water level, temperature, NPK, and urea) impacting fertilization requirements for rice production. An IoT-based fuzzy fertilization decision-making algorithm was designed to incorporate knowledge from agricultural experts and expresses the context of soil properties, climate, and irrigation conditions in Muvumba Valley. This work has the hypothesis that an IoT system using a fuzzy nutrient balance algorithm can provide rice farmers information that will allow them to reduce the amount of fertilizer from current practice while increasing yield. The formulation of the fuzzy algorithm was based on interviews with experts and existing knowledge of site conditions. In the long term this methodology can be used within a low-cost system which will control fertilizer automatically at the plot level according to inputs available from soil sensors and the growth stage of the rice. For fault tolerance to the commonly occurring case of network communications failure, an dissimilar subtraction algorithm was designed. Finally, minimum fertilization recommendations are provided to farmers who have few resources so they have the opportunity

to prevent crop loss under critical conditions.

1.5 The Organization of The Thesis

The thesis is organized into chapters as follows:

Chapter 1: Presents the general introduction of the thesis

Chapter 2: Provide the background.A number of work has been done on various aspects of automatic irrigation and fertilization. We give a brief review of some important work which are related to our work.

Chapter 3: Presents the IoT to control irrigation with fault tolerance

Chapter 4: Presents effects of NPK fertilizer on paddy rice yield and soil on irrigated land in Rwanda and how can be managed to increase yield.

Chapter 5: Present IoT to control both irrigation and fertilization with fault tolerance. We also present simulation results of the proposed scheme.

Chapter 6: Present IoT-based fuzzy fertilization decision-making algorithm .We also present simulation results of the proposed scheme.

Chapter 7 concludes the thesis with a brief discussion on the possible extension to our work in future.

CHAPTER 2

BACKGROUND AND THEORY

This chapter describes the scientific theory and technologies, which underpins smart agriculture,specifically of irrigation and fertilization. First, in section 2.1, The existing irrigation and fertilization method for rice. Section 2.2 describes the major application of smart agriculture, section 2.3 covers smart farming approaches in developing countries,section 2.4 covers the overview of modern intelligent technologies for application in smart agriculture. Finally discussion, conclusion, and future work.

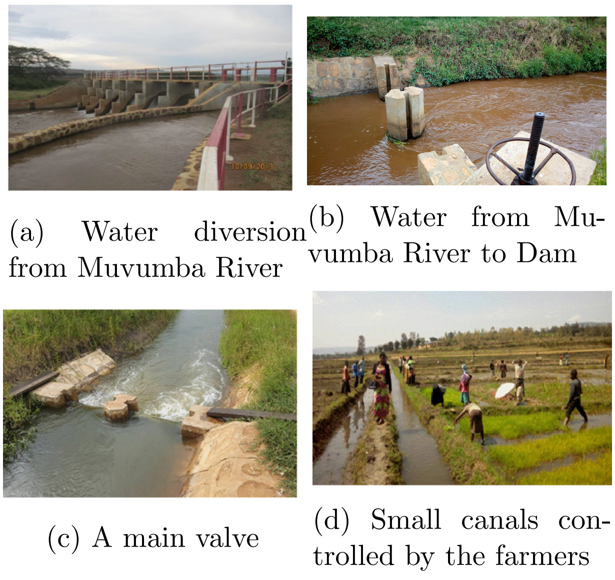
2.1 The Existing Irrigation and Fertilization Method for Rice

The efficient of water and fertilizer for agriculture can be critical to ensure high yields, and maximize economic benefits for regions considered to be facing annual or seasonal.

2.1.1 Irrigation Monitoring System

In Rwanda, irrigation and modernization of agriculture are promoted by the Government of Rwanda(GoR) with the goal to increase agricultural production to feed the growing population and reserve any surplus for export. The GoR has promoted draining and conversion of some swamp areas to agricultural lands and in particular to increase rice production. The GoR established the Muvumba Valley irrigation scheme in northeastern Rwanda in 2012 as part of a multipurpose dam construction project [16]. Based on the two dry and wet seasons per year, there are two rice crops per year in Muvumba Valley. The Muvumba Valley weather is characterized by high temperature and high relative humidity[17], increasing the water demand in the dry seasons. Rice requires a large amount of water during its growth cycle, so water availability is a critical parameter for successful and sustainable rice production. At Muvumba Valley traditional methods of irrigation are used. The main problem affecting rice farming at Muvumba Valley is poor management of water leading to water scarcity[16].

The basic construction of the irrigation project begins when water is diverted from the Muvumba River to a reservoir through a large canal over a distance of 4.2 km as shown in Figures 2.1a, and 2.1b. Main valves to control water are managed by the government (Figure 2.1c). The individual farmers are able to control water once it reaches their fields, as show in Figure 2.1d. During this flow of water from the Muvumba River to the rice fields, some is lost through deep percolation and surface runoff that contributes to water scarcity and ultimately less rice production[18].



(a) Water diversion from Muvumba River

(b) Water from Muvumba River to Dam

(c) A main valve

(d) Small canals controlled by the farmers

Figure 2.1: Traditional irrigation at Muvumba Rice Plantation Valley

Despite the fact that the Muvumba irrigation scheme was established in an attempt to improve the social, economic, and food security of the people, it remains an urgent issue since economic and social difficulties continue to afflict plot holders to the point where controlling irrigation is very challenging, irrigation schemes effectiveness has been harmed, leaving their efforts unfulfilled. Muvumba was built through Basin irrigation which was appropriate method for paddy rice, which was grown on the fields. To obtain an even water level in the basins the slope need to be tremendously flat. Basins could also be constructed in a steeper slope but are then usually constructed as terraces, which appears like staircases. Paddy rice are best grown on clay soil which allows a low loss of water through percolation. It may be full-grown on sandy soils then again the percolation loss will increase and needs additional water to keep up a high water level. looking at the wetting pattern and also the management of the basins the crop growth is often affected. the correct amount of water should be equipped to the basis zone and wetted uniformly. With insufficient water the crop will suffer from drought stress and with an excessive amount of water losses will occur through deep percolation[19]. Furthermore different studies have found[20, 21] to be led factors indicating that climate which also affect amount of water needed for the irrigation, the study by[22, 23, 24] has shed more light on largest amount of water diverted to irrigate, even though, distribution of available water for irrigation to meet crop water requirements is still problem. A recent analysis by[13], reveals that the intensive practice of agriculture across Rwanda places a large demand on water resources, with an estimate of 70% of the available water used in agriculture specifically in rice. Before transplanting, water is needed to saturate the root zone. The water demands for rice are considerable during the succession of growth stages with varying water requirements for the each stage.In their widely acclaimed work, [25] discuss the total demand value of water requirement for the growth stages of rice in different environment. The water balance and water requirement for rice Crop where water balance refers to the accounting of water going into and out of an area. The quantity of water added to, extracted from, and stored within a set volume of soil during a given period of time is considered. It is assumed that in a given volume of soil, the difference between the amount of water added (W_{ad}) to the soil and the amount of water extracted (W_{ex}) from the soil during a certain period is equal to the change in soil water content (ΔW) during the same period of time [26]:

$$\Delta W = W_{ad} - W_{ex}$$

Figure2.2 describes various items entering into the water balance of a hypothetical rooting zone for a flooded rice system where the entry of water into the soil may happen into two different conditions. When water is ponding from above to the soil surface by irrigation, it typically penetrates the surface and is absorbed into successively deeper layers of the profile. However, a portion of the arriving water may fail to penetrate but instead will tend to emanate at the surface or flow over it. The penetrated water is itself later partitioned between the amount that returns to the atmosphere by direct evaporation from the soil or by the extraction and transpiration of plants and the amount that continues to seep downward and eventually recharges the groundwater reservoir. Infiltration is the term used to the process of water entry into the soil by downward flow through all parts of the soil surface. According [27, 28], the process determining how much water will enter the root zone and run off. Hence, the rate of infiltration affects not only the water economy of plants but also the amount of overland flow and its attendant dangers of soil erosion and flooding. The soil conditions, especially at the surface, limit the rate of infiltration, plants conceivably denied sufficient moisture while surface erosion increases. Knowledge of the infiltration process affects both soil's properties and transient conditions by the mode of water supply is therefore a prerequisite for efficient soil and water management.

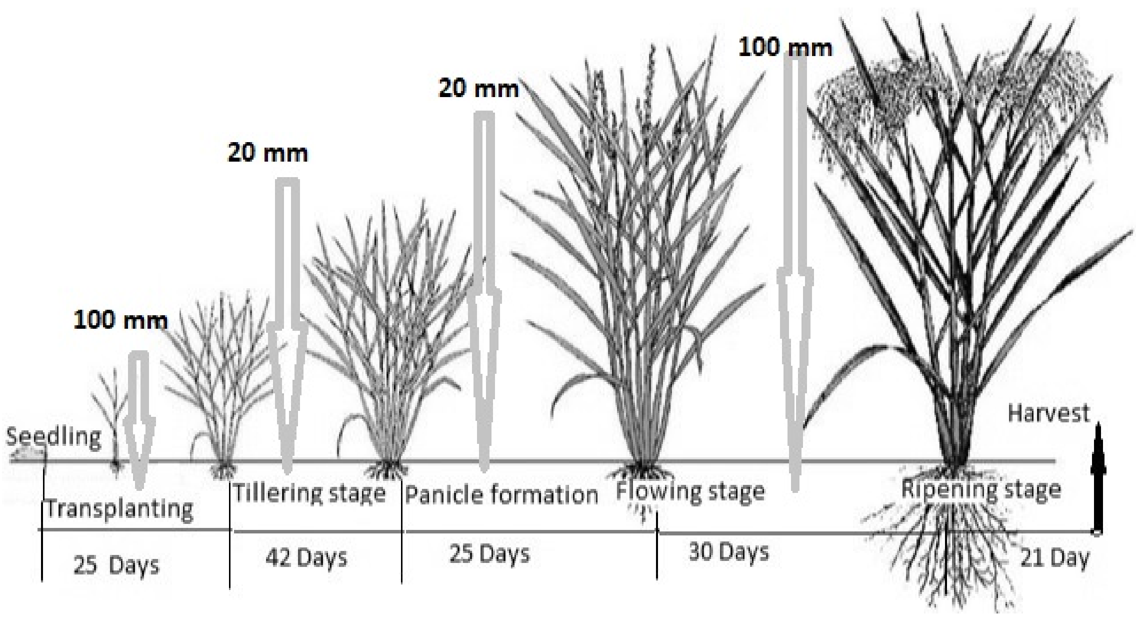


Figure 2.2: Water balance in a flooded rice field

2.1.2 Effect of Fertilizer to the Rice Plant

Globally, agriculture is challenging because of climate change and soil degradation. fertilizer is a key component to keep soil alive and productive for providing better ecosystem services[29, 30]. The fertilization helps in rice for growth, development, and increasing of rice yields. The knowledge of how much to apply are critical during plant growth and development depending on environmental parameter[31]. On the other hand, rice development is defined as the sequence of five stages includes seedling, tillering, panicle growth, flowering,and Ripening which are genetic events that involving differentiation, leading to change in function and morphology form[32]. Development is most clearly manifested in changes in the form of organisms and each stage needs certain amount of fertilizer which is different from previous one.

2.1.3 Fertilization Management Approaches for Rice Growth

The nutrient management system integrates one of the all-natural man-made sources of plant nutrients to keep and preserve soil fertility to enhance rice crop productiveness in an efficient, environmentally safe, ecologically compatible, socially acceptable, and economically conceivable way. The system continues a stability between nutrients eliminated by using the crop and nutrients brought to the soil. The nutrient management system takes into account the availability of nutrients in all kinds of soil, crop requirement, and different factors, such as the elimination of nutrients from the soil by means of the crop, economics of fertilizer profitability, farmers' capability to invest, soil moisture level, bodily and microbiological situation of the soil, reachable soil nutrient status, nutrient recycling and cropping sequence, limiting loss to the surroundings was once very essential to crop growth [33, 34]. Soil is complex substance with thousands of soil types exist in the world having arisen from different material under various ecological conditions. Some are fertile, tillable and wonderfully suited for agriculture. Sustainable agriculture aim to produce food and fiber on a sustainable basis and to repair the damage caused by destructive procedure[35, 36]. The fertilizer should be applied depending on availability of different parameters as shown in figure4.2. When fertilizer are applied in the flooding plot,some are lost through volatilization, leaching, denitrification, or surface runoff[37, 38]. [39] offers a comprehensive overview of agronomic efficiency of fertilizer in marshland was higher when fertilizer was applied in three split application (one at tillering stage, the second at panicle initiation, and third on flowering stage). Minimum grain yield was obtained when fertilizer was applied at flooding, where one part at seedling, the second at tillering, third at panicle initiation and the fourth at flowering. This information demonstrates the ability of decision modeling to adequately monitor and invoke fertilization actions incorporating soil conditions. unfortunately, Muvumba Valley farmers still apply 200 kg/ha of NPK and 100 kg/ha of Urea per season during weeding and planting based on their own knowledge combined with agronomist recommendations[10]. The information demonstrated that due to the poor of applied NPK and Urea, the rice yield is very low. The current practice is not increasing the yield,but soil degradation. It is essential to apply fertilizer where close control of fertilization actions is required to maintain efficient uptake of nutrients over time, which will potentially increase the return on investment by more precise control of fertilization to decrease costs while boosting yield.

2.2 Major Applications of Smart Agriculture

Early works in this area focused primarily on smart farming, but a few agricultural businesses utilizing the Internet of Things. Every element of traditional farming operation may be substantially improved by combining cutting-edge sensors and Internet of Things technology. Now, the Internet of Things (IoT) and wireless sensors' harmonious incorporation into smart agriculture can increase agriculture production. Appropriateness of land, pest monitoring and control, irrigation, and yield optimization are just a few of the conventional agricultural issues that IoT may assist in resolving through the implementation of smart agriculture approaches[40]. Figure 2.3 illustrates the comprehensive paradigm of smart agricultural monitoring system applications, facilities, and sensors. Agriculture applications are classified as IoT agricultural apps, smartphone-based agricultural apps, and sensor-based agricultural apps. Wireless sensor networks (WSNs) have been used to enable IoT applications for smart agriculture, including irrigation sensor networks, yield prediction, precision agriculture, and soil monitoring[41]. Significant instances of how new technology assists in the general improvement of agriculture.

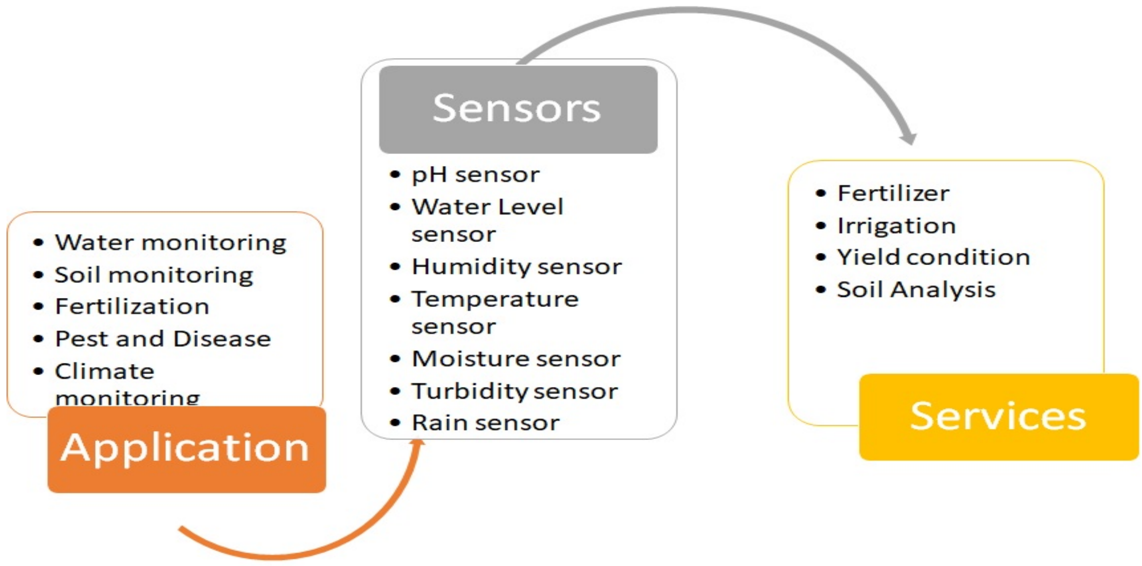


Figure 2.3: General structure of smart agriculture.

2.3 Smart farming approaches in developing countries

The implementation of smart farming technology is considered very important around the globe, and developing countries are interested in localized such technology[42, 43]. The developing countries have several challenges in implementing smart systems regarding the availability of infrastructure, and other capabilities possessed by individuals[44]. Therefore, the obstacles to the implementation of smart agricultural technology in developing countries can be summarized as follows; 1) The availability of a suitable network is the most crucial factor in terms of data transmission between sensors via the Internet. 2) The availability of sensors as they are responsible for measuring the different conditions on the farm. 3) Availability of devices and equipment that can achieve agricultural operations. 4) trained experts based on smart farms. Though, their several approaches in the developing countries, especially in Rwanda, several factors affect the majority of farmers regarding the implementation of smart farming technology such as low socio-economic backgrounds and face many challenges due to increasing cost of cultivation and fertilizer. Furthermore, one of the significant natural problems influencing agricultural productivity is climate change.[45, 46, 47]suggested algorithms concerning the implementation of smart systems such as weather forecast to mitigate the effects of climate change in East Africa.Although this approach is interesting, it fails to account considered system which efficient use of water and fertilization for crops compared to traditional agriculture,which can make it more resistant to drought and soil degradation, and contributing to reducing climate impacts in rural areas.

Table 2.1: Different research studies on Smart Agriculture

Authors	**Research Purpose**	**Technology Used/Techniques**	**Benefits**	**Findings and Challenges**
[48, 49]	Water management	Bluetooth, WiFi, RFID, Zigbee, LoRa, and Raspberry pi	Can identify the moisture, humidity, temperature, and irrigation.	casual workers cost ,Water consumption Crop from irregular irrigation
[50]	Irrigation monitoring	WSN, data analytic,node sensors and web Application	Optimum irrigation of the water for farming crops	Power consumption,and network
[51]	Crop management, Irrigation management	Mobile technology, GPRS, Wi-Fi, Raspberry pi, Zig Bee	Improve the yield, low cost	Unstable weather water shortage, irregular water usage

[52, 53]	Harvesting nodes	WSN, Solar energy system. Image processing technique	Prevents data loss and collusion, increases the lifetime of WSN	there are many of challenges in deploying the Wireless network system for harvesting and one of many is the periodic replacement of batteries
[54]	Crop growth	green-crop (gCrop) based on ML model, Wireless Sensor Network and IoT	Obtained accuracy was 95% using polynomial of third-degree of Regression model while the computation time is very high	there are many factors affecting crop growth which includes: climate change, soil erosion, and biodiversity loss
[55]	Nutrient Management	Raspberry pi, Mobile technology, Wi-Fi	Can monitor weather conditions,cost-effective, automatically monitored disease associated with rice species	Low or high watering, lack of cope with climate change, soil erosion and biodiversity loss nutrition management

[56, 57]	Crop productivity	Big data storage and analytics, IoT, Data Mining, Cloud computing, Data Analytics	Network architecture,platform and design helps access to IoT,improves crop productivity, Provides an overview of IoT applications, sensors, protocols And data-enabled technologies.	genetic plant improvement, sustainable land use, water management, and integrated nutrient management as well as control of pests, diseases and weeds

2.4 Intelligent Irrigation, Fertilization,and Post-Harvest Management with IoT Technology: Challenges and Setbacks

2.4.1 Introduction

Smart technologies in agriculture can increase the assembly of agricultural crops and eutherian, since autonomous systems are ready to effectively control actuators, improve the use of resources of utility management, and guarantee the merchandise adapted to promote needs while increasing profits and minimizing the value of production[58]. smart agriculture refers to the utilization of technologies like IoT for assortment of weather knowledge, observance of crop's growth, early detection of crops diseases,water level,fertilizer, barrier of crops wastage dues to effective harvest of crops inside and outdoors the farms, increase of production for each crops and eutherian[59, 60]. From Fig 2.4, it is inferred that agriculture has evolved from 12,000 B.C [61, 62], using of application of numerous and improved farming ways, techniques for crop planting, monitoring and harvest, and therefore the use of mechanized tools for agriculture. Throughout the prehistorical farming was practiced victimisation by sticks, hoes, and hand gathering of crops in agriculture[63, 64]. Farmers will currently monitor their farms remotely from their smartphones and management devices. Farmers cultivate crop victimisation seeds that are genetically changed to forestall illness and infestation on the farm. These seeds additionally facilitate improving the standard of the crops made and boost the production. Most research on [62, 65], has focused on the improved quality of crops by reducing food inadequacy across the world. This paper discusses an summary of the assorted state of the art intelligent technologies for sensing in agriculture farming.

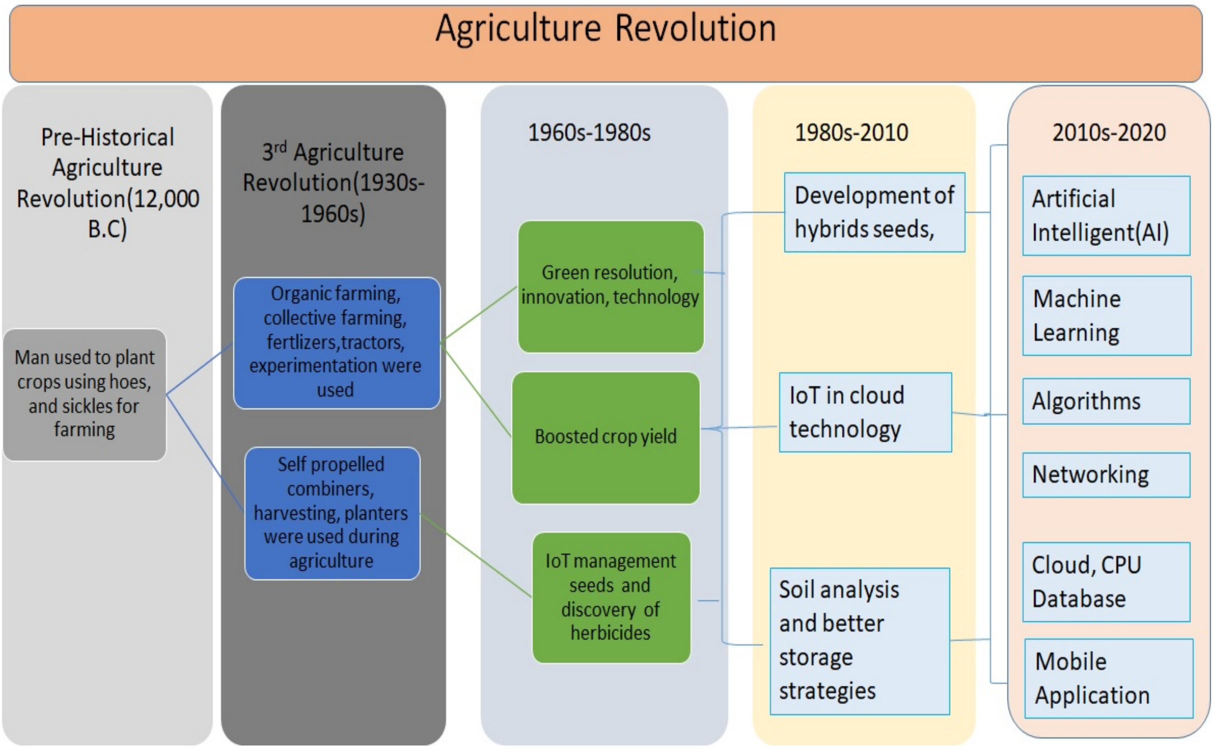


Figure 2.4: Transformation of Agriculture

2.4.2 Overview of Modern Intelligent Technologies for Applications in Smart Agriculture

2.4.2.1 Smart Agriculture

Smart agriculture is that the application of intelligent data and communication technology systems like sensors, IoT, cloud-based processes, machine learning, computer science, networking to the agriculture system like crop cultivation,irrigation system, fertilization management system,to say with the only purpose of boosting the production[66, 67, 60]. It may be inferred that smart farming involves the implementation of technological, computer code, and hardware solutions to boost the farm's outcome. Farmers within the past years have ploughed soil mistreatment holes to power the plow, and used bush burning practices to clear farmland for planting. Some have used animal waste for manure, however nowadays fertilizers are used that are made of elements, nitrogen (N), phosphorus (P), and potassium (K),Urea and many more minerals to create the soil appropriate for effective farming practices.Farming practices have modified over the years, from using holes and cutlasses to machine cultivation fields and machine gathering crops. During this respect, smart agriculture has introduced an additional economical technique wherever farmers use IoT to boost all farming practices and methodologies. Nowadays, farmers will monitor remotely their farmers several kilometers faraway from their farms and remotely activate the actuators mistreatment IoT put in on the farms. The authors in [68, 69], have bestowed that IoT systems may be accustomed to monitor each stage of crop production. These IoT systems use AI to spot either low, commonplace or faulty merchandise within the organic phenomenon. This can facilitate to spice up client safety needs through the clear life cycle system. The limitation of this analysis is said to the safety of the knowledge system and therefore the ability of the various networks to completely different players of the IoT system. In line with [70, 71], smart agriculture has improved water management system mistreatment IoT technologies. It may be deduced from their paper that higher irrigation of water through smart agriculture devices is doable. smart agriculture has increased the period of time climate forecast and soil management practices for agriculture. The authors mentioned that smart agriculture has improved crop planting and growth, soil temperature, moisture, pest infestation, observance processes within the farms. The limitation of this analysis is that recommendations on the management of the data generated in smart agriculture have not been provided. The authors mentioned that by the year 2050, farmers can use IoT to spice up food production. Their analysis has thought that sensors are going to be employed in roughly 525 million farms globally by the year 2050. This paper reveals that a sized variety of sensors are going to be used, and a large amount of information are going to be collected, analyzed, and transmitted across varied smart agriculture. Smart farming could be a non-manual farming system that makes use of knowledge technologies like IoT at intervals within the farm and has helped the irrigation system and plant food usage in farming. Therefore, smart agriculture techniques have reduced water wastage on the farms, enhanced higher crop yields, and offered higher plant food application procedures. Smart farming has increased agriculture mistreatment robots for fruit gathering and crop yield prediction, this technology through digital image mapping system has increased insect pests, disease, and fires observance. The big information generated throughout the utilization of image mapping need high-end process power computers to method and analyze them, thereby limiting the effective use of smart agriculture technologies. Additional work is needed in computer code development to handle the demand for giant information set analysis at intervals the agricultural sector and discuss the utilization of visual images in information analysis for smart agriculture applications. Their model has used a period of time applied math analysis approach to handle period-of-time responses to users' requests. It may be deduced from their work that statistical analysis may be accustomed to validate the snap and quantifiable of a farming system.Subsection 2.4.2 discusses smart agriculture technologies, which gives a summary of the application of intelligent technologies to smart agriculture, crops, and post-harvesting. Alternative intelligent technologies such as sensors, IoT, and pilotless drone area units are mentioned in Subsection 2.4.3. The impact of climate on agriculture is discussed in Subsection 2.4.4. A review of the known challenges and problems from the existing analysis on smart agriculture is mentioned in Subsection 2.4.5. the utilization of cloud technologies and machine learning area unit is mentioned in Subections 2.4.6 and 2.4.7, respectively.

2.4.2.2 Crops Production

The marked watershed rule has been used for the separation of a specific leaf from a background obstructive of overlapping leaves [72, 73]. It will be deduced from their analysis that the rule enhances the filtering of crop leaves. It will be inferred from their analysis that higher segmentation of cucumber spot edges has been obtained by weighted neighborhood grey values. The algorithm helped the researchers to get the associated intersection, thereby minimizing the computation time. It had been mentioned in their paper that a single-chip laptop that implements neural network analysis with little or no computation power for the identification and separation of plant diseases within the strawberry plant has achieved successful rates of 97%. The procedure time for the analysis is around 1.2 for the illness identification and grouping of diseases within the region[74, 75]. The limitation of their analysis is that the single-chip laptop has low procedure power and for top vision resolution capturing and analysis of disease,a high-end laptop quicker than the human eye must be provided. The challenge of segmentation of the illness has not been overcome in their work, the plants will show several symptoms at identical time or show totally different—completely different symptoms at different stages, which makes it terribly cumbersome to observe the precise variety of infection of the crop. K-Means is that the most reliable methodology for the separation of plants with diseases. It will be inferred from the existing analysis that their approach involves victimization, support vector machines, and neural networks. Their approach is incredibly quick, reliable, and precise. Its been identified in [76, 77], that smart agriculture has helped to watch infections in crops at a way quicker detection rate. However,there exist limitations within the algorithms, and the communication interaction among the sensors, laptop devices, transmission protocol used for quicker diagnosing, and detection systems for crops.

2.4.2.3 Post-Harvesting in Agriculture

Acquiring the colour and form options of the sweet peppers through the RGB-D detector, that are used for the geometrical relationship between the sweet pepper and therefore the peduncle for the harvest of the crop [78]. It may be deduced from their research that this approach has enabled the analysis's to calculate the size of the pepper. The limitation of their analysis is that the detection speed of the device is incredibly slow. This approach has been applied solely to the sweet pepper peduncle. The best harvest age for a coconut plant may be determined using exploitation and the Monte Carlo simulation[79]. It may be deduced from their analysis that the determined harvest age of 16 days of coconut per crop cycle has been achieved, that invariably influences the commerce price of the coconut exploitation multivariate analysis. The limitation of their analysis is that the simulation has been tested solely on their farm. However, different factors like demand, inventory, holding value, and transportation value have not been thought of, which can influence the price of the coconut crop. Post-harvesting has been improved upon by introducing smart agriculture as rumored in [80, 81]. In one of these reports[82, 83], some limitations like rewriting of the model used for sweet pepper harvest to enhance the speed of the machine which can boost crop production[84, 85]. It may be inferred from[82, 83] that they need not think of different factors to assist and enhance the performance of this algorithmic rule that embodies the demand of the market, holding costs, transportation value, government laws regarding agriculture and government levies, taxes that moderately affect the selling price of the determined harvest age of coconut. It may be deduced from table 2.2 below that the smart agriculture devices used in crop production expertise are power problems [86, 87]since the devices used for observance crop area unit battery operated. From this same table, it noted that transportation value, inventory assortment,communication protocol, and market demand have been a challenge for smart agriculture farming as cited in [88, 89].

2.4.3 Technologies Used in Smart Agriculture

2.4.3.1 Sensors Used in Smart Agriculture

It was mentioned in [90, 91] that sensors are factory-made that square measure the accustomed sight, the water level among the leaves of plants, these sensors change researchers to analyze the variation of the water level in leaves of plants, a number of these sensors square measure embedded with the frequency chip, this technical detective work leaf water stress level is a new advantage in Smart agriculture. It was mentioned that the employment of junction rectifier lighting and dimming system incorporated with sensors therefore reduced power consumption in farm and up safety conditions for men. Sensor square measure devices that facilitate the transmission of information from soil or liquid to networks [92, 93],that the IoT sensible stick device transmits soil wetness knowledge among the network. As an associate degree example, the DS18B20 temperature device could be a terribly reliable device used for capturing temperature knowledge, and it are often reduced that the soil wetness devices are accustomed to capture knowledge of the soil condition and transmitted by the sensor to the network. It can be inferred from [94, 73] that sensors facilitate researchers to automatize the farming system and collect knowledge among the farms.

Table 2.2: Correlation of crop production and post harvesting in smart agriculture

Properties	**Crop production**	**Post harvesting**
System computational power	N	Y [95]
Language of Algorithm Communication	N	N/A[96]
Crowd control and counting	N	N/A
Batteries power it	N	N[97]
Psychological effect	N	N/A
Detection speed	Y	Y[98]
Demand of market	Y	N
Inventory	Y	Y[94]
Carrying cost	N	Y[79]
Fare	N	Y[79]

Yes = Y, No = N, N/A = Not Applicable

2.4.3.2 Drones in Smart Agriculture

Early findings on [99, 100] led to use deep learning technical for crop image classification, vegetation identification of segmentation, disease, weed, and crop nutrient detection with the help of sensors with cameras mounted on the drone. Therefore, drones were used for numeration crops and yield prediction victimization deep learning. drones were accustomed to capture information in smart agriculture,the drone was equipped with cameras, sensors, and GPS, enabling the device to capture information within the sensible farm from possible heights for various victimization's applications in sensible farm management observance. The information assortment and process technique that still needs a lot of sweetening as a result of imaging and voice information was terribly advanced to process compared to different formats could be a challenge. Using drones in smart agriculture was facilitated to attain a special localization system that permits the drone to scan chosen areas on the farm, thereby collection information from chosen IoT nodes. Their work conjointly educates America that this method helps to preserve node energy since the drone handles the operating load. drones treat low power frequencies to save their energy usage. Moreover, their analysis indicates that the drone enhances localization of cluster head and shunting of connected nodes. However, the limitation of their work is that they need not test their model during a farm wherever victimisation sensors, actuators, AI, and drone are deployed at an identical time to see if most preservation of the drone energy will be achieved. Some drone devices have special imaging modules like multi-spectral, thermal, and visual video pictures that are result-oriented for timely reliable info analysis for smart agriculture. The analysis results, victimisation, spectral, thermal, and video imagination are ready to generate 3D models from their analysis. They inform America that drone has been used for the mapping of weeds and management, vegetation growth observance and yield estimation, vegetation health observance and sickness detection, irrigation management, and crop spraying. It was deduced from the analysis of[101], drone has improved smart agriculture and increased crop yield. In the drone picture victimisation segmentation methodology, crops was spaced on the farmland. It was deduced from their paper that the strategy of crop line segmentation is not terribly effective once the crops are terribly about to one another. Double cameras were accustomed to capture crop pictures, serving to researchers to come up with 3D dimensional models. This has helped to discover that the rice crops have a lot of efficiency from the pictures captured from the drone. There is a necessity to conduct a lot of varied experiments on totally different crop fields to administer a lot of behaviour to the current approach. The authors in[102] mentioned that edge nodes expertise challenges throughout the transmission of information over long distances at intervals within a network. They urged that employing an utterly farm will facilitate to breakdown it since the drones will establish property between the nodes and the base station victimisation using the LoRa protocol. The limitation of their analysis is that they need not test their network style during a state of affairs victimisation, various edge nodes wherever the drones will fly in high altitudes. It will be inferred from Fig. 2.5 showing a spectrum wherever a drone is employed during a farm to capture data via Wi-Fi properties from the sensors put in on the stock and crops. The drone transmits these information via wireless connectivity to the bottom station, so the information eventually is transmitted to the cloud. According to [103], drones was accustomed and collected thermal and multispectral information from a farm to work out the link between the options of the pictures collected and the onion irrigation treatment. It was deduced from their analysis that the drone flight height will be influence accuracy of the onion irrigation system. In addition, onion irrigation estimation will be affected by victimisation neural networks with totally different image spectral bands. Their result educates America that the Blue, green, red, and near-infrared (RGB-NIR) image band has created the most effective accuracy in the analysis for the onion irrigation estimate. Several drones are developed for agriculture over the years. A number of [100] mentioned drones in their publication that Agdrone with the ability to hide 600–800 acres at intervals associated degree hours at altitude of 400 ft. In addition, the DJI matriculation one hundred encompasses a double the battery facility and has an additional 40 min flight amount compared to different drones. This drone is incorporated with GPS navigation system. Moreover, knowledgeable America of different drone systems like Agras MG-1-DJI with the distinctive ability to hold 10 KG of liquid over a region of 4000–600M^3 within 10 min, manual spraying is 70 times slower than this drone, DJI T600 will capture 4K video pictures, the EBEE SQ used in the main for plant observance from early growth to maturity, Lancaster five preciseness Hawk equipped with sensors for temperature and humidity information capturing and SOLO AGCO with high preciseness image capturing capabilities. It will be deduced from their paper that drone has improved farming through high preciseness information capturing, quicker spraying of farms, and effective observance of farms as shown in figure 2.5.

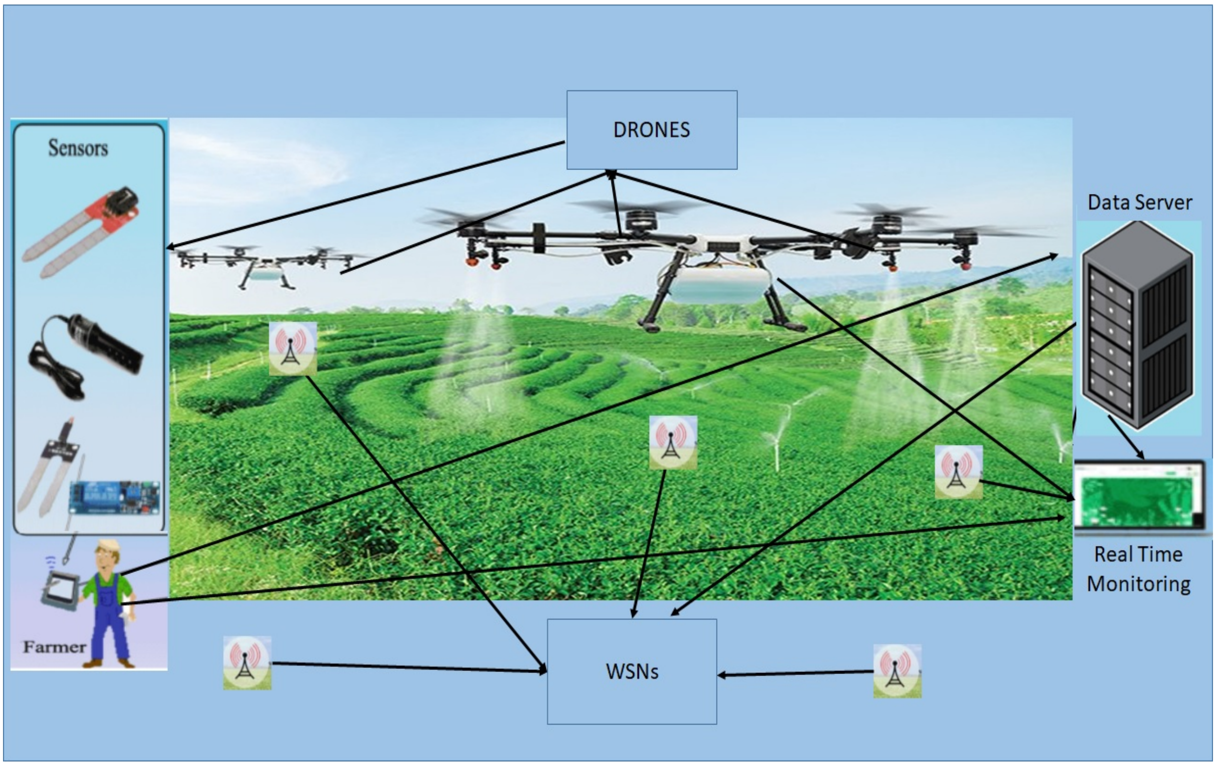


Figure 2.5: Network architecture for a farm monitoring system using Drones

2.4.3.3 Internet of Things Applied in Agriculture

IoT involves the association of network hardware, devices, software, and most significant personalities that exchange information for specified functions, the researchers mentioned that the flexibility of computers among a network to require bound choices while not human involvement has been evolving over the years. It will be deduced from existing analysis publications that intelligent technologies such as intelligent IoT among a farm will cut back crop loss and invariably cut back the loss of revenues by the farmers[104]. According to [105], IoT in agriculture contains the exchange and use of knowledge among sensors, information streams, processes, web-based services, farm entities, open data, exploitation, and linguistics technologies to attach net information. It will be deduced from their analysis that the ability of IoT in agriculture has helped the farmers to attain higher product quality, increase productivity, defend the surroundings, reduce the waste of resources, higher respond to unpredictable events, and supply transparency to the purchasers. The limitation of their research is that the precise answer cannot defend crops throughout adverse climatic conditions. The utilization of IoT in farming helps to reduce the danger of pesticides that consume the crops. It is been mentioned in [106], that exploitation good farming diseases will be detected during the exploitation image process. It will be deduced from their work that farmers will take preventive measures to bound unwillingness outbreaks whereas planting their crops to attain a high yield, however, their analysis did not counsel techniques regarding the eruption of the new trend of diseases. Their analysis discusses that the sensing and actuators as a service can give a cloud service, wherever the information square measure changes in the infrastructure via the sensors, actuators, and therefore the user through the cloud. They highlighted some existing challenges within the IoT together with light-weight coding for IoT, failure detection, recovery prediction for IoT, information dependable and access management in IoT, and real attacks in IoT. It will be deduced from [107] that the IoT-cloud will be wont to give good solutions permitting the farmer to receive data from the farm via the web on device periods of time at varied locations. Another IoT challenges square measure, security, information validation and integrity, and trust. Their analysis inferred that IoT will be will not boost food production through the assembly of healthy and high-quality crops and invariably reduce drastically the loss of crops in the process of the information received. What is more, algorithms are used for unwillingness recognition in crops, and deep learning techniques for texture recognition, it has been mentioned in [63], that exploitation map reduce and Hadoop framework for IoT, big data, cloud, and wireless sensing element network will influence the performance of the wireless sensor networks to attain optimum accuracy in error detection. It will be inferred that exploitation compression techniques, low information measure,low latency, and improved performance will be achieved in IoT information transmission.According to [108, 109, 110], IoT permits the infrastructures to update data at a constant rate, and they receive the data, computerization, and economical chase of put-in devices. They further mentioned that the mixing of the intelligent installation (ITS), IoT devices, and therefore the management of its devices are referred because the cyber–physical system (CPS) despite the tremendous contribution regarding the improved machine capability of the mix, these technologies attract high value for readying, management of the mix of ITS and IoT network still function limitations. It is discovered from[108, 110] that Ad-hoc network, fog servers, and technologies improve agriculture, the researchers assume that exploitation as fog servers for IoT end up in improved quality of service, CPU. Performance, network performance, energy-saving potency of 62.14% and low latency however, the management of this technology remains a challenge that ought to be addressed . It will be deduced from the existing analysis cited higher than that, IoT has contributed absolutely to agriculture to reinforce the number and quality of food production. It is an improved process of crops by fast-tracking gathering, enforced management of unwillingness and tormentors, and avoids the excessive and short application of fungicides or pesticides. With of these achievements, the analysis outcome has indicated that there square measure still challenges with the safety of exploitation IoT in agriculture, particularly with the problems of privacy and trust of information management. These challenges have opened a window for more analysis by researchers to enhance on the existing work that has improved agricultural production exploitation IoT. The concept of characteristics these challenges to researchers to act could be a contribution of this paper with a successive step to be taken by future academic professionals.

2.4.3.4 Artificial Intelligence Applied in Smart Agriculture

Artificial Intelligent will not often monitor the limitation of the unsupervised learning technique that is not reliable since there is no previous data in the input file. As cited in [111], the united Learning (FL) methodology permits the network to use a sub-urbanised approach to process data, not like the centralized deep learning system. It are often inferred from their analysis that the networks that involve user instrumentality and edge nodes will handle unbalanced and non-Independent Identical Distributed (non-IID) information with success. The system will train the information mistreatment mini-batches to scale back the communication value. Some of the restrictions of their work embrace the difficulty of the AI management at the sting nodes and the multidimensional resources for the AI at the sting that makes the cacophonous of AI tasks a difficult drawback that indicates opportunities for any analysis. Machine Learning that could be a set of AI has been employed in several sectors, specifically foretelling stock exchange patterns, identification, maladies,estimating business patterns, making circuits, speech monitored gadgets, human–computer interaction, self-driving vehicles, and natural language process simply to say a number of. It are often ascertained from table6.2, that implementation of sensors, drone, IoT and AI in smart agriculture comes with its concerns and problems. Sensors are low cost to deploy in a farm, however drones, IoT, AI are terribly costly to deploy on a mechanized farm[112].

Table 2.3: Correlation of sensors, unmanned aerial vehicles (drones), internet of Things (IoT), Artificial Intelligence (AI) in smart agriculture

Properties	**sensors**	**drones**	**IoT**	**AI**
High transmission speed	N	Y	N/A	Y
Provide connectivity where no internet is available	N	Y	N	Y
Cover long range of distance for data transmission	N	Y	N/A	Y
Mobility within the farm	N	Y	N/A	N/A
High processing power	N	N	N/A	Y
Analyze data aggregate	N	N	N/A	Y
High security in transmission of data	N	Y	Y	Y
Capturing of data by direct contact	Y	N	N	N
Run out of power over time	Y	Y	N/A	N/A
Psychological effect on Livestock	Y	Y	N/A	N/A
Low cost of deployment	Y	N	N	N

Yes = Y, No = N, N/A = Not Applicable

2.4.4 The Impact of climate on Smart Agriculture

Comparing the soil heat storage energy consumed throughout chemical action are factors that influence the surface flux and temperature change of the soil[113]. It is ascertained from this analysis that higher surface heat fluxes are relative to a diluent, well-watered cover with regular temperature changes. The limitation of this analysis is that the information used was collected over a brief amount. A protracted amount of captured knowledge set would have given a much better result and powerful analysis. It is ascertained that early knowledge set capture would have produced an improved analysis result if they are captured at the start of the planting season. It is ascertained from their analysis that a shortened picture amount and diminished daily minimum temperature will begin the leaf senescence method. This is often accustomed confirming the leaf coloration and brown-down dates indicating the temperature change impact on vegetation and carbon cycle, however, they need not discuss the speed of vegetation coloration amendment among each day or a specific amount. The most potency of photosystem II (Fv/Fm) is that the most reliable indicator for policy investigation strategy planning stage is heat stress, solely the chemical change parameters vary in wheat (Triticum aestivum L.) plant production. It are often deduced from the existing analysis that the photo-chemical reflection factor index (PRI) is effective in the policy investigation of late-stage heat stress within the wheat plant once the pigment parameters (i.e. physical and chemical variables) of the plant are influenced. A sensible surface sensing system (4S) may be accustomed to monitor vegetation indices (VI), which is part of the chemical change active radiation (fPAR) and Leaf space Index (LAI). 4S has increased information in bio-sphere atmospherically relationships. It are often inferred from the existing analysis, that vegetation indices are collected employing a micro-computer, camera,multi-spectral prism spectroscope embedded in a junction rectifier. It is been ascertained from the revealed papers that the planned system could be an affordable solution for the remote observance of the sensing of the cover structure functions of the plant. There is a priority that it cannot be used for observance of multiple remote sites at the same time. In line with[114], winter wheat species yield a lot of harvest that invariably boosts agricultural business markets and production. It are often inferred from their analysis that the planned model performs higher or offers higher results for knowledge obtained from areas with high spatial resolutions or mountainous areas. The limitation of this analysis is that the system has not been applied to different crops in different counties to modify the statement of the yield of the wheat plant. Vegetation indices (VI) and Gross Primarily Productivity (GPP) affinity are stricken by several factors like frequency, duration of knowledge capture. It are often inferred from this analysis that the VI-GPP relationship is incredibly weak since the VI variable is incredibly uncertain and unstable at lesser frequency timescales in an exceedingly ground scheme. To boot, the planned model has been applied to mosquito grass ligneous plant alone and its application has not been enforced to different crops to determine its performance. The results obtained throughout the correlation of the ascertained sowing dates and simulated dates of sowing for winter wheat crop show that the latitude of the situation of the planting of the crop influences the climate of the flowering of the crop. It are often inferred from their analysis that higher great circle locations give a climate for effective flowering to maturity of the winter wheat crop production. There, there are considerations that the model cannot predict the winter wheat crop yield inter-annual across Europe and cannot think about the impact of excess water conditions on winter wheat crops on the farm. The model has not been applied to simulate results considering various species of the winter wheat crop. Farming and climate are often the same to control in an exceedingly dependent relationship as a result of which they affect and influence the end result of every other daily. It is been ascertained from[40] that thinner crop leaves influence the warmth illumination unit storage of the plants. The reduction of the minimum daily temperature controls the leaf senescence, therefore climate affects the leaves' coloration rate of the crops. Nowadays, farmers are aware that latitudes affect the climate of the wheat crop throughout the flowering of the crop that has fairly improved the notice in managing the crops. There are some limitations and challenges exist in their analysis like the gathering of knowledge for a brief amount.

2.4.5 Challenges and Setbacks for Smart Agriculture

Author[49] have expressed their considerations within the communication protocol used for interaction inside the sensible farms, these protocols were effective under short distance coverage areas. It is been discovered in[66, 67] that a number of intelligent devices are operating victimisation batteries, this has reduced the operational hours of the sting node devices since they stop transmission information once they run out of power. There is a requirement for effective trust, privacy, and security of that information. It is been expressed in [68, 115] that there area unit challenges related to information security, privacy, and trust management. Quality of Service (QoS) and network latency area unit alternative network problems inside sensible farms that need additional analysis. It is inferred from the existing analysis that a great deal of considerations have arisen in sensible pesticides on the farm. The authors in [41] have mentioned the shortage of correct detection of climatic conditions that has drastically affected farming across the world. The authors in [60] have mentioned the communication price issue regarding the transmission of knowledge in smart agriculture and believe that there exists a high overhead communication price in information transmission in smart agriculture, additional analysis work will facilitate to deal with this issue. It is deduced from [50] that encryption in IoT is another serious challenge that has affected smart agriculture and improvements in encryption sanctioned farmers to implement IoT in smart agriculture for higher agricultural productivity and enhance IoT in smart agriculture analysis. IoT application in smart agriculture is not any doubt ever changing the trend of labor in smart agriculture, but there exists a limitation within the quicker illness detection in crops and analysis during this space according to[48]. smart agriculture provides the technology for farmers to watch their farms remotely through analysis attention since effective watching of health of the crop. Some analysis work has been conducted to use machine learning for early detection of illness in crops, despite these efforts there is a limitation during this space and additional models need to be developed to predict illness early enough before the farm harvest is reduced drastically thanks to illness infestation. In a mixed cropping state of affairs, there is a challenge to spot the fruits.There is a requirement to develop models or algorithms to assist farmers to discover the crops' fruit early enough to forestall over-ripening of fruits and wastage. smart agriculture has opened a chance for researchers to research the leaf water stress level in plants as cited in [113, 116], which can facilitate perceiving the impact of climate on crops and plant water loss through their leaves. It is deduced from tables 2.4-2.6, several challenges exist in the appliance of IoT to sensible agriculture farming. These challenges vary from watching crops' leaf water stress levels to the watching of location health, however, some of these challenges have created opportunities for analysis for academics.

Table 2.4: Correlation of IoT Setback in smart agriculture(Part 1)

Properties	[68, 78]	[104]
Security	N	N/A
Control actuators	Y	N
Network lifetime	N	N/A
Network latency	N/A	N/A
Transmission reliability	N	N
Quality of experience (QoE)	N	N
Reduce risk of pesticides harming Animals or Human	N/A	N/A
Semantic interoperability	N	N
Detection of weather conditions	N	Y

Yes = Y, No = N, N/A = Not Applicable

Table 2.5: Correlation of IoT Setback in smart agriculture(Part 2)

Properties	[109]	[68]	[111]	[67, 75]	[113]
Security	N	N	N	N/A	N/A
Preventive measures using IoT	Y	Y	Y	N	Y
Semantic interoperability	N	N	N	N	N
Architecture	N	N	N	N	Y
Reduce communication cost	N	N	N	Y	N
Quality of Service (QoS)	N	N	Y	Y	Y
Sensing and actuators as a service (SAaaS)	N	N	N	N	N

Continued on next page

Table 2.5: Correlation of IoT Setback in smart agriculture(Part 2) (Continued)

Handle multi-keyword search	N	N	N	N	N
Increase in computation overhead	N/A	N/A	N	N	N
Lightweight encryption for IoT	N	Y	N	N	N
Failure detection	N	Y	N	N	N
Prediction for IoT	N	Y	N	N	N
Data reliability	N	Y	N	N	N
Access control in IoT	N	Y	N	N	N
Real attacks in IoT	N	Y	N	N	N
Management of IoT designs and software	N	Y	N	N	N
Noise filtering capacity	Y	N	N	N	N
Increased computational time	N	N	N	N	N
Faster detection rate for crop disease	Y	Y	N	N	N
Enhanced data transmission	N	N	Y	N	N
Color, Shape from 3D sensor	N/A	N/A	N/A	N/A	Y
Validation of safe trust in IoT	N	Y	N	N	N

Table 2.6: Correlation of IoT Setback in smart agriculture(Part 3)

Properties	[73]	[117]	[118]	[72, 49]
Interactive voice response with farmers	N	N	N	N
Determination of soil condition	N	N	N	N
Soil conductivity	N	N	N	N
Protection of crop disease using IoT	N	N	N	N
Color segmentation to determine grapes for harvest	N	N	N	N
Early disease detection using image capture technique	N	N	N	N
Support vector machine for recognition of fruit	N	N	N	
Three dimensional point cloud(TDPC)	N	N	N	N
Monitor the leaf water stress	N	N	N	N

Yes = Y, No = N, N/A = Not Applicable

2.4.6 Cloud-Based IoT Smart Agriculture

ICT technologies will improve the extent of interaction as explicit by [119] between small-scale farmers and the farming skilled tremendously. It is inferred from their analysis that the farmer resolution will facilitate the farmers share their expertise with both the favorable experiences and challenges they encountered within the farm [120]. It is been determined that the GeoFarmer resolution also provides Interactive Voice Response (IVR) options sanctioning farmers to own voice conversations with the facilitators via their smartphones. This has helped them to allow a much better rationalization of the end result of the skilled recommendation they received from the farming consultants, particularly in areas wherever web property is extremely restricted. it's noticed that the answer provided an skilled to the farmer, farmer-to-farmer interaction that helped data sharing, knowledge assortment, and analysis methods. The limitation of their analysis cannot monitor the farmers' attitudes and practices with the farmer solution that provides an area for any study within the analysis. The involvement of users with very little or no ICT skills has created a challenge for these classes of users. IoT is wanted to regulate the gap of valves for actuators put in for the irrigation system to avoid water stress on the crops. It is deduced from their analysis that farmers square measures sophisticated remotely of the soil water condition via text message saving time of travel at intervals within the farm, creating the farming system an automatic one and offers a precise measurable water condition of the soil on the farm. This may facilitate stopping illness at intervals within the soil thanks to excessive watering of the soil. The limitation of this work is that the applied developed cannot live the daily water wants of the plant. Mistreatment associated with Nursing IoT with varied sensors for knowledge transmission via the cloud to a server for an assortment of temperature and wetness knowledge square measures analyzed by the researchers. This helps management mould illness unfold at intervals within a farm. It is deduced from the existing analysis that this approach will assist to control the applying of fungicides at intervals within the farm. It absolutely was mentioned that the choice network used by the researchers cannot collect the pictures of the leaves, analyze the transformation of the leaves like amendment of color that indicates the signs of illness infestation of the plant. Strategic management decision-making techniques yield much better production than adopting short-run call ways that have been exemplified by fruit farmers. Their analysis is extremely informative as a result of revealing that there are square measures, various techniques that crop farmers can contemplate for the management of their farms like a cohort. From table 2.7, a broad read of the comparison of the assorted observed benefits of the net-of things cloud-based good farming is illustrated. As cited in[121], it was been determined that knowledge creation of IoT sensing knowledge is applied within the cloud methodology to enhance the retrieval of lost knowledge. The adopted Map Reduce and graph-based compression techniques have resulted within the distributive squeeze of the data set. It is inferred from this research that the error detection in IoT considerable sensing knowledge is spectacular, however, this resolution offers higher stability of the information in the cloud. Their work conjointly has old some limitations like in things wherever there exists an associate in nursing identity curve performed between cheat series, their regression model was not able to win spectacular predictions, and its been explicit in[118] that mistreatment Fog-assistant framework for good transport system network with good police investigation functionality use case square measure terribly reliable for crime investigation. It is inferred from their analysis that this intelligent IoT cloud-based device, once tested in a laboratory, resulted in an associate in nursing execution of the network , saving of energy , and computer performance after they compared it with the traditional installation of the system. It is deduced that Cloud web of Things is an open area for any research in cloud computing and IoT thanks to its limitations like quantifiable, dependable, privacy, security, non-uniformity of the hardware used, energy and power optimisation, service level agreement implementation, request and rating. Humans are using technology to combat the food shortage, old global mistreatment, IoT, robotics, and AI to observe crop diseases early to scale back crops throughout harvest. Technology has been the want to cut back physical labor on the farm and boost crop production geometrically. Observance of crops with the help of technology has taken lesser time manufacturing optimal results so that the square measure is a lot of informative compared to the physical review of the farm.

Table 2.7: Correlation of advantages of IoT cloud based Smart Agriculture in existing papers

Properties	[73]	[112, 80]	[118]	[50]	[78]	[107]	[109, 111]
Better segmentation of crop spot edges	Y	N	N	N	N	N	N
Fast identification and separation of plant disease	N	N	N	N	N	N	Y
RGB-D sensor used for harvesting	N	N	N	N	Y	N	N
Monte Carlo simulation used to determine the best harvest age	N	N	N	N	N	Y	N

Continued on next page

Table 2.7: Correlation of advantages of IoT cloud based Smart Agriculture in existing papers (Continued)

A model developed for predicting autumn phenology	N	N	N	N	N	N	N
Photo-chemical reflectance index (PRI)	N	N	N	N	N	N	N
Smart surface sensing system (4S)	N	N	N	N	N	N	
Evaluation of the near-surface air temperature data sets from the ERA-Interim (ERAI)	N	N	N	N	N	N	N
Relationship between vegetation greenness and productivity across dry land ecosystems	N	N	N	N	N	N	N
AI in edge computing	N	N	N	N	N	N	N
FL is used to handle user equipment and edge nodes for unbalanced and non-Independent Identical Distributed data	N	N	N	N	N	N	N

2.4.7 Application of Machine Learning to Agriculture

Authors in [122, 123] have reported that farms' performance over the years has not met their expectations thanks to illness infestations, poor farm management ways, adoption of recent farming practices, and lack of technical skills for early illness detection in crops. Optical master scanning of the surface form of rice seeds supporting the three-dimensional purpose cloud (TDPC) methodology, the form dimensions of the rice seed may be calculated[124]. It may be deduced from this analysis that the TDPC methodology result had a median error in comparison with the physically measured in table2.8. Its been observed that the dished package formula enabled the researchers to get the contour of the projected purpose cloud, and this helped to obtain the amount of the rice seed unit, in summary, the amount of vectoral contour triangle space that was obtained by the add of the sectional space of the purpose cloud for the rice seed. It may be inferred that there is high accuracy in their analysis when the measured extent obtained from the triangular formula is compared to the theoretical extent of the rice seed. The analysis has indicated that a marginal error of 0.58 mm^3, the typical error of 0.37%, variance of 0.10 once the theoretical volume is compared to the measured volume. Technology usage in agriculture has enabled researchers to work out the volume of grain seed despite the small size[121, 125], information assortment in developing countries, square measure is currently realizable thanks to IoT. We are approaching a stage wherever IoT applications employing a cloud-based farming system can reveal data that has been mystery over the years regarding crop diseases, fruit leaves, and color detection for deciding on, however best to cultivate and increase food production worldwide. Associate IoT example system was developed that was tested within the vinery for the spraying operation of the farm and it absolutely was able to effectively monitor and acquire information from the operation. Once the experimental values and theoretical values were compared, particularly the spray pressure, flow rate, and application rate to determine the potency. The result of their analysis was terribly informative, however the limitation of their work was found once the system was applied to a tractor with a sprayer hooked up, moving uphill that generated an associated inaccurate application rate, additional therefore regular cleanup of the calibrator for spraying chemicals was required to get correct experimental results [109, 111], however, the limitation of their analysis is that this approach has not been applied to different crops to work out the effectiveness and potency of the technique. Fig 2.6 shows a cloud-based IoT network for agriculture designed to implement machine learning models to capture and analyze information inside a farm, the IoT uses processors for quicker process of information received, a model running on different sensors for mobile devices for remote accessibility of the information inside the farm. Application of technology in agriculture has enabled researchers to live with the soil wet content and therefore the information was displayed on a developed website and can be accessed via mobile devices by SMS or application. This has assisted folks operating remotely to look at the end of a period on their mobile phones.The limitation of their work is that their analysis has not been applied to different environmental parameters like temperature,fertilizer and humidity.

Table 2.8: Correlation of advantages of Machine Learning to Smart Agriculture

Properties	[126, 127]	[128, 50]	[129]	[130]	[131]	[124]	[132, 125]
Crop recognition	Y	Y	N	Y	N	N/A	N
Plant disease detection	N	N	N	N	N	N	Y
Yield prediction	N/A	N	N	N	Y	N	N
Crop quality	N	N	N	N	N	Y	N
Water management	N	N	N	N/A	N	N	N
Soil management	N	N	N	N	N	N	N
fertilization management	N	N/A	N	N	N	N/A	

Yes = Y, No = N, N/A = Not Applicable

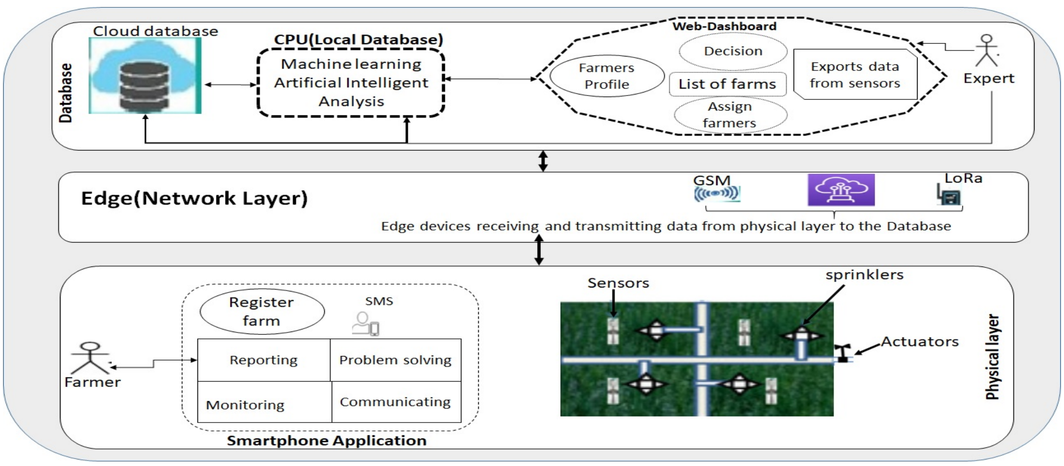


Figure 2.6: Architecture for Smart Agriculture

2.5 Discussion

The use of IoT has improved crop production through observation, tracking, and tracing, agriculture machinery and greenhouse production. IoT has reduced water wastage in irrigation and improved water quality, a lot of thus increased weather and soil observation, helped to manage the sickness and gadfly management, improved information analytic, and boost the automation of farming. The utilization of remote-controlled aerial vehicles for observation of crops hence contribution of IoT to smart agriculture. Thermal image options are accustomed to estimate irrigation accuracy, and the assortment of data exploitation sensors has additionally increased smart agriculture. Most of these varied achievements within the use of IoT in smart agriculture have increased farming apply, however these have not accompanied its share of limitations like security and privacy issues, data governance, lack of amendment in culture by the stakeholders to simply accept the IoT system innovation. This paper reveals sectors in smart agriculture that analysers will think about for additional research to feature a lot of educational information to the world with immense contributions by numerous educational professionals globally. These opportunities for additional analysis range from wireless detector network, Unmanned area vehicles, cloud-based smart agriculture, application of IoT to crop production, post-harvesting, observation of crops, the result of climate on agriculture, use of computing in farming, latency problems in data transmission in smart agriculture, improvement of smart agriculture specification, incorporation of a cloud platform to smart agriculture network, cubic centimeter for smart agriculture whereas coaching information in the sting nodes, coaching of edge nodes in united learning network within a smart agriculture.

2.6 Summary

A review of intelligent IoT in smart agriculture has been done extensively. Several problems about wireless sensor application in smart agriculture, application of IoT in crop production, post-harvesting, use of drone, and metric capacity unit are known. This write-up contributes to information through the identification of the gaps and challenges in existing analysis in smart agriculture. Such challenges embody the procedure power of IoT devices utilized in smart agriculture, AI for early sickness detection, detection of water level in crops, detection of soil condition, and behavior pattern among the farm. The globe population is increasing daily, large wastage of crops through poor storage and sickness infestation remains evident. An efficient Intelligent IoT system for smart agriculture will begin the start of the journey with the reduction of food wastage, boost food production, and provide a lot of data among the farming system for decision making,future use and researchers.

2.7 Further work

A lot of analysis has been done on intelligent IoT for smart agriculture, however, these praiseworthy contributions have opened opportunities for additional analysis, specifically the implementation of the Fog-technology framework for farming, application of the mix of unsupervised learning algorithms, and united learning to good farming. It will be a fascinating analysis to be ready to use intelligent IoT to grasp the physiological activities among a plant throughout a fast amendment in atmospheric condition among its environment. Additional work is need to investigated different technologies using intelligent IoT in smart agriculture for decryption voice data and send reaction to farmers.

CHAPTER 3

SIMULATION OF IOT WATER MANAGEMENT FOR EFFICIENT RICE IRRIGATION IN RWANDA

3.1 Introduction

Efficient use of water for agriculture is important to ensure high yields and maximize economic benefits, especially in areas facing annual or seasonal water availability constraints. About 90% of Rwanda's population is engaged in agriculture, which is used for both self-sufficiency and economic development [10, 133]. Intensive agriculture throughout Rwanda is a major demand for water resources, and it is estimated that up to 70% of the available water resources are used for agriculture [13]. The increasingly important water-consuming crop in Rwanda is now the second most important grain, rice (*Oryza sativa*). As shown in the table 6.1, the water requirement of rice is important throughout the sequence of growth stages, and each stage has a different water requirement. The total requirement is the typical seasonal water requirement for the rice growth stage in the tropical environment [25], but the actual requirement is plus or minus up to 500 mm, mainly depending on the soil type and infiltration.

Table 3.1: Water requirements for depth and total soil water on each stage.

Stage Number	**1**	**2**	**3**	**4**	**5**
Stage Name	Seedling	Tillering	Panicle growth	Flowering	Ripening
Length of the stage in days	25	42	25	30	21
The depth of the threshold (mm)	100	20	20	100	100
Cumulative total soil water (mm)	50–60	200–250	400–550	400–450	100–150

One aspect of Rwanda's food security is to increase domestic rice production, as previous forecasts of domestic demand for rice were underestimated, according to the Government of Rwanda national rice program [134]. However, according to the Rwanda National Statistical Institute-(NISR), by 2018, production was only about one-third of demand, which was an economically unfavorable result [11]. For this reason, GoR has made rice production a priority area for improving agricultural production, and addressing inefficient use of water in irrigation is part of the solution [12, 135].

3.1.1 The Current Situation for Rice Irrigation in Rwanda

Due to the hilly nature of the Rwandan countryside, most existing irrigation schemes are typically local and designed for intensive agricultural practices in the relatively flat marshland terrain of valley bottoms [136, 133]. These irrigation schemes are necessary to increase production, since rainfall alone is excessively variable and, especially in Eastern Rwanda where this research site were study, rainfall for rice cropping is inadequate in a typical year. With irrigation, these marshlands can support two rice crops per year due to the two rainy seasons in this equatorial region; Season A is March to August and Season B is September to January. Each growing season starts in a rainy season and ends in a dry season. Even in the rainy season, irrigation is required to respond to rainfall variability and in the dry season, it is mandatory for the final growth stages before harvest. According to [8],the current system is manual, where farmers observe the water depth and when the water is reduced to a certain level they contact the authorities to divert water to the canals so they can irrigate. However, conflicts arise in this system. First, there has to be a collective request of the farmers to achieve maximum consumption. As a result, the farmers are obliged to plant at the same time. Second, water control structures are minimal, causing further conflicts among farmers when inadequate control of water creates flooding of plots when it is not needed. Finer control of water would decrease conflicts and provide the farmers more choice in planting and harvest. An existing irrigation scheme in Rwanda with these characteristics for which our study is designed is Muvumba Valley Rice Plantation in Nyagatare District, Eastern Province (Figure 3.1).

Figure 3.1: Irrigation canals at Muvumba Valley Rice Plantation in Nyagatare.

Due to the rice growth, different conditions should be avoided: (i) Rice field to rice field irrigation should be avoided.(ii)they should be control the flow of water which may flow to the main canal of the rice field at a distance of 30 to 45cm within the field to avoid leakage of water through other rice field where it is not needed.(iii) To minimize percolation loss, the depth of stagnated water should be applied depending on the stage of rice, (iv) Finally the surface should be taken not to allow development of cracks. Internet of Things (IoT) technology has great potential to solve problems such as irrigation control at low cost [**9**]. Irrigation control does require core algorithms for irrigation decision-making that are sensitive to the growth stage, to make the IoT system more autonomous. Like any IoT agriculture system, there are field sensors for detecting the desired parameter; in this case, the water level in flooded rice fields. When the water level is below a threshold, the system will irrigate, send field sensor data to a cloud network, and then send system status updates by smartphone or short message service (SMS) to those farmers without a smartphone, for normal operation. In the case of system failure in the field, farmers will receive an alert and an irrigation recommendation so the farmer can manually intervene. The system will react automatically to water levels through an algorithm that adjusts irrigation needs according to growth stage, evapotranspiration, and rainfall.In this research, the core algorithms for water control for normal operation and for failure mode operation are tested through simulation.

3.1.2 Related Work

In this section, this research explains some examples of IoT sensors and common system components and architectures for agricultural systems as well as the important role of decision modeling for translating data into actionable information. The research then summarizes the objectives of this study.

3.1.3 Sensors and Systems for Agriculture

Previous work on IoT systems describes components to be adapted to the Rwanda context. Sensors for measuring water level in real time in disaster prone areas are one example, where the water level sensor value is compared to a threshold and if the water level reaches the threshold, the signal is fed in real time to social networks [137]. That system also uses a cloud server configured as a data repository and the water level alarm is also displayed on a remote dashboard. Water level measurement in tanks is widespread in process industries when it is necessary to measure the level of a liquid [138]. A variety of level measurement technologies for field deployment are on the market today, such as ultrasonic level sensors, capacitance level sensors, and others [139]. An example irrigation system is outlined in [137] with sensor components for soil moisture, light, temperature, and humidity. Other examples relevant to our study include a complete IoT architecture for irrigation [140] and a low cost architecture for heterogeneous data sources [141]. In direct relation to smart farming, several researchers have promoted scalable network architectures for monitoring and controlling agriculture and farms in rural areas [142, 143]. Such systems have the goal of improving data communication with methods such as a cross-layer-based channel access and routing solution for sensing and actuating to improve coverage , throughput, and latency [144, 106]. Most of these systems have common components of sensors for field measurements, cloud computing for data analysis, and decisions for actuators returned to the farmer or farming system.

3.1.4 Decision Modeling

Given the technologies assessed above, other researchers have described how IoT systems have the potential to collect field sensor data in real time and feed the data to integrate modeling tools for producing decision outputs for irrigation and other farming activities [145]. According to [146], an information system for precision agriculture will depend on how data are stored, managed, accessed, and ultimately combined to make sound decisions. With knowledge based on these prior explorations of typical components of IoT for agricultural systems, this work focuses on an IoT system that first includes not only sensor data, but also Web-based weather services, and second, modeling of irrigation requirements for decision making in the context of rice farming in Rwanda. These key components take advantage of freely accessible data via the Internet, knowledge from offline agricultural decision tools, and computational modeling approaches to build the irrigation decision system. The system is also designed for a certain level of fault tolerance, necessary for communicating decisions in a low-income country, where sensor faults may not be readily repaired, power may not be reliable, and internet access and end user technology ranges from short message service (SMS) only, to smartphones.

3.1.5 Objectives

The objectives of this study are to investigate how control algorithms within an IoT water management system might be adapted for rice farming in Rwanda and to use simulations to demonstrate the key components of the appropriate automatic control of irrigation as well as fault tolerance.

3.2 Materials and Methods

This section presents an overview of the control algorithms for an IoT water management system. Details are provided of the Markov chain process used to model the irrigation decision algorithm when the IoT system is fully functional as well as details of the SARSA temporal difference algorithm for when the system has a fault. This built-in fault tolerance is important in the context of a low economic development country, where power or communications losses can be common and because rice has critical stages, such as flowering, where water deficits can lower yields.

3.2.1 Overview of Proposed IoT Irrigation System

The flowchart of the IoT system (Figure 5.1) has two decision pathways, one is the fully functioning automatic system (white), while the second initiates if there is a fault in the automatic system (gray), thereby still providing actionable recommendations for the farmer until the fault is fixed. The fault may arise from communication breakdown, or sensor or actuator failures that prevent data flow. In the fully automatic mode, the farmer is informed on system status and actions via smart phone or SMS, since some farmers will have smartphones but others will not. The mobile phone market is sufficiently developed in Rwanda so that every farmer will at least have a mobile phone that can receive SMS. In the fault mode, the farmer is notified of the fault and irrigation recommendations are communicated, but the farmer must manually control the irrigation (turn the pumps on and off according to their observations). Different modeling processes are used to model irrigation decisions for the data rich automatic pathway and the data starved pathway when a fault occurs. In the automatic pathway, the irrigation decision is modeled as a Markov chain process (MCP) [147]. The IoT system will check the water level in the field and the rainfall prediction by Web service. If the level in the field is below the established threshold for the current growth stage, the amount to add will be calculated by taking into account the predicted rainfall. If irrigation water is needed, the system will engage to extract water from the supply to a tank and flow to the field through pipes. This IoT system will allow individual farmers to control the irrigation of their individual plots to overcome the limitations of the current practice. The system interface for the farmer can be smartphone or SMS. If there is a fault in the IoT system, the pathway switches to the SARSA temporal difference method to propagate the recommended control action to the farmer [148, 136]. When the system moves to a fault state, the conditions are initialized as the last valid MCP output. The SARSA model is used until the fault is identified and repaired. Once the IoT system is again operational, the MCP method resumes with initialization based on the last state of the SARSA method. The farmer will manually control the irrigation until maintenance allows restart of the IoT system. The details of the two pathways are presented in the next two subsections.

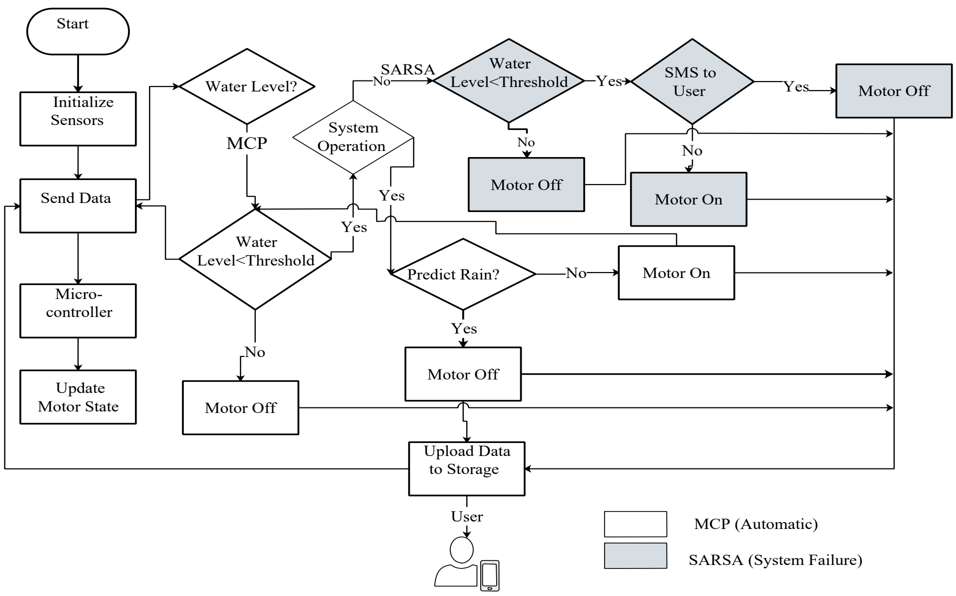


Figure 3.2: Flowchart of the irrigation optimization system

3.2.2 Markov Chain Process for a Fully Functional IoT System

MCP has been demonstrated to be a valid modeling approach for agricultural crop systems [147] because once a crop reaches a particular growth stage, growth progress to the next stage is independent of prior history. Rice water requirements change for each stage of growth, so the Markov chain process deals with this set of possible stages S and the set of possible actions A, where the effects of an action taken in a stage depend only on that stage and not on the prior history.This Research thus uses the MCP approach to model the probabilistic transitions among a set of stages $S = \{s_1, s_2, \cdots\}$ [149], where each stage $s_i \in S$ is defined with a predetermined cumulative total soil water (TSW) range

(Table 6.1). Water loss from each plot is monitored with a water level sensor and daily TSW calculations are summed to provide the cumulative value. Weather variables and the weather forecast are accessed by a Web service query. When no rain is forecast, plot-level water deficits are determined as a calculated needed water (CNW), by accounting for the area of the plot and the water depth, and irrigation occurs to provide the CNW. If the web query indicates impending rainfall, the system will wait, then recheck the water level sensor reading after the predicted rainfall period. If the water level is still below range, the system determines the CNW within that specific plot to release only the required water to avoid a complete water deficit and crop failure while waiting for forecasted rain. A minimum threshold water level is set as a backup [25]. The system reacts to the ingested data to indicate a state of deficit, a sufficient amount, or an excess of water according to the growth stage, and thus defines the actions to take to satisfy the irrigation demand. The total soil water (TSW_j, mm) during an irrigation period j can be modeled as the sum of crop evapotranspiration (ET_j, mm) and seepage and percolation in the soil (SP_j, mm) minus effective rainfall (ERF_j, mm), which reduces the irrigation demand [25]. TSW is calculated each day and summed as a way to track the targeted cumulative TSW for each stage.

$$TSW = ET_j + SP_j - ERF_j \tag{3.1}$$

Following [25], $ERF_j = 0.6 \times RF$ since rainfall is typically less than 50 mm per week at the study site. $ET_r = K_c \times ET_o$ where ET_r is rice evapotranspiration (mm/day), K_c is the rice coefficient [6], and ET_o is the reference evapotranspiration (mm/day) according to the FAO Penman Monteith method [150]. The irrigation decision is to choose among a set of actions $A = \{a_1, a_2, \cdots\}$ defined as to irrigate, not irrigate, or extract water from the field. This decision is made every other day (2-day time step) with the assumption that daily irrigation is not required, although the system can take daily action since the TSW is calculated daily. The decision of what action to take directly affects the state that can be reached at the next time step as a Markov decision process (MDP). In this MDP, the action is $a_w \in A$, where a_w is the irrigation action to take, given a certain state $s_i \in S$, where s_i is one of five stages which defines the condition $C(s_i, a_w)$. The strategy of choosing actions at each time step is summarized as a policy, which usually aims to control the condition, which in this case is the flooded water depth as indicated in Table 6.1.

To illustrate the case where the decision is made to irrigate (which is the usual case for the Muvumba site), this decision depends on the current state $s \in S$, and a valve is opened as action $a \in A$, which changes the condition C. The decision depends on the water level sensed in the field and the rain forecast. $Tsw_{\gamma}(s^1, a^1)$ is defined as when the water level reaches the desired range between the threshold and the maximum. If the weather forecast indicates impending rainfall, the system immediately tests the condition to check if irrigation can be delayed to take advantage of the rainfall. Whatever the decision, the new condition C is received and the state transits to S. The cumulative $TSW_{\gamma}(s^1, a^1)$ value of the state-action pair is updated with the calculated water needed (CNW) using Equation (6.2). This process is repeated until 12 days before harvesting, at which point the field is drained and allowed to dry to enhance conditions for harvest.

$$CNW = C + TSW_{\gamma}(s^1, a^1) - TSW(s, a) \tag{3.2}$$

The modeling system keeps a record of the calculated water needed, amount of rainfall, and total soil water in the field. After each model step, the value of the current state action pair is added by Equation (6.2). After each step, all entries of TSW water to the field are updated according to the Equation (6.3) with time step α.

$$TSW(s, a) \leftarrow TSW(s, a) + CNW_{\alpha}(s, a) \tag{3.3}$$

The fully operational IoT irrigation system proceeding as described above is summarized in Algorithm 1. The algorithm first translates the time step i to 2 days $[j, j + 2]$. Then, it calculates the irrigation water depth I_j for day j according to the current TSW_j in Equation (6.1), the CNW in Equation (6.2) using a function Irrigation Amount(mm), records the field condition using Equation (6.3), and takes action A depending on stage of the rice as in Table 6.1.

Algorithm 1 : Generating daily TSW and record function

Generate daily TSW and irrigation record function $CalTSW(i, a)$

$j = 2 \times (i - 1) + 1$

CNW $\leftarrow$ Irrigation Amount

Case: $s \leftarrow (1, 2, 3, 4\&5)$

if $i_j > Threshold$ **then**

  Take action $a(-1)$

else if $i_j = Threshold$ **then**

  Take action $a(0)$

else if $i_j < Threshold$ **then**

  Take action $a(1)$

end if

for $k = j + 1, k + +$, while $k < j + 3$ do $TWS_k \leftarrow CalTSW(TSW_{k-1}, I_{k-1}, ET_{k-1}, C_{k-1})$ **do**

  Return TSW_{j+2} and I_j

  $CNW \leftarrow C + TSW_\gamma(s^1, a^1) - TSW(s, a)$

  $TSW(s, a) \leftarrow TSW(s, a) + CNW_\alpha(s, a)$

end for

Depending on the stage of the rice crop, there will be minimum and maximum water levels above the soil to produce TSW values for the following 2 days. The system will assess the current TSW, CNW, and rainfall. Total soil water at a certain level (TSW_k) will be determined and when the water is found to be above the maximum level due to heavy rainfall, water can be extracted from field (TSW_{k-1}) by opening the valve and allowing water to flow from field to the tank then to the dam to minimize water waste. The 2-day time step is not fixed, if the water requirement is high, the system will provide water daily. If the water requirement is low, the system will allow days without irrigation. The condition will indicate a need for more irrigation by analysis of real-time data from sensors.

3.2.3 Modeling in the Context of a System Fault

When there is an interruption of irrigation because of a technical problem (a fault in the IoT system), the farmers will be notified and reminded to perform daily TSW monitoring. To provide the farmer with recommended actions during the fault condition, the system reverts to a reinforcement learning technique called SARSA [148, 136]. SARSA is a temporal difference learning algorithm and uses a state-action pair tuple which maps the action to be taken at each state, and the control method chooses the action for each state during learning, by following Markov decision process rules applied at every time step, and by letting the agent transition from one state action pair to another. A factor λ will be initialized to the last valid values of $TSW(s, a)$ when the MCP stopped. Later, $CNW(s, a)$ are updated according to the relevance of the previous state-action pair.

$$CNW(s, a) \leftarrow \lambda CNW_{\gamma}(s, a) \tag{3.4}$$

This approach will allow information flow to the farmer to continue when the system that uses the Markov chain process is not working normally. Algorithm 2 provides a complete description of the learning process when the IoT system fails to operate normally with some faults. Every rice crop stage is considered as an episode, consisting of n time steps. The program is initialized with the last valid TSW value from MCP. At each time step, the agent takes an action and runs the function $CNW(mm)$ from Equation (6.2) and obtains the TSW and the irrigation record for the current time step with Equation (6.3). The condition function is assigned such that all immediate conditions are 0, except for the last one.

Algorithm 2 : System using SARSA during irrigation.

Initialize $TSW(s,a)$ based on the last valid MCP output.
for All $CNW(s,a)$ **do**
  $CNW(s,a) \leftarrow 0$
  for $i = 1, i++$ while $i < n+1$ do $s \leftarrow$ State (i, TSW_i) **do**
    Take action a
    $[TSW_{i+1}, I_i] \leftarrow CalTSW(i,a)S^1 \leftarrow State(i, TSW_i)$
    $a^1 \leftarrow greedy(TSW, S_{i+1})$
    $CNW \leftarrow C + TSW_\gamma(s,a) - TSW(s^1, a^1)$
    for All $s\&a$ **do**
      $TSW(s,a) \leftarrow TSW(s,a) + CNW(s,a)$
      $CNW(s,a) \leftarrow \lambda CNW_\gamma(s,a)$
    end for
  end for
end for
Until $TSW(s,a)$ policy sufficiently stabilized

3.3 Results

To evaluate the effectiveness of the proposed decision modeling system, this research used historical data from Meteo Rwanda of rainfall and evaporation from March 2017 to January 2019 for four seasons. Figure 3.3 is a plot of rainfall and evaporation for Season B from September 2018 to January 2019. Data for the other seasons are provided as supplementary material. These data are from the Nyagatare weather station in Eastern province of Rwanda adjacent to the Muvumba Rice Plantation and provide us ET and ERF values for Equation (6.1). The SP value is taken from [151].

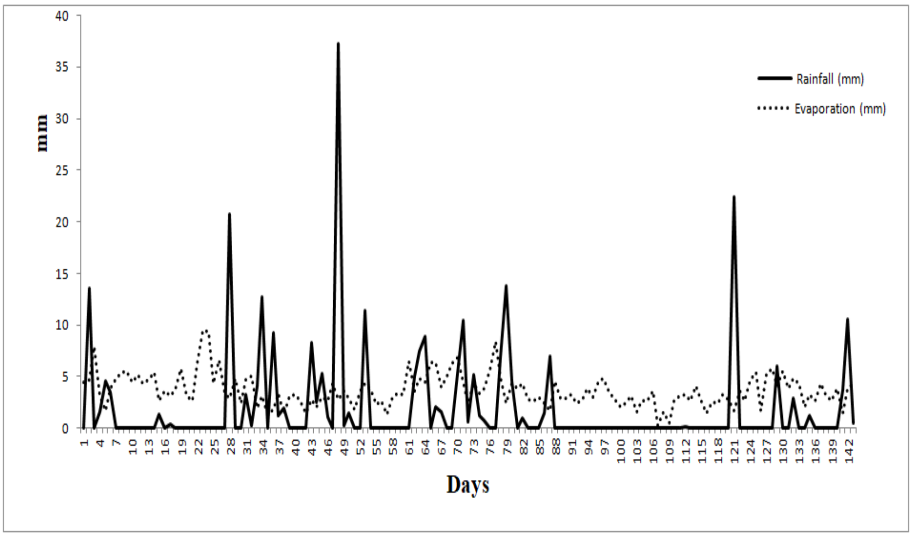


Figure 3.3: Evaporation and rainfall data from September 2018 to January 2019.

3.3.1 System Simulation

Figure 3.4 shows a notional system architecture. The architecture has components for field sensors and web data,actuators, system state modeling, and the user interface. The system will take action depending on the information from the state modeling system either to irrigate (1), not irrigate (0), or extract water from the field (−1). The display system is used to communicate the rice field status to the farmer through the smartphone app or short message service (SMS) using GSM protocols.

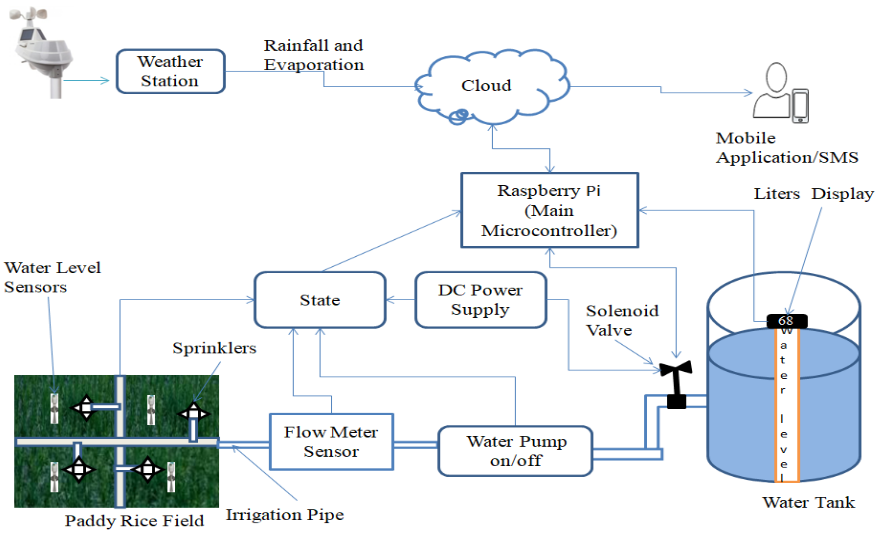


Figure 3.4: System architecture that shows the complete irrigation system.

The weather station provides daily rainfall and evaporation and other weather variables and sends them to the cloud database, while the weather forecast can be obtained from the Web. Hardware such as the Raspberry Pi Compute 3 lite can be used as the controller and processing unit. Water level sensors in the field help monitor irrigation needs and solenoid valves and pumps will allow water to flow from storage tanks to the rice field under the control of the Raspberry Pi. The farmer can check the irrigation status of the field using a smartphone app. If the farmer does not have a smartphone, their phone number can be registered to receive the notification for changes made to their field via SMS. The flow meter sensor will measure the volume of water used for irrigation at every irrigation time step and all sensed data will be collected to take action based on the decision algorithms embedded on the Raspberry Pi.

3.3.2 System Simulation Result

The simulated outputs for the fully operational system for the four fields with weather data from different seasons from March 2017 to January 2019 are shown in Figure 5.2. The timing of the five rice growth stages as indicated in Table 6.1 are shown at the bottom of the figure.

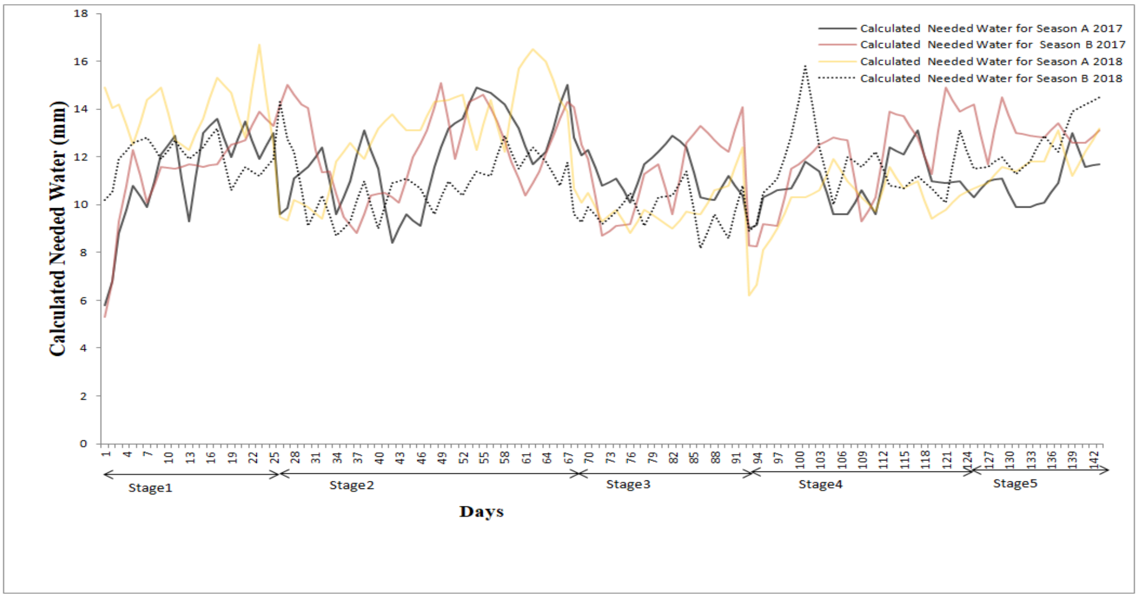


Figure 3.5: Results for Matlab simulation of four seasons using the Markov chain process (MCP).

The simulation results for the fully functioning automatic system show the calculated needed water (CNW) is maintained at a steady level by the system during the four different seasons with variable rainfall and relatively steady evaporation (Figure 3.3).

The simulation of a fault is done for the Season B 2018 data except with the assumption of a fault in the system from day 110 to day 116 during stage 4 (Figure 3.6). This simulation shows the SARSA simulation filling in where the MCP left off providing the farmer with the suggested irrigation values. The SARSA process retains knowledge of the stage water depth requirement and in this case fills in for missing predicted rainfall from the historical evaporation and rainfall.The simulated fault when the model switched to SARSA is days 110 to 116. The irrigation action taken each day is indicated with values of irrigate (1), not irrigate (0), and extract water (-1). Comparison of Figures 3.3 and 3.6 also demonstrates the system reacting to heavy rain on Day 48 by extracting water from the field on Day 49, skipping irrigation on Day 111 due to negligible evaporation on Day 109, and skipping irrigation on Day 123 due to heavy rain on Day 121.

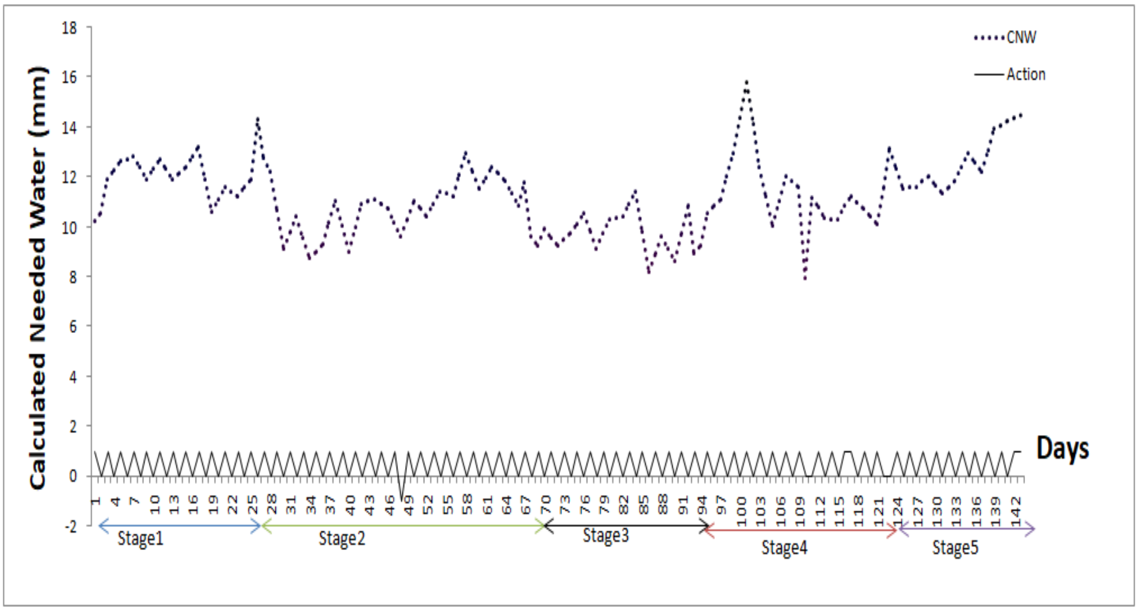


Figure 3.6: Calculated needed water output by the system for Season B 2018 using the Markov chain process and SARSA.

3.4 Summary

These system simulations demonstrate the capability of decision modeling to precisely monitor and take irrigation actions incorporating weather predictions and to have fault tolerance. The modeling components of the IoT system include the irrigation decision process that is ultimately presented to the farmer. The farmer can receive the decision information, assess the reliability of the information, and remotely interact with irrigation controls based on their own expert knowledge combined with the system data. The system has a level of fault tolerance to prevent crop loss by adaptively switching the modeling modes. The system demonstrated here could be adapted to other crops by adjusting IoT sensor types and prediction models. The system has the promise to minimize the human effort for manual operations, reduce water use, and potentially increase the return on investment by precision control of irrigation with fault tolerance. Furthermore, data collected over time can be used for long-term analysis and inform policy makers in better decision making and efficient resource utilization. While this simulation was done for flood irrigation, the system has the potential to be applied in the Alternate Wetting and drying irrigation method used to reduce water use in rice production by close control of irrigation while monitoring crop conditions. In this study, we have described adapting the MCP and SARSA models relevant to rice production within a low cost and appropriate technology version of an IoT system to manage rice irrigation in Rwanda. Modeling the irrigation process using MCP and SARSA algorithms will allow advanced field-specific variable rate irrigation at sites such as Muvumba Valley Rice Plantation. Future improvements for this IoT system include integrating data from remote sensing platforms to follow crop growth and linking real-time economic data such as power costs and market prices in seeking to maximize profit while meeting production demands.

CHAPTER 4

EFFECTS OF NPK FERTILIZER ON PADDY RICE YIELD AND SOIL ON IRRIGATED LAND IN RWANDA

4.1 Introduction

The rice (*Oryza sativa*)in Rwanda, has been distinguished and advanced as one of the needed nourishment crops and a major product within the rural and urban family, 76% of the rice purchased is imported from other rice-producing countries to meet the demands [8]. According to the National Rice Program of the GoR [9, 10], past predictions for the national demand for rice were underestimated, so one aspect of food security in Rwanda is to increase domestic rice production. In addition, based on the National Institute of Statistics of Rwanda[14] indicates that production in 2021 was only about a third of the demand, thus leading to negative economics[12].To increase rice crop production, there is always a need to apply fertilizers to produce enough rice production[152]to secure the future by applying NPK. According to previous research, the appropriate administering of nitrogen (N), phosphorus (P), and potassium (K) fertilizers helps in rice growth and hence improve yield[153]. In general, fertilizers containing N basic plant supplements are imperative for productive crops[154]. Although different generations requires fertilizers, the excessively measurement and utilize of fertilizers with chemically unequal NPK proportions in rice growth has brought about soil problems, such as fermentation, the misfortune of natural matter,soil degradation, weakening of the structure, and reductions in organic exercises and richness [155, 60, 156]. The high rice yield require exceptionally responsive to fertilizer inputs [157], It is troublesome to maximize the yields of crops developed in corrupted soils, and the effort required to moderate debased soil is unsustainable in Rwanda especially in Muvumba Valley where this research is conducted. In previous years,Muvumba Valley farmers have generally depended on chemical fertilizers, especially NPK fertilizers to boost rice yields where farmers are advised to apply 200kg/ha per season[158]. In this case, farmers are facing the problems of soil degradation, loss of yields, and other natural issues. NPK fertilizers are environmentally feasible that keep up soil well-being when appropriately utilized [159, 33]. In different studies indicates that the utilization of much fertilizer can lead to significant increases in the levels of natural matter, zinc,and copper within the soil[160]. Mostly, agriculturists apply fertilizer by weight without considering adding up to NPK substances or the percentage of NPK within soil. When the excrement is connected to the soil, a field of natural N is changed over into ammonium N (NH_4^-N) by soil organisms and the NH_4^-N is at that point changed over into nitrate by nitrifying soil. In this case, natural fertilizer application should be based on mineralizable NPK substances instead of adding up to the fertilizer weight to fulfill NPK demand [59]. In this consider, plants developed with natural fertilizer alone may endure nutrient deficiencies and create very low yields[161]. In many cases, the application of natural fertilizer together with NPK makes changes in soil by neutralizes soil pH,leads to higher levels of natural carbon, micro-nutrient accessibility, physical properties, microbial action, and increasing crop yields[162, 163, 164]. Therefore, it is crucial to explore the appropriate application amount of NPK fertilizer, which can not only reduce the waste of NPK fertilizer but also reduce the pollution of soil and the environment while increasing yield. There have been many studies on the effect of NPK fertilizer on rice showing that rice yield increases with the increase of NPK application in a certain range, but also decreases when applying too much NPK[**lui**, 165, 166]. According to[167, 168] overlooked the compact of NPK in different rice varieties including the loose rice variety as the test materials to explore the differences in NPK metabolism between the different stages of rice, and the results showed that more NPK application would affect the growth of the plant. [169, 170], studies showed that rice usually higher NPK efficiency and sensitive results have high yield. For this purpose, previous studies discussed on the effect of NPK on rice yield, quality and NPK utilization rate, but none reported on the effect of NPK on paddy rice stage. To date, there is no unified NPK utilization efficiency evaluation system for rice in Muvumba located in northern-eastern Rwanda, and there are many factors affecting NPK utilization, so it is necessary to determine the optimal NPK application amount of paddy rice. The main goal of this study is to explore the appropriate application amount of NPK fertilizer in paddy rice at each stage to avoid unnecessary waste of NPK fertilizer and soil degradation. Finally, this research suggests minimum NPK fertilization recommendations to farmers with few resources, so they have the opportunity to prevent crop loss in critical conditions and increase the yield .

4.2 Growth and Development of Rice

The fertilization helps in rice for growth, development, and increasing of rice yields. The knowledge of how much to apply in each growth rice stage are critical during plant growth and development that are sensitive to environmental factors [31]. On the other hand, rice development is defined as the sequence of five stages which are genetic events that involving differentiation, leading to changes in function and morphology form. These five stages are: seedling, tillering, panicle growth, flowering,and Ripening[32] . Development is most clearly manifested in changes in the form of organisms, as when it changes from seedling to reproductive stage and from reproductive to maturity,each stage needs a certain amount of NPK fertilizer which is different from previous one. Adequate phosphorus (P) diet of rice is indispensable due to the fact it is wants for strength storage and switch to the plant body. When P is utilized in early maturity, straw strength, and rice crop excellent and sickness resistance. Phosphorus exists in soil in two fundamental pools.one in natural and any other inorganic, the place natural P (Po) is the section of soil natural count number and soil biomass. The alternate nature of soil organic be counted mineralization and immobilization tactics dictate that some of Po contributes to plant reachable P. On the aspect of inorganic P (Pi) regulates P diet for rice plant uptake [171]. Pi in soils has 5 forms: (i) calcium phosphate (Ca-P), (ii) iron phosphate (FeP), (iii) aluminum phosphate (Al-P), (iv) occluded P (O-P), (iv) soluble orthophosphate (Sl-P). P deficiency shows bronzed leaves and very comparable signs and symptoms regarded when rice grown on zinc deficiency soil. In general, P fertilizer charges of 30, 20, and 10 kg P/ha are advocated for rice when the soil exams are very low and medium in P, respectively[**Sharma**].On side of Potassium (K),it also plays an important role in ensuring efficient utilization of N[47].Potassium is difficult to assimilate into organic matter as in the case of N and P, but helps in translocation of photosynthetic rice products and metabolites, as result to improved grain quality[172, 173]. K also plays a role in many important governing processes in the plant such as the grain quality of rice. Rice require a large amount of K, and continuous applying K is necessary up to the flowering stage after completion of the reproduction stage[174]. Figure4.1 indicates nitrogen as the essential element in rice crop. Proper application of N fertilizers is vital to improve crop growth and grain yields,especially in demanding agricultural systems like Muvumba Valley. Inadequate fertilizer N management can be harmful to rice crops and the environment. Organic N is converted to ammonium by a biological process called ammonification (N mineralization) when applied in flooded rice fields. The rate of ammonification is slower in paddy rice fields more than upland agricultural fields because O_2 is depleted in paddy fields [175], however, a low level of O_2 also limits nitrification (i.e., oxidation of $NH_4^+ to NO_3$) also N immobilization converted into inorganic N to organic N primarily by microbial assimilation of NH_4^+[176] ,resulting in the accumulation of NH_4^+ in soil[177].

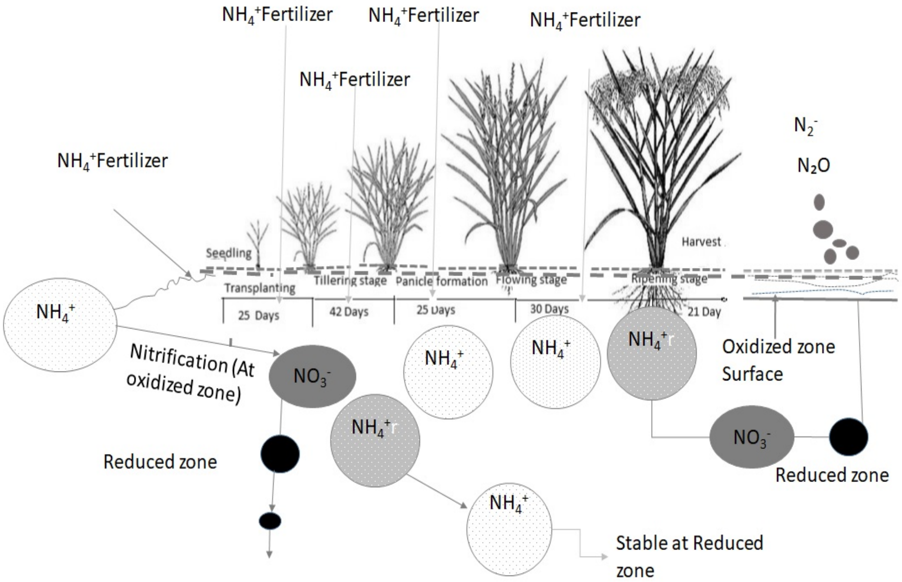


Figure 4.1: Days for each Stage and Nitrogen chemicals forms in Rice Growth

4.3 Nutrient Management Approaches for Rice Growth

Integrated plant nutrient management system is a holistic strategy to combine one of all herbal man-made sources of plant nutrients to preserve soil fertility to decorate rice crop productiveness in an efficient, environmentally safe, ecologically compatible, socially desirable and economically potential way. It makes use of each natural and in-organic plant nutrients to keep away from loss of crop yield and forestall soil degradation. This device can preserve a stability between the nutrients eliminated with the aid of the crop and the nutrients delivered to soil. The clever nutrient administration application takes into account the availability of nutrients in all sorts of soil, crop requirements, and different factors, such as elimination of nutrients from the soil by means of the crop, economics of fertilizer profitability, farmers potential to invest, soil moisture regime, bodily and microbiological circumstance of the soil, handy soil nutrient status, nutrient recycling and cropping sequence, and limiting loss to the surroundings [33, 34]. Soil is a complex substance with thousands of soil types existing in the world having arisen from different materials under various ecological conditions.Some are fertile, tillable, and wonderfully suitable for agriculture, and others may need a great deal of husbandry to become useful, sustainable for agriculture or regenerative farming to produce food and fiber on a sustainable basis and to repair the damage caused by destructive procedure[36, 35]. The fertilizer should be applied based on the stages of rice and availability of different parameters as shown in figure4.2.

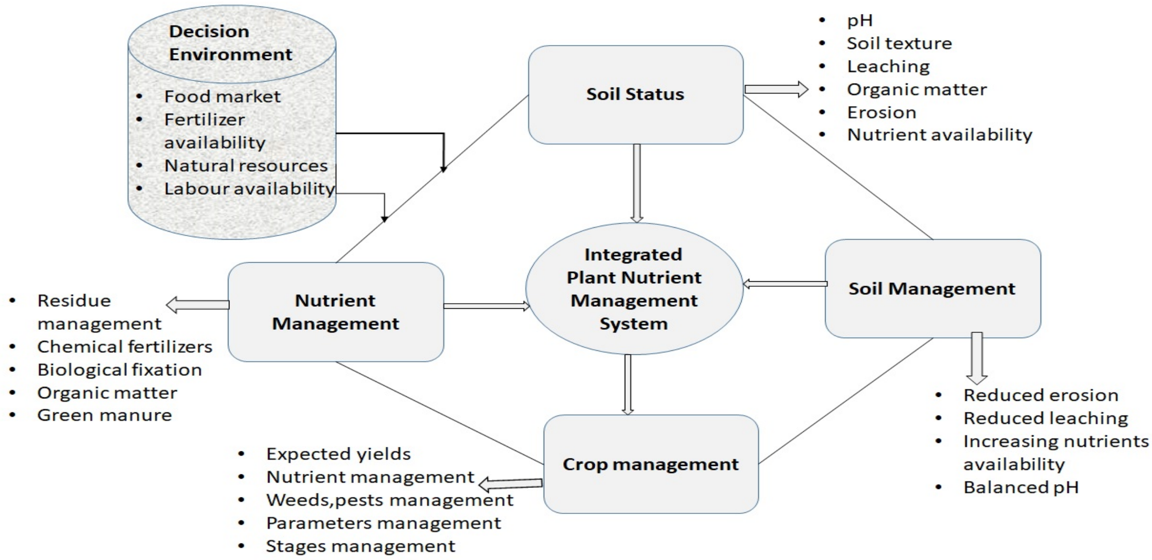


Figure 4.2: Nutrient management system in agriculture

4.4 NPK Concentration and Uptake

Nitrogen,phosphorus,and potassium are essential nutrients that play an essential role in the growth of rice plants. The increasing doses of organic fertilizers and the modification of the grid cropping system had a fairly good effect on increasing levels and uptake of NPK in plant tissues. The increasing uptake of NPK to the rice plant occurs when the water level in the soil is low to reduce leaching and volatilizing and improves the plant growth performance. NPK has an important role in the process of plant metabolism because N is an essential constituent of the amino acids that make up proteins, while potassium plays a role in the movement of water, nutrients, and carbohydrates in plant tissues, and involved in the activation of enzymes in plants that affect the production of protein, starch, and adenosine triphosphate (ATP) where ATP production can determine the rate of photosynthesis. In general, the mobility of NPK is quite high in the soil, especially in the rice fields, as a result of the inundation and drying process. Microbial activity can lead to increased K availability in the soil[178]. However, the K contained in the soil solution in a form that can be absorbed by rice plants, which can be easily washed[179]. In contrast to N and K that only increased 0.02 % N content and 1.6 g/plant N uptake and 0.17 % K content and 7.27 g/plant K uptake, there was a high increase in the P content and uptake in rice, 0.4 % P content and 104.52 g/plant P uptake. The Knowledge of adequate NPK concentration and uptake is an important plant parameter for appropriate NPK management. The adequate NPK concentration and uptake varied with rice yield level, which is affected by crop management practices. The NPK adequate concentration level in rice shoots varies from 43.4 to 6.5 g/kg depending on stage[180]. It decreases with the advancement of stage, reflecting a dilution effect with the advancement[174]. At maturity stage, the optimum NPK concentration in the grain is 10.9 g/kg, which is 68% higher compared to the shoot concentration. This means that NPK uptake determination during this growth stage is more important for knowing the quantity of NPK ,water level,and other soil conditions within the soil[181]. Adopting appropriate NPK management practices to supply the desired NPK rate from seedlings to flow stage[31]. If the farmer can be controlled variables, with a target range for manipulation, and if the variable cannot be controlled by farmer, such as temperature, water level, pH, clay-soil will impact the yield. The more importance are the minimum and maximum amount of NPK (91.24 kg/ha and 113.7 kg/ha) per season to produce good yields. This optimal range of NPK is considerably less than the standard government allotment of 200 kg/ha NPK that farmers typically apply during a growing season.

4.5 NPK Efficiency

It is essential to use Nitrogen (N), phosphorus (P),and potassium (K) in rice crop with the knowledge of improving efficiency and consequently management. In the previous work, NPK use was defined and calculated in several ways[182] and according to[37] suggested five definitions and methods of calculating NPK efficiency in rice crop plant. These efficiencies are known as agronomic efficiency (ARE), physiological efficiency (PE), agrophysiological efficiency (APE), apparent recovery efficiency (ARE), and utilization efficiency (UE). Definitions of these efficiencies and their methods of calculation [183]. These five NPK efficiencies in marshland rice genotypes were distinct in differences among genotypes. Overall, 29% of the NPK applied was recovered,the large amount of NPK which is lost in soil plant system and appropriate management practices are necessary to improve its efficiency. After different studies, the management of NPK fertilizer is essential, especially by knowing how much remains in the soil, at what amount of NPK should be applied in each stage of rice, and at what time. These results are consistent in improving the yield of rice.

4.6 Timing Application for NPK

When NPK is applied in the flooding plot, some are lost through volatilization, leaching, denitrification, or surface runoff[37, 38]. To increase both NPK fertilizer efficiency and NPK uptake by minimizing leaching, NPK should be applied 2 days before irrigation. According[39],agronomist efficiency of NPK in paddy rice will be higher when NPK was applied in the appropriate time in three split applications (one at tillering stage, the second at panicle initiation, and third at flowering stage). Minimum grain yield will be obtained when NPK is applied at flooding, where one part at seedling, the second at tillering, third at panicle initiation, and the fourth at flowering. Figure4.3 indicates the different total NPK applied in each year as well as rice yield in Rwanda. This information demonstrates the ability of decision modeling to adequately monitor and invoke fertilization actions incorporating soil conditions. The information demonstrated that due to the poor of applied NPK in Rwanda, the rice yield is very low, and the current practice have no promise to increase the yield except to change from traditional methods to smart agriculture.

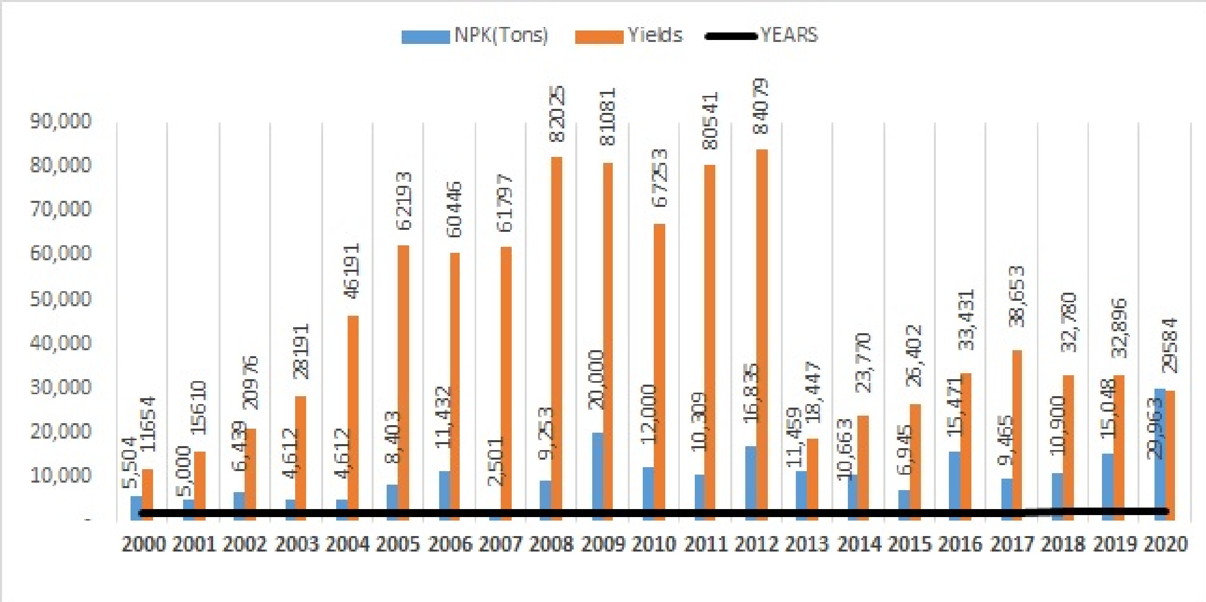


Figure 4.3: Yield vs NPK[11, 13, 8, 9]

Figure4.3 shows a strong correlation between yield and NPK, when an appropriate amount of NPK is applied in the appropriate time. This Research are suggesting that farmers should use decision modeling to adequately monitor and invoke fertilization actions incorporating weather prediction and irrigation status on the field, where the farmer can receive the information, assess the reliability of the information, and interact with the fertilization control-based information provided. Furthermore, data collected over time can be used for long-term analysis of conditions at plantations such as Muvumba Valley, and help agronomists respond to long-term trends such as climate change.

4.7 Summary

In summary, different studies suggested that NPK is an important source to sustain rice yield even in cases where fertilizer NPK is applied at high rates in most situations. If rice crop parameters are at a favorable level like water level, cultivars, control of diseases, insects,and weeds. On average, NPK sources of soil without application of chemical fertilizers can sustain 2000 kg/ha rice yield per season for a long duration under most agroecological conditions. Improving NPK efficiency in rice is important for higher yield and to avoid environmental pollution. NPK as a mobile nutrient in soil plant system, NPK recommendation based on different field studies indicates that the crop response to various rates of fertilizer application are the most efficient and effective. Plant tissue becomes strong compared to specified benchmark concentrations that separate deficient, sufficient, or toxic levels. The most significant observation emerging from different studies suggested that the mount of NPK required for producing the maximum economic yield varied from 90 to 130 kg/ ha per season. The NPK rate generally produces 6500 to 7000 kg/ha rice yields per season. NPK application rate should be applied in split doses under controlled conditions. Half of the required NPK should be banded at flooding, and the remaining half should be applied at active tillering, the second at panicle initiation, and the third flowering stage. Hence, planting NPK efficient genotypes is a very attractive strategy for improving crop yields and keeping a healthy environment.

CHAPTER 5

A DECISION-MAKING MODULE FOR FERTILIZATION AND IRRIGATION CONTROL SYSTEM IN RICE FARMING USING MARKOV CHAIN PROCESS AND SARSA ALGORITHMS

5.1 Introduction

In previous research, this research demonstrated a model to control an Internet of Things (IoT) system for rice irrigation using approaches that are appropriate for Rwanda, a country with low economic development [123]. Here,the research expands this IoT system to include models for controlling fertilization and irrigation. Rice is the second most important cereal and staple food in Rwanda, but the demand is largely met by importing rice from different countries around the world. The government thus supports irrigation schemes to increase agricultural resilience and self-sufficiency in areas such as Muvumba Valley that are otherwise too dry for optimal rice growth. With irrigation and fertilization, Muvumba Valley can support two seasons of rice per year due to the two rainy seasons in this equatorial region; Season A is March to August and Season B is September to January. According to [11], the current irrigation and fertilization system is manual, where farmers irrigate and apply fertilizer according to the instruction of the local agronomist. Conflicts arise in this system because there has to be a collective request of the farmers to achieve maximum water consumption and water control structures are minimal. Fertilizer application is made without regard to soil conditions due to lack of adequate and timely soil testing [184]. The objective of this work is to demonstrate through simulation, a system which uses IoT to control both irrigation and fertilization with fault tolerance to increase rice yield.

5.2 Method

Our IoT system is designed for the Muvumba Valley Rice Plantation located in Nyagatare district, eastern Rwanda (1.302S, 30.310E). [123]. There are two paths in the IoT system flowchart, one is the fully functional automated system "White". The second will only start if auto fails (gray). The Error Trail provides farmers with practical recommendations until the error is resolved. Farmers will receive system status and actions via smartphone or SMS, regardless of whether the system is fully functional or in a fualt state. If a fault is displayed, the farmer will be notified of the fault and will offer watering and fertilization recommendations, but the farmer will have to manually control the system. A variety of modeling processes are used to control data-rich normal mode and data-deficient path irrigation and fertilization event of a failure. In the automatic pathway, irrigation (WL) and fertilization decision is modeled as a Markov chain process (MCP) [**4**]. The IoT system will check the water level (WL) and fertilizer level (FL) in the field and assess the predicted rainfall and temperature by Web service. Irrigation is handled as in [123]. If fertilizer (NPK/urea) is needed, the system will engage to add and deliver the appropriate amount of fertilizer through the irrigation system. This IoT system will allow individual farmers to control the irrigation and fertilization of their individual plots to overcome this limitation of the current practice. When there is a fault in the IoT system, the pathway switches to the SARSA(λ) temporal difference method to propagate the recommended control to the farmer for manual control until the IoT system is repaired[148][136].

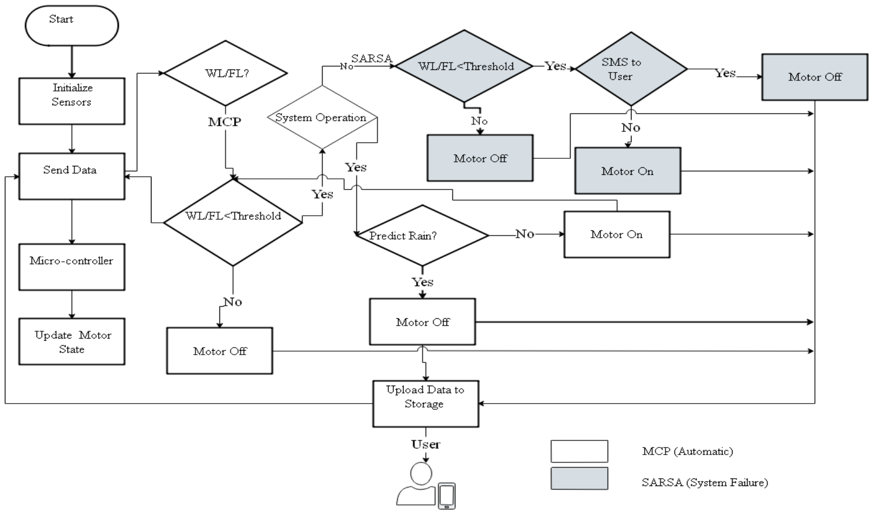


Figure 5.1: Flowchart of the irrigation and fertilization optimization system. White boxes are the MCP modeling flow and the gray boxes are the SARSA modeling flow.

MCP has been demonstrated to be a valid modeling approach for agricultural crop systems [185]. Water and fertilizer requirements for rice change for each stage of growth, so the MCP deals with this set of possible stages S and the set of possible actions A, where the effects of an action taken in a stage depend only on that stage and not on the prior history. As in [123],this research uses MCP to model the probabilistic transitions among a set of stages $S = \{s_1, s_2, \cdots\}$ [149], but here instead of just irrigation requirements we also model fertilization requirements, where each stage $s_i \in S$ is defined with a predetermined cumulative total soil water (TSW) and total soil fertilizer (TSF) range appropriate for Muvumba Valley. Water and fertilizer loss from each plot are monitored with a water level (WL) and fertilizer level (FL) sensors. Daily TSW/TSF calculations are summed to provide the cumulative value. As described in [123], the weather forecast is accessed by a Web service query and a calculated water need (CNW) and calculated fertilizer need (CNF) are obtained by accounting for the area of the plot and fertilizer within soil. The system reacts to weather and soil variables to indicate a state of deficit, sufficient amount, or an excess of water or fertilizer according to the growth stage and thus define the actions to take to satisfy the irrigation and fertilization demand. Target fertilization amounts by growth stage were taken from [186, 143]. TSW/TWF is calculated each day following the method in [10] and summed as a way to track the targeted cumulative TSW/TWF for each stage.

$$((TSW/TSF)(s,a)) \leftarrow ((TSW/TSF)(s,a)) + 1 \tag{5.1}$$

Irrigation decisions are made at 2 day time steps and fertilization decisions are made at weekly time steps. A decision depends on the current state $s \in S$, an action $a \in A$, such as opening a valve, which changes the condition C. The value called γ is defined as when the water level and fertilizer level reaches the desired range between the threshold and the maximum. Whatever the decision, the new condition $C(s,a)$ is received and the state transits to S. The cumulative $TSW/TSF(s^1,a^1)$ value of the state-action pair is updated with the calculated water and fertilizer needed (CNW/CNF). At state s, an action (a) is taken according to a greedy algorithm [136]. Then condition C is received and the state transits to s. The TSW value of the state-action pair (s^1,a^1) is updated with the temporal difference to obtain CNW/CNF:

$$CNW/CNF = C(s,a) + \gamma((TSW/TSF)(s^1,a^1)) - ((TSW/TSF)(s,a)) \tag{5.2}$$

At each time step, all entries of the TSW/TSF water and fertilizer to the field are updated according to the Equation 6.1 and Equation 6.2 with a learning rate α.

$$((TSW/TSF)(s,a)) \leftarrow ((TSW/TSF)(s,a)) + \alpha((CNW/CNF)(s,a)) \tag{5.3}$$

These actions for generating TSW/TSF and taking control actions are outlined in Algorithm 3, where the program first translates the time step i to 2 days for irrigation $[j, j+2]$ and 7 days for fertilization $[j, j+7]$. Then, it calculates the irrigation water depth or fertilizer amount I_j for day j according to current TSW/TSF_j (Total Soil Water) and the CNW/CNF (calculated needed water and calculated needed fertilizer).

Algorithm 3 Algorithm for generating the daily TSW/TSF record function

Generate daily TSW/TSF and irrigation and fertilization record function $Cal((TSW/TSF)(i, a))$

$j = (i - 1) * 2 + 1$ (irrigation)

$j = (i - 1) * 7 + 1$ (fertilization)

$Ij \leftarrow$ Irrigation/Fertilization Amount (TSW/TSF, CNW/CNF, Weather)

if $I_j < Threshold$ **then**

$\quad I_j \leftarrow 0$

end if

for $k = j + 1, k + +$, while $k < j + 3$ do $TWS_k \leftarrow CalTSW(TSW_{(k-1)}, I_{k-1}, ET_{k-1}, C_{k-1})$ **do** irrigation

$\quad$ **for** $k = j+1, k++$, while $k < j+14$ do $TSF_k \leftarrow CalTSF(TSF_{(k-1)}, I_{k-1}, ET_{k-1}, C_{k-1})$ **do** fertilization

$\qquad$ Return $((TSW/TSF)_{j+2})$ and I_j

$\quad$ **end for**

When there is a delay of irrigation or fertilization because of the technical problem, we will use the temporal difference learning algorithm SARSA(λ) [148] instead of the MCP. This policy is a state-action pair tuple which maps the action to be taken at each state, and the control method chooses the action for each state during learning by following MDP rules applied at every time step and by letting the agent transition from one state-action pair to another. The field is discounted by the product of γ and λ so that the conditions being reached at later time steps are updated according to the relevance of the previous state-action pair.

$$((TSW/TSF)(s, a)) \leftarrow \gamma\lambda((TSW/TSF)(s, a)) \tag{5.4}$$

When SARSA is running, the time step is set to be 2 days. Requires a priority, water demand and nutrient demand for each stage of the rice crop because each stage has its own minimum and maximum levels for optimal crop growth. Algorithm 4 provides a complete description of the learning processes, which indicates the operation with MCP when the system is fully functional and operation with SARSA when there is a system fault. The program starts with a randomly generated TSW/TSF table. At each time step, the agent takes an action and runs Equation 6.2 to obtain CNW/CNF. TSW/TSF and updating the irrigation or fertilization record for the current time step uses Equation 6.3 or 6.4. The model can be adapted to other crops by adjusting IoT sensor types and model parameters.

Algorithm 4 Markov and SARSA (λ) in Irrigation and Fertilization

Initialize $((TSW/TSF)(s,a))$ randomly
for All $((CNW/CNF)(s,a))$ **do**
  $((TSW/TSF)(s,a) \leftarrow 0$
  for $i = 1, i++$ while $i < n+1$ do $s \leftarrow$
    $(i, ((TSW/TSF)_i))$ **do**
    Take action a
    $[(TSW/TSF)_{i+1}, I_i] \leftarrow ((CNW/CNF)(i,a))S^1 \leftarrow State(i, ((TSW/TSF)_i))$
    $a^1 \leftarrow greedy((TSW/TSF), S_{i+1})$
    (CNW/CNF) $\leftarrow C(s,a) + \gamma((TSW/TSF)(s^1,a^1)) - ((TSW/TSF)(s,a))$
    $((TSW/TSF)(s,a)) \leftarrow ((TSW/TSF)(s,a)) + 1$
    for All $s\&a$ **do**
      $((TSW/TSF)(s,a)) \leftarrow ((TSW/TSF)(s,a)) + ((CNW/CNF)(s,a))$
      $((TSW/TSF)(s,a)) \leftarrow \gamma\lambda((TSW/TSF)(s,a))$
      Until $((TSW/TSF)(s,a))$ policy sufficiently stabilized

5.3 Result

To evaluate the effectiveness of the decision modeling system, this investigation used historical data from Meteo Rwanda for rainfall, temperature, and evaporation from March 2019 to January 2020. These data are from the Nyagatare weather station in the eastern province of Rwanda adjacent to the Muvumba Rice Plantation. The Nyagatare weather station data provide data relevant to irrigation and fertilization decisions. The soil type and pH value are taken from [151]. Figure 5.2 shows the results of the system for the fully operational system of the calculated fertilizer needed (NPK, urea) and the needed water level for each day as formulated in Matlab. The system will communicate the irrigation and fertilization status to the farmer to communicate what is happening in his rice field. The simulation findings of the system indicated an average of 31.62 kg/ha of NPK and 21.4kg/ha of urea needed for each stage per season. These fertilization amounts are less than the government allotments of fertilizers that farmers receive. This may indicate that fertilization is occurring at the Muvumba Valley rice plantation.

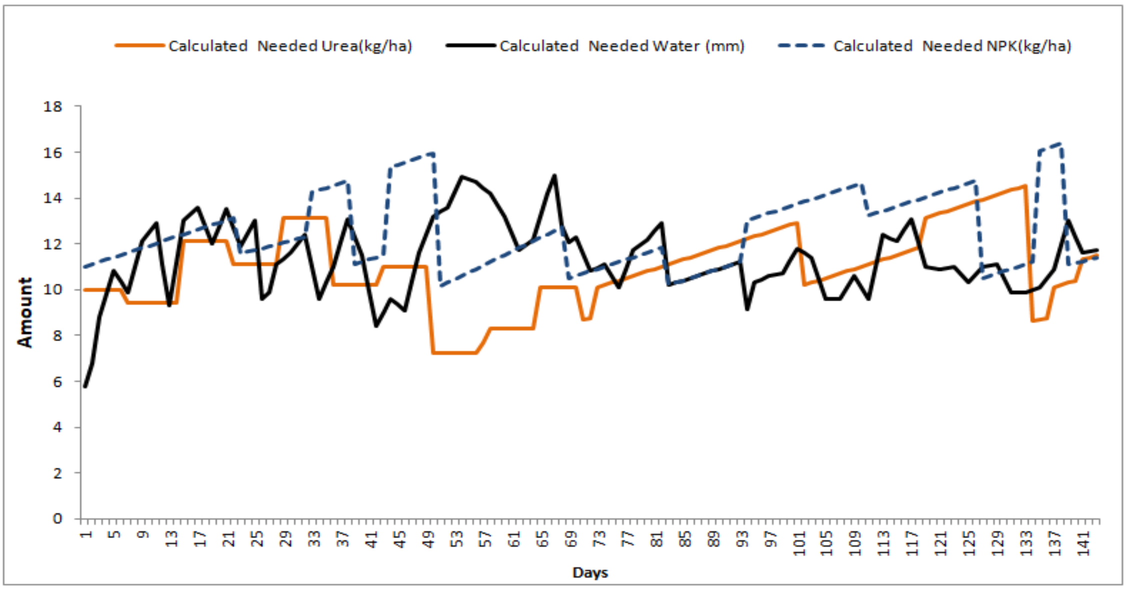


Figure 5.2: Result for Matlab simulation of one season using MCP.

The simulation of a fault is done for the same set of data used for the MCP simulation but assuming a fault in the system for the whole season without any sensor updates. This worst case scenario for the SARSA model thus relies on prior knowledge of water depth and fertilizer requirements for the growth stages, typical soil nutrient content, and climatological temperature and rainfall. Figure 5.3 shows water and fertilization amounts recommended for a single example plot. The irrigation amounts by stage generally follow the needs of the growth stage. Overall, the fertilizer recommendations ranged from 91.24 kg / ha to 113.7 kg / ha for NPK throughout the season. For urea, the recommendations ranged from 69.34 kg / ha to 86.67 kg / ha for the entire season. Similarly to the MCP results, for both fertilizer types, the recommendations are less than the allotments farmers now put on their fields. The method communicates reasonable amounts of irrigation and fertilization to the farmer for manual action.

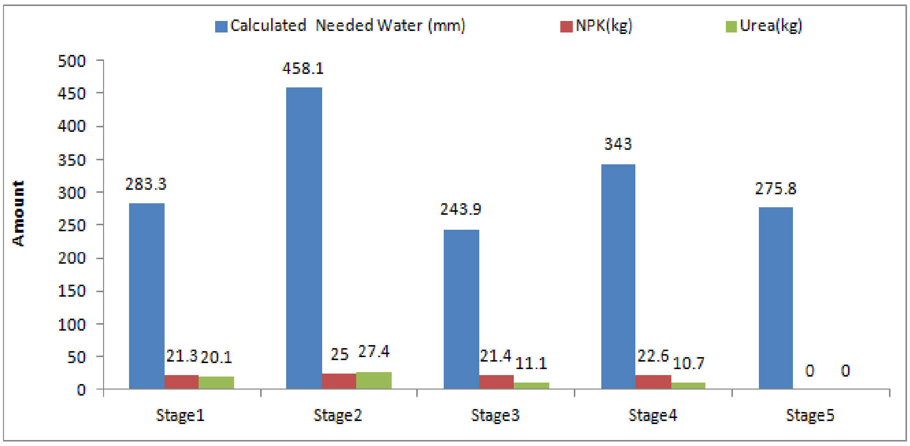


Figure 5.3: Results using SARSA for the five rice growth stages.

5.4 Summary

This research has described the adaptation of MCP and SARSA modeling to improve irrigation and fertilization actions to increase Rwandan rice production using an IoT approach. The simulation results suggest that reasonable irrigation and fertilization decisions are made by the system, and these decisions appear to be more efficient than the current irrigation and fertilization practices in Muvumba Valley. Farmers can remotely interact with irrigation and fertilization controls based on their own expert knowledge combined with the system data. Fault tolerance improves resilience by switching modeling modes. The IoT system has promised to minimize human effort, reduce the use of water and fertilizers, improve productivity, and increase the return on investment. Data collected over time are stored for analysis to improve decision making over time. The system can also work for the Alternate Wetting and drying irrigation method by accounting for wet and dry periods in the growth stages. Future work can include integrating remote sensing data from drones or satellites and economic data for seeking maximum benefits at low cost.

CHAPTER 6

VALIDATING ALGORITHMS DESIGNED FOR FERTILIZATION CONTROL IN RICE FARMING SYSTEM

6.1 Introduction

Rice yields in Rwanda seldom reach the values expected for irrigated production, in part due to poor fertilization management.In previous research, models were demonstrated for use in Internet of Things (IoT) approaches for controlling rice irrigation [123]and rice fertilization[182] in Rwanda, a country with low economic development. Although this previous research demonstrated useful results, the methods used independently addressed single agricultural production variables, that is, irrigation or fertilization. This work expands on prior work by adapting fuzzy logic as a means to account for multiple interacting variables impacting fertilization requirements, such as coming into play in rice production. To increase agricultural yields, the GoR encourages mechanization and fertilizer use [10, 134]. For example, with government support, Rwandan farmers increased fertilizer use from 4 to 32 kg/ha from 2007 to 2015 [187]. However, Rwanda has only one laboratory to test soil nutrients, causing delays in soil testing and dissemination of information. As a result, farmers in Rwanda lack knowledge about the soil nutrient status on their plots and, consequently, often make large errors in fertilization actions [188, 189]. When farmers add fertilizer without knowing the soil nutrient status, their actions can negatively impact soil pH and nutrient availability [190]. In Rwanda, improper timing, amounts, and proportions of nitrogen, phosphorus, and Potassium (NPK) and urea fertilizers result in rice yields that generally fail to rise above an average of about 3000 kg/ha per season[11]. One path to increasing rice yields in Rwanda is to help farmers improve fertilization decisions made at different times during the growing season. NPK fertilizers as well as urea provide critical nutrients for rice plants at different stages of growth

6.1.1 Related Work

According to [191], N deficiency during the early stages causes stunting and can prevent tillering. Flood irrigation of rice crops causes the loss of N through denitrification and leaching. When urea is used as a source of N and is not properly incorporated into the soil, it can rapidly volatilize at warm temperatures [191]. P is critical during later growth stages and when it is deficient, rice will not respond to other fertilizers [39]. Like N, the deficiency of K will also stop tillering and in later stages reduce the number of mature grains [192]. For some practical examples, urea is very effective when applied during rice planting (stage 1) and tillering (stage 2) when N is most critical, while an NPK fertilizer is effective during panicle initiation and booting (stage 3) and reproduction (stage 4) when P and K can be limiting. However, rice farmers in Rwanda tend to apply their government allotment of urea (100 kg/ha) and NPK (200 kg / ha) per season in planting and every time they weed, without knowing the actual requirements for their soil and without regard for the timing of nutrient needs during plant growth. These examples of the importance of timing of plant nutrients demonstrate how effective fertilization control during the growing season can increase the yield of the rice crop. Other factors also impact rice yields. To minimize labor, farmers typically dispose of rice crop residues such as straw by burning them in their fields instead of more effectively recycling the nutrients stored in the residues through decomposition, causing soil nutrient imbalances

(C:N ratio, for example) in their fields. In Rwanda, erosion of the topsoil from the surrounding hills into the rice fields causes constant changes in the texture and nutrient profile of the soil in the fields [193]. Finally, farmers have a wide range of economic status, some can easily afford to purchase extra fertilizer while others lack resources to do so. For all of these reasons, rice farming in Rwanda would benefit from more precise application of fertilizers at the plot level, with better monitoring of soil conditions, such as can be obtained with an IoT system. A wide range of IoT applications have been described for the agricultural sector [194, 195, 196, 197]. These IoT systems have been designed to monitor different agricultural parameters such as pH, soil electrical conductivity, water level, and temperature, for a variety of crops. Any IoT system requires an algorithm to perform the important role of translating data collected by sensors into actionable information. A recent review of IoT applications for rice farming focused on the application of machine learning algorithms within IoT systems and identified many areas where more work is needed to make these IoT systems operational [198]. This work explores one such approach, fuzzy logic. Fuzzy approaches can be effective in agriculture system models because they are robust when imprecise and incomplete field data are used, acceptable inputs and outputs can be dissimilar and represented as ranges, and the linguistic rule base can incorporate local expert knowledge. Furthermore, fuzzy systems allow the aggregation of dissimilar input variables in a consistent and reproducible way. Many other researchers have described fuzzy systems applied to agriculture for predicting yields, managing nitrogen, and optimizing fertilization [199, 200, 201]. This work has the hypothesis that an IoT system using a fuzzy algorithm can provide rice farmers with information that will allow them to reduce the amount of fertilizer in current practice while increasing the yield. The objective of this study is to create and demonstrate, through simulation, an IoT-based fuzzy fertilization decision making algorithm that incorporates knowledge from agricultural experts and expresses the context of soil properties, climate, and irrigation conditions in Rwanda. The formulation of the fuzzy algorithm is based on interviews with experts and existing knowledge of the conditions of the site. The long-term goal is to develop a low-cost system which will control the fertilizer automatically at the plot level according to the inputs available from soil sensors and the growth stage of the rice. To provide fault tolerance in the common case of network communication failure, an alternative algorithm pathway is designed. Finally, minimum fertilization recommendations are provided to farmers with few resources, so they have the opportunity to prevent crop loss under critical conditions.

6.2 Materials and Methods

6.2.1 Study Site

This work describes the context of rice cultivation in the Muvumba Valley Rice Plantation located in Nyagatare district, eastern province of Rwanda. Rice is grown at a variety of sites on the plantation, in different geographic settings, resulting in significantly different growing conditions. Overviews of the construction of the fuzzy models are provided and validation methods using simulations are described. Details are provided for the variables that will be measured as inputs for the fuzzy system, the rule base for the fuzzy system, and as well as two sub-algorithms used to form the decision outputs. This system is designed to work in parallel with the irrigation control system described in [123].

6.2.2 Overview of the Fuzzy Fertilization Decision Making System

A conceptual flowchart of an IoT fertilization system (Figure 6.1) illustrate a possible design, with the sensors as input to the fuzzy fertilization decision algorithm and its sub-algorithms. Overall, this flow chart follows that of [202], but with modification of functions and interactions. The decision process takes the sensor data and operates on those data using a fuzzy system created with rules derived from expert knowledge of rice farming fertilization requirements and expected yields in Rwanda. The output of the fertilization decision can then take either of the two pathways (sub-algorithm 1 and 2) to calculate the fertilization amount, followed by an actuation pathway (sub-algorithm 3) to act on the fertilization recommendation and automatically deliver fertilizer doses through the irrigation system. When system communications are ascertained as fully functioning, cloud-based processing ensues through a fuzzy nutrient balance method (sub-algorithm 1,in Fig.6.1) and data are stored. Basing this sub-algorithm and data in the cloud provides broader access via SMS or mobile applications and more flexibility for deeper data analysis. The fuzzy sub-algorithm output is translated into recommended fertilization amounts [203] which are passed on to the locally embedded sub-algorithm 3 (Fig.6.1) for control actions. If there is a fault in system communications blocking cloud access, the pathway switches to the locally embedded sub-algorithm 2 (Fig.6.1). Sub-algorithm 2 applies an empirical estimation method to pass actionable information on to sub-algorithm 3, and the farmer is informed on the system status and recommended actions via SMS through a GSM connection. Because growth stages and soil nutrient changes occur on timescales of several weeks, these fertilizer decision communications need only operate on a time scale of about one week. The details of the creation of the fuzzy rule base and sub-algorithms 1 and 2 are presented in the following subsections. Sensor data feeds into the fuzzy decision algorithm. The fuzzy output decision is translated back to the fertilization amount by either sub-algorithm 1 or 2 and the fertilizer amount is distributed by actuators controlled by sub-algorithm 3.

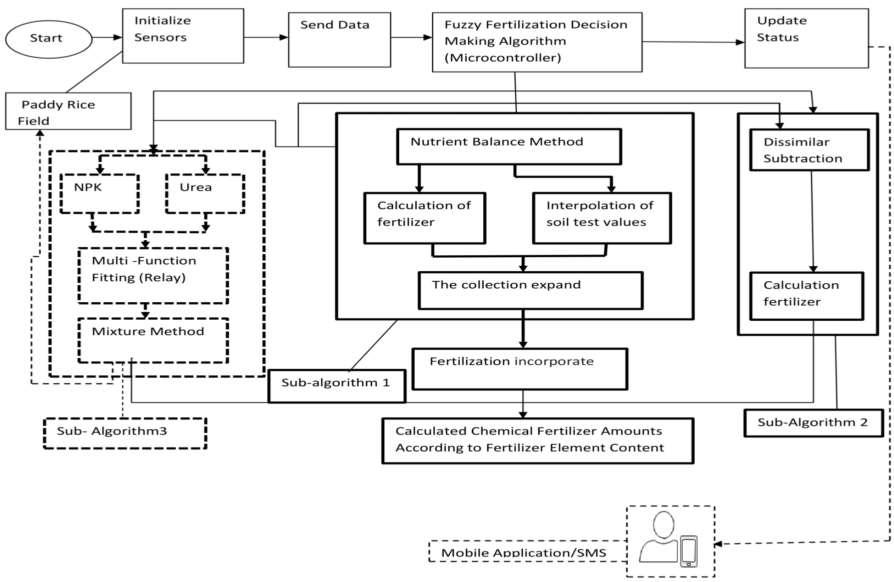


Figure 6.1: Conceptual flowchart of an IoT-based fuzzy fertilization decision-making algorithm

6.2.2.1 System Variables

It is assumed that the appropriate sensors are commercially available, but deployed sparsely across the agricultural plots, rather than as a dense network [204, 151]. The sensor will directly or indirectly measure the six pertinent agricultural variables, namely soil pH, air temperature, water level, clay soil content, and urea and NPK nutrient content in the soil. These sensors will monitor field conditions and send information to the fuzzy fertilization decision algorithm for analysis. The variables, measured with different accuracy and precision, are expected to have certain ranges (membership functions) that are expressed linguistically in fuzzy rules.

6.2.2.2 Fuzzy rule base formation

The six input variables are linked to the fuzzy rule base as IF THEN statements. Rules were formulated from related work and interviews with experts on current agricultural practices and conditions at Muvumba Valley rice plantation. These experts on Rwandan rice production included personnel from the Rwanda Agriculture Board and government agronomists working in the Muvumba Valley. The interview questions were designed to obtain responses on practices and knowledge related to fertilizer application, fertilizer requirements for rice growth stages, and the appropriate quantity and quality of fertilizer for different soil conditions. Fuzzy rules were formulated for the six sensor inputs, which yielded a single output.

Three linguistic variables, low, medium and high, were used for input and output, except for pH, which is expressed at a finer level of detail since the status of the nutrient is strongly affected by pH, as it ranges from acid to alkaline. This number of variables could lead to many hundreds of permutations of rules. However, because many permutations are similar, a subset of 183 rules was ultimately formulated. To arrive at this subset of rules, the impact of soil pH, soil clay content, temperature, and water level on the fate of soil nutrients was considered. Residual soil nutrients, leaching of nutrients, denitrification, and volatilization of nutrients all depend on the environmental conditions that the sensors measure. Example rules with their conditions leading to low, medium, and high yields are provided in Table 6.1. The complete set of rules are provided in the supplementary materials.

Table 6.1: Seven examples of the 183 fuzzy rules for evaluating soil conditions leading to low, medium, and high yields.

Rule number	Rule
1.	IF soil pH is strongly acid AND clay percentage is low AND temperature is low AND soil water level is low AND NPK is low AND Urea is low THEN yield is low.
⋮	
6.	IF soil pH is strongly acid AND clay percentage is high AND temperature is high AND soil water level is high AND NPK is high AND Urea is high THEN yield is low.
⋮	
51.	IF soil pH is strongly alkaline AND clay percentage is high AND temperature is high AND soil water level is high AND NPK is high AND Urea is high THEN yield is low
⋮	
117.	IF soil pH is slightly acid AND clay percentage is medium AND temperature is low AND soil water level is medium (satisfied) AND NPK is medium AND Urea is medium THEN yield is medium
⋮	
166.	IF soil pH is slightly acid to medium alkaline AND clay percentage is medium AND temperature is medium AND soil water level is medium (satisfied) AND NPK is medium AND Urea is medium THEN yield is medium
⋮	
176	IF soil pH is slightly acid to medium alkaline AND clay percentage is medium AND temperature is low AND soil water level is medium AND NPK is medium AND Urea is medium THEN yield is high
⋮	
183.	IF soil pH is slightly acid to medium alkaline AND clay percentage is low AND temperature is low AND soil water level is medium AND NPK is high AND Urea is high THEN yield is high

6.2.2.3 Fuzzy Nutrient Balance Method: Sub-Algorithm 1

The same information used to formulate the rule base is used to create the fuzzy membership functions for sub-algorithm 1, a nutrient balance method. This nutrient balance method is the process used to make management decisions throughout the growing season to improve yields while minimizing fertilization. This method is intended to be the primary method used by the system when it is fully functional, without communication faults. Triangular membership functions for the variables are used since the linguistic rule base has three levels of low, medium, and high. For example, Eq. 6.1 provides these functions for fertilizer requirements for each stage of growth, where f is the total fertilizer amount required during the growing season, x is the total available fertilizer within soil without amendment, r is the fertilizer requirement for each stage, and z is the fertilizer uptake by the rice. Top to bottom in Eq. 6.1, these sets describe conditions of insufficient soil fertility, added fertilizer but less than optimal, a minor excess of fertilizer that may yet be taken up by rice, and excess fertilizer that can lead to soil degradation. The other variables affecting fertilizer availability have similar triangular membership functions and are provided in the supplementary materials.

$$Y(f;x,z,r) = \left\{ \begin{array}{cc} 0 & f \leq x \\ \frac{f-x}{z-x} & x \leq f \leq z \\ \frac{r-f}{r-z} & z \leq f \leq r \\ 0 & f \leq r \end{array} \right\} \tag{6.1}$$

6.2.2.4 Fuzzy Inference of Minimum and Maximum Fertilizer

The fuzzy nutrient balance method identifies the optimal fertilization conditions to maximize the yield given environmental constraints. However, some farmers do not have the resources to fully follow the optimal recommendations, while others may over- fertilize. To accommodate situations and provide feedback when a farmer might not be taking the recommended actions, the system will send alerts when crop loss is predicted and recommend a minimum fertilization action to take to prevent complete crop failure and maintain a reasonable yield. In this sense, the system considers the socio-economic conditions that may be present. This minimum recommendation is achieved through Eq. 6.2, which includes the pH fuzzy set, p, in addition to the fuzzy sets for residual soil nutrients and nutrient uptake, x and z. $Y_p(f)$,$Y_x(f)$, and $Y_z(f)$

are their respective membership functions.

$$Y_z(f) = min\left[Y_x(f), Y_p(f)\right] \quad f\epsilon f \tag{6.2}$$

The system also informs farmers if their actions have led to the maximum fertilizer for each stage being met (Eq. 6.3), thereby providing a warning of added costs, potential degradation of soil properties, and reduced yields if more fertilizer is added.

$$Y_z(f) = max\left[Y_x(f), Y_p(f)\right] \quad f\epsilon f \tag{6.3}$$

6.2.2.5 Empirical estimation method: Sub-algorithm 2

If there is a fault in Internet communications (a common occurrence in Rwanda), the cloud-based nutrient balance method (sub-algorithm 1) will fail to send commands to sub-algorithm 3. In the case of an extended communication outage, the system will switch to sub-algorithm 2, an empirical estimation method which would be embedded in the field of a node manager. Sub-algorithm 2 will initialize as the last valid output of the nutrient balance method. The sensor data are still available for analysis with the fuzzy rule base, while the fertilizer demand for each stage is estimated from prior data, thus providing a means to estimate yield using Eq. 6.4. The measured fertilizer within the soil, x, is subtracted from the estimated fertilizer demand for each growth stage, r, to derive the fertilizer estimates to be sent to sub-algorithm 3. Estimated yield, Y, in Eq. 6.4 will depend on the fertilizer applied and measured fertilizer within the soil, while the combined effects of environmental conditions α (pH, water level, clay soil content, and temperature) are derived with a fuzzy analysis.

$$Y = \alpha\left(\sum_{i=0}^{n}(r-x)\right) + \sum_{i=0}^{n}(x) \tag{6.4}$$

This method is used until cloud communications are reestablished. Once the IoT system is fully operational again, the nutrient balance method resumes with initialization based on the last state of the empirical estimation method. Estimates α and r estimates for Eq. 6.4 can be updated as needed over time as more data is analyzed. Simulations were performed for the two pathways of subalgorithms 1 and 2. The fuzzy system was modeled using the MATLAB® fuzzy simulation tool in Simulink®. All combinations of the three levels of linguistic variables (except for pH with 12 levels) lead to approximately 2,900 instances. The data inputs used historical Meteo Rwanda data [205] for temperature from September 2019 to January 2020, and water level from our previous research [123], clay soil content from [151], pH from [133], and NPK and urea data provided by the agronomists responsible for the Muvumba rice plantation. All data are provided in the supplementary materials.

6.3 Results and Discussion

6.3.1 Model Testing

To provide a level of validation of the algorithms, simulation results for a variety of conditions were examined. For example, measured field water levels are not available for farmers' plots, whereas typical values for fertilizer and other variables are known. Therefore, validation simulations use a range of water levels that correspond to different amounts of irrigation, with the additions of NPK and urea remaining constant, since many farmers apply the government recommendations of NPK and urea [187]. Table 6.2 shows these simulated yield results for seven representative cases of seasonal averages, with different water levels, constant NPK and urea additions, but variable pH, clay soil content and temperature. The resulting yield values indicate that the simulations successfully incorporate all variables. Within each case (each column of Table 6.2), the yield is shown to respond to different levels of water. Comparisons across cases illustrate the importance of pH, clay soil content, and temperature. For example, Cases 3 and 7 have significant differences in the average seasonal values for these three variables, leading to a large difference in yield between these cases when the water level is constant. In contrast, Cases 5 and 6 have roughly similar average values for these three variables, leading to roughly similar yields for any given irrigation level. For each case, various irrigation levels were simulated, while NPK and urea are kept constant at 200 kg/ha and 100 kg/ha per season, respectively.

Table 6.2: Simulated yields for different cases of pH, clay soil content,and temperature.

Input	Case 1	Case 2	Case 3	Case 4	Case 5	Case 6	Case 7
pH	4.85	5.92	7.99	6.34	7.42	7.78	7.07
Clay soil (kg/m^3)	352.41	592.68	384.44	432.5	480.55	416.48	368.43
Temperature (°C)	18	28	24	20	22	19	18
Water level (mm)	10.61	10.61	10.61	10.61	10.61	10.61	10.61
Simulated yield (kg/ha)	3070.71	3050.51	2757.58	4181.82	5101.01	6010.10	5707.07
Water level (mm)	50.71	50.71	50.71	50.71	50.71	50.71	50.71
Simulated yield (kg/ha)	4080	4140.4	3750	5170	6070	7000	6670
Water level (mm)	21.11	21.11	21.11	21.11	21.11	21.11	21.11
Simulated yield (kg/ha)	4010	3919.19	3676.77	5161.62	6151.52	6878.79	6656.57
Water level (mm)	23.03	23.035	23.03	23.03	23.03	23.03	23.03
Simulated yield (kg/ha)	4140	4240	3878.79	5280	6270	7000	6780

Next, simulations were done to replicate known yields for specific farmers' plots for the September 2019 to January 2020 growing season. The amounts of NPK and urea applied to these plots were known to be the amount recommended by the government. The pH, clay-soil content and temperature were known, so the only unknown was the water level. With the known input set, the average water level for the season was varied to find a good match to the actual yield. The range of average water levels that produce matching yields spans between 10 and 50 mm, similar to the range of water levels shown in Table 6.2. The reasonable range of water levels needed to produce yields matching the measured yields provides additional validation for the simulations. Some general trends observed are a lower yield range for more acid soils and conditions with very high or very low seasonal temperatures. The best simulated yields that match are compared to the measured yields in Fig. 6.2. The average measured yield is 2900 kg/ha per season. This value can be compared to the prediction results described next.

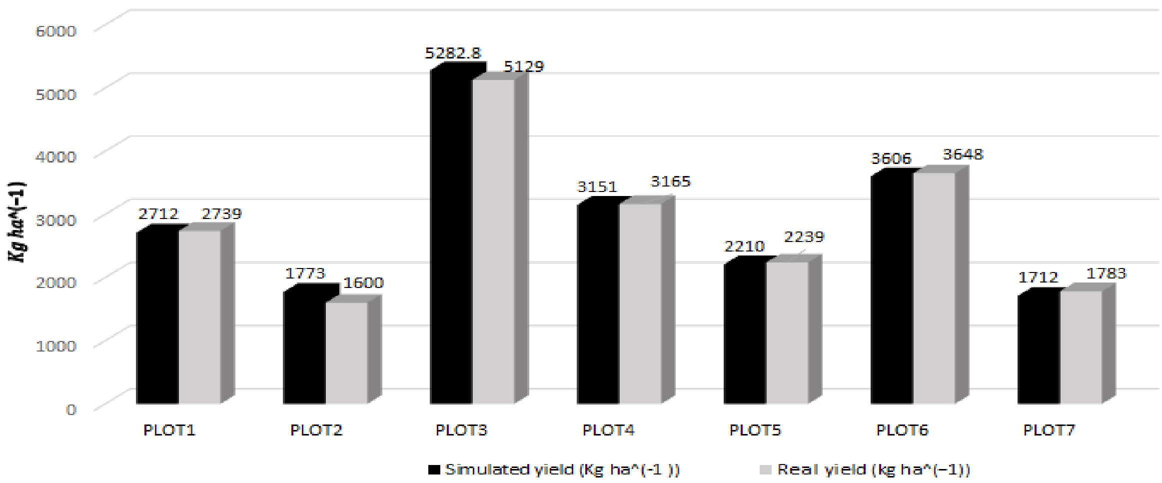
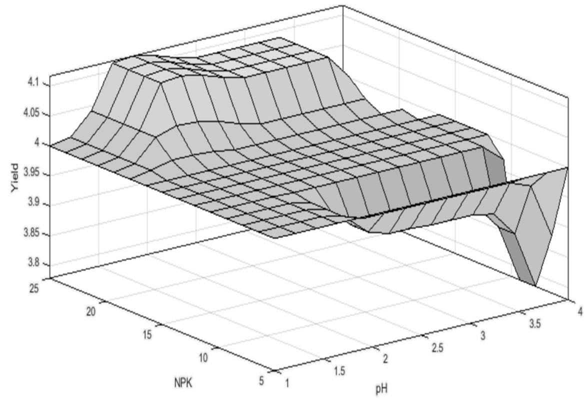


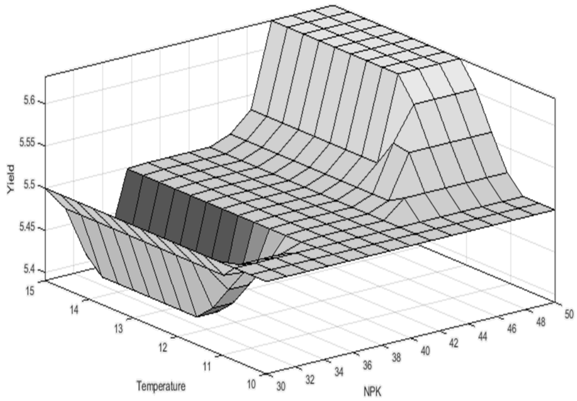
Figure 6.2: Simulated and measured yields for similar plot conditions.

6.3.2 Prediction Results

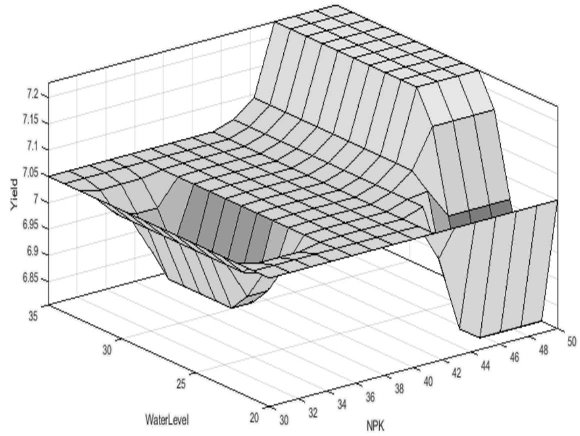
This section describes the prediction results, that is, predicted yields across a wide range of inputs when either sub-algorithms 1 or 2 are used to manage field conditions during the growing season. These predicted yields can be compared to the average measured yield of 2,900 kg/ha determined for the September 2019 to January 2020 growing season. Details of the four selected simulation outputs for the fully operational system (sub-algorithm 1) are presented in Fig. 6.3. These are some examples of yield (kg/ ha*1000) depending on the environmental variables corresponding to the specific rules listed in Table 6.1. Fig. 6.3a shows the conditions of Rule 1 translating into a yield of about 4100 kg/ha. Fig. 6.3b shows the conditions of Rule 117 translating into a yield of about 5,600 kg/ha. Fig. 6.3c indicates the conditions of Rule 176 that lead to a yield of about 7200 kg/ha. Fig. 6.3d shows some optimal conditions such as in Rule 183, which can demonstrate the production of up to 8,000 kg/ha. These graphical results illustrate how relatively minor changes in the interacting variables impact the yields.



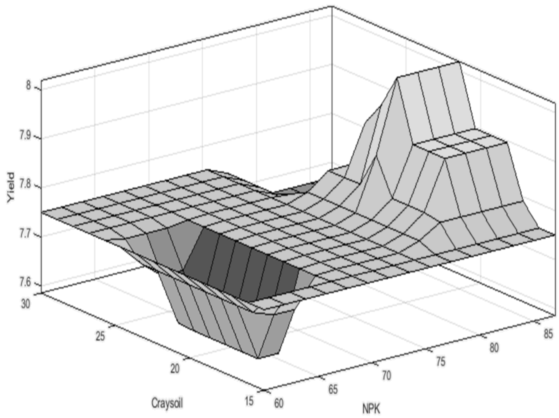
(a) Yield variation when pH is low and NPK is low.



(b) Yield variation when temperature is low and NPK is medium.



(c) Yield variation when the water level is medium and NPK is medium.



(d) Yield variation when clay soil content is medium and NPK is high.

Figure 6.3: Rice yields (kg/ha*1000) as a function of various soil and nutrient conditions. Although these 3D visualizations can show only two inputs at a time, all input variables contributed to the result.

The results of simulations for sub-algorithm 1 specifically for high yield cases are summarized in Table 6.3. Thus, the reported minimum and maximum variable values define the ranges of variables for each growth stage that lead to optimized rice yields. If the variables can be controlled by the farmer, then these are a target range for manipulation. If the variable cannot be controlled, such as temperature, the farmer can assess how conditions might impact their yield. Of particular importance are the minimum and maximum total NPK requirements for the growing season to produce good yields that are 91.24 kg / ha and 113.7 kg / ha per season, respectively. This optimal range of NPK is considerably less than the standard government allotment of NPK of 200 kg/ha that farmers typically apply during a growing season. The minimum and maximum total urea requirements for the growing season to produce good yields are 69.34 kg/ha and 86.67 kg/ha, respectively. Similarly to NPK, this optimal range of urea is considerably less than the standard government use for urea of 100 /ha. These simulation results are consistent with reports of over fertilization of Rwandan rice plantations in recent years [189]. Taken as a whole, the simulated yields range from about 2721 kg/ha to 7257 kg/ha, with an average of 4064 kg/ha, which is a large improvement over the average measured yield of 2900 kg/ha.

Table 6.3: Range of variables (Minimum and Maximum) according to rice growth stage that lead to optimized yield.

	Seedling		**Tillering**		**Panicle growth**		**Flowering**	
Inputs	**Min**	**Max**	**Min**	**Max**	**Min**	**Max**	**Min**	**Max**
pH	5.6	5.9	5.30	7.49	7.07	7.14	6.4	6.89
Clay Soil	336.39	608.70	384.44	416.48	400.46	480.55	432.49	448.51
Water level	50.00	100	10	20	10	20	50	100
Temperature	13.7	26.9	22.6	18	23.27	22.42	13.47	14.6
NPK	20.30	25	24	30.40	25.36	32.3	21.58	26
Urea	20.10	25.81	27.42	30.25	11.11	18.79	10.71	11.82

Sub-algorithm 2 is intended to replace sub-algorithm 1 when communications fail. To test the output of sub-algorithm 2, simulations were done with the algorithm for the entire September 2019 to January 2020 growing season. Table 6.4 presents examples of simulation variables averaged over the whole growing season and the yield for different rules using the empirical estimation method of sub-algorithm 2. For the 183 rule conditions, yields range from 2268 kg/ha to 6486 kg/ha with an average of 3538 kg/ha. Although not as effective as the nutrient balance method of sub-algorithm 1, this method produces simulated yields that are on average larger than the measured yields from the September 2019 to January 2020 season, as previously described.

Table 6.4: Average simulated seasonal variable values for pH, clay soil content, water level, temperature, NPK, and urea, for example, rule conditions and corresponding rice yield.

Rule	pH	Claysoil (kg/m^3)	Waterlevel (mm)	Temperature (°C)	NPK (kg/ha)	Urea (kg/ha)	Yield (kg/ha)
1	5.05	341.19	10.61	13.01	67.88	58.6	2267.96
6	5.14	329.34	50.71	26.25	77.08	61.96	3556.16
51	7,9	403.67	17.27	14.89	84.24	69.48	3764.82
71	7.3	336.55	21.11	20.51	78.12	40.8	4481.49
117	5.9	330.30	22.22	21.53	89.88	59.8	4808.08
140	6.71	368.75	10.10	15.22	97.8	78.36	5125.59
154	7.14	431.06	50.71	26.45	104.12	67.84	5533.83
176	6.68	444.03	23.03	21.24	110.52	72.64	5896.7
183	7.71	329.49	21.52	11.08	126	84	6486.37

Taken together, the simulations described here demonstrate the potential of fuzzy algorithms to provide actionable information to improve rice yield. These system simulations demonstrate the ability of decision modeling to adequately monitor and invoke fertilization actions that incorporate weather predictions, pH values, clay soil content, and irrigation status from field sensors. Upon creation of the system hardware, the farmer can receive the decision information, assess the reliability of the information, and remotely interact with fertilization controls based on their own expert knowledge combined with the system data and recommendations. The system is designed to make optimal recommendations, but also has flexibility in response to anticipated problems, such as Internet communications failure and under or over fertilization. The system demonstrated here could be adapted to other crops by adjusting the types of IoT sensor and the fuzzy rule base. The system has the promise to lower the human effort for manual operation of irrigation and fertilizer control, and potentially increasing the return on investment by more precise control of fertilization to decrease costs while boosting yield by as much as 1000 kg/ha per season. Furthermore, data collected over time can be used for long-term analysis of conditions at plantations such as Muvumba Valley, and help agronomists respond to long-term trends such as climate change. Although this simulation was performed for flood fertilization, the system has the potential to be applied to the alternate wetting and drying irrigation method for rice, where close control of fertilization actions is required to maintain efficient uptake of nutrients over time.

6.4 Summary

In this study, a fuzzy algorithm was designed to monitor and control rice production in the Muvumba Valley Rice Plantation in Nyagatare District, Eastern Province of Rwanda. The rule base for the fuzzy algorithm was created from interviews with local agronomists and published data. The algorithm was created for future operation in an Internet of Things system, with three sub-algorithms to enable a flexible response to local conditions and the technical challenges typical of a low-income country. Simulation was used to test the operation of the system and assess the possible impact on rice yields compared to the measured yields. The system could reproduce actual yields when conditions were set to be the same as known conditions for weather, soil, and fertilizer application. The exact irrigation amounts were unknown, so the range of amounts of irrigation was adjusted to arrive at the yields. However, these amounts of irrigation were well within the realistic range of values. Simulations in which the system adjusts the timing and amount of fertilizer and water use resulted in predicted yields approximately double the measured yields, despite the application of less fertilizer in total. Even in the case of a system fault, the alternative sub-algorithm 2 produces yields in excess of the measured yields.This research concluded the development of a low-cost IoT system and its algorithm for controlling and monitoring rice farming in Rwanda can reduce fertilizer use while improving yields.

CHAPTER 7

CONCLUSIONS

The work of this thesis was to examine how to design and develop machine learning algorithms within the structure of an IoT irrigation and fertilization support system for rice farmers in the Muvumba Valley, Rwanda. The following sections provide a summary of the work carried out in the thesis to fulfill the purposes and requirements identified in Chapter 1 and recommendations for the actions needed to create a functioning system based on the algorithms developed.

7.1 Contributions of the Thesis

The contributions of the thesis consist of the development and testing of several different algorithms for IoT control which can lead to efficiency in irrigation and fertilization and thereby improve rice production. Four different algorithms with different goals and approaches are summarized as follows:

7.1.1 Decision modeling of irrigation actions incorporating weather forecasts and fault tolerance

The first algorithmic approach was to adapt the Markov chain process and the SARSA model to manage rice irrigation in Rwanda. The Markov chain process provides the primary algorithm for controlling irrigation, while SARSA models are used in case of system fault. Modeling the irrigation process using the Markov chain process and SARSA algorithms will allow advanced field-specific variable-rate irrigation at sites such as the Muvumba Valley Rice Plantation. System simulations were used to demonstrate the ability of decision modeling to precisely monitor and take irrigation actions incorporating weather predictions and to have fault tolerance. With relatively simple communication such as SMS, the farmer can receive the decision information, assess the reliability of the information, and remotely interact with irrigation controls based on their own expert knowledge combined with the system data. The system has a level of fault tolerance to prevent crop loss by modeling adaptive switching modes from the Markov chain process to SARSA. The system demonstrated here could be adapted to other crops by adjusting the types of IoT sensors and prediction models. The system has the promise of minimizing human effort for manual operations, reducing water use, and potentially increase the return on investment by precision control of irrigation with fault tolerance. Furthermore, data collected over time can be used for long-term analysis and inform policy makers in better decision making and efficient resource utilization. While this simulation was done for flood irrigation, the system has the potential to be applied in the alternate wetting and drying irrigation method used to reduce water use in rice production by close control of irrigation while monitoring crop conditions.

7.1.2 Intelligent Irrigation, Fertilization, and Post-Harvest Management with IoT Technology: Challenges and Setbacks

An extensive review of the application of intelligent IoT to smart agriculture was performed. Several known problems examined are related to wireless sensor applications in smart agriculture, the application of IoT in crop production and post-harvest processing, and the use of drones. This research review contributes to information by identifying the gaps and challenges in existing in smart agriculture. Some of these gaps and challenges for boosting the potential power of IoT devices utilized in smart agriculture include AI for early sickness detection, detection of water level in crops, detection of soil condition, and identification of behavior patterns on farms. Global population is increasing daily, so large wastage of crops through poor storage techniques leading to post harvest losses remains an obvious problem. An efficient Intelligent IoT system for smart agriculture will contribute to the journey to reduce food wastage, boost food production, and increase data access about farming systems will improve future decision making and analysis by researchers.

7.1.3 Effects of NPK Fertilizer on Yield at Muvumba Valley Rice Plantation

A review and synthesis was performed to examine the current state of fertilization practices, climate, and soil conditions relevant to the Muvumba Valley site. A variety of studies taken in total suggested that for the Muvumba Valley site, on average, NPK provided by the soil without application of any chemical fertilizer can sustain 2000 kg/ha of rice yield per season without soil degradation and under most agroecological conditions. A past field study of the mobility of NPK in the Muvumba Valley indicates that the availability of NPK at various growth states changes significantly and continuous monitoring of NPK status is required to apply the most effective fertilizer rates. The most significant outcome emerging from different studies is the amount of NPK required to produce the maximum economic yield ranges from 90 to 130 kg/ ha per season.

7.1.4 Decision-making Module for an Fertilization and Irrigation Control System

This part of the research was to adapt the MCP and SARSA models to simultaneously improve both irrigation and fertilization actions leading to increased production of rice at Muvumba Valley. The simulation results suggest that reasonable irrigation and fertilization decisions are made by the system, and these decisions appear to be more efficient than the current irrigation and fertilization practices in Muvumba Valley. The system was designed so farmers can remotely interact with irrigation and fertilization controls based on their own expert knowledge combined with the system data. Fault tolerance improves resilience by switching modeling modes. The IoT system has promised to minimize human effort, reduce the use of water and fertilizers, improve productivity, and increase the return on investment. Data collected over time are stored for later analysis which may improve decision making over time. The system can also work for the alternate wetting and drying irrigation method by accounting for wet and dry periods in the growth stages. Future work can include the integration of remote sensing data from drones or satellites to take advantage of the benefits of these geospatial technologies. Further integration of economic data into the modeling flow in terms of technology costs, market prices, and transportation or processing costs can help optimize benefits from the technology by maintaining economic efficiency.

7.1.5 Fuzzy Fertilization Decision Making System

In this research, a fuzzy algorithm was designed to monitor and control rice production at Muvumba Valley Rice Plantation. The rule base for the fuzzy algorithm was created from interviews with local agronomists and from published data. The algorithm was created for operation in an IoT system, with three sub-algorithms to enable a flexible response to local conditions and technical challenges typical of a low-income country. Simulation was used to test the operation of the system when the system is fully functioning by using sub-algorithm 1 (nutrient balance) and assess the potential impact on rice yields compared to actual yields. The system could reproduce actual yields when conditions were set to be the same as known conditions for the application of weather, soil and fertilizers. The exact amounts of irrigation were unknown, so the range of amounts of irrigation was adjusted to arrive at the yields. Simulations in which the system adjusts both the timing and amount of fertilizer plus water use resulted in predicted yields approximately double the measured yields, despite the application of less fertilizer in total. Even in the case of a system fault, the alternative sub-algorithm 2 (dissimilar subtraction) produces yields in excess of the measured yields. This research concluded the development of a low-cost IoT system and its algorithm for controlling and monitoring rice farming in Rwanda can reduce fertilizer use while improving yields.

7.2 Future Work

The following are possible future works for our this thesis.

Future improvements for this IoT system include integrating data from remote sensing platforms to follow crop growth and linking real-time economic data such as power costs and market prices in seeking to maximize profit while meeting production demands. In the future, the researchers plan to perform experiments by deploying sensors and actuators in rice field which will either take action depending on the information from the state modeling system to fertigate, irrigate, not irrigate, or extract water from the field. The farmer will check the irrigation status of the field using a smartphone application. If the farmer does not have a smartphone, his phone number can be registered to receive the notification for changes made to his field by SMS. Further, the researchers would like to study in detail how the system improves on existing traditional methods.

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LIST OF PUBLICATION

Below in the table are the list of our publications

Paper Name	Link	Publisher
Simulation of IoT Water Management for Efficient Rice Irrigation in Rwanda	https://doi.org/10.3390/ agriculture10100431.	Agriculture-MDPI
Intelligent Irrigation,Fertilization, Post-Harvest Management with IoT Technology: Challenges and Setbacks	https://www.shin-norinco.com/article/intelligent-irrigation-fertilization-post-harvest-management-with-iot-technology-challenges-and-setbacks	AMA-Agricultural Mechanization in Asia Africa and Latin America
Decision-making Module for Fertilization and Irrigation Control System in Rice Farming using Markov Chain Process and SARSA Algorithms	http://www.wcse.org/WCSE%202021/052.pdf	The 11th International Workshop on Computer Science and Engineering (WCSE 2021)