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Edge IoT Driven Framework for Experimental Investigation and Computational Modeling of Integrated Food, Energy, and Water System

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EDGE IOT DRIVEN FRAMEWORK FOR EXPERIMENTAL INVESTIGATION AND COMPUTATIONAL MODELING OF INTEGRATED FOOD, ENERGY, & WATER SYSTEM

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To: Dean John L. Volakis
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This dissertation, written by Yemeserach T. Mekonnen, and entitled Edge IoT Driven Framework for Experimental Investigation and Computational Modeling of Integrated Food, Energy, & Water System, having been approved in respect to style and intellectual content, is referred to you for judgment.

We have read this dissertation and recommend that it be approved.

Shekhar Bhansali

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The dissertation of Yemeserach T. Mekonnen is approved.

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Vice President for Research and Economic Development and Dean of the University Graduate School

Florida International University, 2019

DEDICATION

To my parents, for their love, sacrifice, and unwavering support.

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ABSTRACT OF THE DISSERTATION

EDGE IOT DRIVEN FRAMEWORK FOR EXPERIMENTAL INVESTIGATION AND COMPUTATIONAL MODELING OF INTEGRATED FOOD, ENERGY, & WATER SYSTEM

by

Yemeserach T. Mekonnen

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Professor Arif Sarwat, Major Professor

As the global population soars from today's 7.3 billion to an estimated 10 billion by 2050, the demand for Food, Energy, and Water (FEW) resources is expected to more than double. Such a sharp increase in demand for FEW resources will undoubtedly be one of the biggest global challenges. The management of food, energy, water for smart, sustainable cities involves a multi-scale problem. The interactions of these three dynamic infrastructures require a robust mathematical framework for analysis. Two critical solutions for this challenge are focused on technology innovation on systems that integrate food-energy-water and computational models that can quantify the FEW nexus. Information Communication Technology (ICT) and the Internet of Things (IoT) technologies are innovations that will play critical roles in addressing the FEW nexus stress in an integrated way. The use of sensors and IoT devices will be essential in moving us to a path of more productivity and sustainability. Recent advancements in IoT, Wireless Sensor Networks (WSN), and ICT are one lever that can address some of the environmental, economic, and technical challenges and opportunities in this sector. This dissertation focuses on quantifying and modeling the nexus by proposing a Leontief input-output model unique to food-energy-water interacting systems. It investigates linkage and interdependency as demand for resource changes based on quantifiable data. The interdependence of FEW

components was measured by their direct and indirect linkage magnitude for each interaction. This work contributes to the critical domain required to develop a unique integrated interdependency model of a FEW system shying away from the piece-meal approach. The physical prototype for the integrated FEW system is a smart urban farm that is optimized and built for the experimental portion of this dissertation. The prototype is equipped with an automated smart irrigation system that uses real-time data from wireless sensor networks to schedule irrigation. These wireless sensor nodes are allocated for monitoring soil moisture, temperature, solar radiation, humidity utilizing sensors embedded in the root area of the crops and around the testbed. The system consistently collected data from the three critical sources; energy, water, and food. From this physical model, the data collected was structured into three categories. Food data consists of: physical plant growth, yield productivity, and leaf measurement. Soil and environment parameters include; soil moisture and temperature, ambient temperature, solar radiation. Weather data consists of rainfall, wind direction, and speed. Energy data include voltage, current, watts from both generation and consumption end. Water data include flow rate. The system provides off-grid clean PV energy for all energy demands of farming purposes, such as irrigation and devices in the wireless sensor networks. Future reliability of the off-grid power system is addressed by investigating the state of charge, state of health, and aging mechanism of the backup battery units. The reliability assessment of the lead-acid battery is evaluated using Weibull parametric distribution analysis model to estimate the service life of the battery under different operating parameters and temperatures.

Machine learning algorithms are implemented on sensor data acquired from the experimental and physical models to predict crop yield. Further correlation analysis and variable interaction effects on crop yield are investigated.

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CHAPTER 1

INTRODUCTION

The global population is expected to soar from today's 7.3 billion to an estimated 10 billion by 2050. Naturally, the demand for Food, Energy, and Water (FEW) resources is expected to follow suit. The demand for water, energy, and food resources is expected to increase by 55%, 80%, and 60%, respectively, by 2050 [1-3]. In addition to population growth, economic development and urbanization are among the major driving forces for the increase in demand for these resources. These factors pose critical challenges in the availability, accessibility, and utilization of FEW resources with a focus on reduced ecological footprint. The FEW resources are interlinked; therefore, in solving for one of the sectors directly impacts the other, requiring a nexus-centered system and approach [4]. This calls for a solution that can handle the ubiquitous and continuous flow of heterogeneous data about each of these infrastructures, understand their behavior holistically, and synchronously exploiting their interdependencies using dynamic, real-time cyber-solutions that contribute towards revolutionizing the traditional decision-making process and its veracity.

Information communication technology (ICT) and the Internet of Things (IoT) technologies are innovations that will play a key role in addressing the FEW nexus stress in an integrated way. The use of sensors and IoT devices is more than necessary to move the world's agriculture to a more productive and sustainable path. Recent advancements in IoT, Wireless Sensor Networks (WSN), and ICT are one lever that can address some of the environmental, economic, and technical challenges and opportunities in this sector.

1.1 Research Background and Motivation

Almost 70% of fresh groundwater is used for irrigation purposes, and 75% of the industrial water withdrawals are for energy production. The food production and supply chain account for 30% of energy consumption. Food security, along with water and energy supply, poses key issues in the availability, accessibility, and utilization of these resources. In order for supply to keep up with the forecasted demand of FEW resources, the current agricultural systems and processes will need to be more efficient. A viable way to improve our farming techniques is to incorporate an IoT WSN approach in an integrated FEW system. Smart agriculture or precision farming is a new concept that came out of IoT applications [7]. The combination of IoT, along with predictive data analytics in agriculture, can equip farmers with critical information on soil and environmental parameters, making it possible to take actions in crop yield, irrigation events, and weather information in real-time. The IoT framework can be used to understand the interdependency of energy, water, and food resources through WSN for each sub-system [9]. With real-time data, farmers can predict their yield, optimize water utilization through smart irrigation control and precisely know when to harvest, thereby reducing energy and labor input. Past research in FEW interactions has exhibited the downside of a "piecemeal" approach where only one or two of the FEW components are quantified. These approaches influence a "piecemeal" policy, which brings unforeseen problems. This research further explores the interactions in FEW systems using a dynamic optimization method. The FEW systems do not only owe to their complexity but challenges in visualization and computation of data as well. Some of the critical gaps in quantifying the nexus include data uncertainty, issue of scalability, and data complexity arising from various temporal and spatial scales.

The goal of this research is to design and deploy Internet of Things (IoT) devices for monitoring energy, water, and crop yield to develop a nexus model based on real-time data. Real-time data of all three resources are modeled and optimized to investigate food production profiles as a function of energy and water consumption. Deviating from the "peace-meal" approach, this holistic model explores the nexus between water and energy resources and crop yield for several essential crops in an attempt to design a more sustainable method to meet the forecasted surge in demand. This research implements an IoT framework to aid in understanding the interdependency of FEW resources through Wireless Sensor Network (WSN) nodes for each sub-system. The research significantly advances understanding of the food-energy-water system through quantitative and computational modeling evidenced and supported by smart farm testbed. Real-time data collection, monitoring, and cyber-enabled interfaces supported by WSN help improve the understanding of the behavior of FEW systems, interdependency and increase decision support capability. It enables various segments of research that will lead to innovative systems and technological solutions to critical FEW problems. Outcomes from this research will have a critical influence on farm level decisions and understanding better linkage of FEW systems.

1.2 Literature Review: Experimental and Computational Approaches in Integrated FEW Systems

The FEW nexus modeling involves and requires the multi-scale level challenge that comes with various dimensionality and time scale variance within the systems. This presents unpredicted consequences and complexity to decision making. The three dynamic interacting infrastructures require a mathematical framework for analyzing such an extensive complex system. Part of the challenges for the modeling is directly related to the data acquisition gaps, such as visualization of these data models and gaps. Another case is that most of the data collected are over different space and time scales with missing values. There are different types of models depending on the sectors, stakeholders, and area of the expertise, models can be data-driven [6], process-driven [7] or cost-driven [8].

The increasing acceptance of the interconnectedness between the FEW systems has led to the demand for a tool or methodology to model these systems as a nexus. One of the biggest challenges in the FEW nexus modeling is the lack of interlinkages data, access to data within private sector stakeholders (e.g., energy data), the inconsistency of collected data with the requirements of the nexus tool and nonexistence of interdisciplinary exchanges [23]. Due to the early-stage research in FEW nexus, most of the analytical tools and the overall research focuses on a macro level. However, the purpose of this work is to direct the FEW nexus modeling approaches from a bottom to top-down scale through the understanding of the FEW interactions on a small scale smart farm testbed.

Smart Farm as Integrated Food, Energy, and Water System

Data accessibility and acquisition is a massive challenge in nexus modeling. Often, there exists a lack of data on the footprint among the FEW resources making it hard to quantify and model the nexus [6]. Understanding this gap, the first segment of this research is focused on designing a smart farm prototype where all the three FEW elements are involved [9]. Technology will play a central role in mitigating pressure the farming industry will face as a result of factors in the rising population, consumer needs, and the growing shortages of land, water, and energy. Smart farming synonymous with other M2M based implementation such as smart metering and smart city is also referred to as precision agriculture (PA). According to Libelium, a primary IoT solution industry driver, the total market value for PA solutions is expected to reach $4.7 billion in 2021, almost double the amount in 2016 [10]. Despite a growing level of exciting research and new smart farming projects, the agriculture industry has been slow to adopt the emerging M2M and IoT technologies as compared with other industries [11]. Smart farming requires the integration of sensor technologies that collect data from the soil, crop, various environmental attributes, animal conduct, and tractor status. These sensor data through edge IoT computing and analytics can afford farmer valuable information on weather conditions and forecasts, crop monitoring and yield prediction, plant and animal disease detection [12].

The implementation of smart agriculture is dependent on the type of farming at hand. In a large farm setting, the use of farm vehicles like smart tractors equipped with GPS, and several embedded sensors, data visualization tools are currently in place with the ability to transmit real-time data [13]. Drones are a big player in this setting where built-in sensors provide different types of aerial imaging, field survey, and location mapping [14]. In small to medium-sized arable farming, spatially enabled mobile sensing technologies that provide detail analysis of field conditions in the different soil layer, nutrient levels, and overall ambient environmental conditions are being utilized [9, 15]. Besides, the implementation of smart irrigation by looking into the evapotranspiration parameter of plants to optimize the irrigation cycle is well in play. The use of soil moisture content and temperature sensors are widely prevalent in scheduling irrigation [16, 17, 18, 19, 20]. IoT solutions are also deployed in monitoring location and health of livestock where sensors are placed within the animal to transmit these data wirelessly [21]. Other popular applications of IoT technologies are in greenhouses and its extension in vertical farming integrated with emerging practices such as aquaponics, aeroponics, and hydroponics [22, 23].

1.3 Research Objectives and Original Contributions

The research reported in this dissertation is aimed at developing a holistic sectoral linkage model to address the critical interdependency for integrated food, energy, water system. For the experimental part of the work, the development of edge IoT and wireless sensor network-based smart farm that employs all the three resources was achieved. This smart farm incorporates an off-grid solar PV to meet all its energy demands. Machine learning techniques were used in forecasting crop yield prediction from environmental, soil, crop sensor data. In general, the dissertation has completed the following four major activities:

1) **Investigate a mathematical framework to understand the food-energy-water synergy through quantitative, predictive, and computational modeling. Considering both spatio-temporal and the multi-scalability of the three systems**

The main contribution of this objective is in the quantitative assessment of specific interventions, to analyze how they perform from a nexus perspective. It explores the FEW nexus using the Leontief input-output model to quantify the FEW interdependences. The FEW input-output models can account for demand as a result of stressors. It allows for the computation of intersectoral usage of various FEW components. The technical coefficient allows for the direct and indirect effect of resources on each other with the ability to trace back. The Leontief inverse matrix summarizes the network effects generated when the final output changes. Furthermore, this objective demonstrates how interdependence is measured by the linkage magnitudes. The direct forward and backward linkage of the resources can be visualized in directed graph theory. The data that is used to run the model comes from the experimental set, hypothesized, and previous literature work.

2) **Develop an experimental real-time, IoT driven interfaces to improve understanding of the behavior of FEW systems**

The goal of this objective is to design and deploy Internet of Things (IoT) devices for monitoring energy, water, and crop yield to develop a nexus model based on real-time data. A Successful smart farm testbed that implements an IoT framework to aid in understanding the interdependency of FEW resources through Wireless Sensor Network (WSN) nodes for each sub-system was developed. This smart urban farm was constructed on FIU's Engineering campus with three raised garden beds sized 4ft x 25ft. It consists of distributed WSN, off-grid PV with a backup battery, smart irrigation, and data infrastructure. The system design, development, and modification are discussed. Furthermore, the data acquisition scheme for each sub-system: food, energy, water, is detailed.

3) **Model affirmation through theoretical and experimental work**

The experimental data obtained from this prototype was used running the proposed Leontief input-output model to investigate the footprints, direct, and indirect linkage of the food-energy-water resources. Additionally, sensor data from the experimental prototype was analyzed using selected machine learning algorithms to understand the correlation and their effect on crop yield. It also attempts to understand the effect of extreme weather conditions on food production. The experimental data obtained from this prototype is modeled and optimized to investigate the food production profile as a function of energy and water consumption. Simple and higher-level regression algorithms were used and evaluated for predicting crop yield from collected sensor data.

4) **Off-grid renewable energy system reliability analysis** This objective was added to focus on and ensure energy system reliability. The smart farm testbed energy demand is entirely supplied by a solar PV panel supplemented with two lead-acid batteries. It provides clean PV energy for all energy demands of farming purposes, such as irrigation and devices for the wireless sensor networks. The off-grid energy system in an integrated FEW system and its especial applicability in regions access to electricity is a challenge is presented in this objective. It further addresses the reliability aspect of the lead-acid batteries in the long term. Factors affecting the state of health of the lead-acid battery and

its reliability are discussed. It further demonstrates the reliability analysis of the backup battery units to predict their end of service life using the Weibull distribution model.

1.4 Dissertation Organization

The listed contributions in Section 1.3 are discussed in detail in the remaining chapters, which are structured as follows:

Chapter 2 presents an overview of fundamental Leontief inverse concepts and its applications in different disciplines applied to a sectoral linkage and interdependent analysis.

Chapter 3 proposes a Leontief input-output framework to the food-energy-water nexus problem. A FEW nexus using the Leontief input-output model to quantify the FEW interdependences. It further presents a graph theory framework to analyze a FEW interdependence matrices as a network from FEW intensity coefficients. Section 3.2 presents the nexus by delving into a detailed coupled dependency of each system. Section 3.3 describes the FEW nexus challenges. Section 3.4 discusses the modeling challenges and presents the Leontief IO model as applied to the FEW nexus.

Chapter 4 examine a comprehensive review of the application of IoT and WSN within the agriculture and farming sector. It extensively covers the wireless communication protocols supporting the IoT devices and how they are applicable within the smart agriculture ecosystem. It further explores the latest advances in the design of intelligent systems that use an integrated Food-Energy-Water (FEW) nexus approaches. New farming innovation, such as vertical and modular farming and how it fits into the smart city model, is presented. This chapter focuses on three areas of challenge: application of sensors and IoT, design of intelligent system through integrated nexus approach, and the future of smart agriculture within the smart city paradigm. Section 4.2 presents the recent advances in sensor technologies and their application. Section 4.3 describes recent advances in designing an intelligent system that couples the FEW nexus approaches. Section 4.4 delves into the smart farm framework and how it supports the smart city paradigm.

Chapter 5 describes the overall system design and deployment of WSN for monitoring energy, water, and crop development to develop further a nexus model based on real-time data. This chapter explains the overall system description, schematics, and deployment mechanism for the experimental part of the work. Section 5.2 presents the motivation behind the testbed as an example of an integrated FEW systems. Section 5.3 describes the overall system design and implementation, including the electrical unit, irrigation system unit, and wireless sensor unit. Section 5.4 delves into the architecture of the data management infrastructure.

Chapter 6 presents a detailed insight into the off-grid renewable energy system for an integrated farm with an application to developing countries with minimal access to the central grid. It further addresses the reliability aspect of the system in the long term. Section 6.2 describes the off-grid renewable energy part of the testbed and its broader application in integrated farms. Energy storage reliability is presented in section 6.3. Factors affecting the short and long term span of battery life are detailed in section 6.4. Reliability analysis based on data from previous literature work is presented in the experimental section 6.6. Section 6.7 deals with the service life span of the battery based on accelerated life testing.

Chapter 7 presents the application of different machine learning algorithms on collected sensor data to predict crop yield from the experimental testbed. The structure of this chapter is organized as follows: Section 7.2 presents the recent advances in AI application in agriculture. Section 7.3 delves into some of the commonly used machine learning techniques within the WSN based PA. Section 7.4 outlines the description of the sensor data attributes, and data preprocessing and further presenting the problem statement. Section 7.5 discusses the methodology and results. Section 7.6 concludes the chapter and outlines future work.

Chapter 8 summarizes the dissertation outcomes, concludes the significance of this research, discuss the results, and finally makes recommendations for the future works.

CHAPTER 2

LEONTIEF INPUT-OUTPUT MODEL TECHNIQUE

2.1 Leontief Input-Output Model Concept

Nobel laureate Wassily Leontief developed the Leontief input-output analysis framework. The basic Leontief input-output model was generally created from observed economic data for a country. Therefore, its prime application is in transactional flow within regions or with other countries. It traces the movement of goods and services among different sectors of the economy. It is mainly useful in analyzing the interdependency of all sectors of the economy and how the production of output in one industry or sector affects the national economy. The other areas of application are include forecasting and impact analysis. The vital information used in input-output analysis concerns the flows of products from each sector, considered as a producer, to each of the sectors, itself, and others, considered as consumers. This necessary information from which an input-output model is developed is contained in an intersectoral transaction table. The rows of such a table describe the distribution of a producer's output throughout the economy. Leontief's input-output approach can be used to identify interdependencies and interconnectedness between and among different infrastructure systems. Many adaptations of the model have been used for environmental, energy demand prices, supply chain, and international trade. The basic input-output equations are

$$x_j = \sum_{k=1}^{n} a_{jk} x_k + b_j \tag{2.1}$$

where,

x_j = output from industry or sector j

b_j = the units available or required at industry j

a_{jk} = technical coefficients representing units of output of sector j required per unit output sector k

2.2 Mathematical Framework

The Leontief input-output analysis has been used to explore the direct and indirect intersectoral linkages systems specifically for economic and cost-driven models [24]. The model is great for the economy that has several interrelated industries whose output is dependent on the output on other industries. It has been used in supply chain linkage, energy input-output, environmental pollution impact, and many other interdependent applications. The algorithm contains three major components,

1) An intersectoral use matrix from sector i to sector j usually denoted as Z

2) A final demand vector matrix f of sector i,

3) Total produced or utilized vector matrix x noted as output

Given there are n sectors, the way sector i distributes to the other sectors can be expressed;

$$x_i = Z_{i1} + ... + Z_{ij} + Z_{in} + f_i = \sum_{j=1}^{n} Z_{ij} + f_i \tag{2.2}$$

where x_i is the total of sector i output. For multi-sectoral instances the output economic quantity expressed below for i = 1,2,...n^{th} sectors,

$$\begin{aligned} x_1 &= Z_{11} + ... + Z_{1j} + Z_{1n} + f_1 \\ &\vdots \\ x_i &= Z_{i1} + ... + Z_{ij} + Z_{in} + f_i \\ &\vdots \\ x_n &= Z_{n1} + ... + Z_{nj} + Z_{nn} + f_n \end{aligned} \tag{2.3}$$

The above system of the equation can be expressed in matrix form as follow;

$$\underbrace{\begin{bmatrix} x_1 \\ \vdots \\ x_n \end{bmatrix}}_{\textbf{output}} = \underbrace{\begin{bmatrix} Z_{11} & \dots & Z_{1n} \\ \vdots & \ddots & \vdots \\ Z_{n1} & \dots & Z_{nn} \end{bmatrix}}_{\textbf{component linkage}} + \underbrace{\begin{bmatrix} f_1 \\ \vdots \\ f_n \end{bmatrix}}_{\textbf{demand}} \tag{2.4}$$

The direct input coefficient or technical coefficient is defined as;

$$a_{ij} = \frac{Z_{ij}}{x_j} \tag{2.5}$$

a_{ij} is a measure of the fixed relationship between sectors output and its input. Rearranging the above main output function of Eq.(2) with a_{ij};

$$\begin{aligned} x_1 &= a_{11}x_1 + ... + a_{1j}x_j + a_{1n}x_n + f_1 \\ &\vdots \\ x_i &= a_{i1}x_1 + ... + a_{ij}x_j + a_{in}x_n + f_i \\ &\vdots \\ x_n &= a_{n1}x_1 + ... + a_{nj}x_j + a_{nn}x_n + f_n \end{aligned} \quad \Rightarrow \quad \begin{aligned} x - Ax &= f \\ (I - A)x &= f \\ x = (I - A)^{-1}f &= Lf \end{aligned} \tag{2.6}$$

Where $L = (I - A)^{-1}$ is known as the Leontief inverse matrix, indicating the total requirements. The Leontief inverse can further be used to predict future sector output based on final demand changes. If final demand for one sector increases, the final output (x) and intersectoral use (Z) can be calculated;

$$x^{new} = Lf^{new} \tag{2.7}$$

$$Z^{new} = A\hat{x}^{new} \tag{2.8}$$

2.3 Linkages in Input-Output Models

In the framework of an input-output model, production by a particular sector has two kinds of economic effects on other sectors in the economy. If sector j increases its output, this means there will be increased demands from sector j (as a purchaser/consumer) on the sectors whose goods are used as inputs to production in j. This is the direction of causation in the usual demand-side model, and the term backward linkage is used to indicate this kind of interconnection of a particular sector with those ("upstream") sectors from which it purchases inputs. On the other hand, increased output in sector j also means that additional amounts of product j are available to be used as inputs to other sectors for their own production – that is, there will be increased supplies from sector j (as a seller) for the sectors that use good j in their production. This is the direction of causation in the supply-side model. The term forward linkage is used to indicate this kind of interconnection of a particular sector with those ("downstream") sectors to which it sells its output.

Measures have been proposed to quantify such backward and forward linkages, or economic "connectedness." Comparisons of the strengths of backward and forward linkages for the sectors in a single economy provide one mechanism for identifying "key" or "leading" sectors in that economy (those sectors that are most connected and therefore, in some sense, most "important") and for grouping sectors into spatial clusters. And if data are available for more than one time period, the evolution of these interconnections can be studied. Traditionally intersectoral linkages are measured by two main categories. One is based on input or output coefficients and Leontief inverse or Ghosian inverse coefficients [24]. The other is the hypothetical extraction method developed by Strassert mainly measures what happens if intermediate demand goes down, changes in output.

2.3.1 Backward Linkage

In its simplest form, a measure of the strength of the backward linkage of sector j –the amount by which sector j production depends on interindustry inputs – is given by the sum of the elements in the j^{th} column of the direct input coefficients matrix as follow;

$$BL(d)_j = \sum_{k=1}^{n} a_{jk} \tag{2.9}$$

where,

$BL(d)_j =$ denotes the backward linkage of sector j

$a_{jk} =$ technical coefficients representing units of output of sector j required per unit output sector k

To capture both direct and indirect linkages, columns sums of the total requirements matrix, L are proposed as total backward linkage measure.

2.3.2 Forward Linkage

Forward linkage analysis is a measure of the strength of the forward linkage of sector j- the amount by which sector j is used in the production of interindustry as an output. There are two methods to computing forward linkage, one based on Chenery and Watanabe (CW) and the other being the Rasmussen method. The CW method computes forward linkage as the sums of rows of the matrix of the output coefficient matrix B defined as follow;

$$FL(d)_j = \sum_{k=1}^{n} b_{jk} \tag{2.10}$$

where,

$FL(d)_j =$ denotes the forward linkage of sector j

$b_{jk} =$ the output coefficient of sector j to sector k

The Rasmussen method defines the forward linkage as the row sums of the Leontief inverse matrix L. It measures the magnitude of output increase in sector j, if the final demand in each sector were to increase by one unit.

$$FL(d)_j = \sum_{k=1}^{n} l_{jk} \tag{2.11}$$

where,

$FL(d)_j =$ denotes the forward linkage of sector j

$l_{jk} =$ the jk^{th} element of Leontief inverse matrix denoted by $L = (I - A)^{-1}$

2.4 Summary

The Leontief input-output analysis has been used to explore the direct and indirect inter-sectoral linkages systems specifically for economic and cost-driven models. The model is great for the economy that has several interrelated industries whose output is dependent on the output on other industries. It has been used in supply chain linkage, energy input-output, environmental pollution impact, and many other interdependent applications.

CHAPTER 3

APPLICATION OF LEONTIEF INVERSE IN FEW SYSTEM

3.1 Introduction

Currently, almost 70% of the global freshwater is being used of agriculture and along being used to transport and produce energy in different forms [2, 25]. The demand for water is set to increase to 55% by 2050 [1]. Similarly, 30% of total global energy consumption is spent on producing, transporting and distributing food as well as in the application of pumping, extracting, treating and transporting water [4, 26]. Global energy consumption is projected to increase to 80% by 2050 [27, 28]. As the demand for food soars to 60% by 2050, food security along with water and energy supply poses key issues in the availability, accessibility, and utilization of these resources. The interlinkage and interdependency of the water, energy and food systems known as the nexus is a key concern globally for all involved stakeholders in pursuing and meeting their sustainable development strategies. Increased population growth, economic development, and urbanization are the driving factors in the demand for food, energy and water resources more than ever [29] as illustrated in Fig. 1. Another challenge has been urban population expansion where the solution to solve food demand has to be more innovative with the use of technology such as building modular and vertical farming accounting for land scarcity. The conventional way of thinking about these intertwined problems focuses on the "peace-meal approach" where decisions are made in one of the nexus areas of water, energy, and food without making an allowance for the consequences on the other areas [27, 28, 29]. The nexus approach provides decision makers with better information through optimization of synergies and trade-offs. The three main objectives of the nexus approach are addressing resource scarcity and security as opposed to environmental impacts, developing synergy and collaboration between stakeholders directly influencing the nexus, and development

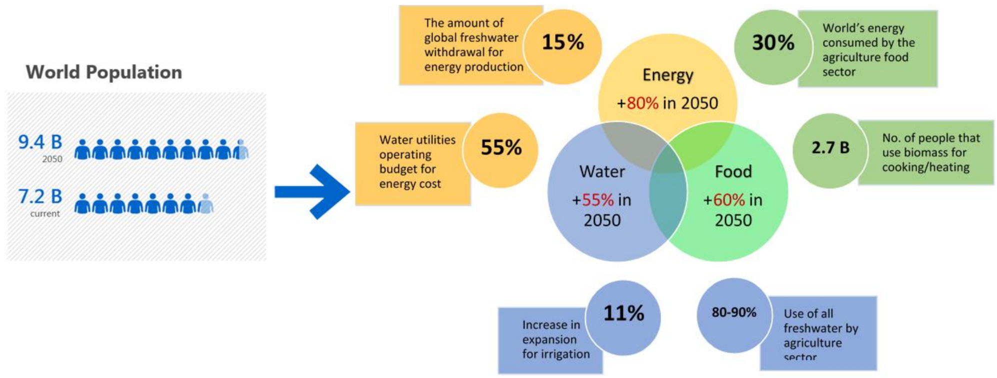


Figure 3.1: The future of FEW resources [1]

of modeling tools to support integrated decision making [29, 30]. In this chapter, the third objective will be further explored. Quantitative assessment of specific interventions, to analyze how they perform from a nexus perspective. This work explores the FEW nexus using the Leontief input-output model to quantify the FEW interdependences. It further presents a graph theory framework to analyze a FEW interdependence matrices as a network.

3.2 The Nexus

In addition to increased population, rapid urbanization and industrialization, further complicating these resources challenges are that they are interlinked. Water is needed to produce energy; energy is essential in sourcing, treating and distributing water; and both the use of water and energy are required to produce food as shown in Fig. 6.2. The nexus approach encourages addressing these resources' scarcity jointly, as decisions taken about one resource are likely to influence the other two. Recent works have shown that the FEW security can be improved through an integrated management approach that will bring all involved sector which is called nexus [29]. A nexus approach can also support the transition into a circular economy where renewable sources utilization and byproduct/ waste recycling are encouraged. Although it is a long way from achieving food, water, and energy security for all, the solution can be facilitated through an approach that integrates management and governance across all sectors and scales.

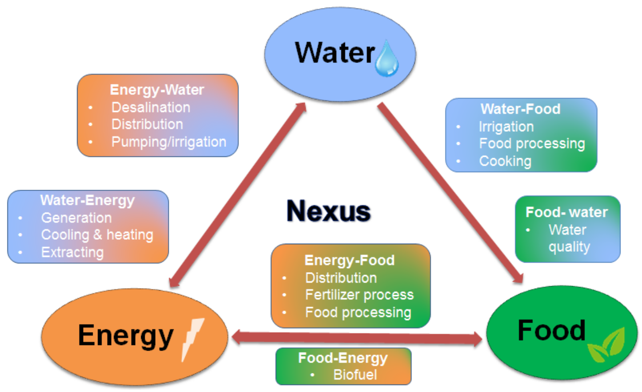


Figure 3.2: The FEW nexus

3.2.1 Energy-Food Nexus

Agricultural production consumes energy directly in the form of fuels for land preparation, crop and pasture management, and transportation or electricity supply. Indirectly, the use of fertilizers and pesticides which are energy-intensive inputs. A huge chunk of the energy is spent on the food supply chain which includes the processing and distribution of the food products [1, 2]. Energy link to food by sector varies among developed and developing countries stated in Fig.3. To alleviate the food security problem, some countries are heavily invested in the use of bioenergy. In the face of climate change and rising energy security, the demand for more viable renewable energy use for food is at a critical point. Over 20% of total Green House Gas (GHG) emission comes from the food sector [3].

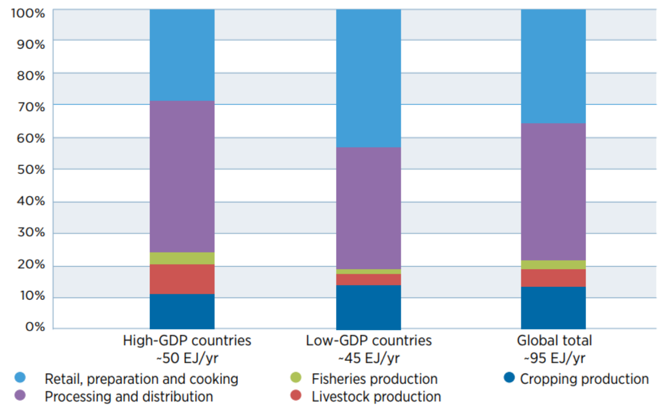


Figure 3.3: Direct and indirect energy use link to food sector[2]

3.2.2 Water-Energy Nexus

The use of water for energy currently accounts for 8% of global water withdrawals, in industrialized countries, this number reaches to 45% in developing countries (Europe) [31]. Water is used for extraction, mining, processing, refining and residual disposal of fossil fuels and growing biofuels for energy generation. Water is used in renewable and fossil fuel energy sources. Bio-fuels and hydropower are the two renewable energy sources that require a large number of water [3]. However, Biofuels are more water-intensive than fossil fuels using 10,000-100,000 L/GJ of energy [32]. Comparing this number to the fossil fuel production in oil and gas, fossil fuels only use 0.01% of biofuel's water consumption [33]. Overall energy sources that require the use of water are Biofuel, Hydropower, non-conventional fossil fuels such as fracking [34]. The use of water in the electricity market for hydropower production is evident as water is used as a primary source for generating power as shown in Fig.4. Hydropower currently provides 16% of global electricity generation accounting to 86% of the global renewable energy. This number is very far below the feasible potential like in Africa where only it taps 5% of its potential [35, 36]. Another renewable energy source that uses water is a Photo-voltaic thermal (PVT) unit that still widely used in parts of the world [37, 38]. Energy is required for lifting, moving,

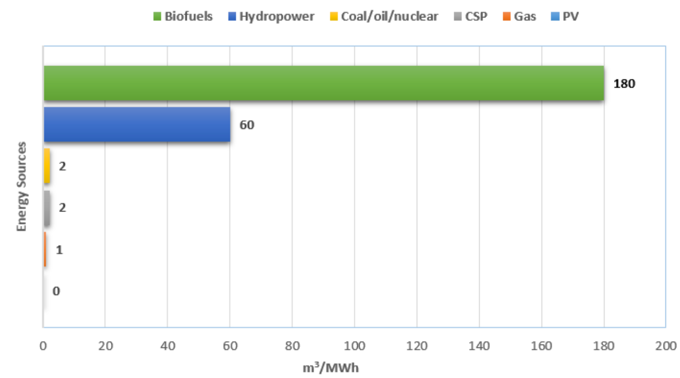


Figure 3.4: Water use by various energy source in electricity production [3]

distributing and treating water. The majority of energy which is about 40% total energy is used for pumping groundwater. Energy is also utilized in the desalination process which is expected to grow by 500% in 2030 especially in Asia [39]. Besides, energy is used directly and indirectly in irrigation practices in large scale farming practices. Generally, various systems of irrigation are currently in practice such as rain-fed agriculture, sprinkler, and drip irrigation. Drip irrigation practices are more energy-intensive since the water must be pressurized [40].

3.2.3 Food-Water Nexus

The demand for a FEW resources is estimated to grow by 30-50 % over the next two decades due to economic and population growth [41]. Food is the largest consumptive of water use. Agricultural production is projected to increase by 60% in 2050 causing an increased water consumption for irrigation to 11% [42]. This increase is especially noticed in an area where water is already scarce not fulfilling the demand. Growth in agricultural production has to meet the demand for feeding 9 billion population in 2050 by increasing crop yields and expanding arable land areas. This is where innovative methods are adapted to provide sustainable solutions to increase crop yield productivity. With the advent of IoT and sensor technologies, it has become possible to monitor crop health, yield, environmental parameters which further can be used in future prediction [9, 43, 44]. To meet such demand the use of fertilizer and pesticides has a direct effect on water quality through pollution. Water contamination from a discharge of pollutants originating from pesticides and fertilizers as a result of poor agricultural practices is one of the risks associated with the food-water nexus. Furthermore, one of the big issues facing the food system more than the shortage is the accessibility of existing food reaching consumers [2]. Moreover, the demand for agricultural goods is directly dependent on consumption patterns, market variability, policies, and the economy. Almost 40% of food produced is wasted in transportation from distribution to consumers [31]. This, directly and indirectly, means the waste of water and energy that was embedded in the production, transportation, and processing of this food.

3.3 FEW Challenges

3.3.1 Towards A Circular Economy

There are many inputs and outputs of the agriculture, water and food systems that should be designed and managed to minimize inputs and inequality, and maximize outputs. By closing the loop and adopting a more circular economy, the system will be immune to wastage and negative environmental impacts. Targeting the life cycles of a FEW resources, a solution to close the loop in the urban and rural communities can be implemented. Managing the FEW systems from an integrated perspective will be key to the successful loop closure where waste products from one resource can be used as an input in other resources. For example, food waste can be used as a biofuel as an energy source to power irrigation or satisfy other energy demands. However, this requires di-

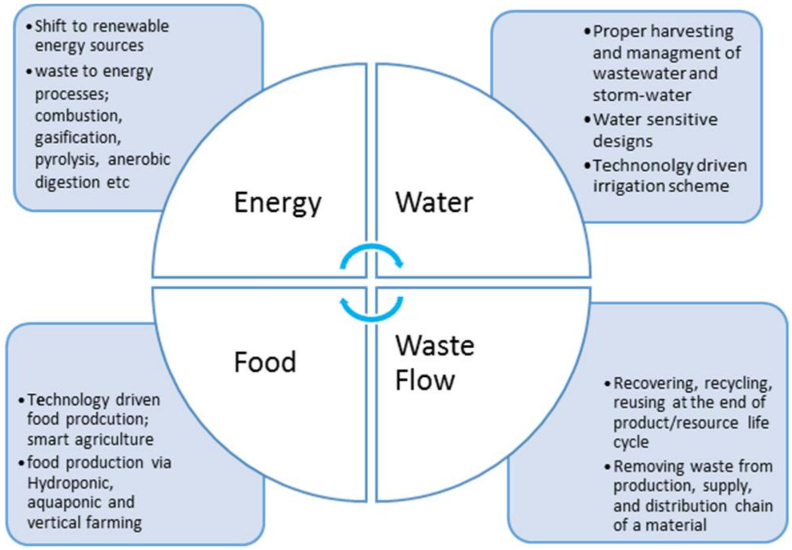


Figure 3.5: Circular economy linkage [4]

verse stakeholders working together across various sectors in terms of governance and policy. Currently, with the advent of technology and its impact on shaping the future of the smart city policy, major global alliances are pushing the idea from "linear to circular" economy [45]. The idea of a circular economy that closes the loop across the production of FEW systems is presented in Fig.3.5. Integrative management of wastes in a FEW systems is presented in [46] by averting one system's by-products to satisfy the need of another. It further explains how different FEW systems can be optimized to design a closed-loop production system.

3.3.2 Spatio-temporal Variation in FEW Systems

There is a divide between time and space among the supply and demand of FEW resources. The use of water and energy is embedded in the production and delivery of food which makes it hard to quantify. In addition to this, the spatial disparity in food is observed in changing demands between the urban and rural areas. Harvested food is now transported for longer duration and making the supply chain process complex as to pre-serve and make the food fresh especially on green produces, fruits and seafood. Although food waste can be eliminated as a result of such complex supply chain processes and it solves the spatio-temporal disconnect between food produced and food waste, it intensifies the demand for energy [47]. In [48], energy use in the agricultural sector is linked to increased drought year by 17.5%, in part as higher energy is needed to maintain chilled transportation within the supply chain of food. The spatio-temporal disconnect in water and energy sectors vary in frequency and complexity. Water demand and supply divides are in seasonal and geographic location. For energy, the demand for electricity is at its peak in the afternoon where in most cases currently it is met by fossil fuels. The drive in implementing renewable energy sources like solar and wind presents a challenge as these resources can be intermittent and may not supply the peak time demand [49]. Alleviating the spatio-temporal disparity in FEW systems require an innovative solution that will be able to address the integrative optimization of these resources.

3.4 Modeling Review

The FEW nexus modeling involves and requires the multi-scale level challenge that comes with various dimensionality and time scale variance within the systems. This presents unpredicted consequences and complexity to decision making. The three dynamic interacting infrastructures require a mathematical framework for analyzing such a large complex system. Part of the challenges for the modeling is directly related to the data acquisition gaps such as visualization of these data models and gaps. Another case is most of the data collected are over different space and time scales with missing values. There are different types of models depending on the sectors, stakeholders and area of the expertise, models can be data-driven [6], process-driven [7] or cost-driven [8].

The increasing acceptance of the interconnectedness between the FEW systems has led to the demand for a tool or methodology to model these systems as a nexus. One of the biggest challenges in the FEW nexus modeling is the lack of interlinkages data, access to data within private sector stakeholders (e.g energy data), the inconsistency of collected data with the requirements of the nexus tool and nonexistence of interdisciplinary exchanges [23]. Due to the early stage research in FEW nexus, most of the analytical tools and the overall research focuses on a macro level. However, the purpose of this work is to direct the FEW nexus modeling approaches from a bottom to top-down scale through the understanding of the FEW interactions on a small scale smart farm test-bed.

Data accessibility and acquisition is a huge challenge in nexus modeling. Often, there exists a lack of data on the footprint among the FEW resources making hard to quantify and model the nexus [6]. Understanding this gap, the first segment of this research is focused on designing a smart farm prototype where all the three FEW elements are involved [9]. The test-bed is optimally designed to maximize crop yield, minimize energy consumption and extreme environmental effects through real-time sensor data. From this physical model, the data collected will be structured into three different FEW components through a robust data acquisition infrastructure. Data obtained from here will be used in the model that will be introduced in section 3.4.1.

3.4.1 Leontief Input-Output Model

Input-Output (IO) analysis was first proposed by Nobel prize economist Wassily Leontief. The Leontief input-output analysis has been used to explore the direct and indirect intersectoral linkages systems specifically for economic and cost-driven models [24]. The model is great for the economy that has several interrelated industries whose output is dependent on the output on other industries. It has been used in supply chain linkage, energy input-output, environmental pollution impact, and many other interdependent applications. The algorithm contains three major components,

1) An intersectoral use matrix from sector i to sector j usually denoted as Z

2) A final demand vector matrix f of sector i,

3) Total produced or utilized vector matrix x noted as output

Given there are n sectors, the way sector i distributes to the other sectors can be expressed;

$$x_i = Z_{i1} + ... + Z_{ij} + Z_{in} + f_i = \sum_{j=1}^{n} Z_{ij} + f_i \tag{3.1}$$

where x_i is the total of sector i output. For multi-sectoral instances the output economic quantity expressed below for i = 1,2,...n^{th} sectors,

$$\begin{aligned} x_1 &= Z_{11} + ... + Z_{1j} + Z_{1n} + f_1 \\ &\vdots \\ x_i &= Z_{i1} + ... + Z_{ij} + Z_{in} + f_i \\ &\vdots \\ x_n &= Z_{n1} + ... + Z_{nj} + Z_{nn} + f_n \end{aligned} \tag{3.2}$$

The above system of equation can be expressed in matrix form as follow;

$$\underbrace{\begin{bmatrix} x_1 \\ \vdots \\ x_n \end{bmatrix}}_{\textbf{output}} = \underbrace{\begin{bmatrix} Z_{11} & \dots & Z_{1n} \\ \vdots & \ddots & \vdots \\ Z_{n1} & \dots & Z_{nn} \end{bmatrix}}_{\textbf{component linkage}} + \underbrace{\begin{bmatrix} f_1 \\ \vdots \\ f_n \end{bmatrix}}_{\textbf{demand}} \tag{3.3}$$

The direct input coefficient or technical coefficient is defined as;

$$a_{ij} = \frac{Z_{ij}}{x_j} \tag{3.4}$$

a_{ij} is a measure of the fixed relationship between sectors output and its input. Rearranging the above main output function of Eq.(2) with a_{ij};

$$\begin{aligned} x_1 &= a_{11}x_1 + ... + a_{1j}x_j + a_{1n}x_n + f_1 \\ &\vdots \\ x_i &= a_{i1}x_1 + ... + a_{ij}x_j + a_{in}x_n + f_i \\ &\vdots \\ x_n &= a_{n1}x_1 + ... + a_{nj}x_j + a_{nn}x_n + f_n \end{aligned} \quad \Rightarrow \quad \begin{aligned} x - Ax &= f \\ (I - A)x &= f \\ x = (I - A)^{-1}f &= Lf \end{aligned} \tag{3.5}$$

Where $L = (I - A)^{-1}$ is known as the Leontief inverse matrix indicating the total requirements. The Leontief inverse can further be used to predict future sector output based on final demand changes. If final demand for one sector increases, the final output (x) and intersectoral use (Z) can be calculated;

$$x^{new} = Lf^{new} \tag{3.6}$$

$$Z^{new} = A\hat{x}^{new} \tag{3.7}$$

3.4.2 FEW IO Mathematical Framework

The FEW nexus can be represented with the IO model. An equivalent of Z vector matrix will explore the interdependence of one resource in the other FEW resources i.e *F-F, F-E, F-W, E-F, E-E*, ...etc. The A matrix will indicate the different sources' intensity of use in others. Finally, the L matrix also known as the Leontief inverse will be used to track and find how an increase in demand will change final output and intercomponent usage. This work will use the input-output model to investigate the interlinkage of FEW nexus. Using the foundation of the input-output model, the FEW nexus will be framed as follow;

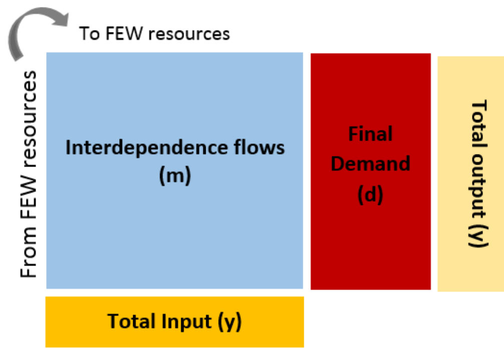


Figure 3.6: FEW IO framework

	FEW Intersectoral Inputs			Final Demand (d)	Total Output (y)
	Food (F)	Energy (E)	Water (W)		
Food (F)	m_{ij}^{ff}	m_{ij}^{fe}	m_{ij}^{fw}	d_i^f	y_i^f
Energy (E)	m_{ij}^{ef}	m_{ij}^{ee}	m_{ij}^{ew}	d_i^e	y_i^e
Water (W)	m_{ij}^{wf}	m_{ij}^{we}	m_{ij}^{ww}	d_i^w	y_i^w

Table 3.1: FEW interlinkage based on IO Model

Furthermore the above framework in Fig.3.6 can be explicitly described in Table 3.1 below. The interdependence flow from one source to the other is denoted by the m matrices with i x j dimensions.

d_i^f, d_i^e, d_i^w are the final demand vector for each sources respectively. The total output matrix for each resources are denoted by y_f^i, y_e^i, y_w^i. Mathematically the FEW component linkage matrices which are equivalent to the intersectoral inputs mentioned in Table 1 can be expressed as follow in Eqn. (7). Here the V_i and the U_i are simply rows and column labeling indicating the different FEW sources involved.

$$
\begin{array}{c}
\\ V_1 \\ V_2 \\ \\ V_{i-1} \\ V_i
\end{array}
\underbrace{
\begin{array}{c}
\begin{array}{ccccc}
U_1 & U_2 & & U_{j-1} & U_j
\end{array}
\\
\begin{bmatrix}
m_{11} & m_{12} & \dots & m_{1,j-1} & m_{1j} \\
m_{21} & m_{22} & \dots & m_{2,j-1} & m_{2j} \\
\vdots & \vdots & \ddots & \vdots & \vdots \\
m_{i-1,1} & m_{i-1,2} & \dots & m_{i-1,j-1} & m_{i-1,j} \\
m_{i1} & m_{i2} & \dots & m_{i,j-1} & m_{i,j}
\end{bmatrix}
\end{array}
}_{\text{FEW component linkage}}
\tag{3.8}
$$

Where, both V_i and U_j are in $\{F_1, ..., F_p, E_1, ..., E_q, W_1, ..., W_r\}$, which are different food, energy, and water sources. p, q, and r are the number of FEW sources respectively. $\{V_1, V_2, ..., V_{i-1}, V_i\}$ are the different FEW sources being used in the same $\{U_1, U_2, ..., U_{j-1}, U_j\}$ sources creating m_{ij} interdependence flow.

For i^{th} and j^{th} sources, m_{11} is the use of V_1 source in U_1;

m_{21} is the use of V_2 source in U_1,

m_{ij} is the use of i^{th} source in j^{th} source, etc

Applying the Leonteif equation eq.3 to Table 1 framework, the general FEW system IO can be expressed as follow;

$$
\underbrace{\begin{bmatrix}
m_{11} & m_{12} & \dots & m_{1j} \\
m_{21} & m_{22} & \dots & m_{2j} \\
\vdots & \vdots & \ddots & \vdots \\
m_{i1} & m_{m2} & \dots & m_{ij}
\end{bmatrix}}_{\text{Interdependence flow matrix}}
+
\underbrace{\begin{bmatrix} d_f \\ d_e \\ d_w \end{bmatrix}}_{\text{demand}}
=
\underbrace{\begin{bmatrix} y_f \\ y_e \\ y_w \end{bmatrix}}_{\text{output}}
\tag{3.9}
$$

However, for a given computation it is possible to have many different sources of food, energy or water. Given p number of food sources, q number of energy sources, and r number of water sources, Eqn. (3.9) expression can be mathematically formulated below as the total output of each FEW sources. Therefore, the total food source output is given

p number of food sources based on Leontief IO Eqn. (2) formulation is;

$$\sum_{j=1}^{p} m_{ij}^{ff} + \sum_{j=1}^{q} m_{ij}^{fe} + \sum_{j=1}^{r} m_{ij}^{fw} + \sum_{i=1}^{p} d_i^f = \sum_{i=1}^{p} y_i^f, \text{ for } i = 1, 2, ..., p \tag{3.10}$$

Similarly, given q number of energy sources, the total energy source output is;

$$\sum_{j=1}^{p} m_{ij}^{ef} + \sum_{j=1}^{q} m_{ij}^{ee} + \sum_{j=1}^{r} m_{ij}^{ew} + \sum_{i=1}^{q} d_i^e = \sum_{i=1}^{q} y_i^e, \text{ for } i = 1, 2, ..., q \tag{3.11}$$

Finally, the water source output given r number of water sources is;

$$\sum_{j=1}^{p} m_{ij}^{wf} + \sum_{j=1}^{q} m_{ij}^{we} + \sum_{j=1}^{r} m_{ij}^{ww} + \sum_{i=1}^{r} d_i^w = \sum_{i=1}^{r} y_i^w, \text{ for } i = 1, 2, ..., r \tag{3.12}$$

The above three equations can be rewritten with the technical coefficient as indicated in Eqn. (4). The technical coefficient measures the direct linkage of each source revealing the dependence of one source on another. It is the interdependence flow divided by the total output of the receiving sector. Ideally, within the FEW input-output flows there will be nine FEW technical coefficients expressed as follow;

food for food, $\gamma_{ij}^{ff} = \frac{m_{ij}^{ff}}{{y_j}^f}$; food for energy, $\gamma_{ij}^{fe} = \frac{m_{ij}^{fe}}{{y_j}^e}$; food for water, $\gamma_{ij}^{fw} = \frac{m_{ij}^{fw}}{{y_j}^w}$;
energy for food, $\beta_{ij}^{ef} = \frac{m_{ij}^{ef}}{{y_j}^f}$; energy for energy, $\beta_{ij}^{ee} = \frac{m_{ij}^{ee}}{{y_j}^e}$; energy for water, $\beta_{ij}^{ew} = \frac{m_{ij}^{ew}}{{y_j}^w}$;
water for food, $\alpha_{ij}^{wf} = \frac{m_{ij}^{wf}}{{y_j}^f}$; water for energy, $\alpha_{ij}^{we} = \frac{m_{ij}^{we}}{{y_j}^e}$; water for water, $\alpha_{ij}^{ww} = \frac{m_{ij}^{ww}}{{y_j}^w}$

Replacing the interdependence flow variables with the above FEW technical coefficient;

$$\sum_{j=1}^{p} \gamma_{ij}^{ff} y_j^f + \sum_{j=1}^{q} \gamma_{ij}^{fe} y_j^e + \sum_{j=1}^{r} \gamma_{ij}^{fw} y_j^w + d_i^f = y_i^f, \text{ for } i = 1, 2, ..., p \tag{3.13}$$

$$\sum_{j=1}^{p} \beta_{ij}^{ef} y_j^f + \sum_{j=1}^{q} \beta_{ij}^{ee} y_j^e + \sum_{j=1}^{r} \beta_{ij}^{ew} y_j^w + d_i^e = y_i^e, \text{ for } i = 1, 2, ..., q \tag{3.14}$$

$$\sum_{j=1}^{p} \alpha_{ij}^{wf} y_j^f + \sum_{j=1}^{q} \alpha_{ij}^{we} y_j^e + \sum_{j=1}^{r} \alpha_{ij}^{ww} y_j^w + d_i^w = y_i^w, \text{ for } i = 1, 2, ..., r \tag{3.15}$$

where γ, β, and α are the FEW nexus technical coefficient associated with food, energy, and water respectively. Furthermore, the FEW systems can be expressed as follow;

$$\underbrace{\begin{bmatrix} \gamma^{ff} & \gamma^{fe} & \gamma^{fw} \\ \beta^{ef} & \beta^{ee} & \beta^{ew} \\ \alpha^{wf} & \alpha^{we} & \alpha^{ww} \end{bmatrix}}_{\text{FEW coefficient matrix}} \begin{bmatrix} y^f \\ y^e \\ y^w \end{bmatrix} + \begin{bmatrix} d^f \\ d^e \\ d^w \end{bmatrix} = \begin{bmatrix} y^f \\ y^e \\ y^w \end{bmatrix} \tag{3.16}$$

Let A be the n x n denote the FEW technical coefficient matrix, Eqn.(16) can be arranged in a matrix notation,

$$AY + d = Y \tag{3.17}$$

$$Y = Ld \tag{3.18}$$

$$\text{where, } L = (I - A)^{-1}$$

If the demand of the FEW resources (d) are prespecified and assuming the per-unit amount of the food, energy and water outflow used in sector j which is the A matrix remains unchanged, new total FEW outputs can be calculated,

$$Y' = Ld^{'} \tag{3.19}$$

where $Y^{'}$ and $d^{'}$ are the new total output, and changes in final demand respectively. Furthermore, the changes in the interdependence flow matrix $Z^{'}$ due to changes in final demand $d^{'}$ can be traced and calculated per Eqn. (7),

$$Z^{'} = AY^{'} \tag{3.20}$$

The Leontief inverse matrix summarizes the network effects generated when the final output changes. A single coefficient of matrix entails the direct and indirect effects created in resource i to supply a single unit of final demand for resource j. The challenge of such a model in a FEW resources is the absence of flow data for all components in such an application. In addition, the input-output system is an ideal test-bed for network science. The future work will further extend the FEW the technical coefficient in understanding the FEW nexus from a network perspective using graph theory [50].

3.5 Data

In this example a FEW interdependence flow matrix is provided with available data in Table 3.2.

a) Food inflow includes two sources (f_1) vegetables and (f_2) is poultry all measured in $ton/year$

b) Energy sources include electricity from solar (e_1), and diesel (e_2) measured in $toe/year$

c) Water inflow include sources from rain harvested (w_1), and dehumidification (w_2) measured in $m^3/year$

Using the interdependence flow values (m_{ij}), the technical coefficient values (A_{ij}) can be computed. The total output (y_1) for f_1 is the sum of all its outflow to all j^{th} resource and the final demand (d_1).

FEW Resources Supply (Outlfow)	FEW Resources Consumption Inflow						Final Demand (d)	Total Output (Y)
	Food (ton)		Energy (toe)		Water (m^3)			
	f_1	f_2	e_1	e_2	w_1	w_2		
f_1	150	500	50	25	75	200	45	1000
f_2	200	100	400	200	100	150	50	1150
e_1	300	500	50	60	40	120	200	1070
e_2	75	100	60	200	250	140	500	825
w_1	50	25	25	150	100	145	50	495
w_2	90	150	420	500	200	140	120	1500

Table 3.2: A FEW input-output data table

The technical coefficient matrix that represents the i^{th} resource footprint in the production or use of j^{th} resource is presented in Table 3.

Food for food: the total output of all food resources is m^{ff} 2150 ton/year. The total footprint of food outflow into other food sources γ^{ff} is 2.19.

Food for energy: the total footprint food use in energy is γ^{fe} 0.69 ton/toe. This means 0.69 tons of food have been used per unit toe of energy.

Food for water: the total direct effect of food in water sources is γ^{fw} 0.59 ton/m^3.

Energy for food: the total footprint of energy in food use is 2.31 toe/ton. Solar energy use in irrigated vegetable has the highest footprint with β^{ef} 1.43 toe per unit ton of vegetables.

Energy for energy: the total use of energy to energy is β^{ee} 0.42 toe.

Energy for water: energy for water footprint is β^{ew} 0.76 toe/m^3. This scenario is evident in diesel hybrid microgrids, PV thermal plants, and hydropower plants.

Water for food: food sources use of water (α^{wf}) is 0.82 m^3/ton.

Water for energy: water footprint in the energy use is at α^{we} 1.204 m^3/toe.

Water for water: the use of water for water intensity is α^{ww} 0.796. The total water outflow in the production of all the other water resources m^{ww} is 585 m^3.

In the FEW input-output frameworks, computing the total FEW requirements in each source which will be referred to in this article as FEW footprints or intensity is similar to computing the total cost requirement or Leontief inverse of the traditional input-output model. The different food, energy, and water sources intensity are combined together and summarized in Table 3. These values are the direct FEW requirement matrices (A_{ij}). Table 4 presents the water and energy source intensity in food production. The intensity values indicate the requirement of resources in per unit linkage in the production of vegetables and poultry. Furthermore, the intensity interconnection among the FEW sources can further be visualized as a network of three systems as presented in Fig.7.

Nexus	FEW Intensity (γ, β, α)
F to F	0.84 ton/ton
F to E	0.524 ton/toe
F to W	0.537 ton/m^3
E to F	0.859 toe/ton
E to E	0.283 toe/toe
E to W	0.693 toe/m^3
W to F	0.28 m^3/ton
W to E	0.841m^3/toe
W to W	0.726 m^3/m^3

Table 3.3: FEW intensity coefficients

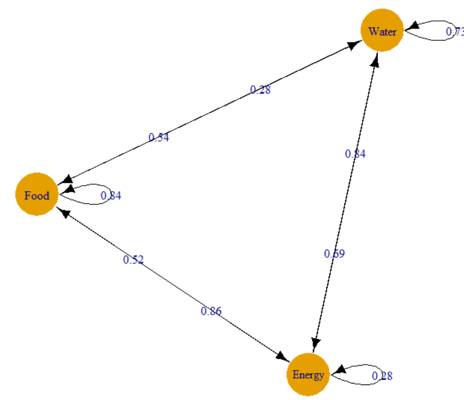


Figure 3.7: Graphical representation

Footprints	Vegetables (f_1)	Poultry (f_2)
β^{wf}_{1j} (m^3/ton)	0.048	0.021
β^{wf}_{2j} (m^3/ton)	0.086	0.125
α^{ef}_{1j} (toe/ton)	0.287	0.417
α^{ef}_{2j} (toe/ton)	0.072	0.083

Table 3.4: Water and energy footprints in food production

The FEW Leontief inverse matrix is computed in R programming based on the mathematical framework given in Section 3.4.2. These values shown below in Table 5 are also known as multipliers that capture in each of its element all of the infinite series of a round by round direct and indirect effects that new final demands have on the outputs of each FEW resources. It will thereby enable to forecast for new total output (Y') and the new interdependence flow $(m^{'}_{ij})$ as noted in Eqn. (19) and (20). The column and row sums of this matrix are a measure of the total backward and forward linkage of the FEW resources.

Assuming there will be a demand increase of 60% in poultry (f_2), 80% in solar energy (e_1), and 55% in dehumidification (w_1) as a result of an increase in population and other stress drivers. The new final total output can be computed as stated per Eqn. (19). The

	f_1	f_2	e_1	e_2	w_1	w_2
f_1	2.12	1.65	0.99	0.98	1.72	0.8
f_2	1.26	2.49	1.24	1.15	1.9	0.82
e_1	1.35	1.79	2.05	1.05	1.77	0.8
e_2	0.75	0.95	0.68	1.9	1.74	0.6
w_1	0.44	0.53	0.39	0.55	1.94	0.39
w_2	1.35	1.75	1.44	1.64	2.56	1.98

Table 3.5: The FEW Leontief inverse matrix values

percent change in the total output of all the FEW sources is presented in Fig. 3.8 with highest percent increase induced in solar energy (e_1) at 34%, poultry (f_2) at 27% and dehumidification (w_2) at 25%. Similarly, the percent change in the FEW interactions flow is presented in Fig. 3.9. These values are the delta between the original and new flow. The highest percent increase inflow is to solar energy (e_1). Interdependence, in this case, can be measured by linkage magnitudes. Within the Leontief IO model, there is direct backward and forward linkage. The combined effect of direct and indirect linkage is known as total backward or forward linkage. Backward linkage measure of a source 'j' signifies the amount by which source 'j' production depends on inter-FEW inputs. In other words, it is an indication of source 'j' utilization of other FEW inputs. It is calculated by the sum of the elements in the j^{th} column of the direct technical coefficient matrix (A). The total backward linkage captures both direct and indirect linkage as displayed in Fig. 10 in an inter-FEW system. It is the column sums of the total requirement matrix (L) which is summarized in Table 5. The row sums of the i^{th} elements of the technical coefficient matrix (A) measures the direct forward linkage. Similarly, the row sums of i^{th} FEW inputs of the L matrix is associated with the total forward linkage. Fig. 10 presents the total backward and forward linkage magnitude for the FEW data given in Table 2. The total linkage considers the impact of the final demand change in the FEW sources. FEW inputs

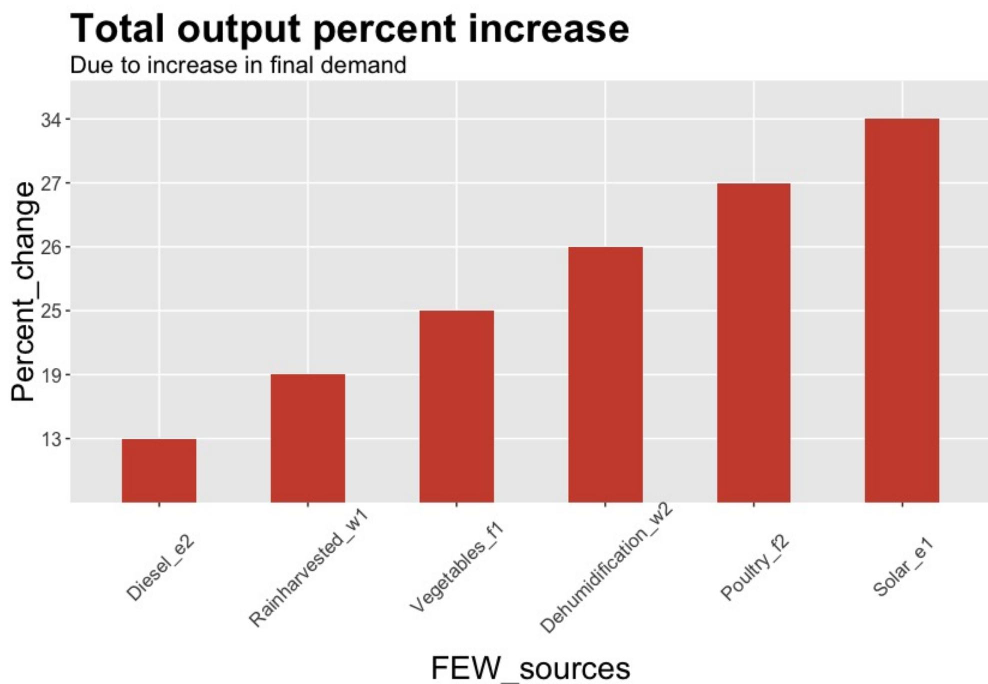


Figure 3.8: Percent increase in the total FEW output as result of change in demand

with higher backward linkage values are resource-intensive. They are highly dependent on the other source. Rain harvested water source (w_1) has the highest backward linkage, followed by poultry, diesel, and vegetable. Dehumidification has the highest total forward linkage followed by poultry and solar energy. These resources are the biggest supplier of the FEW input-output systems.

3.6 Summary

The FEW nexus problems involve and require the multi-scale challenge problem that comes with various dimensionality and time scale variance within the systems which presents unpredicted consequences and complexity to decision making. The three dynamic interacting infrastructures require a mathematical framework for analyzing such a large complex system. FEW IO model can account for demand as a result of stressors. It

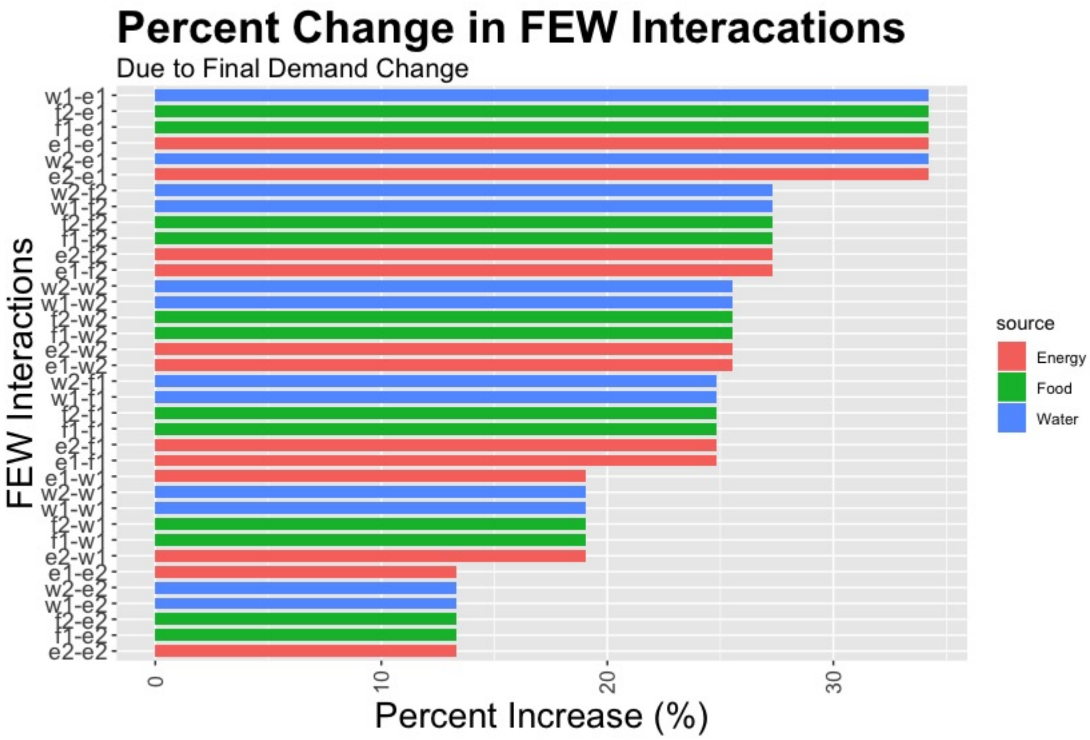


Figure 3.9: A change in FEW flow interaction as a result of change in final demand

Figure 3.10: Total backward and forward linkage

allows for the computation of intersectoral usage of various FEW components. Technical coefficient allows for the direct and indirect effect of resource on each other with the ability to trace back. The Leontief inverse matrix summarizes the network effects generated when the final output changes. A single coefficient of a matrix 'L' compiles all direct and indirect effects generated in the FEW element 'i' to provide a single unit of final demand for FEW element 'j'. This work presented a framework for a FEW nexus based on Leontief input-output model and how it further will be developed to a networked model as interdependent systems. Quantifying the FEW nexus is more important than ever as the demand for FEW resources will be exacerbated in the quest to achieve a sustainable smart city.

CHAPTER 4

EDGE IOT IN SMART FARM

4.1 Overview

As the world population rise to a staggering 10 billion [51], the Food and Agriculture Organization (FAO) of the United Nations (UN) predicts the global demand for food will rise by 60 % in 2050 [52]. This coupled with rising climate change, urbanization, and limited arable land put pressure in the demand for food production [42]. This means, food production must increase by 70% [53, 54] to meet such demand. Approximately 66% of the global population will reside in urban areas in the coming years [55]. FAO report that such demand will be met in the timeframe but unclear whether if it will be in a sustainable manner. As the demand for food soars, water and energy supply and demand also poses key issues. Water and energy are also major resources that their availability, accessibility, and utilization pose a threat. More importantly, the many overlapping interdependencies of these resources to produce and outsource each sector has forged a nexus approach to the problem [29]. Currently, food production accounts for 70% of the total global freshwater withdrawals [28, 33]. Overall food production and supply chain accounts to 30% of total global energy consumption [56]. These numbers with the aforementioned stressors are set to increase in the coming years. It is also important to note that there will be an imbalance of resource distribution across global regions. As wealth and income level disparity goes up poor developing countries will be struggling to get clean water, proper nutrition and basic access to electricity as wealthy nations are looking to change their diet. To address this disparity, the UN has set an ambitious agenda to meet selected sectoral goal also known as Sustainable Development Goals (SDG) for the developing world [57]. SDG places food security in number 2, clean water access in number 6, affordable clean energy in number 7 as part of the sustainable goal to meet for all developing countries by 2030.

Hence, the subsequent years will likely see the rapid shifts in the food system catapulted by changing consumer needs, technological advances, and many other factors.

The FAO and the International Energy Agency (IEA) together with researchers direct possible solutions in three overarching ways [53]: integrating Information and Communication Technologies (ICT) including IoT, understanding the resource problems through a nexus approach model [52, 29], and supporting the smart city initiatives. Recent advances in ICT are finding ways to propose concerns of food security through smart agriculture. Precision agriculture and smart farming make use of GPS services, machine to machine (M2M) communication protocols, IoT technologies, sensors, and big data to optimize crop yield and reduce waste [9]. In discussing the issue of sustainability, solving global food demand needs to be fulfilled by marinating the integrity of ecosystems. A nexus approach of key resources needs to be emphasized in addressing the Food-Energy-Water (FEW) security due to the interlinkage nature of all these three systems. A smart city model combines the above two efforts in technology and a nexus approach to address the critical demand in clean energy, water, agriculture, and transportation to name a few. It is an active systemic effort that integrates technology, governance, policy-making, and society to cover critical infrastructure challenges [58].

The objective of this section is to give a comprehensive review of sensor and IoT applications in smart farming practices. It attempts to address three concepts: the use of IoT smart farm to address the global challenge in food security, design of intelligent system through integrated nexus approach and how it ties to the smart city framework. The paper only uses research works selected from the past two years. The paper is organized as follows: Section 2 presents the recent advances in sensor technologies and their application. Section 3 describes recent advances in designing an intelligent system that couples the FEW nexus approach. Section 4 delves into the smart farm framework and how it supports the smart city paradigm.

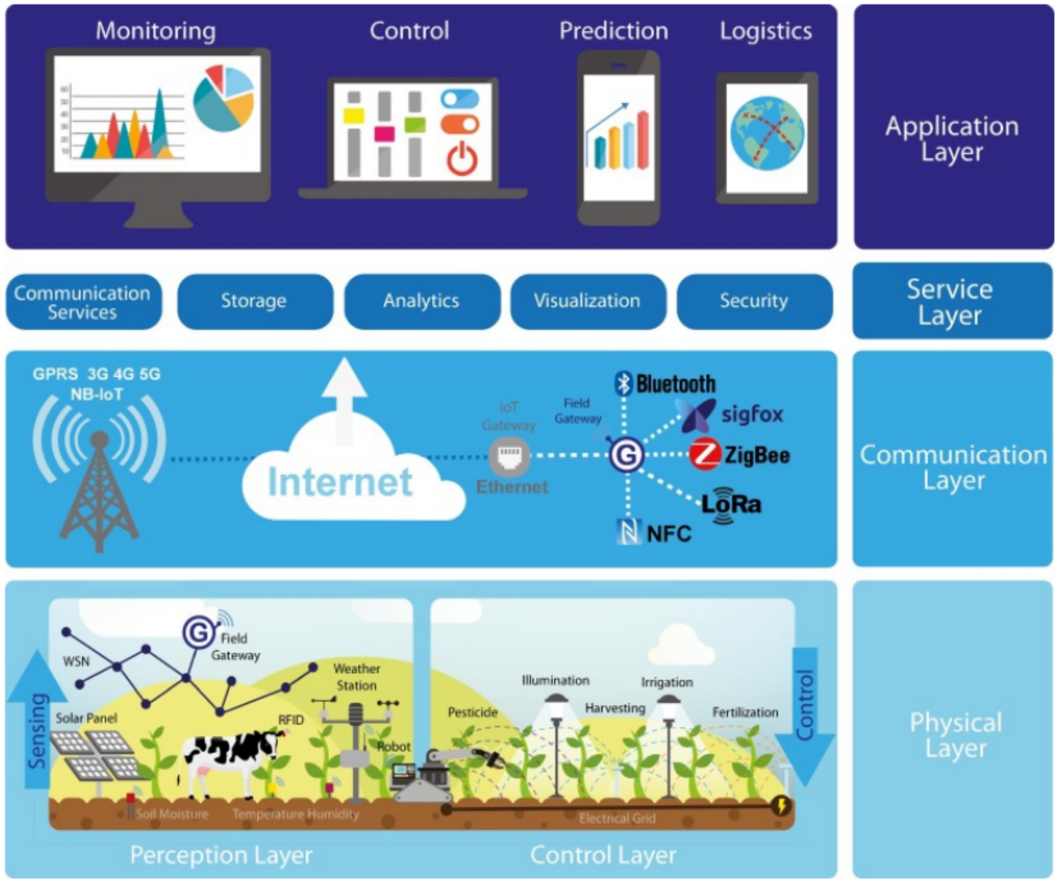


Figure 4.1: IoT architecture in precision agriculture application [5]

4.2 Smart Agriculture Ecosystem

Technology will play a central role in mitigating pressure the farming industry will face as a result of factors in the rising population, consumer needs and the growing shortages of land, water, and energy. Smart farming synonymous with other M2M based implementation such as smart metering, smart city, etc is also referred to as precision agriculture. According to Libelium, a major IoT solution industry driver, the total market value for precision agriculture solutions is expected to reach $4.7 billion in 2021 almost double the amount in 2016 [10]. Despite a growing level of exciting research and new smart farming projects, the agriculture industry has been slow to adopt the emerging M2M and IoT technologies as compared with other [11]. Smart farming is an integration of sensor technologies that collect data from the soil, crop, various environmental attributes, animal conduct, and tractor status. These sensor data through edge IoT computing and analytics can afford the farmer valuable information on weather conditions and forecasts, crop monitoring and yield prediction, plant and animal disease detection [12].

Smart agriculture implementation is dependent on the type of farming at hand. In a large farm setting, the use of farm vehicles like smart tractors equipped with GPS, and several embedded sensors, data visualization tools are currently in place with the ability to transmit real-time data [13]. Drones are a big player in this setting where built-in sensors provide different types of aerial imaging, field survey, and location mapping [14]. In small to medium-sized arable farming, spatially enabled mobile sensing technologies that provide detail analysis of field conditions in the different soil layer, nutrient levels, and overall ambient environmental conditions are being utilized [9, 15]. In addition, the implementation of smart irrigation by looking into the evapotranspiration parameter of plants to optimize the irrigation cycle is well in play. The use of soil moisture content and temperature sensors are widely common in scheduling irrigation [16, 17, 18, 19, 20]. IoT solutions are also deployed in monitoring location and health of livestock where sensors are placed within the animal to transmit these data wirelessly [21]. Other popular applications of IoT technologies are in greenhouses and its extension in vertical farming integrated with emerging practices such as aquaponics, aeroponics, and hydroponics [22, 23].

4.3 Sensing

Precision agriculture is a management system that demands accurate site-specific data such as soils, crops, nutrients, pests, moisture or yield, for the profitability, sustainability, and protection of the environment[13]. This precision data has become the most valuable resource to farmers in the ‘ag-tech’ revolution. To obtain such data in a real-time manner, researchers have already explored and made commercially available[9], various types of sensors that can be interfaced with radio-enabled micro-controllers for in situ monitoring of farm and environment. Of the studied sensors, the numerous measurement methods used to reflect the condition of farmland and environment include: 1) electrical and electromagnetic sensors[59], 2) optical and radiometric sensors[60], 3) force mechanical sensors, 4) acoustic sensors, and, 5)electrochemical sensors.

Electrical and electromagnetic sensors are more frequently used to measure electrical resistivity, conductivity, capacitance, and inductance affected by soil composition. Most soil moisture sensors operate using these principals by way of directly inserting conductive probes into the soil and measuring electrical changes between the electrodes due to moisture content.

Optical and radiometric sensors use electromagnetic waves to detect the level of energy absorbed, reflected, and transmitted by molecular bonds within soil particles to identify the presence of functional groups, moisture content, organic matter, nutrients, and pH. The common sensor systems, which utilize this method are diffuse reflectance visual infrared (Vis-IR) sensors, attenuated reflectance spectroscopy (ATR), and Raman spectroscopy. All of which have been employed in agriculture for real-time in situ analysis. Optical sensors are also employed for determining nitrogen and chlorophyll content in plants based on a normalized vegetative index (NDVI) and soil-plant analysis data (SPAD) readings of crop canopies and leaf structures.

Mechanical sensors measure forces and are more common in measuring soil physical properties such as compaction. Pneumatic sensors are also used to assess the soil’s physical properties through the injection of air. Acoustic sensors utilized for quantifying the sound produced by other devices or the environment.

Electrochemical sensors use ion-selective membranes that produce a voltage output in response to the activity of selected ions (i.e nitrate, phosphate, and potassium). They are commonly interfaced with controlled flow injection analysis (FIA) systems attached to heavy farm vehicles for acquiring real-time soil nutrient analysis while traversing the farm terrain.

These real-time in situ sensing methods have demonstrated the capability to produce results comparative to laboratory analysis. Due to the low-costs, accuracy, and availability of these sensor devices, they have become a critical component in monitoring air quality, water quality[18, 19], soil quality[15], crops[61], weeds[12], livestock[21, 62], and animals[62, 21]. Pioneers in the IoT sensor sector are producing commercial sensing platforms for addressing key global concerns such as environmental protection from pollution, urban planning, social cohesion, and risk prevention.

4.3.1 Air and Quality Monitoring

Monitoring air quality has become a popular topic, especially in urban cities, agricultural farms, and factory dominated areas. As described by the USEPA, Ambient air monitoring is the systematic, long-term assessment of pollutant levels by measuring the quantity and types of certain pollutants in the surrounding, outdoor air(cite). Advanced sensing technologies such as Micro-ElectroMechanical Systems (MEMS) and Wireless Sensor Network (WSN) have allowed researchers to further the concept of The Next Generation Air Pollution Monitoring System (TNGAPMS) and achieve excellent progress. The application of ZigBee based WSN has been reviewed in [9, 17]

Monitoring air quality and humidity have also been a domain in agriculture. Design and implementation of a low-cost, real-time, vineyard micro-climate monitoring system based on ZigBee wireless sensor network were proposed in [9], the researchers demonstrated the use of solar-powered smart farm to transmit real-time humidity data via ZigBee communications to a web-based data logger. Researchers in [20] explored real-time monitoring of micro-meteorological parameters such as relative humidity, temperature, and radiation) in an apple orchard.

4.3.2 Water and Quality Monitoring

TThe demand for water, food, and energy increases with the global population, however, access to quality water has become a continued challenge, with poor water sanitation contributing to millions of death each year. A survey of WSN water quality was done in [18], and revealed the great benefits of low-cost, real-time in situ infrastructure for water quality monitoring. Water monitoring using WSN has also been employed in agriculture for soil monitoring. These technologies include soil water sensors which can be considered a soil quality senor, and for that reason will be further discussed in the proceeding subsection.

4.3.3 Soil Quality Monitoring

Throughout the green revolution, resources such as water irrigation and nitrogen fertilizer have been excessively applied to increase yield production and profit, however, these have caused widespread concern about environmental pollution and public health. Therefore, interests have been placed on sensor networks which can monitor soil condition in a real-time high-density manner. Soil quality is considered the capacity of a soil to function, within natural or managed ecosystems, to sustain plant and animal productivity, maintain or enhance water and air quality, and support human health and habitation[]. The physical and chemical characteristics of soil commonly investigated include the texture, structure, porosity, water content, organic matter and microbes, cation exchange capacity, and available nutrients.

Researchers [15] developed IoT sensor sheets for real-time soil nutrient analysis in south Florida limestone derived underneath soils. The platform was interfaced using LoRa communication technologies. In [12] a WSN monitoring system was designed and implemented to monitor multi-layer soil temperature and moisture in the farmland field. It provided basic studies for understanding soil infiltration models.

4.3.4 Crop, Pest, and Forest Monitoring

Researchers in [61] reported on the preliminary experiences with deploying 100+ nodes for a large-scale pilot project concerned with protecting the potato crop against fungal disease phytophthora. The authors focused on the experiences and lessons learned from the large scale project which was the first of its kind to take place in the Netherlands. The authors also emphasized the proper use of software engineering principles, the need for worst-case design, and the necessity for large-scale testing, given the many challenges they faced throughout the first year of the project. In [61] designed and developed a WSN system for detecting forest fires by monitoring temperature, smoke, and humidity.

4.3.5 Livestock and Animal Monitoring

In [62], researchers deployed delay-tolerant networks (DTNs) for free-roaming animal monitoring, wherein information was either transmitted or carried to static access-points by the animals whose movement was assumed to be random.

A GPS based WSN system for monitoring micro-climate, the behavior and migration patterns of Swamp Deer was explored in [21]

4.4 Wireless Communication

Advances in ICT such as radio frequency identification systems (RFID), short-range wireless communication such as WiFi, ZigBee, Bluetooth, and cellular networks have played a huge role in the technological revolution of IoT. In smart farm applications, wireless sensor networks (WSN) are usually equipped with different radio interfaces supporting different protocols: 2G to 4G, 802.15.4, ZigBee-Pro, RF, LoRaWAN, Sigfox, 802.11b/g, and Bluetooth. Sensor data is then transmitted to a gateway. The gateway transmits the data acquired from the sensors with similar communication modes to the farm management system where data analytics and decisions are made. In rural areas where cellular connectivity can be weak, satellite and GPRS communication can be optional. However, this can be costly for farmers with small to medium-sized holders. Low Power Wide Area Network (LPWAN) is seen as the potential substitute for cellular connectivity with long transmission range and power-saving capability [63, 12]. Long Range (LoRa) and Narrowband (NB)-IoT are the two popular leading LPWAN technologies [64, 65]. Key concerns in selecting wireless communication protocol are power, transmission range, latency, cost, scalability, and security.

This section will go in detail on the leading wireless networking protocols that are currently supported by IoT devices and in use within precision agricultural applications.

Radio	Standard	Frequency	TxPower	Range	Data rate	Network type
ZigBee	IEEE 802.15.4	2.4 GHz - 900 MHz	50 -315 mW	7- 12 km	20,40, 250 kbps	LAN
WiFi	IEEE 802.11	2.4 GHz	0-16 mW	50-500 m	11-54 and 150 Mbps	LAN
2G/3G/4G	3GPP	700, 850, 1700, 1900 MHz	200 mW	km-typical carrier range	100 Mbps	WAN
Sigfox	Sigfox	868 MHz	25mW	km-typical base station	100 bps	WAN
LoRaWAN	LoRa-Alliance	868/433 MHz, 900-915 MHz (Unlicensed)	25 mW	km-typical base station range	50 kbps	WAN
LoRa	LoRa-Alliance	868/900 MHz (Unlicensed)	25 mW	22 km	300 bps - 50 kbps	WAN
NB-IoT	3GPP release 13	868/900 MHz (Licensed LTE)	25 mW	22 km / $<$ 10 km	160-200 kbps	WAN
Bluetooth	IEEE 802.15.1	2.4 GHz	2 mW	8-10 m	160-200 kbps	PAN

Table 4.1: Comparison of different wireless communication interfaces

4.4.1 Bluetooth

Bluetooth is low power, low cost, a wireless M2M communication protocol that complies with the IEEE 802.15.1 standard. It operates within a short distance range by defining a PAN communication using 2.4GHz frequency of the ISM band [66]. Bluetooth can discover up to 250 devices in a single inquiry which makes suitable in WSN application in agriculture. The Bluetooth 4.0 standard also known as Bluetooth Low Energy (BLE), introduced by Nokia in 2006 is the slightly robust version of the Bluetooth classic. They are optimally designed for ultra-low power and low-cost applications [67].

Bluetooth application in smart agriculture spans from water management to sensor data acquisition. A Bluetooth based integrated control for drip irrigation based on temperature, solar radiation, soil moisture, and humidity is developed in [68]. A hybrid BLE and near field communication (NFC) sensor node are implemented in [69, 70] for agricultural monitoring and supports streaming of in-field agriculture information via smartphone.

4.4.2 ZigBee

ZigBee is a low power, short to medium range, low throughput, and energy efficient communication protocol that is suitable for wireless ad-hoc networks. The operational range of ZigBee varies from 7km - 12km making it a Local Area Network (LAN) and it can support up to 64,000 nodes depending on the module. There are several XBee modules distributed by IoT suppliers such as XBee-Pro 802.15.4, XBee-Pro DigiMesh, XBee ZigBee 3, and XBee 900HP are few. The range, transmission power, frequency and data rate are dependent on the module. ZigBee modules comply with the IEEE 802.15.4 standard [71, 72, 73].

ZigBee network operates by defining three different device types: coordinator, router, and end devices. The coordinator assigns a Personal Area Network (PAN) ID and channel for the network and allows routers and end devices to join the network. End devices join a router or coordinator with the intent to transmit data. ZigBee modules can adopt a star, tree and mesh topology to create a network. In star topology, a central node that acts as the coordinator is linked to all the other nodes using either a MAC or network address. The coordinator collects all the data coming from the network nodes which are the end devices. A tree network has a top node with a branch structure where a message travels up the coordinator to the router and the end device. Mesh, also referred to as peer-to-peer topology, has a similar connectivity scheme. In a mesh topology, packets pass through multiple hops to reach their destination, creating a multi-hop network. With a mesh network, Zigbee can send data at a long distance where intermediate nodes relay the data packet.

Zigbee is one of the best candidates in smart farm applications due to its superb characteristics. In [9], wireless sensor nodes with XBee Pro module were used in a star topology to transmit agricultural and environmental sensor data to the gateway. Another popular Zigbee application is in the implementation of a smart irrigation system based on soil moisture content and temperature [16]. A disposable IoT gardening soil sheet with the potential to measure soil nitrate concentration is demonstrated in [15].

WiFi enables the use of heterogeneous architectures that connect multiple-type devices through an ad-hoc network. WiFi module offers and supports various features including DHCP client/server, DNS, HTTP, FTP, and NTP client. It has a LAN communication capability covering medium-range transmission. In WSN, sensor nodes have the option to connect to any standard router which is configured as Access Point (AP) then send data to other devices like laptop or smartphone in the same network. This can be achieved through a DHCP protocol or using a preconfigured static IP. Sensor nodes also can connect to a standard WiFi router equipped with DSL or cable connectivity to send data to a web server (cloud) located on the internet. A WiFi based remote monitoring system was investigated in [74] where sensor nodes transmit data wirelessly to a central server. In [75] a WiFi-based long-distance "WiLD" network is successfully implemented to connect agriculture and farming stations for rural areas.

4.4.3 Cellular Technology

General Packet Radio Service (GPRS) is a packet data service for Global System for Mobile Communication (GSM) based 2G cellular phones. The biggest advantage of GPRS is the wide-area network capability taking away range limitation. However, in precision agriculture where real-time monitoring by sensor nodes are needed, GPRS is not the best option. GPRS is fitted for application where periodic monitoring is needed such as interval irrigation. Automated irrigation systems using hybrid Zigbee and GPRS were proposed in [17] where the GPRS protocol is used to transmit acquired soil moisture and temperature data to the web-based server. In the cases the amount of data is small and the speed of the transmission is not of concern, GPRS might be suitable for better coverage compared to 3G/4G networks [18].

3G, 4G and currently 5G are the third, fourth and fifth generation of mobile communication technology. The 3G/4G module allows sensor networks and M2M devices to connect to the cloud using high-speed cellular networks in the same way as smartphones do. Especially 4G enables the connectivity to high speed LTE [76, 77]. Their application is especially sought in distributing data from gateway to farm management information system (FMIS) where long-range transmission is required. In large farms located in rural areas network coverage is often a challenge. Generally the 2G/3G/4G networks good in long-distance and high data rates. The downside for this they tend to be power intensive and coverage is not reliable.

4.4.4 Low Power Wide Area Network

In recent years to meet the needs of optimal communication threats and the rapid ubiquitous nature of IoT devices, a new low power wide area network (LPWAN) communication technologies have emerged [64, 63]. Many of the LPWAN technologies work in both licensed and unlicensed frequency spectrum. The leading technologies are Sigfox, LoRa, and NB-IoT. LPWAN is highly suitable for IoT applications where a small amount of data needs to be transmitted in long-range [67, 59, 14].

Sigfox

The Sigfox technology was developed in 2010 by Sigfox startup in France [78] which is LPWAN network operator that also offers end-to-end IoT connectivity solutions. It uses 915 MHz (North America) in unlicensed ISM bands and co-exists in these frequencies with other radio technologies without any risk of collision or traffic capacity problems. It is one of the mature LPWAN technologies after LoRa with current deployment in 31 countries including the U.S. Sigfox modules experience very low noise interference attributed to their use of ultra-narrow radio band to efficiently use the frequency bandwidth. This also makes them energy-efficient technology. The support of several numbers of end devices one of the key attractions of LPWAN technologies and Sigfox allows connectivity of 50 K per cell [79]. Sigfox is suitable only on IoT application that has small data size as it can only support 12 bytes of payload size [67]. As noted in Table 4.1, Sigfox provide superior network coverage with one base station covering more than *40km* [79, 59].

Sigfox is an ideal candidate in PA application. In [61], a hybrid 3G/GPRS and Sigfox protocols were used in WSN to compare the effect of irrigation strategies in a kiwi plantation in Italy. A Sigfox communication protocol has been used in the development of a smart garden system to monitor green areas in Spain [61]. As a result, 30% of water and pumping cost reduction is achieved. In [20] a wireless underground sensor network with Sigfox network is designed in a university campus to analyze different kinds of soil properties and their influence on the performance of the wireless transmission.

LoRa

Developed by Semtech, this radio technology is based on the physical layer (PHY) modulation technology that uses unlicensed ISM bands [79, 64]. LoRa contains only the link layer protocol and is perfect in point to point (P2P) node communication. Nodes use parameters like node addresses to establish a star topology network architecture. A maximum of 10 nodes can be set to a gateway. LoRa is cheaper than LoRaWAN modules.

A LoRa based communication protocol called LoRaWAN was standardized by LoRa alliance in 2015. LoRaWAN works at different frequencies by connecting an antenna. It runs on an advanced protocol known as LoRWAN protocol. It supports bi-directional communication, mobility and localization services which are key requirements of IoT devices [80]. In addition to P2P communication mode, nodes with LoRWAN module can send data to the base station. Base stations are used as gateways to transmit collected sensor data to the cloud. Their network layout is a star of stars topology in which gateway is a transparent bridge relaying messages between end-devices and a central network server in the back-end [64]. Gateways and end-devices communication is spread out on different frequency channels and data rates. Data rate selection happens at the expense of transmission range and speed [67]. An adaptive data rate (ADR) scheme is used by LoRaWAN network server to manage the data rate an RF output thereby maximizing the battery life of end-devices and the overall network capacity [80]. LoRaWAN technology is in its early stage as the specification of the second version is yet to be released. The cost associated with the LoRaWAN network deployment might be higher as it requires multiple base stations to improve successful message acquisition to the target application server [67, 79].

As a recent technology, LoRa is recently gaining traction within the smart farm ecosystem providing low power low-cost communication solutions that require prolonged monitoring operation. A neuro-fuzzy algorithm based smart irrigation scheme uses LoRa module as an alternative to energy intensive 3G system in [19]. Similarly, LoRa based water and energy management focused IoT systems for agriculture are proposed in [81, 82]. Climate and environmental parameters were measured and monitored with LoRaWAN end-devices in a greenhouse for mushroom production [83].

NB-IoT

NB-IoT is a LPWAN technology that is based on narrowband radio scheme and is standardized by the third generation partnership project (3GPP). It is based on the long-term evolution (LTE) protocol enhancing the LTE [77] functionality specifically for IoT applications [73]. NB-IoT can co-exist with GSM and LTE under licensed frequency bands. This makes it ideal for guaranteed quality of service (QOS) at the expense of cost. This technology can allow connectivity of up to 100 K nodes per cell with the capability of scaling up by adding more carriers. Therefore, this gives NB-IoT an advantage of superior scalability compared to Sigfox and LoRa [63]. NB-IoT offers the advantage of low latency and battery lifetime up to 10 years when transmitting 200 bytes per day on average [84]. Since its inception in 2016, the NB-IoT technology is still in its early stage and is not yet available in certain regions like Europe. Compared to the other LPWAN technologies, NB-IoT has the lowest range and coverage capabilities. Since it relays on the LTE infrastructure, its deployment is limited to LTE base stations.

A blockchain and LoRa /NB-IoT technology based food traceability solution is proposed in [85] to help people in improving food safety status. Generally in PA application, since the majority of large scale arable farming is located in rural areas where LTE cellular coverage is nonexistent, NB-IoT is not an ideal candidate for agriculture in the current and near future.

4.5 Data Management

The ability of IoT enabled agriculture is to have a better sense of land, environment, livestock, and crop through high resolution data. Data-driven agriculture involves the collection of complex, dynamic, enormous data that requires a data management scheme [13, 11]. The data management scheme is concerned with the acquisition, storage, and

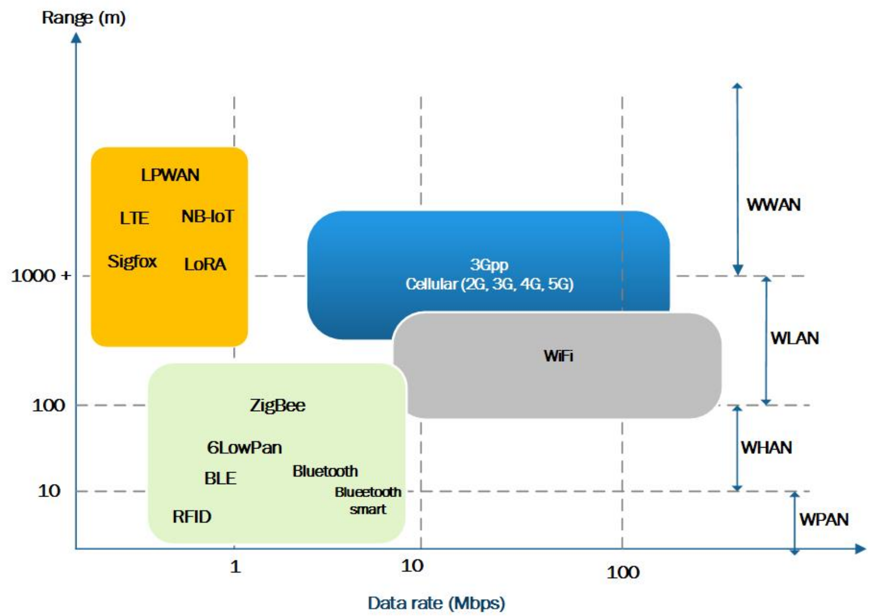


Figure 4.2: Data rate vs. range capacity of wireless communication technologies

processing of the range of data in the IoT framework. Data acquisition happens in the perception layer of the IoT architecture by WSN, drones, GPS or any devices intended for capturing data. Storage of captured data occurs in the service layer where the process of storing data in a database or cloud platform is initiated. The third part of the data management process is in the application layer where sensor data are used in the monitoring, control, and prediction supporting FMIS.

Once sensor data are acquired by a gateway which is able to work with the different communication protocol mentioned in section 4 it can be stored in a database or cloud platform. Some gateways are capable of storing acquired sensor data in a built-in MySQL database within the device itself. In addition, gateways with WiFi or cellular communication capability can synchronize captured data to an external database existing in a server or virtual machine of the end-user. Individual sensor nodes can also directly transmit data to an external database or the cloud via HTTP or MQTT requests as shown in fig. 4.3. The use of a cloud platform makes data more accessible to different stakeholders in addi-

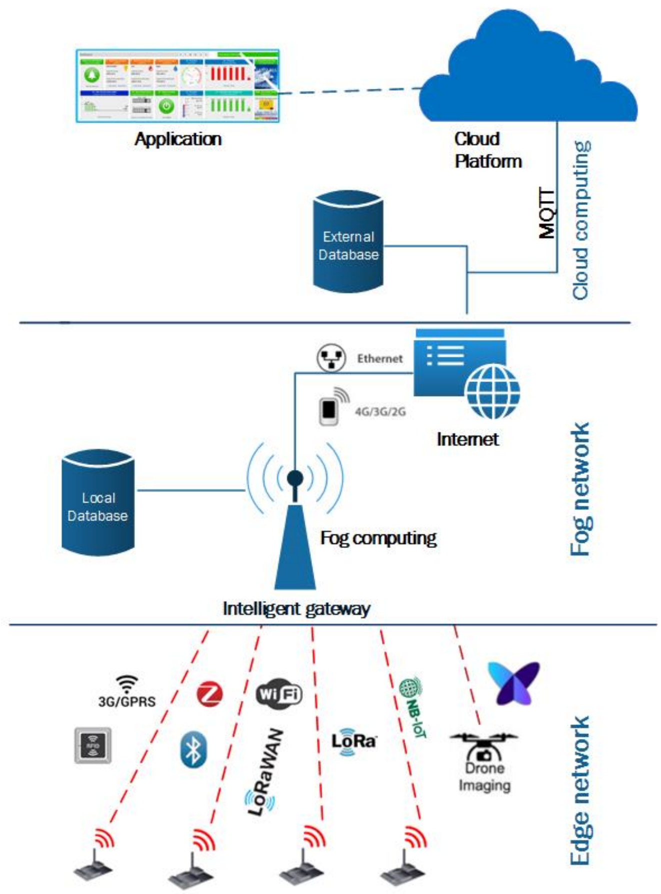


Figure 4.3: Data synchronization and storage scheme

tion to the farmer. Cloud computing is a key component of the IoT based solutions which makes data centers available to a vast number of internet users. Cloud platforms such as IBM's Bluemix, Microsoft's Azure, Amazon's AWS and Google's cloud IoT are the big players in cloud computing for agriculture application. Most of the cloud platforms have integrated domain specific visualization, analytics, and forecasting, machine learning, and mobile computing feature making them an ideal and integral part of the IoT ecosystem. New cloud computing paradigms such as fog and edge computing is advocated where IoT devices and gateways carry out computation and analysis to increase QoS and reduce cost and latency [86, 87]. Fog and edge computing although not exploited currently promises advances in PA connectivity although not exploited currently [88].

4.6 Smart City and Nexus Approach

The staggering increase in the world population that is expected to live in urban areas has made governance cognizant in building advanced infrastructure to meet such demand. The smart city initiative promotes more interconnected governance in housing, environmental issues, water, transportation and energy putting ubiquitous ICT and IoT technologies as key drivers [89]. The smart city promotes a shifting from a linear model to a circular model of metabolism [25], whereby resources are used efficiently and optimally by minimizing waste [90]. ICT and IoT technologies are innovations that will play

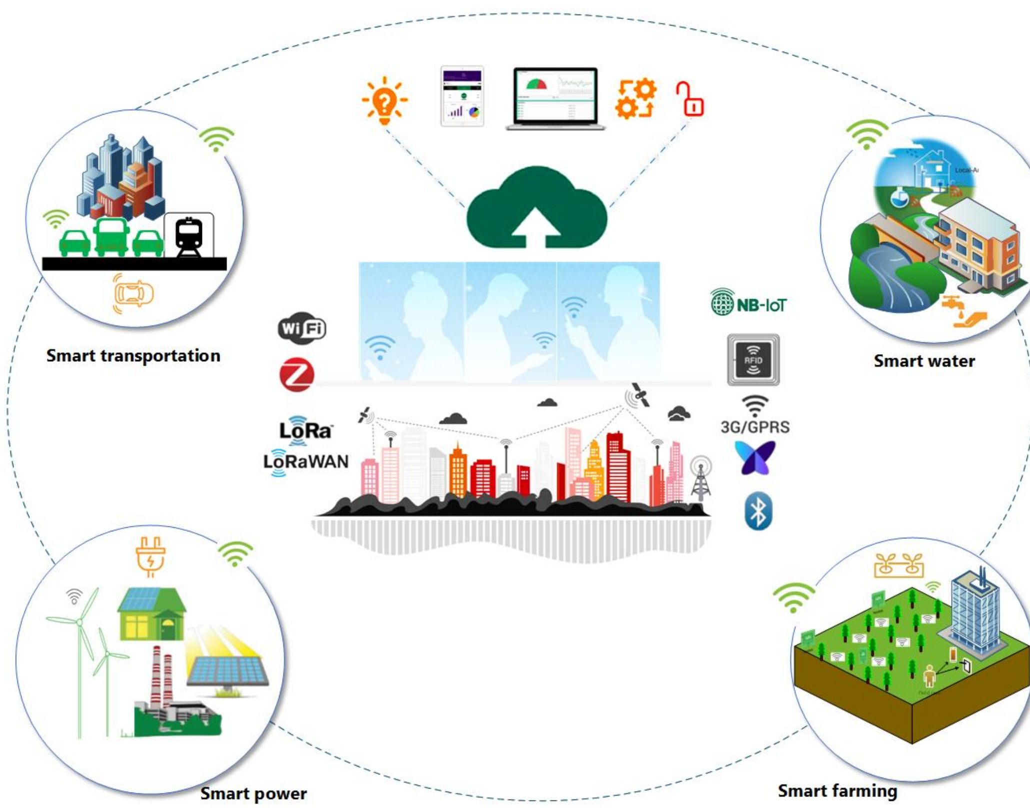


Figure 4.4: Smart city model at the nexus with key infrastructures

a role in addressing the FEW nexus stress in an integrated way. Such technologies as discussed in the previous section equip city-wide stakeholders with essential big data that can be insightful in patterns, practices, consumption trends, forecasting and better management of resources. As a result of improvements in sensing technology and reductions in costs, sensing capability is expected to be integrated from everyday objects to major infrastructures. Food, water, and energy are the many resources and infrastructure that are critical to the smart city initiative [65]. The power grid as it is transitioning into the smart grid will be critical in ensuring reliability, availability, and efficiency of power. As higher penetration of renewable energy sources is expected in future power consumption, the smart grid will play a huge role in monitoring data-driven power generation, demand, and energy storage decisions. Similarly, a smart water management system is a critical aspect of smart cities where water consumption, transportation, and prediction of future water use will be monitored. Environmental friendly treatment of wastewater, use of water harvesting mechanisms and groundwater monitoring supported by wireless sensors, smart meters and GPS are all important verticals of smart water [25, 87]. Leveraging ICT in the electric grid, agriculture, water resources foster more efficient and effective utilization of these critical resources. Several technology incubator and researchers are currently specializing in developing technologies illustrating the possible synergies [91].

Agriculture is an important part of smart cities as it contributes to the food supply chain that facilitates a large number of communities concentrated into cities. Urban agriculture plays a key role in addressing food security, promoting the idea of growing food in the cities cutting the transportation time of “food to table”. A recent innovation in vertical farming, hydroponics, and aquaponics are paving the way in bridging the food gap to cities. Vertical farming first conceptualized in [92, 23] is a way to produce food in closed structures such as warehouses, containers or household garages. Plants are grown in long, narrow beds that are stacked in layers making use of the hydroponic or aeroponic system and varieties of sensors monitoring optimal LED lights, nutrient and heat use. Vertical farming is an extension of the greenhouse hydroponic farming model and addresses problems land requirements, fertilizers, pesticides, and herbicides [22, 23]. Commercial examples of vertical farming sustainably addressing the use of land, and FEW resources are Singapore's Sky Greens [92], Vancouver based Verticrop, and Japan's Mirai is few. Smart cities use data and digital intelligence to make a better decision, to better serve citizens and improve their quality of life. A better way of managing the data has to be implemented with fog computing by using fog gateway devices and platforms to perform edge analytics [93]. This will make both the computational and communication process more efficient and sustainable.

4.7 Research Challenges and Opportunities

The challenges and opportunities associated with IoT applications in agriculture are listed as follows. From surveying numerous papers, it is concluded these are the main but not all the factors for the slow adoption of IoT in agriculture.

- *Interoperability*: IoT platform and architecture by nature require various devices and standards to work together. This deals with technical (hardware/software of devices), syntactic (data formats), semantic (content exchange), and organization (data transfer) interoperability [11, 13]. A great amount of research opportunity is in the integration of various heterogeneous systems. The interoperability of heterogeneous components, communication protocols, and sectors will enhance the goal for IoT in agriculture application rather than bring chaos.
- *Security and privacy*: advanced security measures are required to protect information transfer in the on and off fields. Moreover, field-based privacy solutions are required such that information from multiple fields can be used for more accurate decisions while preserving the privacy of farmers. Security issues in the perception layer include tampering with data acquisition and the actual physical security

of the hardware. Devices must be secure against external attacks. In agriculture application devices are usually deployed in open fields and are expected to function without surveillance for long periods. A secure way of data aggregation must be in place in the network layer where only authorized entities can access and modify data in the application layer. Encryption algorithms, distribution policies, intrusion detection mechanisms, and security routing policies are still an area of opportunities given hardware restriction on IoT devices.

- *Cost*: the cost associated with high-quality sensors and actuators is high depending on the number of nodes being deployed. Despite the cost of embedded computing decreasing through the years, the overall deployment of the hardware, internet access, and roaming costs are hefty. The future developments in reducing cost will depend on the fabrication of cheaper sensors, alternative operating and deployment mechanisms in wireless connectivity. The latter will focus partly on exploring the coexistence of licensed and unlicensed spectrum for wireless connectivity.
- *Networking and energy efficiency*: one of the bottlenecks for IoT connectivity is the energy consumption of wireless communication technology. LPWAN technologies aim to achieve the goal of energy efficiency of IoT devices, however, it is highly dependent on node usage and computing power of the embedded hardware [86]. Clustering and in-network algorithms have been implemented to make WSN energy efficient. Other opportunities that promise to optimize energy consumption such as energy harvesting IoT devices and simultaneous wireless power and information in IoT are being explored.
- *Data*: with millions of IoT devices connected and enormous flows of data, the need for increased storage and computational resources is inevitable. Currently, cloud computing provides services in computational data processing, application development, and sufficient storage. Recent developments in edge and fog computing

are however slightly changing the landscape in bringing the computational power to the edge network [87]. This can induce latency and high cost as a result of the huge data that later needs to be transferred to the cloud. Therefore the trade-off and optimal balancing between edge storage and cloud processing need to be heavily investigated in future applications.

4.8 Summary

The development of smart farming must accelerate rapidly and learn a lesson from the smart city projects to meet the goal set by FAO. The agriculture industry remains greatly unpenetrated by IoT technologies. Different sources expect the precision agriculture and IoT driven food chain to grow from a minimum of multi-billion to trillion market in the coming years. The advancements of LPWAN technologies will facilitate the IoT application to any domain especially in the agricultural remote monitoring.

An overview of IoT and its enabling technologies has been presented in this paper. Several areas related to the deployment of IoT in agriculture have been discussed in detail. The driving factors, current trends and future development of the smart agriculture ecosystem are presented. A detailed overview of sensing and networking technologies is discussed. Recent advances that implement the integrated FEW nexus approaches within the smart city paradigm such as vertical farming is reported. Major technical challenges in the realization of IoT in agriculture and future development areas are highlighted.

CHAPTER 5

AN EXPERIMENTAL TEST-BED FOR INTEGRATED FEW SYSTEM

5.1 Overview

As the global population soars from today's 7.3 billion to an estimated 10 billion by 2050, the demand for Food, Energy and Water (FEW) is expected to more than double [27, 51, 57]. Such an increase in population and consequently, in the demand for FEW resources will undoubtedly be a great challenge for humankind. A challenge that will be exacerbated by the need for humankind to meet the greater demand for resources with a smaller ecological footprint. This chapter is proposing a system developed to optimize the use of water, energy, fertilizers for agricultural crops as a solution to this great challenge. It is an automated smart irrigation system that uses real time data from wireless sensor networks to schedule an irrigation. The test-bed consists of a wireless network monitoring soil moisture, temperature, solar radiation, humidity, and fertilizer sensors embedded in the root area of the crops and around the test-bed. Wireless sensor data transmission and acquisition is managed by an Access Point (AP) using ZigBee protocol. An algorithm was established based on threshold values of temperature and soil moisture content that were automated into a programmable micro-controller to control irrigation time. The system's energy demand is completely supplied by a solar Photo-voltaic (PV) panel supplemented with an energy storage unit. The experimental data obtained from this prototype will be modeled and optimized to investigate food production profile as a function of energy and water consumption. It will also attempt to understand the effect of extreme weather conditions on food production. This holistic approach will explore the nexus between water and energy resources, and crop yield for several essential crops in an attempt to design a more sustainable method to meet the forecasted surge in demand.

Currently, almost 70% of the global fresh water is being used for agriculture [28]. The demand for water is expected to increase to 55% by 2050 [1]. Similarly, 30% of total global energy consumption is spent on producing, transporting and distributing food as well as in the application of pumping, extracting, treating and transporting water [1, 28]. Global energy consumption is projected to increase to 80% by 2050 [1, 2, 3, 39].

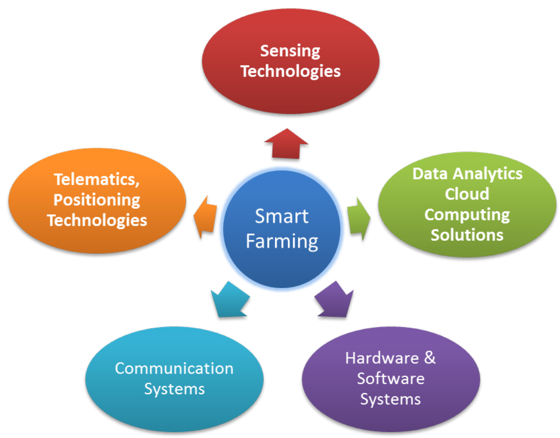


Figure 5.1: Drivers of smart farming technology

As the demand for food soars to 60% by 2050, food security along with water and energy supply pose key issues in the availability, accessibility and utilization of these resources. Increased population growth, economic development and urbanization are the driving factors in the demand for food, energy and water resources more than ever [29]. The solution to solve the food requirement has to be more innovative.

Smart agriculture or precision farming is a recent concept that came out of the Internet of Things (IoT) applications [61, 94]. The growing IoT landscape can almost be applied to different sectors and the agriculture field has been a recent one [58]. The combination of IoT along with predictive data analytics in agriculture can equip farmers with critical information on soil and environmental parameters to take actions.

The driving factor behind smart agriculture has been the demand for more food production to increase yields, optimize interdependent resources of energy, water and land

and impact of urbanization [27, 29]. With advances in technology, there is more push by global stakeholders like the Food and Agriculture Organization (FAO) for farmers to use innovative tools and digital technologies [2, 27, 28]. The agricultural sector is faced with challenges connected to limited availability of arable land, water and energy, global climate change, and labor supply [42].

The IoT framework can be used to understand the interdependency of energy, water and food resources through wireless sensor networks (WSN) for each sub-systems [14]. With real-time data, farmers can predict their yield, optimize water utilization through smart irrigation control and precisely know when to harvest thereby reducing energy and labor input.

Although, smart agriculture is a recent phenomena with the saturation of digital technologies, there is a great body of work in IoT enabled farming [17, 41]. Several works have been done in smart irrigation as part of smart farming model to optimize water utilization. The design and implantation of novel wireless mobile robot is demonstrated in [94] to monitor environmental parameters suitable for optimal crop yield. The use of distributed WSN of soil-moisture and temperature to automate irrigation system has been implemented in [16, 17, 18]. Remote sensing and the use of distributed WSN for a site-specific irrigation scheme is implemented in [95] based on soil property map. The key components in smart agriculture; data sensing, communications, storage and processing are integral in achieving robust predictive capabilities [96]. Once data has been collected, it has to be analyzed using different algorithms to get predictive capabilities. In [97] prediction models based on linear regression, neural networks and Support Vector Machines (SVM) are proposed from WSN data. Machine learning algorithms like Artificial Neural Network (ANN) are often used in the data analytics to manage the bid data [98] side of smart farming [99].

The objective of this work is to design and deploy a WSN for monitoring energy, water and crop development to further develop a nexus model based on real-time data. The scope of this work is to describe the overall system description and deployment outlining the future proposed work. This chapter is organized as follows: Section 5.2 presents the general level system and sub-system of the smart farm experimental test-bed. Section 5.3 describes the overall system design and implementation. Section 5.4 details the infrastructure for the data acquisition and management. Section 5.5 presents the future work.

5.2 Smart Farm Test Bed

The smart farm test bed hereby reported consists of distributed WSN, off-grid PV panel, smart irrigation and data infrastructure. The purpose of the project is to develop an optimized smart solar-powered farm systems that maximize vegetation yield, minimize energy consumption, environmental effect through real-time monitoring from sensor data. The design requirements are to optimize input of fertilizers and pesticides, energy consumption using an off-grid PV and battery backup system and water consumption.

The end goal is to build a circular system where energy, water, weather, and crop data will be collected to develop a nexus computational model. The conventional way of thinking about the challenges of FEW systems had focused on "peace-meal approach" where decisions are made in one of the nexus areas without making an allowance for the consequences on the other areas [29]. The nexus approach provide decision makers with better information through optimization of synergies and trade-offs. One of the objectives of the nexus is the development of modeling tools to support integrated decision making. Big, precise and reliable data from all the three systems are required to address the computational challenge for FEW nexus. This creates the primary reason for designing intelligent agriculture infrastructure.

5.3 System Design and Implementation

The design of the smart farm prototype included field preparation which incorporated crop-line accommodation and soil preparation, along with solar panel footing foundation and pole placement. The farm consists of three 4x25 ft raised beds as shown in Fig.6.2

Figure 5.2: Field preparation

5.3.1 Electrical System Units

The system's energy demand is completely supplied by a PV panel supplemented with an energy storage unit. A 320W at peak power with V_{mpp} of 37.2V PV panel with 16.3% module efficiency is used. The tilt angle is fixed at 26° same as the latitude of the location. The default tilt angle for a PV panel is set to the latitude of the location which will maximize annual energy production [100]. The PV panel is connected to a 20A 12V DC Maximum Power Point Tracking (MPPT) solar charge controller to prevent overcharging of the batteries. The MPPT charge controllers vary from the traditional PWM charge controller by allowing the solar panels to function at their optimum power output voltage thereby increasing their performance. The charge controller is installed between the PV and the batteries to automatically maintain the charge on the batteries using the bulk, acceptance and float charge cycles. In addition, the load for the system which comes mainly

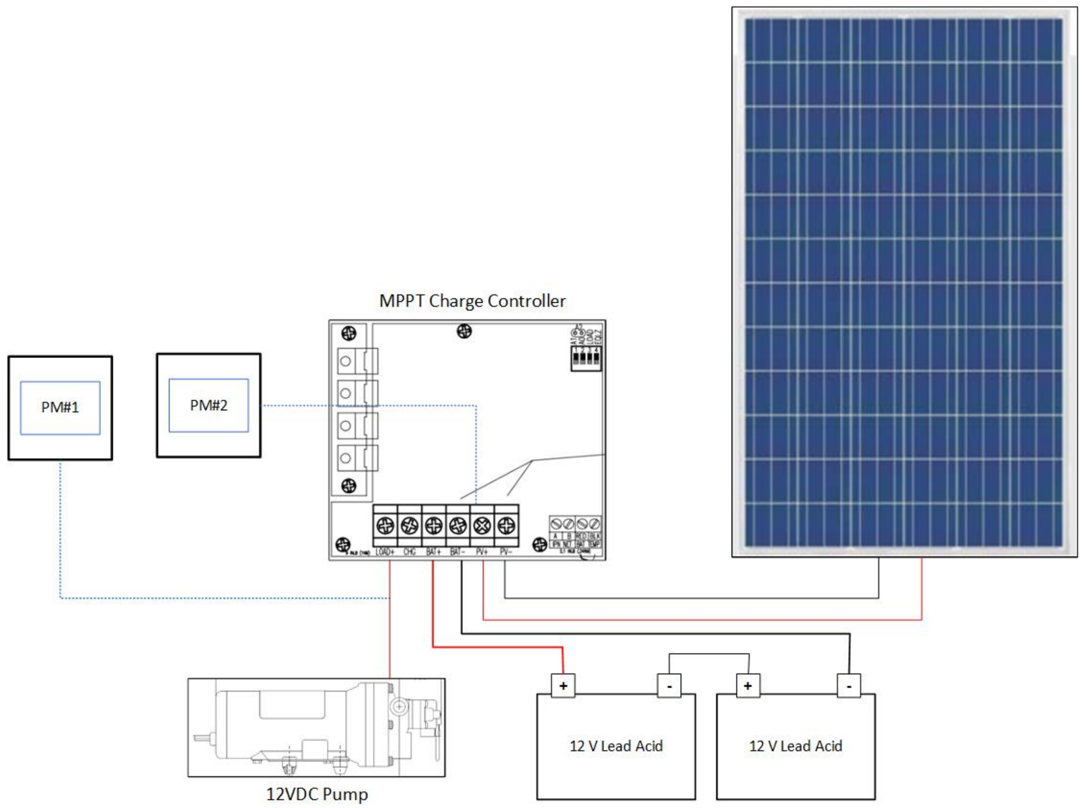


Figure 5.3: Electrical System Unit

from the water pump is controlled by the MPPT. Two 12V, 250 Ah are connected in series to the MPPT. Power meters with RS485 serial communication capability from the generation and load side are connected. They have an RS485 serial communication capability for energy data acquisition. Energy data is acquired from the power meter through RS485 serial communication to Arduino and then sent to gateway through Zigbee protocol.

5.3.2 Wireless Sensor Unit

WSU are equipped with different types of sensors with the capability of measurement, acquisition and synchronization of data. The WSU used for this project is an Arduino based node with various radio options for connectivity. It has two main component boards consisting of the sensor board and main functionality module board. Environmental and

Figure 5.4: WSU connected to a weather station

agriculture parameters are measured by the sensor board. Ambient temperature and humidity, atmospheric pressure, pluviometer, anemometer, solar radiation, soil temperature, soil moisture and leaf wetness data are collected every hour interval. The WSU device has been programmed to sense and transmit these data to a gateway router using XBee-Pro S2 module. All functionality such as sensing, data collection, communication and power is programmed in open source Integrated Development Environment (IDE). As part of the power saving mechanism, the micro-controller has real time clock (RTC) module that can be programmed to only wake the device at the time of measurement. The device is programmed to operate in deep sleep mode and wakes up every hour to collect and transmit sensor data. The device is powered by 6600 mAh rechargeable lithium ion battery. The charge on the battery is maintained by a 7V 500mA solar panel for full energy autonomy.

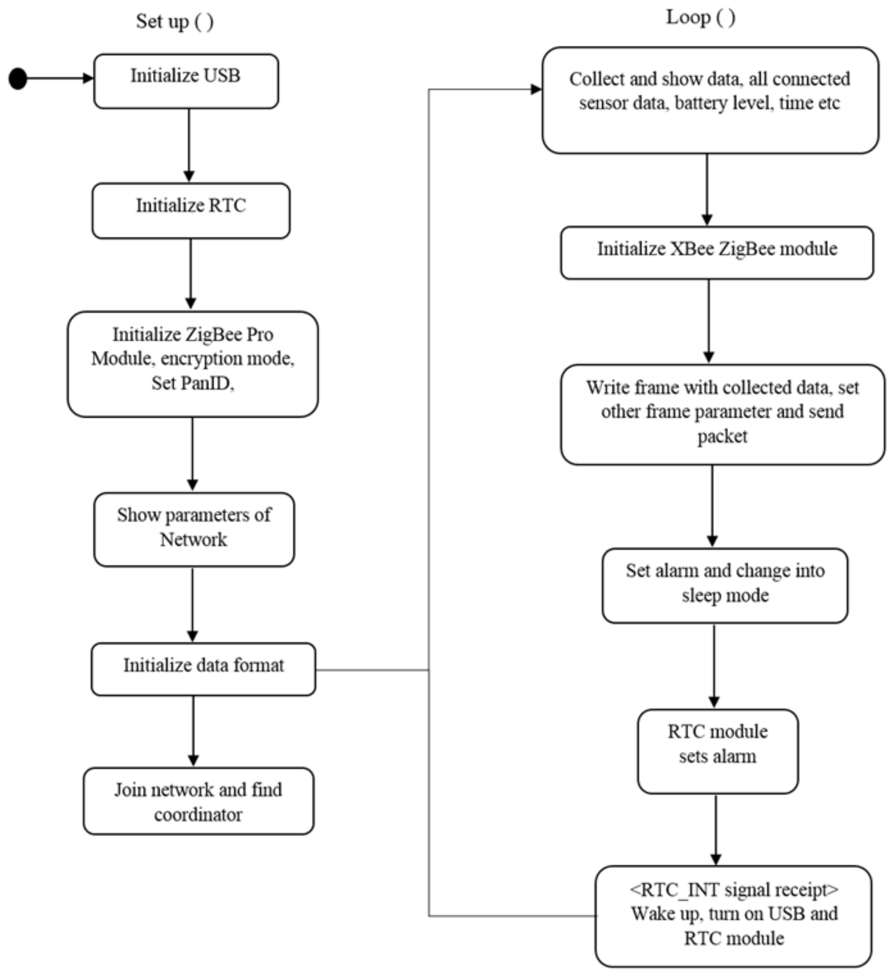


Figure 5.5: WSU operational program flow chart

5.3.3 Irrigation System Unit

A drip-irrigation system is implemented for irrigation scheme. Drip-irrigation is a method to water crops by dripping near plant roots through a network of pipes. It is the best option for irrigating crops by reducing water usage, improving productivity and is relatively cheaper. In addition, it requires low operating pressure thus reducing overall energy consumption. The system is fully automated that uses real time data from the WSU to schedule irrigation events. The control system integrates a switch regulator, 24 V DC water pump, 24 V DC solenoid valves, relays and Arduino. Soil moisture and temperature sensors are connected to the Arduino and the relays activate the solenoid valves and the pump at threshold value.

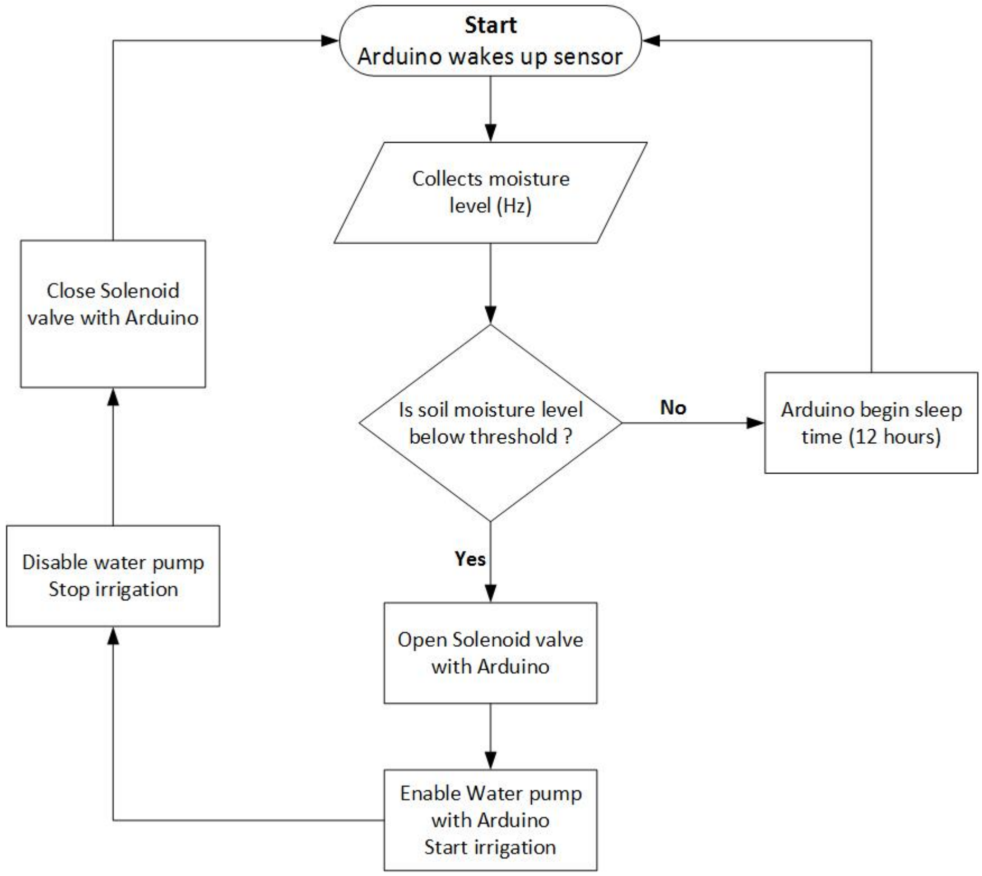


Figure 5.6: Flow chart for control system algorithm

5.4 Data Infrastructure

Wireless sensor data transmission and acquisition is managed by IoT gateway router designed to connect to the WSN. The router can work as an RF-XBee interface, local and external database for WSU. For this project the WSU sends sensor data to gateway via ZigBee protocol. The gateway automatically stores the data on its local storage with an additional capability to synchronize to an external database or connect to a cloud platform. At the time of reception in the router, sensor data are timestamped, parsed and stored in

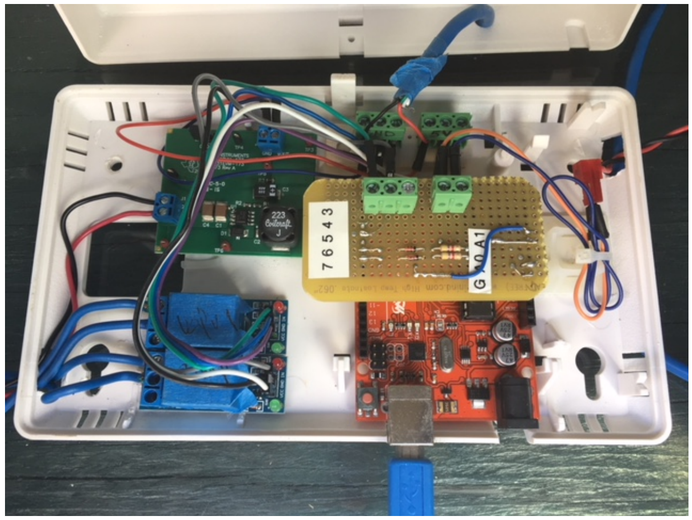


Figure 5.7: The control unit for scheduling irrigation events

local or synchronized to an external database. Energy data infrastructure is connected similar to the wireless sensor nodes. The protocol uses Max485 for serial communication between an Arduino Mega and the power meters. Arduino sends voltage, current and power data in frames to router with ZigBee protocol as shown in Fig.5.8.

5.5 Future Work

The experimental data obtained from this prototype will be modeled and optimized to investigate food production profile as a function of energy and water consumption. It will also attempt to understand the effect of extreme weather conditions on food production. Instead of the peace-meal approach, a holistic approach will be developed and explore the nexus between water and energy resources, and crop yield for several essential crops in an attempt to design a more sustainable method to meet forecasted surge in demand. The conventional way of thinking about these intertwined problems focus on "peace-meal approach" where decisions are made in one of the nexus areas of water, energy and food without making an allowance for the consequences on the other areas. In the future work,

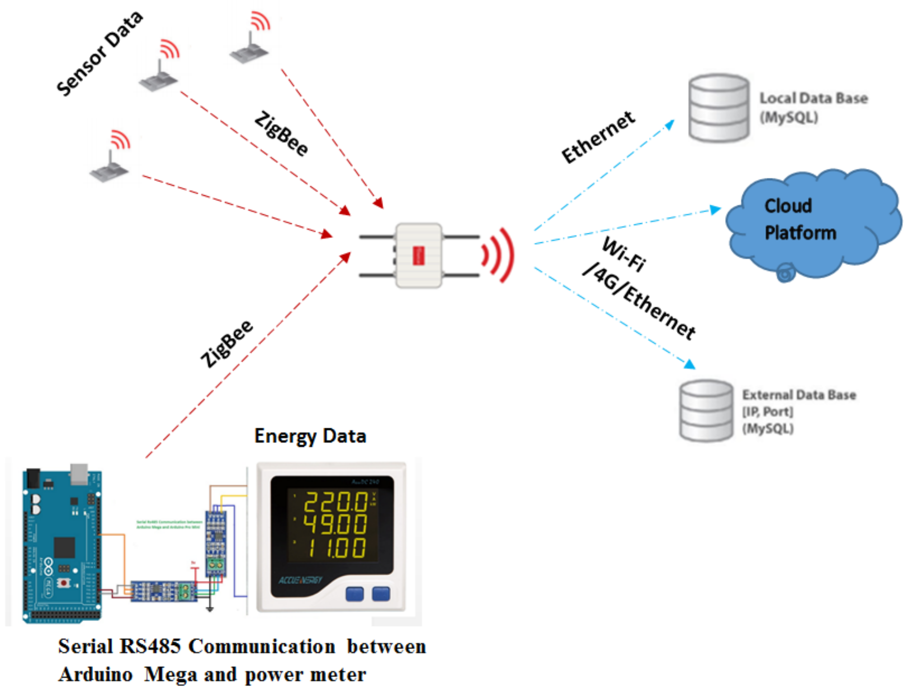


Figure 5.8: Data transmission, reception and storage scheme of the system

data collection from this smart farm will be crucial in analyzing the gap between the water, energy and crop data will be used to model the interdependency of these systems.

5.6 Summary

The abundance of vast amount of data and the ability of analyzing data to make decisions have quickly become part of any sector with the advent of IoT technologies. Agriculture is one of the sectors with smart farming that relies on machine to machine communication to get precise and reliable data. This chapter presents the design and implementation of smart farm prototype to further investigate and model the energy, water and food nexus in the future. The overall system design, implementation and functionality is explained. The test-bed consists of distributed WSN that monitors different agricultural and environmental parameters. Wireless sensor data transmission and acquisition is managed by IoT gateway router through ZigBee protocol. An algorithm was established based on threshold values of temperature and soil moisture to automated into a programmable micro-controller to control irrigation time.

CHAPTER 6

OFF-GRID RENEWABLE ENERGY SYSTEM FOR INTEGRATED FARM

6.1 Overview

Renewable energy has become extremely attractive and highly used in the past decades as nations have come about in seeking a cleaner and greener form of energy. Minimal attention has been paid however in examining off-grid renewable systems for farming applications. Off-grid solutions can be transformational for small farmers especially in parts of the world where access to energy is still a challenge. In sub-Saharan Africa, small farmers contribute to 80% of the overall food supply without the supply of energy for their farm [42]. Most of the farm tasks such as irrigation, grazing, and cultivation are achieved through manual labor which affects agriculture productivity. The appeal for an off-grid renewable energy system is at a peak in the world currently. It is an attractive system in that it is a decentralized system requiring less infrastructure planning, low distance-related transmission losses while providing electricity like a conventional grid [6]. Off-grid systems are especially crucial for sub-Saharan African countries and all other developing countries where dismal energy access is an important driver [35]. Most of the population without access to electricity in these regions live in rural areas, plenty of them with no access to the nearby central grid. Poor access to energy services has a tremendous effect on income generation activity and the overall economy of a country where in most cases it is dependent on the agriculture sector. Although off-grid solutions to agriculture are still in a nascent stage, an array of off-grid solutions to the integrated farm exist from small to medium farm holders. In this work, for the experimental integrated test-bed, solar PV and energy storage are used to design a practical energy system to supply power to a small farm. The system provides clean PV energy for all energy demands of farming purposes such as irrigation and devices in the wireless sensor networks.

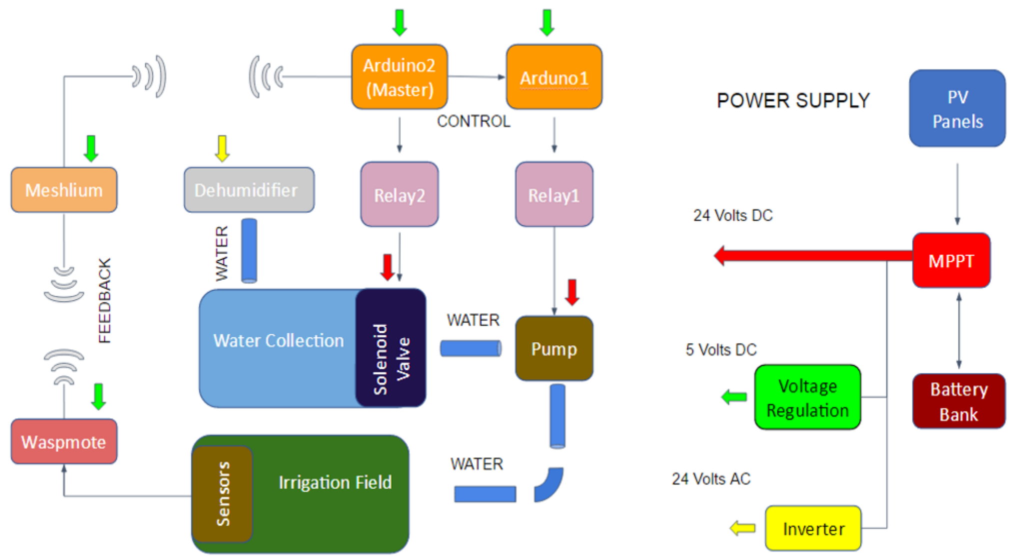


Figure 6.1: Off-grid PV supported integrated FEW system schematic

This chapter will discuss off-grid energy system in integrated FEW system and its especial applicability in regions access to electricity is a challenge. It will further address the reliability aspect of the system in the long term. Factors affecting the state of health of lead acid battery and its reliability will be discussed. It further demonstrate in analyzing the overall reliability of the back up battery units to predict their end of service life.

6.2 Off-grid Renewable Energy System

The system's power demand is completely supplied by a solar PV panel supplemented with an energy storage unit [9]. A 320 W at peak power with V_{mpp} of 37.2 V PV panel with 16.3% module efficiency is used. The tilt angle is fixed at 26° same as the latitude of the location. The default tilt angle for a PV panel is set to the latitude of the location which will maximize annual energy production [100].

The PV panel is connected to a 20A, 12V DC Maximum Power Point Tracking (MPPT) solar charge controller to prevent overcharging of the batteries. The MPPT charge controllers vary from the traditional pulse width modulator (PWM) charge controller by allowing the solar panels to function at their optimum power output voltage thereby increasing their performance. The charge controller is installed between the PV and the batteries to automatically maintain the charge on the batteries using the bulk, acceptance and float charge cycles. In addition, the load for the system which comes mainly from the water pump is controlled by the MPPT. Two 12V, 250 Ah lead acid batteries are connected in series to the MPPT. Power meters with RS485 serial communication capability from the generation and load side are connected. They have an RS485 serial communication capability for energy data acquisition. Energy data is acquired from the power meter through RS485 serial communication to Arduino and then sent to gateway through ZigBee protocol.

Off-grid electrification takes different forms; standalone home energy, and minigrid or microgrids systems. Microgrids are similar to minigrids. They however operate on a smaller scale. Minigrid consists of three subsystems [35]. An electric generation system with some source of RES or diesel generators. In addition, mini-grid system will have a distribution system and interface equipment between the end user installation and the distribution system. According to United States Department of Energy, microgrids are defined as collection of interconnected loads and distributed energy sources within a specific electrical parameter as a single manageable entity with respect to the grid. This system can be grid-connected or off-grid ‘island mode’ [15]. The distinction between standalone systems and mini-grids can be made by their level of application, sizes and system components. Different international and national organizations use different indicator for measuring and reporting mini-grids and standalone systems. Mini-grids are further classified as microgrids, nano-grids and pico-girds. In this paper, it will be collectively titled microgrid on the basis it has a semi-autonomous capability to control its load and supply. Mini-grids require concentrated planning since they not only serve single but a community of consumers. Fig. 3 shows a simplified model of microgrid that incorporates some type of RES sources or micro-generators supplying power to controllable loads supported with some form of storage device [16].

6.3 Energy Storage Reliability

Lead Acid (LA) batteries are still widely used in different small and large scale applications along with Lithium-ion (Li-ion), Nickel-Cadmium (NiCd) batteries [101, 102]. Despite competition from Li-ion batteries, LA batteries still enjoy a large market share in utility applications and even in the current smart grid infrastructure [103]. The LA battery used for the test-bed will be referred as Sealed Lead Acid (SLA) cells. Its application resides as a back up battery unit for the smart farm test-bed.

State of Charge (SOC) and State of Health (SOH) are two most common terms used to describe the overall status of a battery at anytime [104]. SOC shows the available capacity of the battery whereas the SOH is an indicator of the battery's ability to store and supply energy over a period of time [105]. Different methods of SOC and SOH estimation exist for LA batteries such as ampere-hour counting, voltage method, impedance spectroscopy and various other heuristic approach of charge-discharge curves [106, 107]. In [108] fuzzy modeling is used to characterize the relationship between Open Circuit Voltage (OCV), SOC and discharge current. Artificial neural network is implemented to predict the SOH of LA batteries in electric vehicle and renewable energy hybrid systems applications [109, 110]. In [111, 112], genetic algorithm is used to model the internal characteristics of LA batteries. Modified Weibull distribution for unspecified battery chemistry is used in [113] to improve operational time and system reliability. Accelerated life data of LA batteries were used to model the life cycle based on Weibull distribution [114] and propose a new battery design for electric vehicle application. Life cycle modeling of Li-ion batteries using Weibull distribution is used in [115] and [116] to assess the reliability parameters. Similar work has been done in [117] where nonlinear regression model is used to determine the remaining life of Valve Regulated LA battery by modeling the relationship between capacity depreciation and aging. Due to the field application of the SLA batteries considered in this work, temperature is a key factor in the degradation of lifetime capacity. It is discussed in detail in Section 6.7 of this work. The SLA batteries undergo thermally accelerated aging to simulate a lifespan of ten years and their lifetimes are predicted under field condition temperature. Similar work has been done in [118] for Li-ion batteries using holistic aging model to predict their lifetimes. Life cycle of induction motors at field temperature condition is predicted in [119] by using the Arrhenius relation on the accelerated aging failure data. Although a large body of research exist in the areas of distribution analysis for battery life cycle prediction specifically using Weibull model, most are catered to the Li-ion and NiCd batteries [115, 116, 118, 120]. The works on lifetime prediction for LA batteries using Weibull model exist but are limited to renewable energy, electric vehicle and telecommunication applications.

6.4 Shelf and Service Life Stressors

6.4.1 Self-discharge

Batteries have stringent requirements on their shelf and operational life due to their complex chemistry [121]. Through time their expected life is reduced by various conditions such as excessive discharge-charge cycling, temperature, and improper storage and handling leading to self-discharge and sulfation. To evaluate the proper maintenance and storage practices, OCV and shelf life condition of batteries were carefully studied. OCV data was collected on all the sampled batteries before undergoing cycle life tests. The average OCV recorded for the batteries was 12.73V at the time of arrival. Fig. 6.2 shows the deviation of each measurement from the nominal voltage of 12.84V. SLA battery's OCV can be correlated to its SOC [122, 123]. A battery with 100% SOC has OCV reading at 12.84V provided it has not been charged or discharged in the previous 24 hours.

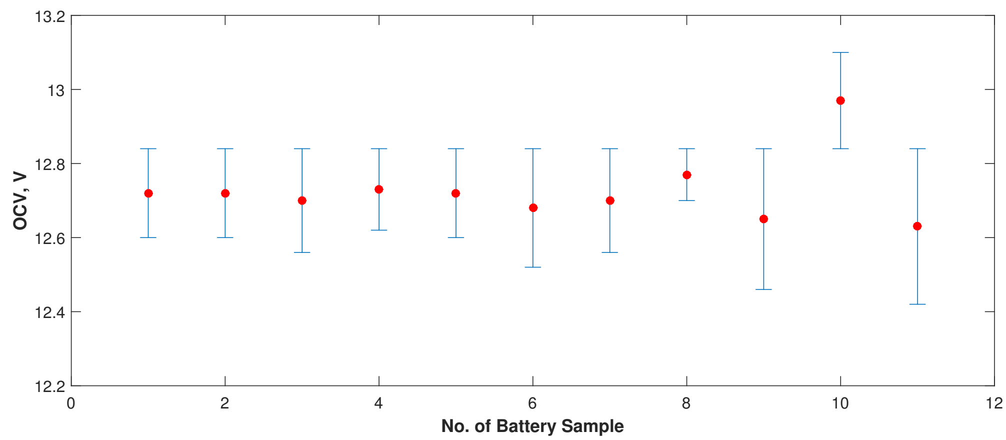


Figure 6.2: Measured OCV of new batteries

OCV of a battery should be regularly checked if it is being stored for long duration of time. During the preliminary investigation into the storage practices, it was discovered that batteries were kept in storage at higher temperature exceeding the recommended 25 °C for indefinite duration of time without any refreshing charge. This has led to a rapid self-discharge and shorter life span in the field for the batteries. This is evident as shown in Fig. 6.3 based on historical data collected on failed SLA batteries from the field averaging 12 months in storage. The rate of self-discharge is dependent on both the chemistry and temperature at which the battery is stored [121, 122]. Self-discharge is a phenomenon when batteries are left in open circuit standby mode for a long duration of time resulting loss of charge over time [122, 124]. If the capacity loss is not compensated by recharging in timely fashion, the battery capacity may become irrecoverable due to irreversible sulfation. Sulfation occurs when the active materials from the positive and negative plates are gradually converted into lead sulfate, making the chemistry electro-inactive [121, 122]. Key factor influencing self-discharge rate is elevated temperature. To alleviate such issues, IEEE std. 450 [123] recommends a refreshing charge every 6 months for batteries kept in storage. On average, SLA batteries lose about 30-40% capacity after one year of storage when kept at 20 °C [122, 124]. If there is a need for long-term storage, it is highly recommended batteries are periodically charged; typically once every 6 months [123, 125].

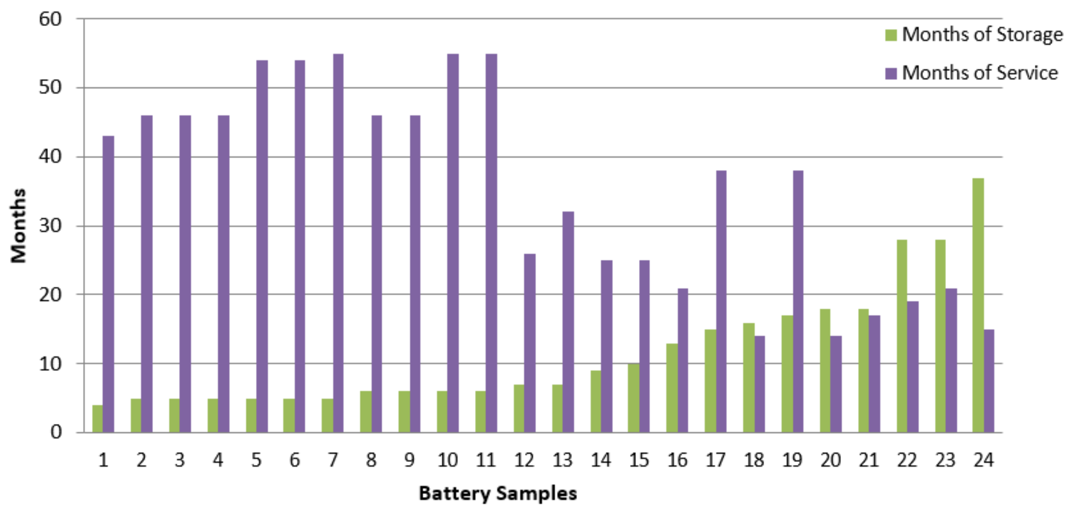


Figure 6.3: SLA battery service span against storage time

6.4.2 Temperature

Temperature is one of the critical variables that affect the SOH of a battery. Lifespan of SLA batteries drops to a half incrementally for every 8 °C above the recommended 25 °C storage temperature [122, 126]. However the challenge comes when accounting for erratic temperature variation rather than continuous operation at a specific temperature. Short sporadic temperature variation ages battery faster [127] than a continuous temperature condition. The SLA batteries considered in this paper are being used at a warmer location with average temperature at 29 °C. To understand variable temperature effect on the SLA batteries when the time period is known, Eq.(6.1) can be used to calculate the remaining life of the batteries. The equation is empirically derived from the temperature effect on battery's life.

$$\mathrm{L(T_N,\ t_n, x)} = T_N \left(\sum_{i=1}^{j} \left(\frac{t_{j,n}}{x_n} \right) \right)^{-1} \tag{6.1}$$

Where T_N is nominal life expressed in months, $t_{j,n}$ is time in months at the *n* temperature and *x* is the acceleration factor at the *n* temperature. For example, the SLA battery considered here is designed for 10 years at 25 °C, however it will be exposed to variable temperatures in the field for certain period of time. Given that exposure time, the remaining life of the SLA battery due to temperature variation will be the designed life divided by the summation of the aging factors from the variable temperatures multiplied by the exposure period at the specified temperature. For SLA battery, for every 8 °C increase in temperature the battery life is reduced in half [124]. Therefore, the accelerated degradation factor (ζ) can be empirically formulated as follow;

$$\zeta = 2^{(0.125t - 3.125)} \tag{6.2}$$

Where *t* is temperature in °C

6.5 Reliability Analysis

Reliability is theoretically defined as the probability that a product will last at least a specified time under a specified experimental condition. Reliability can also be expressed as the number of failures over a period of time. Most challenges in reliability engineering are concerned with quantitative measures, such as time-to-failure of a component, or qualitative measures like defectiveness of a component. Mean Time To Failure (MTTF) and Mean Time Between Failure (MTBF) are two of the most widely used terms in reliability engineering. MTTF applies to SLA battery since once failed they are not repairable and is defined as the number of discharge-charge cycles until failure. Reliability is critical for this application since continuous and dependable power supply to the smart farm system during the night time and in the event of cloud coverage. One of the main challenge for energy storage management has been the uncertainty associated with the overall SOH assessment of the batteries. Historically, battery's failure is revealed when it fails to provide the necessary capacity to the system it is required to supply. To mitigate such issue, some form of reliability matrix was needed for the batteries to have a threshold value as they are nearing their end of service life based on field conditions. The approach taken for the experimental part is to have new batteries undergo cyclic test with a discharging and charging profile similar its field operational conditions. The failure data was then modeled based on lifetime distribution analysis to extrapolate important reliability parameters. Life distribution is used to describe the statistical probability distributions that is used in reliability engineering and life data analysis. Lifetime distributions applied for reliability and life data analysis are often characterized by three parameters: threshold (location), scale and shape [128]. Weibull distribution is one of the broadly applied method in fitting and analyzing time to failure data [120, 128, 129]. In addition, it can take on the characteristics of different other distribution making it flexible to fitting different sets of data. Its primary advantage is the capability to afford failure predictions with limited sample sizes [104, 116]. This work will focus on 3-parameter Weibull distribution due to the non-linearity of the failure data. These parameters are scale (α), shape (β) and threshold (λ). The Weibull slope expressed by the shape parameter determines the failure distributions that best fits the data. Early failures also known as infant mortality in the product life occur when $0<\beta< 1$. When β=1, failures are considered to be random and independent of age. $\beta >$1 indicates wear-out failures. The scale parameter defines the lifetime for which 63.2% of the device will have failed. This value is equal to α for β=1. The threshold parameter indicates the location where the distribution originates which represents a time shift. The probability density function (f), cumulative distribution function (F), reliability function (*R*) and failure rate (τ) of a Weibull distribution are expressed as follows:

$$\mathrm{f(x)} = \frac{\beta}{\alpha}(\frac{x-\lambda}{\alpha})^{(\beta-1)}e^{(-(\frac{x-\lambda}{\alpha})^{\beta})} \tag{6.3}$$

$$\mathrm{F(x)} = 1 - e^{(-(\frac{x-\lambda}{\alpha})^{\beta}} \tag{6.4}$$

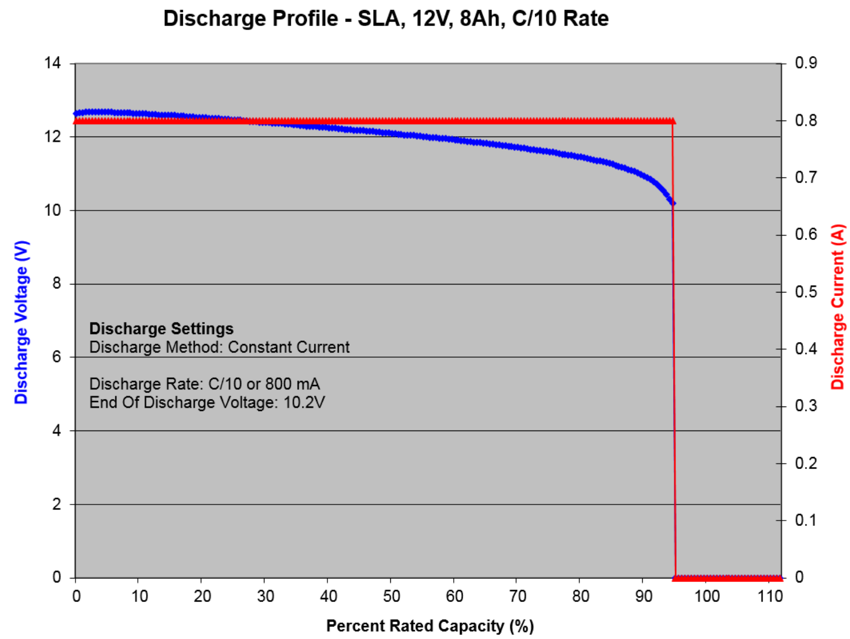
$$\mathrm{R(x)} = e^{-(\frac{x-\lambda}{\alpha})^{\beta}} \tag{6.5}$$

$$\tau\mathrm{(x)} = \frac{\beta}{\alpha}(\frac{x-\lambda}{\alpha})^{(\beta-1)} \tag{6.6}$$

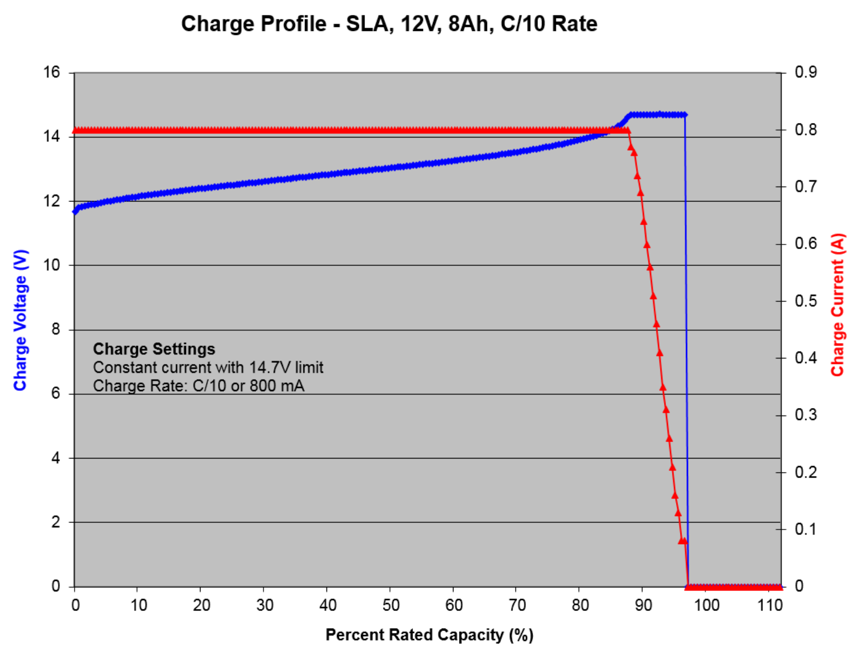
Where α is scale, β is shape and λ is threshold parameters and x is time to failure.

6.6 Experimental Simulation

SLA batteries were subjected to a cyclic test until time to failure. A cyclic test is where the discharge and charge time is the same order defining the life of the battery as a cycle life unit. The tested SLA batteries have 12V nominal voltage and 8 Ah rated capacity. Prior to testing, all batteries were fully charged, given 5 days of stability and their OCV were measured. Deep discharge tests were performed on the batteries using the PCBA 5010-4 battery analyzer. Deep discharging is performed by draining the battery at predetermined current ratings until the battery reaches recommended End Of Discharge Voltage (EODV) value. For this experimental application, the batteries were tested at 100% Depth Of Discharge (DOD). In the field, batteries experience a full DOD cycles only during times of natural disasters like hurricane which causes a prolonged power outage. Current, voltage, time duration, watt-hour were collected and monitored for each cycle during the testing process. In addition, the batteries temperature and OCV were recorded pre and post each cycle. The time interval of the charge and discharge cycles were controlled using the battery analyzer software. In this experiment C_{10}A equivalent to 800 mA discharging-charging profile was used. The C_{10} rate of a battery is the charge or discharge current in amperes that is equal to rated capacity of a cell based on 10 hours of discharge rate. For the



(a) Discharging profile of SLA battery



(b) Charging profile of SLA battery

Figure 6.4: A cycle of discharge-charge test profile

charging profile as shown in Fig. 3b, a constant current of $0.1C_{10}$A were employed until the voltage of the batteries was increased to 14.7V, and later charged at a constant voltage of 14.7V until the current tapers down to $0.01C_{10}$A. After the charging step, batteries were discharged at a constant current of $0.1C_{10}$A until the voltage of the batteries reached to EODV of 10.2V [122]. These discharge-charge steps as captured in Fig. 4 are considered one cycle and repeated in ambient temperature of $23\,^{\circ}\mathrm{C}$ until time-to-failure. Failure criteria is based on IEEE std. 1188 that batteries need to be replaced when they fail to maintain 80% their rated capacity [125].

6.6.1 Lifetime Distribution Analysis

Cycle life is the number of discharge-charge cycles the battery goes through until the battery fail to provide at least 80% of its rated capacity. Although life cycle tests are the best method to measure the life of a battery, it is a time intensive test. Therefore the experimental test samples were performed to a limited number of cycles. Results of capacity were acquired for each cycle test until 100 cycles maximum to failure time. Residual capacity for each cycle is shown in Fig. 6.5. For lead-acid batteries, a reduction to 80% of the rated capacity is usually defined as the end of life and time for replacement [125]. Below this rated capacity, the rate of battery deterioration accelerates. At this point, batteries are more prone to sudden failures resulting from temperature or higher discharge rate.

Utilizing the time-to-failure data obtained in Section 6.6, distribution analysis was performed by arbitrarily censoring the data as shown in Table 6.1. The exact times of failure for some battery units were unknown, for such case the data were censored. The cycle life test data were then fitted into 3-parameter Weibull, Exponential, Lognormal and Loglogistic distributions as indicated in Fig. 6.6. In cases where the threshold value

Battery ID	Failure Time
01	67
02	Censored
03	Censored
04	28
05	30
06	Censored
07	51
08	44
09	36
10	37
11	44
12	Censored
13	Censored

Table 6.1: Failure cycles of tested samples

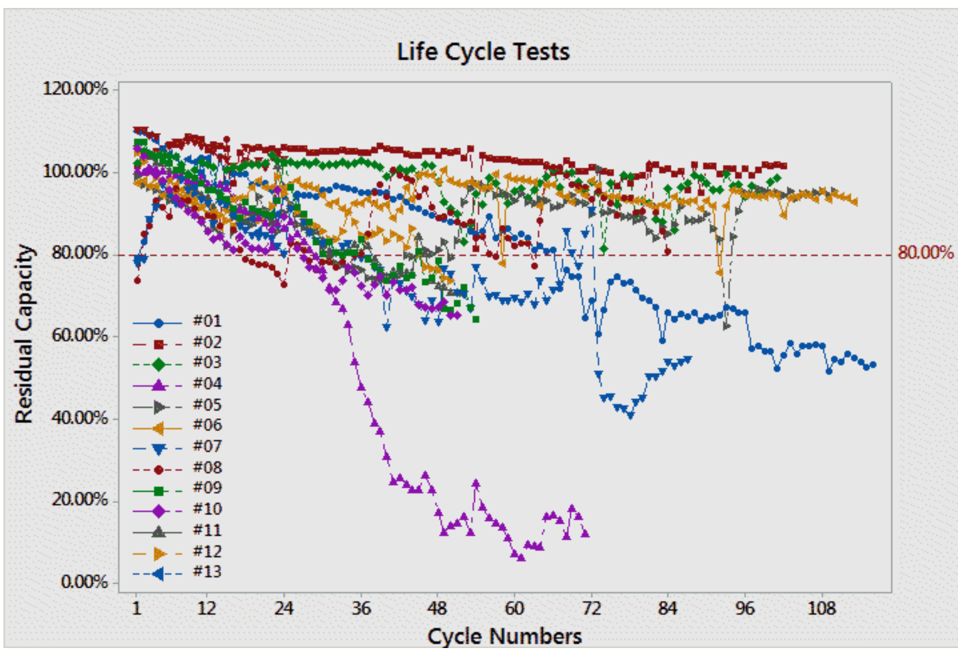


Figure 6.5: Residual capacity against cycle number

is zero, the distribution becomes a 2-parameter distribution. Distribution plots help model life data of the battery samples and estimate critical reliability parameters such as MTTF, survivability, B_{10} and B_{100} life of the samples.

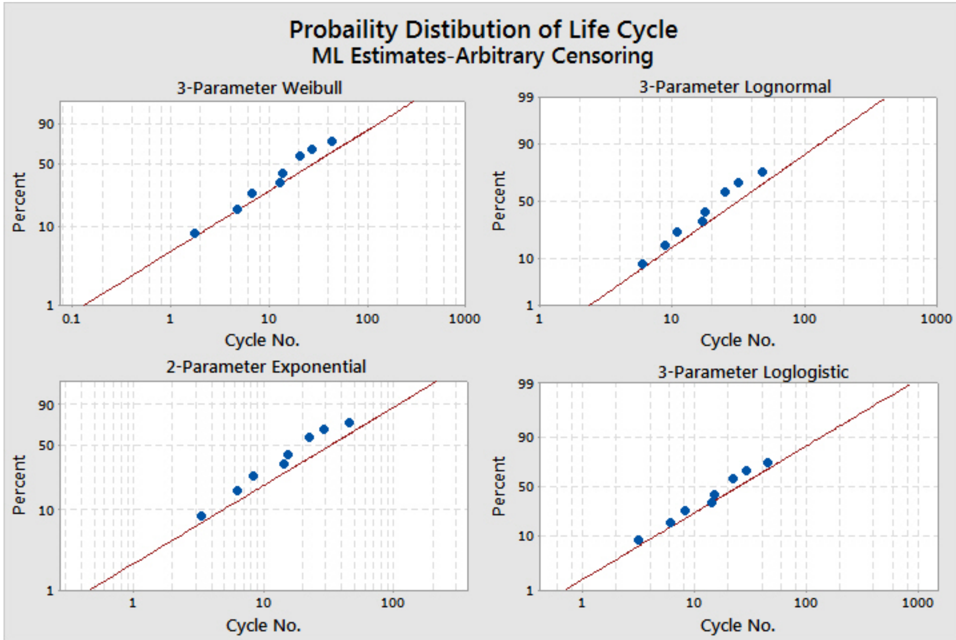


Figure 6.6: Probability Distribution plot of life cycles data of SLA Estimation

In life distribution analysis Maximum Likelihood Estimation (MLE) and Least Squares (LSE) methods are commonly used to estimate the parameters. Both methods provide consistent results for large, complete data sets. However, most reliability data sets are moderate in sample size. The battery sample size for this work is limited where only few samples have failed and the rest are still undergoing cyclic test. For cases like this with small sample data set, extensive simulation studies show that the MLE method is better suited than the LSE method [129]. With MLE method, the distribution parameter estimates are more precise and the estimated variance is smaller. Furthermore, MLE calculation uses more of the information from the data rather from the estimation as it is the case for LSE. In addition, LSE method ignores the information of censored observation in the computations where 40% of the data is censored. Therefore, the MLE method is found to be the optimal method to analyze the four distribution methods.

Distribution	Anderson-Darling (Adj)	MTTF	Error
3-Parameter Weibull	12.57	74	23.79
3-Parameter Lognormal	12.56	76	27.68
3-Parameter Loglogistic	12.49	113	105.72
2-Parameter Exponential	12.68	69	15.63

Table 6.2: Goodness-of-Fit Statistic

To test the goodness-of-fit of the distribution plot, Anderson-Darling (AD) adjustment was used to assess the fit. The better the distribution fits the data, the lower the AD value. The results showed that the life cycles of SLA batteries were effectively represented by a Weibull and Logologisitc distribution. Although Logologistic distribution has lower AD adjustment value, it has a higher standard error as indicated in Table 6.2.

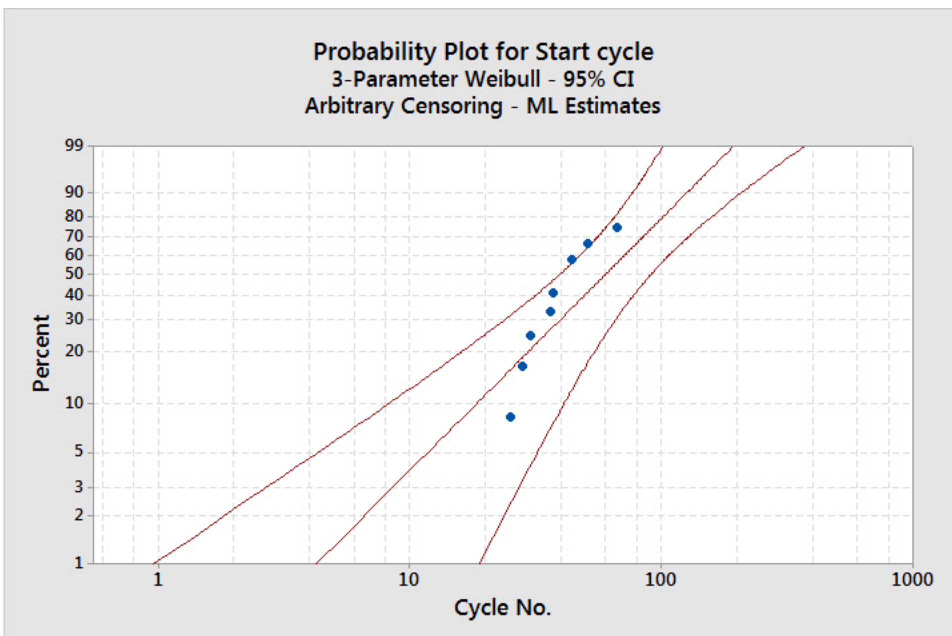


Figure 6.7: Weibull plot fit with the life cycle data for cyclic life tests of SLA battery

Therefore, Weibull distribution is selected to model the life cycle of the data. A Weibull shape β=0.789, scale α=44 and threshold λ=23 were achieved as summarized in Table 6.3. The corresponding Weibull fit for the failure time data with the corresponding two-sided approximate 95% confidence limits is presented in Fig. 6.7.

Parameter	Estimate	Std. Error	95% CI
β	0.789	0.216	0.461–1.349
α	44.022	18.608	19.225–100.802
λ	23.225	0	23.225–23.225

Table 6.3: Parameter Estimates of Weibull Distribution

6.6.2 Service Life Prediction

In reliability, if the failure rate of product is $100_q\%$, then the life of the product at that point of time can be defined as B_{100} life. B(x) life is the estimated time when the probability of failure will reach a specified point (x%) [128]. B(x) life of batteries can be represented by the following equation where *p* is the selected probability of failure, $\hat{\lambda}$, $\hat{\alpha}$ and $\hat{\beta}$ are estimated parameter values:

$$\mathrm{B(x_p)} = \hat{\lambda} + \hat{\alpha}(-ln(1-p))^{\frac{1}{\beta}} \tag{6.7}$$

Threshold parameter, λ = 23 indicates the failure started after this point. Based on the values of β and α, the B_{10} life can be calculated to be 26 cycles. This implies that 10% of the cumulative hazard probability is found when the battery undergoes a cyclical test up to 26 cycles which indicates an early failure for SLA batteries. Furthermore, 50% of the cumulative hazard probability (B_{50} life) is found within the 50 cycles of the test and 90% of the hazard (B_{90} life) will occur when the batteries are tested up to 150 discharge-charge cycles. This indicates most of all the batteries will fail after having been subjected to 150 cycles. Validating this result, the shape (β) parameter value shows an infant mortality

	Lifetime (Cycles)
MTTF	74
Median	51
B_{10}	26
B_{90}	150

Table 6.4: Characteristics of Distribution

for the data samples of the batteries. A value of 0.789 indicates the battery had defects in the initial step which can be attributed to improper storage and maintenance practices detailed in Section 6.4.

In reliability demonstration test, the nominal sample size required to demonstrate reliability value at a given confidence level can be calculated in two ways. The first method uses non-parametric estimation for zero failures without assuming a specific distribution. The second method referred to as Parametric Binomial (Lipson Equality) uses Weibull distribution of shape parameter to solve for random sample size *N*. Eq.(6.8) gives the minimum sample size given reliability requirement *'R'* for mission test time T_m, available test time T_t and estimated shape parameter value ($\hat{\beta}$).

$$\text{N} = \left(\frac{T_m}{T_t}\right)^{\hat{\beta}} \frac{\ln(1-C)}{\ln R} \tag{6.8}$$

In the future where such test needs to be repeated, an optimal number of sample size can be calculated based on the Weibull distribution with estimated shape parameter, β=0.789. An optimal sample size N=48 is obtained imposing 90% reliability requirement at mission test time of 300 cycles based on available testing time of 112 cycles with zero allowable failure. Therefore, testing 48 batteries for a minimum of 112 cycles with zero failures occurring will demonstrate a reliability of 90% for a 300 cycle test at a 90% confidence level.

Sample Size	Allowable Failures	Minimum Cycle Test
48	0	112
82	1	111
112	2	112
140	3	113

Table 6.5: Sample Size to Demonstrate a Reliability of 90% at 90% confidence

The survivability of the batteries which is equivalent to reliability *R(x)* is presented in Fig. 6.8 against failure time. The hazard plot depicts the instantaneous failure rate *h(x)* along time.

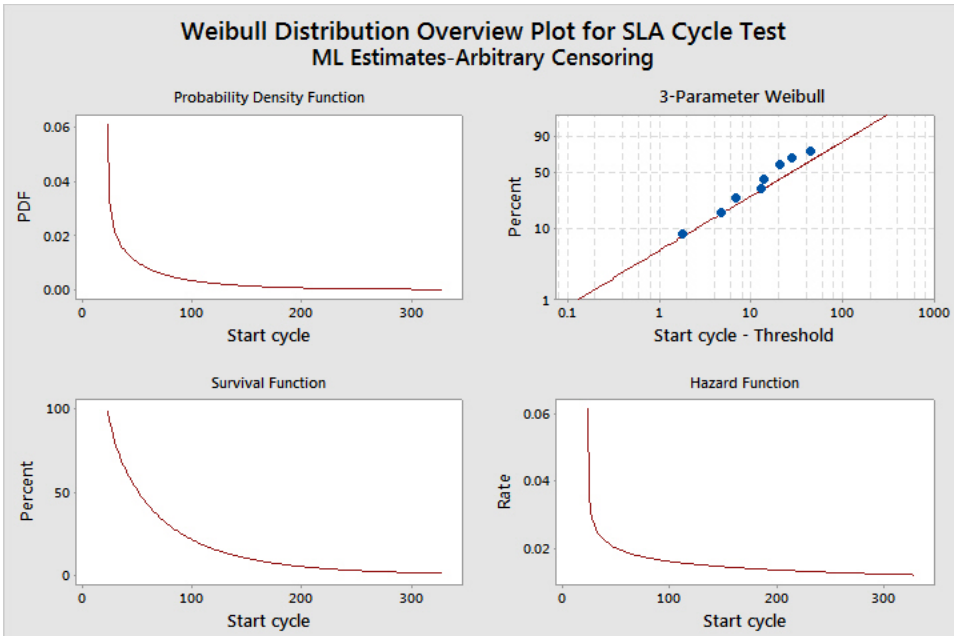


Figure 6.8: Weibull distribution overview plot of life cycle data for SLA battery

6.7 Accelerated Life Testing

Demonstrating time to failure on cyclic testing of SLA batteries is time consuming. Therefore, application of accelerated life testing is implemented to save time under higher temperature values. In this section, SLA batteries were aged at 80 °C, 65 °C and 55 °C temperature and tested at months interval. The Arrhenius equation is the theoretical foundation for the relationship used in practice to derive the overall acceleration factor for a given set of parameters [118, 130]. An accelerated test uses high temperatures to accelerate the battery's aging process. The test utilizes techniques to determine the expected float life projections [119]. The SLA batteries were tested with elevated temperatures to speed up the degradation process. Failure times at the accelerated temperatures can be extrapolated to actual field temperatures of 26 °C and 37 °C to which the SLA batteries will be exposed. Fourteen 12V, 8Ah SLA batteries were prepared for the thermal accelerated aging test. A series of temperature accelerated tests were carried out on the SLA batteries and their capacities were tested until failure, i.e. the capacity fell below 80% of rated capacity. The thermal aging was conducted in a programmable Thermotron 8200 temperature-humidity test chamber. They were then cooled at 25 °C and cycle tested for close to 20 hours. The sequence of the tests was repeated until the batteries age to 10 years or when a battery fail to maintain 80% of its rated capacity during the cycle test. During the thermal aging process, 6 batteries were kept at 80 °C, 4 at 65 °C and 4 at 55 °C for periods of 18.6 hours, 18.6 hours and 5 days respectively. While in the aging sessions, the batteries were float charged with temperature compensated voltage at 13.2V to prevent further degradation from self-discharge. After each interval of aging session, the batteries were then tested at C_{20}A rate to failure. The failure times of sampled batteries are listed in Table 6.6.

Battery ID	Temp (°C)	Failure Time (hours)
01	80	19
02	80	37
03	80	75
04	80	150
05	80	205
06	80	168
07	65	1780
08	65	1523
09	65	3200
10	65	1855
11	55	9000
12	55	10200
13	55	11280
14	55	11400

Table 6.6: Lifetimes Under Thermally Accelerated Aging

In order to analyze the interaction between the temperature and failure times, the data was fitted with different distribution plots. AD goodness-of-fit was applied to all the models to pick the best fit distribution for the data. The accelerated life test data was best fitted by Weibull distribution as shown in Fig. 6.9. Weibull distribution presented smaller AD value compared to Logistic, Normal, and Exponential distribution as presented in Table 6.7.

Distribution	55 °C	65 °C	80 °C
Weibull	3.552	5.088	2.813
Normal	4.300	6.742	3.792
Logistic	3.758	7.258	3.458
Exponential	3.751	5.140	2.310

Table 6.7: Anderson-Darling Goodness-of-fit Values

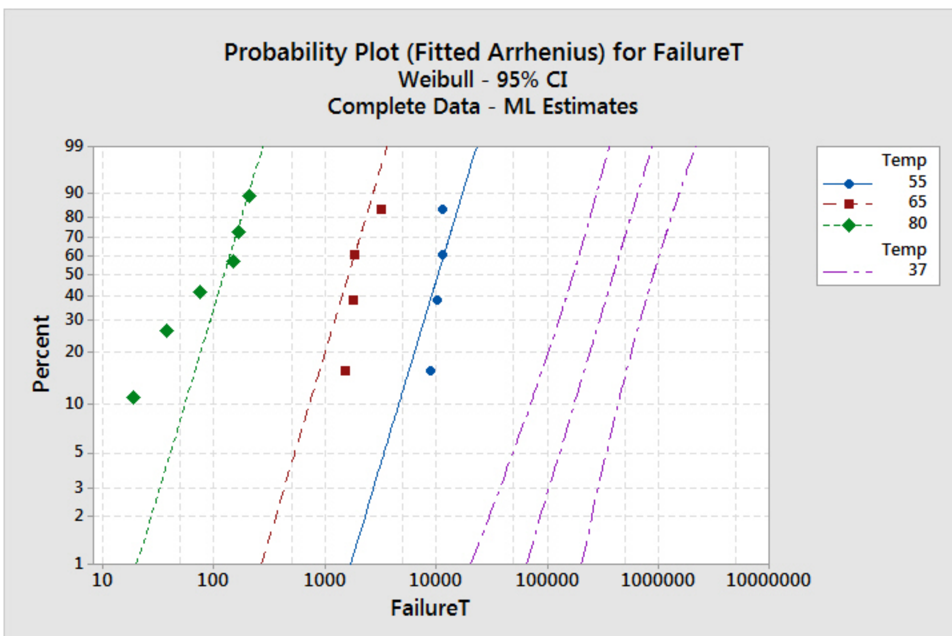


Figure 6.9: A Weibull-Arrhenius life cycle distribution

The probability plot based on the fitted model help define whether the distribution, transformation, and assumption of equal shape at each level of the accelerating variable are suitable. Using the fitted model of the failure times, we can extrapolate what happens to the battery at 26 °C and 37 °C which are the field temperature for operating these batteries. For Weibull distribution, the Arrhenius model in Eq. (6.9) describes the relationship between temperature and failure times of the batteries.

$$Y = \beta_o + \beta_1 \left(\frac{1}{k(\,^{\circ}\mathrm{C} + 273)} \right) + \sigma\epsilon \tag{6.9}$$

Where, Y is the failure time or log failure time

β_o is the intercept

β_1 is the temperature

k is Boltsmann's constant

σ is the reciprocal of the shape parameter

ϵ is the random error term

Predictor	Coefficient	Std.Error
Intercept (β_o)	-52.137	3.514
Temperature (β_1)	1.736	0.103
Shape (σ)	2.562	0.669

Table 6.8: Regression Parameter

The 50th percentiles is a good measure of how long the batteries will last in the field based on design values. The life of the batteries at a design temperature value of 26 °C and 37 °C can be calculated using the estimated parameters from the model listed on Table 6.8 and Eq. (6.9). At design value of 26 °C, the batteries are predicted to last for 23,512 hours or 2.7 years and at 37 °C the batteries are forecasted to last for 18,029 hours or 2.05 years. Comparing this result to the rated value of the SLA batteries, the forecast of the lifetime of these SLA batteries are degrading at a higher rate. The battery is rated for 10 years of service at 25 °C. However the field operational temperatures are slightly elevated than 25 °C. In addition, as explained in Section 6.4 the procurement and storage of these batteries has not followed proper technique resulting early failure and service life depreciation. It was observed that batteries have considerably aged by the time they are deployed to the field. In the investigation, it was detected that there was a time gap between the time that individual cells were manufactured and the time they were packaged by third party. In this span of time the temperature and type of storage conditions the cells were stored were not apparent. In addition, once batteries are procured by utility, they spend on average 12 months in storage without proper storage practices. This has resulted in the early mortality of the batteries as evidenced by the reliability analysis as well.

6.8 Summary

The failure time data of SLA batteries were fitted in different life distribution models. AD adjustment values were utilized as goodness of fit criteria for the distribution plots. MLE method was employed to obtain shape parameter of 0.789, scale parameter of 44 and threshold parameter of 23 with MINITAB. Using the estimated parameters from the Weibull distribution, the B(X) life and the sample size to evaluate the reliability of SLA batteries was computed. In addition Parametric Binomial was implemented using the Weibull estimated parameter to find the optimal sample size for future testing purpose. A minimum sample size of 48 is obtained with zero failures in order to achieve reliability of 90% at 90% confidence level. SLA batteries were also tested under thermally accelerated aging conditions. The failure cycles were recorded and analyzed using life distribution models. Goodness-of-fit test based on AD value and graphical analysis indicated that a Weibull distribution offered superlative fit to the failure times data. The average lifetimes at 55 °C, 65 °C and 80 °C were employed to forecast lifetimes of the batteries at a field temperature of 26 °C and 37 °C. The results revealed that the batteries are expected to operate at designed temperature of 26 °C for close to three years and at 37 °C for 2 years.

CHAPTER 7

MACHINE LEARNING TECHNIQUES IN CROP YIELD PREDICTION

7.1 Overview

The use of sensors and the Internet of Things (IoT) is key to moving the world's agriculture to a more productive and sustainable path. Recent advancements in IoT, Wireless Sensor Networks (WSN), and Information and Communication Technology (ICT) have the potential to address some of the environmental, economic, and technical challenges as well as opportunities in this sector. As the number of interconnected devices continues to grow, more big data with multiple modalities and spatial and temporal variations will be generated. Intelligent processing and analysis of this big data are necessary to developing a higher level of knowledge base and insights that will be used in decision making, forecasting, and better management of sensors.

Machine learning (ML) techniques like deep learning have been implemented in disease detection and soil health monitoring, as well. Plantix, an image recognition app uses ML techniques in its software algorithm that can detect soil defects, and plant diseases in agriculture based on soil patterns [131]. Farmers can see the information through their smartphone camera along with techniques and solutions to fix the problem. Similarly, [132] uses a deep convolutional neural network to identify three crop disease and two types of pest damage targeting cassava plants in Tanzania. The use of drones is currently prevalent in agriculture, where the market for it is projected to reach $480 million by 2027 [133]. Drones can gather massive data of vast acres of land within a short period and are ideal in large arable farms. Through AI, data gathered by a drone can improve crop health, yield, and reduce cost [134].

The most popular use of predictive analytics is in connection with satellite data to predict weather and crop sustainability, in pest and disease identification, and remote PA application [9, 15]. Predictive analytics are used in the data processing, wrangling, and analysis of sensor data for future prediction and decision models. In addition to this, ML techniques are used in IoT WSN based irrigation scheme as a decision support [18].

This chapter employs different machine learning algorithms on collected sensor data to predict crop yield from the experimental test-bed. Linear, nonlinear, decision trees and ensemble learning are used, and their performance is compared. A brief review of sensor and IoT data analytics using machine learning techniques in agriculture applications. Different numbers of relevant papers are presented that emphasize crucial and unique features of ML model specifically in yield prediction. The structure of this paper is organized as follows: Section 2 presents the recent advances of AI applications in agriculture. Section 3 delves into some of the commonly used machine learning techniques within the WSN based PA. Section 4 summarizes some of the recent works utilizing the ML technique for WSN based PA application.

7.2 AI in Agriculture

Artificial intelligence (AI) can help farmers get more from the land while using resources more sustainably. Big data refers to the large volume of data coming from sensors, IoT, GPS, aerial imagery, etc. [98]. IoT is a system of embedded technologies consisting of wired and wireless communications, sensors, and actuators that are capable of acquiring and transferring data to the internet [135]. Today's Farms, with the help of IoT, Unmanned Aerial Vehicle (UAV), and other emerging technologies, is producing millions of data points on the ground daily. With the help of AI, farmers can now analyze weather conditions, temperature, water usage, energy usage, and soil conditions collected from their farm to better inform their decisions. Unlike before, farmers additionally now can use captured sensor data in predicting yield, and making them better equipped to natural disaster and climate conditions through intelligent data processing techniques like machine learning. IoT, combined with AI, is emerging as part of the solutions towards improved agricultural productivity and efficiency [136]. From detecting plant diseases [132] to monitoring harvest time [137], AI's application in ag-tech is enormous and yet to be tapped. In [132], AI has been used to train data set of cassava leaves to detect disease and pest damages, and the algorithm was able to detect the damage with 98% accuracy. Furthermore, AI can be used in training robots to do the mundane labor of tending, harvesting, and maintaining farmland efficiently that usually requires a lot of human capital, time, and effort. AI in agriculture application is emerging in three areas: robotics, soil and crop monitoring, and predictive analytics [138, 133].

Autonomous robots can replace human laborers in efficiently handling essential agricultural tasks such as planting, weed control, and harvesting [138]. Start-up companies like Blue River Technology recently acquired by John Deer implement computer vision in its precision spray to monitor and spray weeds on cotton plants [139]. Robotics and automation are also emerging as a solution to solve the problem of laborers in harvesting. A robot has been developed by Harvest CROO Robotics that support farmers in picking and packing strawberry [140].

Crop disease detection and soil health monitoring are significant areas where ML techniques have been mainly implemented. For instance, Plantix, an image recognition app, uses ML techniques in its software algorithm that can detect soil defects, and plant diseases in agriculture based on soil patterns [131]. Farmers can see the information through their smartphone camera along with techniques and solutions to fix the problem. Similarly, [132] uses a deep convolutional neural network to identify three crop disease and two types of pest damage targeting cassava plants in Tanzania. The use of UAV (drones) is currently prevailing in agriculture, where the market for it is projected to reach $480 million by 2027 [133]. Drones can gather massive data of vast acres of land within a short period and are ideal in large arable farms. Through AI, data gathered by a drone can improve crop health, yield, and reduce cost [134].

The most popular use of predictive analytics is in connection with satellite data to predict weather and crop sustainability, in pest and disease identification, and remote PA application [9, 15]. Predictive analytics are used in the data processing, wrangling, and analysis of sensor data for future prediction and decision models. In addition to this, ML techniques commonly used in IoT WSN based irrigation schemes as a decision support [18].

7.3 Machine Learning Techniques

Machine learning is a type of AI that gives machines the ability to learn from experience. Its algorithms use computational methods to learn directly from datasets without depending on predetermined equations as a model. The algorithms progressively adapt to enhance their performance as the available number of training samples increases [141, 142, 143]. ML approaches are powerful tools capable of autonomously solving extensive non-linear problems using sensor data or other various interconnected sources. It facilitates better decision making and informed actions in real-world scenarios with minimal human intervention. ML techniques are constantly undergoing developments and are widely applied across almost all domains. However, they have fundamental limitations on their applications. The accuracy of the prediction is affected by the data quality, proper model representation, and dependencies between input and target variables [144]. There are two broad categories of machine learning algorithms: supervised and unsupervised learning. Supervised learning uses a known set of labeled data to train a model to predict the target variable for out of sample data [141]. Classification and regression techniques are common applications of supervised learning. On the other hand, unsupervised learning relies on hidden patterns or intrinsic structures in data to draw deductions from unlabelled data. It is useful for exploratory applications where there is no specific set goal, or the information the data consists is not clear. It is also ideal as a mechanism for dimensionality reduction on data that have a number of features. Clustering is the most common learning model under this type of learning, and its application extends to exploratory data analysis, such as gene sequencing and objects recognition [142]. Algorithm selection depends on the size, type, and expected insight into the data. There is, however, no general prescription for algorithm selection; in most cases, it is a trial and error work. Both supervised and unsupervised learning techniques are used extensively in IoT smart data analysis across various domains [145]. Smart farming enabled by WSN and IoT is one of the domains where ML techniques are emerging to quantify and understand the big data in this field. ML application in PA can be categorized as crop management [144, 146, 147, 99], livestock management [21], water management [148, 149] and soil management [144, 150]. ML's application in crop management deals with yield prediction [144, 146, 147, 99], disease detection [132], weed detection[139] and phenotype classification [134]. This work will focus on ML techniques for yield prediction from sensor data.

7.3.1 Regression

Regression is supervised ML techniques that predicts continuous responses such as stock prices, fluctuations in electricity demand, and time series sensor data. Mainly, there are two types of regression algorithms: linear and nonlinear. Linear models rely on the assumption of a linear relationships between independent and dependent variables. The common regression algorithms are linear, nonlinear, Gaussian process regression model (GPRM), support vector machine (SVM) regression, generalized linear model (GLM), decision tree (DT), ensemble methods, neural networks. Four of these techniques were selected to be discussed in detail as they have been relevant to the application of crop yield prediction.

7.3.2 Decision Tree (DT)

This method is also referred as classification and regression trees (CART), can be applied on both categorical and continuous input and output variables [151]. It works by splitting the data into two or more homogeneous sets based on the most significant splitter among the independent variables. DT works by following the decisions in the tree from the root down to a leaf node [152]. A tree consists of branching conditions where the value of a predictor is compared to a trained weight. During the training process, the number of branches and the values of weights are determined. The best differentiator in the splitting process is the one that minimizes the cost metric. The cost metrics for a classification tree is often the entropy or the gini index, whereas, for a regression tree, the default metric is the Mean Squared Error (MSE). Additional pruning or modification can be implemented to also simplify the model. DT is an easy to interpret and fast to fit and is optimal for applications where minimal memory usage and low predictive accuracy is not a priority [153].

7.3.3 Supported Vector Machine (SVM)

Similar to SVM classification, SVM regression algorithms are modified to predict a continuous response [154]. Instead of finding a hyperplane that separates data, SVM regression algorithms find a model that deviates from the measured data by a value no greater than a small amount with parameter values that minimizes sensitivity to error [152]. It is suitable for high-dimensional data where large number of predictor variables exist. Potential applications of SVM in WSNs supported PA are as a regression for yield and sensor data forecasting [97, 155].

7.3.4 Artificial Neural Network (ANN)

ANN is an information-processing system that has certain performance similar to the biological neural networks. This learning algorithm could be constructed by cascading chains of decision units such as perceptrons or radial basis functions. used to recognize non-linear and complex functions [156]. A neural network is characterized by 1) its pattern of connections between the neurons called its architecture, 2) its method of determining the weights on the connections called algorithm , and 3)its activation function. The general architecture of ANN algorithm consists of input units, single or multi layer hidden units, and output units [157]. ANN can be used for regression and classification problems. Commonly implemented ANN learning algorithms include the radial basis function [158], perceptron algorithms, back-propagation, and feed-forward propagation [157, 136].

7.3.5 Ensemble Learning

Ensemble learning (EL) models strive at enhancing the predictive performance model fitting technique by creating a linear aggregate of a “base learning algorithm” [136]. There are two principal strategies for designing ensemble learning algorithms. The first method is to form each hypothesis independently to create a set of hypotheses that are accurate and diverse. One of the common method for this is Bagging also known as “Bootstrap Aggregating” [159] and random forest [160]. The second approach deals on building the hypothesis in a coupled manner so the weighted vote of the hypothesis generates a suitable fit to data [161]. Common method like random forest algorithm unlike DT overcome over-fitting by reducing the variance of the decision trees. They are called 'Forest' because they are the collection, or ensemble, of several decision trees [160]. One major difference between a DT and a random forest model is on how the splits happen. In random forest, instead of trying splits on all the features, a sample of features is selected for each split, thereby reducing the variance of the model.

7.4 Problem Statement and Objectives

In this section, regression algorithms were built and evaluated for predicting crop yield from collected sensor data. This data was acquired from the experimental work specifically designed to evaluate crop yield production along with water and energy sources. The three different crop types are leafy greens, tomato, and okra yield. The data contains 29, 47, and 74 rows, respectively, and five variables. Each crop yield prediction is handled individually. The performance of the model is evaluated using two metrics; R-squared value (R^2) and Root Mean Squared Error (RMSE). Generally, lower RMSE and higher R^2 values are indicative of a good model.

7.5 Methodology

The target variable for this model is the specific crop yield. The predictor variables are soil humidity (HUMB), atmospheric pressure (PA), soil temperature (SoilT), ambient temperature (TCA), and ultraviolet radiation (UV), rainfall, and average ambient temperature (TAVG-f). The data for the predictors were collected from an experimental setup of wireless sensor nodes that are discussed in [9] and further detailed in section chapter 4. The mean soil temperature is 76 °F, while the mean yield for leafy greens is 14g. It is important to mention that there were missing values that were filled with zeros for both target

Attribute code	Attribute name	Attribute description
HUMB	Soil moisture content (Hz)	The amount of moisture content present in the soil
PA	Atmospheric pressure (mmHg)	Ambient atmospheric pressure
SOILT	Soil temperature (° F)	Soil temperature taken at depth of 5ft
TCA	Ambient temperature (° F)	Ambient weather temperature aggregated daily from sensor
UV	Ultraviolet radiation ()	Measurement of sun UV radiation
PRCP	Precipitation (in)	Measurement of rainfall data aggregated daily average
TAVG($_f$)	Ambient temperature (° F)	Average daily temperature data from weather station

Table 7.1: Predictor attributes in crop yield model

and predictor variables. Since all the variables are on a different scale and might influence the modeling process, all the predictors were normalized. All the independent variables were scaled between 0 to 1 via normalization. The target variable remains unchanged. The model is built on the training set, and its performance is evaluated on the test set. The data is split into 70% for training, and 30% for the testing set selected randomly. The correlation of each variable to the other is showed in Fig. 7.1.

7.5.1 Results

The term ”linearity” in algebra refers to a linear relationship between two or more variables. Linear regression performs the task to predict a dependent variable value (Y) based on a given independent variable (x). Therefore this type of regression technique finds out a linear relationship between input (x) and output (Y). For this work, multiple linear regression is one of the many ML techniques used, and its metrics are evaluated with other models. The performance of the algorithm is evaluated based on the values of MAE, MSE, RMSE, and R^2 score.

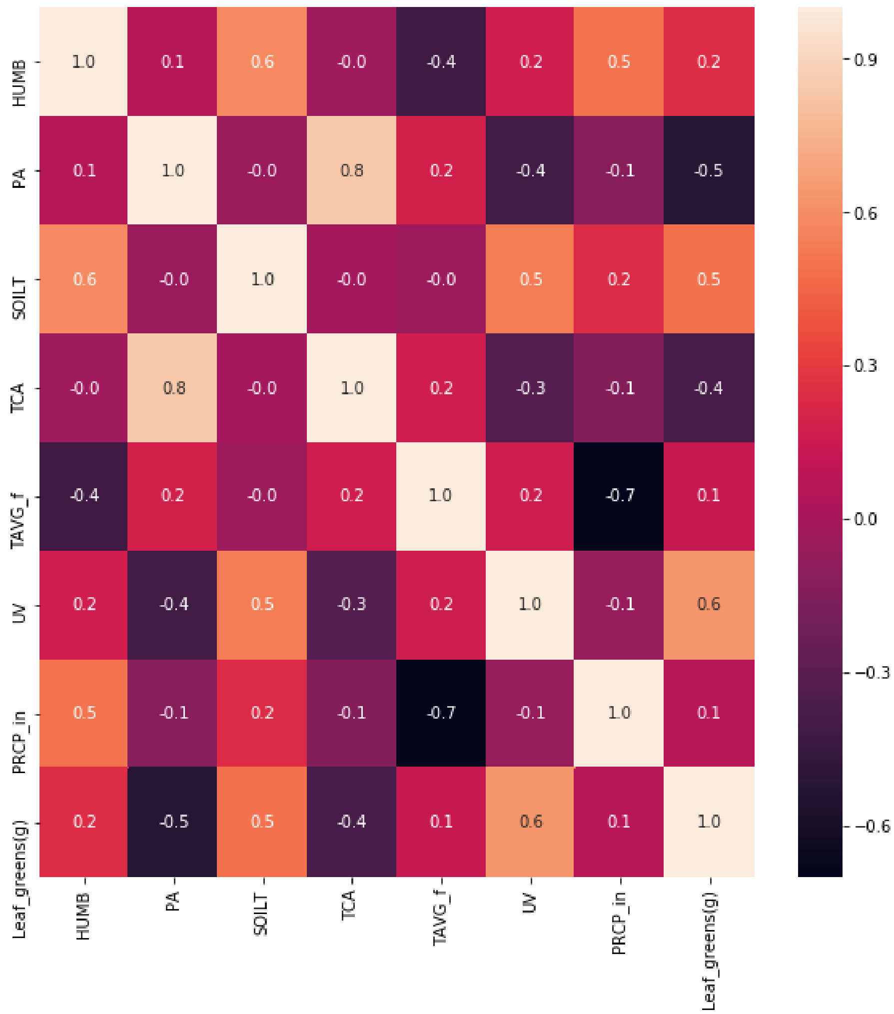


Figure 7.1: Heat map of each attribute correlation to others

Two simulations were done, dividing the attributes into two sets. This was done to avoid redundancy in temperature variables and better improve the model fit. The first simulation consisted of all the seven variables listed in Table 7.1. The result shows that the model performed decently with an MSE value of 85.965 and R^2 score of 60 %. The prediction, as presented in Fig. 7.2 is not quite precise and needs improvement. The second simulation only took account of the first five sensor attributes from Table 7.1; HUMB, PA, SOILT, TCA, and UV. The model performed much better with MSE of 44.869 and R^2 score of 78 %. The comparison of the actual and predicted yield values are indicated in Fig. 7.3.

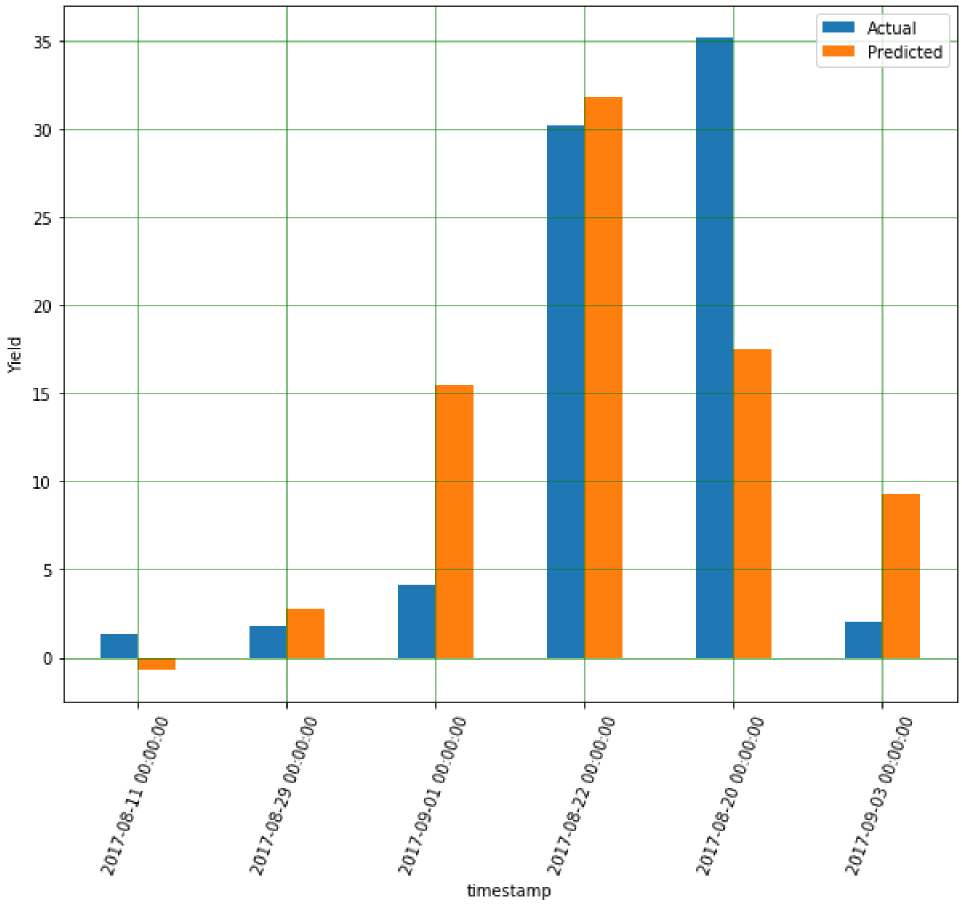


Figure 7.2: Comparison of actual and predicted values accounting all seven attributes for multiple linear regression

7.6 Summary

The first simulation result shows that the RMSE is 10.3018 for train data and 7.0454 for test data. In addition, the R-squared value is 67.2% for train data and 76.1% for test data. Although these are decent metrics, more improvements can be obtained by adjusting the input parameter of the decision tree. Therefore, the values of the parameter, 'max-depth' was changed to 2 and 5 to improve the model performance. The model shows a slight

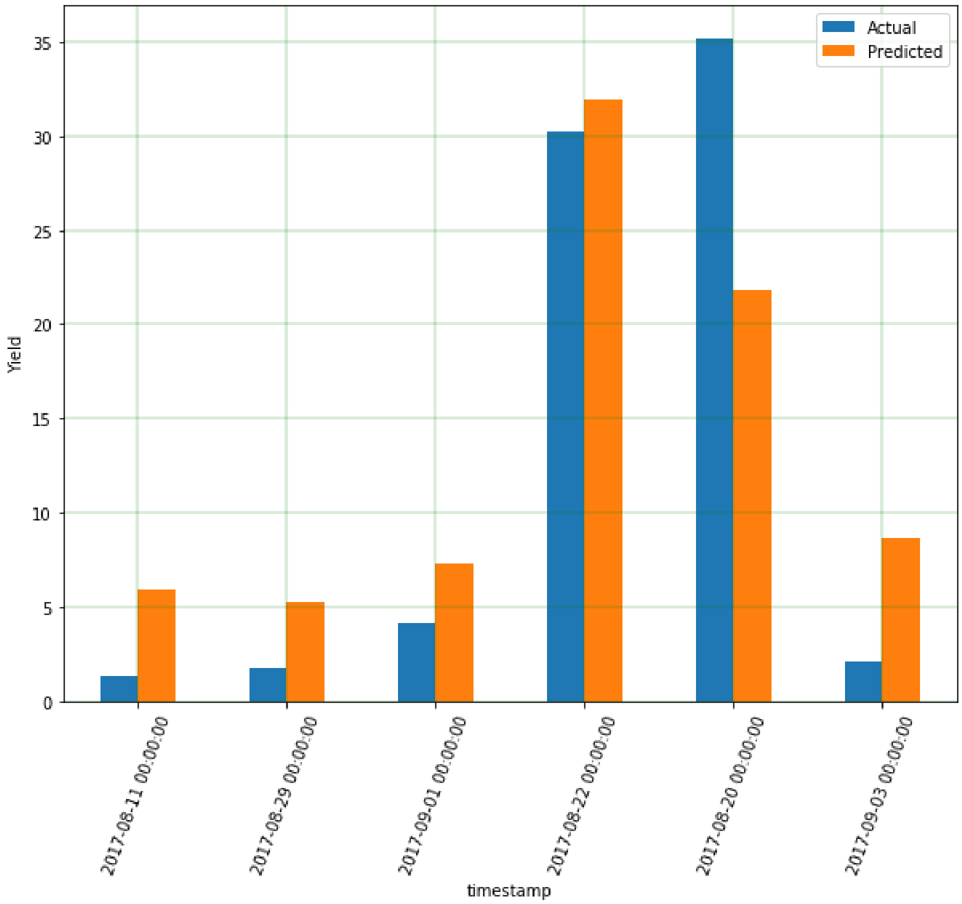


Figure 7.3: Comparison of actual and predicted values accounting selected five attributes for multiple linear regression

improvement when 'max-depth' is adjusted to 2. The RMSE for the training data set is 9.0658, with an R^2 of 74.6%. For the testing data, the RMSE and R^2 have improved to 6.519 and 79.6%, respectively. When the 'max-depth' is adjusted to 5, the RMSE for the training set is 0.602, which is considerably small. The decision tree model shows an excellent fit for the training data with R^2 value of 99.9%. However, the testing data underperformed all the previous model with 13.7304 RMSE value and 9.3% R^2 score value.

CHAPTER 8

CONCLUSION AND FUTURE WORK

8.1 Conclusion

Food, energy, and water (FEW) resources are all fundamental human necessities. With population increase, economic development, and urbanization, and change in diet and lifestyle, challenges on securing adequate food, energy, and water to meet human demand are increasing. This dissertation addresses the FEW nexus challenges through two critical domains: a computational model for the food, energy, and water nexus, and implementing a wireless sensor network-based smart agriculture as a physical model. One of the major challenges within the integrated FEW research area is modeling and quantifying the FEW nexus as interdependent networks. Another significant challenge data accessibility and acquisition that captures all three systems. In addressing the FEW nexus problems, this research has proposed four objectives as follows;

1) Objective 1 approaches the lack of FEW nexus modeling by proposing a Leontief inverse input-output model

2) Objective 2 addresses the FEW nexus through the implementation of an end to end IoT platform for data-driven integrated FEW system

3) Objective 3 looks into model affirmation through both the theoretical and experimental work

4) Objective 4 concentrates on the energy system portion in the implementation of the off-grid renewable energy system and addresses backup battery service life reliability

The experimental portion of this dissertation focuses on IoT based smart farming as an example of a physical model as an integrated FEW system. The development of smart farming must accelerate rapidly and learn a lesson from the smart city projects to meet the goal set by FAO. The agriculture industry remains greatly unpenetrated by IoT technologies. Different sources expect the precision agriculture and IoT driven food chain to grow from a minimum of multi-billion to trillion market in the coming years. The advancements of LPWAN technologies will facilitate the IoT application to any domain, especially in the remote agricultural monitoring. ICT and IoT technologies are innovations that will play a key role in addressing the FEW nexus stress in an integrated way. Such technologies equip stakeholders with essential big data that can be insightful in patterns, practices, consumption trends, forecasting, and better management of resources. As a result of improvements in sensing technology and reductions in costs, sensing capability is expected to be integrated from everyday objects to significant infrastructures. Food, energy, and water are part of the many critical interdependent infrastructures that are crucial to achieving the smart city initiative.

Chapter 3 has presented a FEW mathematical framework based on Leontief input-output model to quantify and model the FEW nexus. The FEW input-output model can account for demand as a result of stressors. It allows for the computation of intersectoral usage of various FEW components. The technical coefficient allows for the direct and indirect effect of resources on each other with the ability to trace back. The Leontief inverse matrix summarizes the network effects generated when the final output changes. A single coefficient of a matrix L compiles all direct and indirect effects generated in the FEW elements i to provide a single unit of final demand for the FEW elements j. Furthermore, it is demonstrated how the linkage magnitudes measure interdependence. The direct forward and backward linkage of the resources can be visualized in directed graph theory. Data from an experimental set, hypothesized, and from previous work has been used to run the model.

An overview of IoT and its enabling technologies has been presented in chapter 4. Several areas related to the deployment of IoT in agriculture have been discussed in detail. The driving factors, current trends, and future development of the smart agriculture ecosystem are presented. A detailed overview of sensing and networking technologies is discussed. Additionally, recent advances that implement the integrated FEW nexus approaches within the smart city paradigm, such as vertical farming, are reported. Significant technical challenges in the realization of IoT in agriculture and future development areas are highlighted as well. An overview of the data management scheme and acquisition utilizing edge and fog computing is described to make the computational and communication process more efficient.

Chapter 5 presents the design and implementation of an experimental prototype of a smart farm to investigate further and model the food, energy, and water nexus in the future. The overall system design, implementation, and functionality are explained. The test-bed consists of distributed WSN that monitors different agricultural and environmental parameters. Wireless sensor data transmission and acquisition are managed by IoT gateway router through the ZigBee protocol. An algorithm was established based on threshold values of temperature and soil moisture to automated into a programmable micro-controller to control irrigation time.

The off-grid energy system component of the experimental test-bed is described in Chapter 6. The system provides clean PV energy for all energy demands of farming purposes, such as irrigation and devices in the wireless sensor networks. This chapter discusses the off-grid energy system in an integrated FEW system, and its especial applicability in regions access to electricity is a challenge. It will further address the reliability aspect of the system in the long term. Factors affecting the state of health of the lead-acid battery and its reliability are discussed. It further demonstrates in analyzing the overall reliability of the backup battery units to predict their end of service life.

The amount of data collected from farms is increasing exponentially. The use of wireless sensor networks, IoT, robotics, drones, and AI is on the upswing. Machine learning algorithms enable the extraction of useful information and insights from the deluge of data. It also has reviewed the ML methods used the most by researchers in the past two years in conjunction with wireless sensor networks. Regression algorithms were built and evaluated for predicting crop yield from collected sensor data in chapter 7. The sensor data was acquired from the experimental work specifically designed to evaluate crop yield production along with water and energy sources. The three different crop types are leafy greens, tomato, and okra yield. The data contains 29, 47, and 74 rows, respectively, and five variables. The performance of the model was evaluated using two metrics; R-squared value (R^2) and Root Mean Squared Error (RMSE).

8.2 Recommendation for Future work

Complex networks can be used to characterize a series of different systems where multiple sources interact with each other through their relationships. This relationship can be represented as nodes for resources and their relationship as edges. The FEW IO system describes a network, a mathematical object defined by a set of nodes or vertices and a set of edges connecting them. The FEW input-output networks can be formulated where nodes are specific FEW resources and the edges as the interdependence flows (technical coefficient) between resources. The IO table, which will be equivalent to is an adjacency matrix whose entry (i, j) represents the flow from node i to node j. The future work will use a FEW nexus coefficients obtained from the IO model to represent the edges with magnitude and direction from one node to another. Each node is specific to FEW sources, with size proportional to its total degree. The edges are directed and weighted representing the use of one resource in the production of the other. The complex FEW networks are analyzed on assortativity, clustering coefficient, and degree and strength distribution. Assortativity measures the propensities of nodes to attach. The clustering coefficient measures the degree to which each node (FEW resources) in a graph tend to cluster together. The degree distribution and strength show the direct and total linkages of the FEW resources. All these properties will be vital in understanding the complex FEW network systems.

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