Title
Cyber-Physical Systems Approach to Irrigation Systems

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Cyber-Physical Systems Approach to Irrigation Systems

DISSERTATION

submitted in partial satisfaction of the requirements
for the degree of

DOCTOR OF PHILOSOPHY

in Computer Engineering

by

Davit Hovhannisyan

Dissertation Committee:
Professor Fadi Kurdahi, Chair
Professor Ahmed Eltawil
Professor Mohammad Al Faruque

2019

DEDICATION

To my wife, our parents, our siblings, our family and in the loving memory of our grandparents...

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NOTATIONS AND NOMENCLATURE

This section provides a concise reference describing **notation** used throughout the thesis. Some of the notations were adapted from

Numbers and Arrays

a	scalar a
a	variable a
$\vec{a}$	vector a
A	matrix A
$\vec{A}$	tensor A
I_n	Identity matrix with n rows and n columns
I	Identity matrix with dimensionality implied by context

Sets and Graphs

$\mathbb{A}$	A set
$\mathbb{R}$	The set of real numbers
$\{0, 1\}$	The set containing 0 and 1
$\{0, 1, \dots, n\}$	The set of all integers between 0 and n
$\mathcal{G}$	A graph

Indexing

a_i	Element i of vector $\vec{a}$, with indexing starting at 1
a_{-i}	All elements of vector $\vec{a}$ except for element i
$A_{i,j}$	Element i, j of matrix A
$A_{i,:}$	Row i of matrix A
$A_{:,i}$	Column i of matrix A
$\mathsf{A}_{i,j,k}$	Element (i, j, k) of a 3-D tensor $\vec{A}$
$\vec{A}_{:,:,i}$	2-D slice of a 3-D tensor

Linear Algebra Operations

$A^\top$	Transpose of matrix A
$\det(A)$	Determinant of A

Calculus

$\frac{dy}{dx}$	Derivative of y with respect to x
$\frac{\partial y}{\partial x}$	Partial derivative of y with respect to x
$\int f(\vec{x})d\vec{x}$	Definite integral over the entire domain of $\vec{x}$
$\int_{\mathbb{S}} f(\vec{x})d\vec{x}$	Definite integral with respect to $\vec{x}$ over the set $\mathbb{S}$

Probability and Information Theory

$\mathrm{a}\perp\mathrm{b}$	The random variables a and b are independent
η	Learning Rate
$\mathrm{a}\perp\mathrm{b} \mid \mathrm{c}$	They are conditionally independent given c
$P(\mathrm{a})$	A probability distribution over a discrete variable
$p(\mathrm{a})$	A probability distribution over a continuous variable, or over a variable whose type has not been specified
$\mathbb{E}_{\mathrm{x}\sim P}[f(x)]$ or $\mathbb{E}f(x)$	Expectation of $f(x)$ with respect to $P(\mathrm{x})$
$\mathrm{Var}(f(x))$	Variance of $f(x)$ under $P(\mathrm{x})$
$\mathrm{Cov}(f(x), g(x))$	Covariance of $f(x)$ and $g(x)$ under $P(\mathrm{x})$
$\mathcal{N}(\vec{x}; \vec{\mu}, \Sigma)$	Gaussian distribution over $\vec{x}$ with mean $\vec{\mu}$ and covariance Σ

Functions

$f : \mathbb{A} \to \mathbb{B}$	The function f with domain $\mathbb{A}$ and range $\mathbb{B}$
$f(\vec{x}; \vec{\theta})$	A function of $\vec{x}$ parametrized by $\vec{\theta}$. (Sometimes we write $f(\vec{x})$ and omit the argument $\vec{\theta}$ to lighten notation)
$\log x$	Natural logarithm of x
$\|\|\vec{x}\|\|_p$	L^p norm of $\vec{x}$
$\|\|\vec{x}\|\|$	L^2 norm of $\vec{x}$
x^+	Positive part of x, i.e., $\max(0, x)$

Datasets and Distributions

p_{data}	The data generating distribution
$\hat{p}_{\text{data}}$	The empirical distribution defined by the training set
$\mathbb{X}$	A set of training examples
$\vec{x}^{(i)}$	The i-th example (input) from a dataset
$y^{(i)}$ or $\vec{y}^{(i)}$	The target associated with $\vec{x}^{(i)}$ for supervised learning

Hydraulic and Electric Nomenclature

m	soil water content
$\vec{P}$	precipitation
$\vec{E}$	evaporation
$\vec{T}$	transpiration
$\vec{R}$	total surface runoff
$\vec{D}$	deep layer recharge
$\theta(t, z)$	moisture function in time and space in soil
q	water flux ms^{-1}
$K(\psi)$	hydraulic conductivity coefficient ms^{-1}
ψ	soil water potential
I	quantity of electrical current flowing per unit time (A)

Hydraulic and Electric Nomenclature 2

L	length (m)
σ	specific electrical conductivity (Siemens/cm)
A	cross-sectional area or area m^2
V_1, V_2	voltages (V)
$(V_2 - V_1)/L$	potential gradient per length (V/m)
R	resistance (Ohms)
ψ_2, ψ_1	hydraulic heads (m)
$(\psi_2 - \psi_1)/L$	hydraulic gradient
$i, i(t)$	infiltration rate as a velocity
I	cumulative measure of infiltrated water
i_s	the steady state infiltration rate
a, b, k	constants
s	sorptivity of the soil
C	water storage capacity of the soil surface
Q_0	initial moisture content
$Q(t)$	moisture content function
i_c	represent the final infiltration capacity
i_0	the initial infiltration capacity

Hydraulic and Electric Nomenclature 3

ET_0	reference evapotranspiration $[mm\ day^{-1}]$,
R_n	net radiation (crop surface) $[MJ\ m^{-2}\ day^{-1}]$,
G	soil heat flux density $[MJ\ m^{-2}\ day^{-1}]$,
T	air temperature at $2m$ height $[^{\circ}C]$,
u_2	wind speed at 2 m height $[m\ s^{-1}]$,
e_s	saturation vapor pressure $[KPa]$,
e_a	actual vapor pressure $[KPa]$,
$e_s - e_a$	saturation vapor pressure deficit $[KPa]$,
Δ	slope vapor pressure curve $[KPa\ ^{\circ}C^{-1}]$,
γ	psychometric constant $[KPa\ ^{\circ}C^{-1}]$.
K_c	crop factor/constant,

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Irrigation Conference

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FOOD CAS from 2019 IEEE International Symposium on Circuits and Systems; Sapporo, Japan

Feasibility Study of Plant Health Monitoring **2019**
FOOD CAS from 2019 IEEE International Symposium on Circuits and Systems; Sapporo, Japan

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ABSTRACT OF THE DISSERTATION

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By

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University of California, Irvine, 2019

Professor Fadi Kurdahi, Chair

The semiconductor industry has successfully brought silicon technology to a price point that is accessible for application domains such as irrigation systems, which currently wastefully utilizes 70% of all fresh water. Moreover, worldwide fresh water resources will soon reach a deficit due to ever growing demand. However, the state of the art precision irrigation systems utilize sophisticated water delivery drip lines, yet are only controlled at source by the gut of the end user. This work demonstrates that the scientific foundation of cyber-physical systems (CPS) can be used to design automated, distributed and intelligent precision irrigation systems that improve irrigation efficiency. Therefore, this work explores and analyzes in depth the cross section of irrigation practices and cyber-physical systems knowledge to show a path toward a successful adaptation of silicon technology that solves one of the greatest challenges of the 21st century: the fresh water scarcity.

To that end, this work presents contributions that complete a novel vision for next generation precision irrigation systems, which can be grouped into three main thrusts: (1) circuit inspired models for irrigation system components and scheduling strategies by analogy method, (2) CPS approach based (a) design methodology capable of comparing irrigation controllers, (b) simulation tools and software for analyzing the distributed behavior of the specialized irrigation controllers, (c) topology adaptation technique that utilizes multi-graphs to mine the

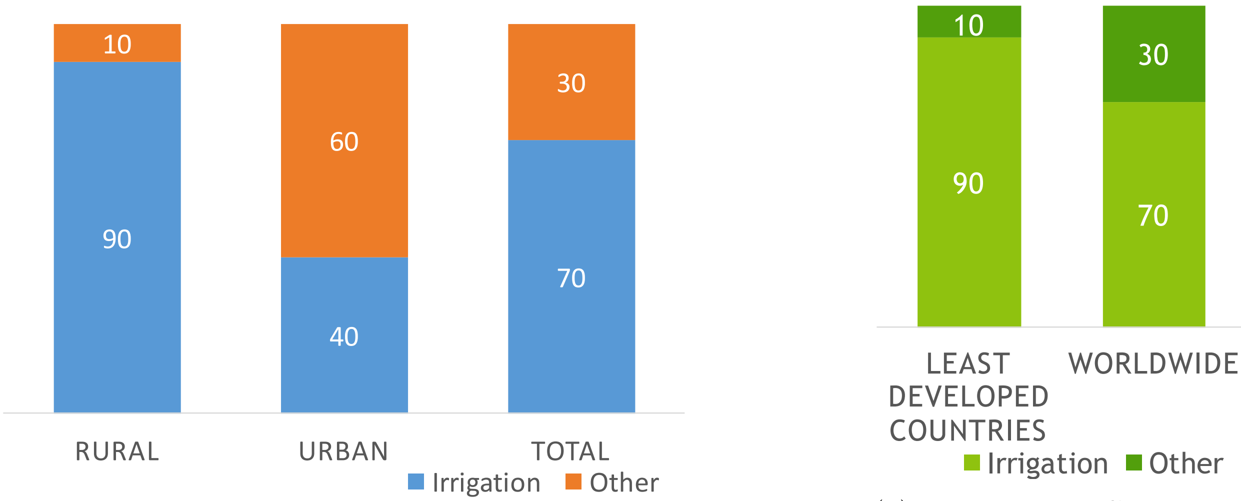
hydro-wireless topology of the IoT controllers, and (d) a distributed controller implementation with novel energy harvesting and low power support for irrigation controllers and sensors, (3) overhead vision solutions for health and growth monitoring. The observations, analysis and insight from experimental studies were in collaboration with Rancho California Water District, growers and practitioners.

Chapter 1

Introduction

Semiconductor industry has successfully brought silicon technology to a price point that it is accessible for application domains such as irrigation systems, which presently wastefully utilize 70% of all fresh water (see Figure 1.1a) [126]. The statistics of irrigation fresh water use is particularly worrysome because under-developed countries and rural settings have much higher dependence on irrigation, which entails that technological advancements are particularly difficult to apply (see Figure 1.1b) [126]. Moreover, worldwide fresh water resources will soon reach a deficit due to ever growing demand. Meanwhile the state of the art precision irrigation systems utilize sophisticated water delivery drip lines, yet are only controlled at source by the gut of the end user. This work demonstrates that the scientific foundation of cyber-physical systems (CPS) can be used to design automated, distributed and intelligent precision irrigation systems that improve irrigation efficiency. Thus, this work explores and analyzes in depth the cross section of irrigation practices and cyber-physical systems knowledge to show a path towards a successful adaptation of silicon technology that solves one of the greatest challenges of the 21st century: fresh water scarcity.

Different methods of irrigation have been developed for reducing water usage; some activities



(a) Breakdown by Setting

(b) Breakdown by Country Development

Figure 1.1: Fresh Water Usage Statistics Comparison of Least Developed Countries and Rural to the World Average [126]

start even before seeding. For example, leveling fields, surge flooding, and run-off capture are done prior to seeding [128]. Remaining methods for water saving practices belong to irrigation techniques. There are three major irrigation methods: surface irrigation, drip irrigation and spray irrigation. Surface irrigation is a traditional method, which is done by completely or partially flooding the field with use of furrows. Surface irrigation is wasteful, as at least 50% never reach near crops, but still is the most widespread irrigation technique to date. Spray irrigation is the method that uses sprinklers to spray water on the soil surface. Common type of spray of irrigation is the center-pivot, which is done with use rotating pivoted pipe, typically 1250 - 1300ft in length. The most modern of all is the drip irrigation technique. Drip irrigation uses perforated pipes to supply water near the root zone and operates under pressure from the applicators, which are placed either on or below the surface of the ground [131].

Although many empirical studies have been conducted, there are no conclusive results as to which method of irrigation has the superiority over others due to differences in irrigation scheduling, geography and climate. Essentially, all of the variables need to be studied together,

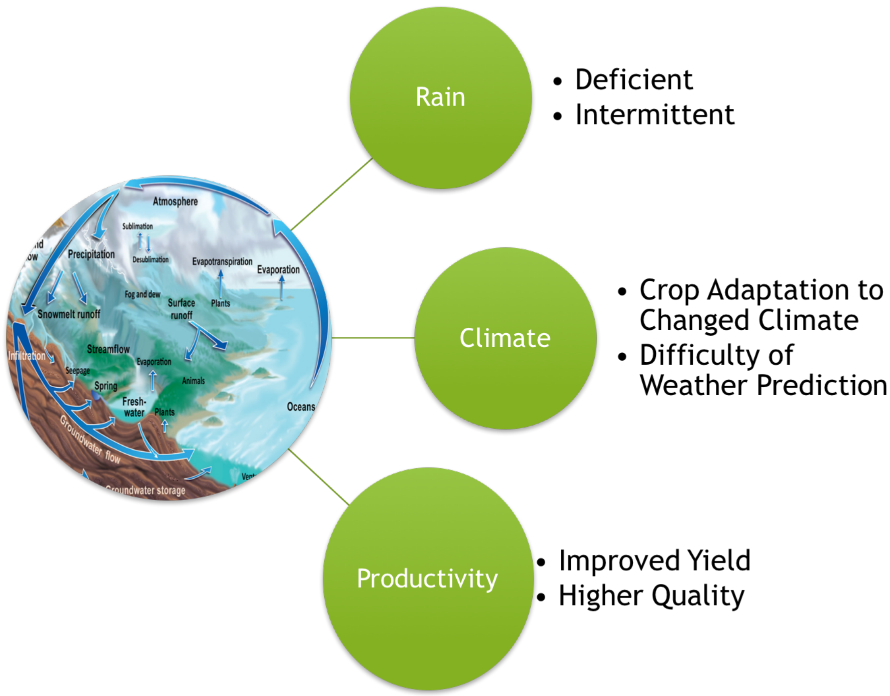


Figure 1.2: Why do we Irrigate?

because complete disassociation of domains is complex if at all achievable.

This dissertation introduces circuit inspired modeling approach for modeling water flow in soil. To evaluate this concept we used IoT based irrigation validation scheme and developed extensible infrastructure by applying Cyber Physical Systems approach to irrigation systems.

1.0.1 Significance of the Problem

The United States ensures dependable access to clean water with a sophisticated system of dams, aqueducts, levees, treatment facilities, and pipelines. Yet, new levels of population growth, urbanization, climate change and aging infrastructure threaten its ability to scale. Indeed, Irrigation systems are at cross layers of scientific subjects and engineering marvels as depicted in the Figure 1.3. Addressing these neverseen before scale of challenges require multidisciplinary, integrative and innovative investments.

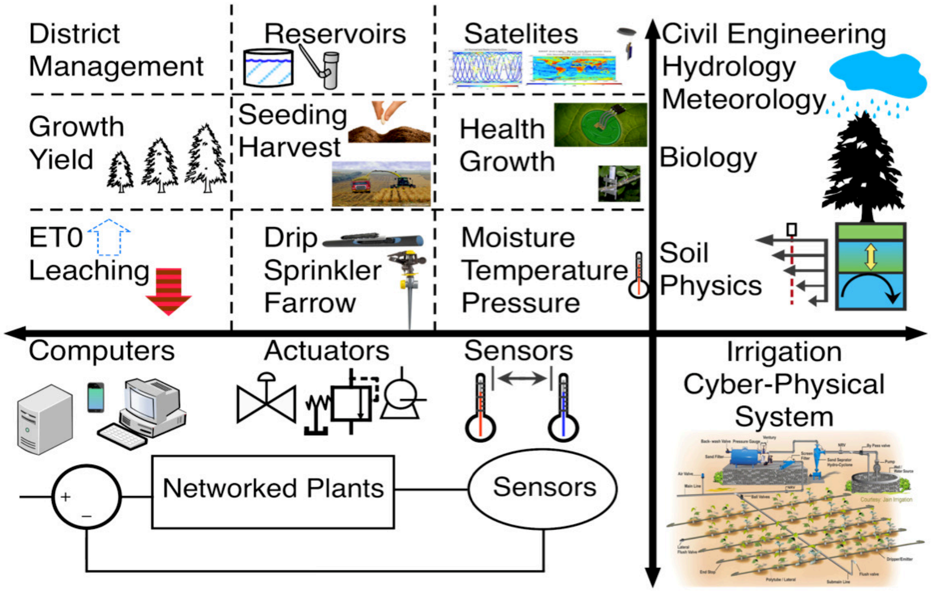


Figure 1.3: Overview of Cross Layer Irrigation CPS

Innovators and investors shy away from novel water technologies due to low rates of adaptation and lengthy validation cycles. This has created a vacuum of technology in the water sector unlike in the power sector where novel, renewable and distributed generation is outpacing the traditional forms of energy production. This is more evident in California where the most severe drought in history is still threatening Southern California. In particular, in the Rancho California Water District (RCWD) the drought is considered an ongoing issue, which motivated a collaboration between local farmers/residents, educators and inventors. This integrative effort yielded a cross domain innovative approach to water management, particularly, to precision irrigation management.

1.0.2 Theoretic Basis for the Study

We believe that to advance irrigation practices the advances in Infrastructure, Analytics and Intelligence must happen in sequence and in parallel as depicted in Figure 1.4. This process flow ensures that each can individually advance, and thus push the boundaries of the possible.

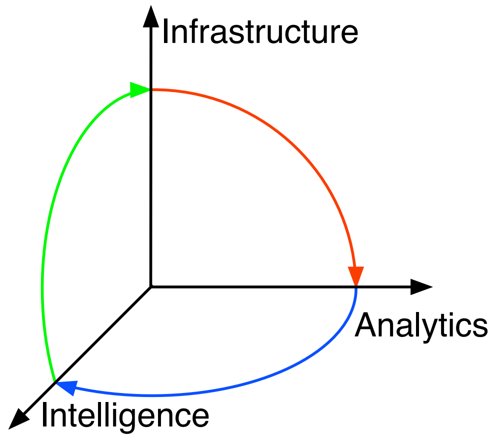


Figure 1.4: Systems Engineering Workflow for Advancing Irrigation Practices

Irrigation science was formed on the foundation of substituting for the water deficit, but today it has broader influences as it is tightly connected with food and fresh water supply chains. Thus, it is not appropriate to approach it as by the naive logic of “if dry then water it”. In fact, researchers have been predicting irrigation influence on modern life and suggesting to extend the expertise of irrigation experts from common civil engineering foundation of hydrology and hydraulics to economics and beyond [91]. Moreover, we can distinguish areas of application from economics science: developmental, decision theory, environmental and etc, biology: crops, fungi and bacteria; soil-physics and etc. Irrigation has really grown from a single user or single field problem into a water district, state or regional agricultural and even technological challenge.

In one hand, studies [21] [57] suggest that improving agricultural irrigation requires improvements at a system level and cannot be achieved by addressing an improvement in a single process. This is evidence that the next generation of irrigation systems will have to take place across layers of the stakeholders: from district managers to all the way down the applicator. This vertical integrative approach crosses the conventional small operation interests where preferences of farmers were in mismatch of the needs and policies of water distribution [58].

One approach to unify the irrigation performance was by Hellegers [46], who presented a work in which the variability in Crop Water Productivity (CWP) is analyzed on the basis of actual water consumption and associated biomass production using the Surface Energy Balance Algorithm for Land (SEBAL). SEBAL generates input for the socio-economic analysis with aims to quantify the foregone economic water productivity (EWP) of policy decisions to socially optimal allocation of water resources. In this particular work, SEBAL was used for the basis of such decisions, but it can be inferred that there will be number of ways in which this may be possible - the key takeaway being that policies can be quantified and evaluated if the CWP parameter is taken into consideration. Thus, it is possible to improve water management strategies even at policy making level with the granularity of the particular district in mind where CWP parameters are utilized with caution.

That said, Alexandridis [5] was able to bring up slow recharging groundwater information for assessment of irrigation efficiency, which means that even groundwater recharge rates need to be taken into account by district managers. Moreover, those with most information would be most effective in preventing possible disaster - yet another link in the system to be accounted for. Fundamentally, irrigation water availability is not as much a social problem as it is a revenue problem due to the expectation of the link between water used and yield [51]. However, [99] proposed to look for sustainable irrigation strategies with the quality of natural resources (land, water, and etc) throughout an irrigated region in mind. The scope there was to look for ways to balance both irrigation water and salts drainage as well as build up throughout the regions, as the two together impact the future of farming altogether, to keep an opportune setting for the future as well. On the other hand, the [146] study shows that water saving practices indeed significantly improve groundwater level even in large district areas, which means that in the scope of hydrological health, there can be trade-offs in between farming short term objectives.

There is also another factor to take into account, which is often overlooked. [29] argued that a mismatch between expected water efficiency improvement and the efficiency actually observed was due to a mismatch between potential savings and actual savings that the approach offers. This further emphasizes that potential losses in potential savings and actual practice may as well be due to lack of integrative solutions available, which would in place track source of losses between expected and potential savings and observed actual consumption.

That said, there seems to be a solution to closing the gap between irrigation management and attractive profits, such as the observations that 60+% of profit and revenue are possible even for row crops with less advanced technology: sensing [108]. The challenge is not only in saving water, but also in fine tuning a very large and complex natural and a cyber-physical system, because over-irrigation also has adverse effects such as nutrient leaching [108] [22] [17][123][10][75][14][18].

However, farmers are not inclined to use advanced tools and technologies as indicated by the USGS 2013 Survey. The statistics are quite simple: more users are inclined to look into what their neighbor is doing than use any sensors or computerized technology as evident from Figure 1.5 [102]. This means that even localized needs of a single operation may be difficult to automate, let alone be governed by district policy.

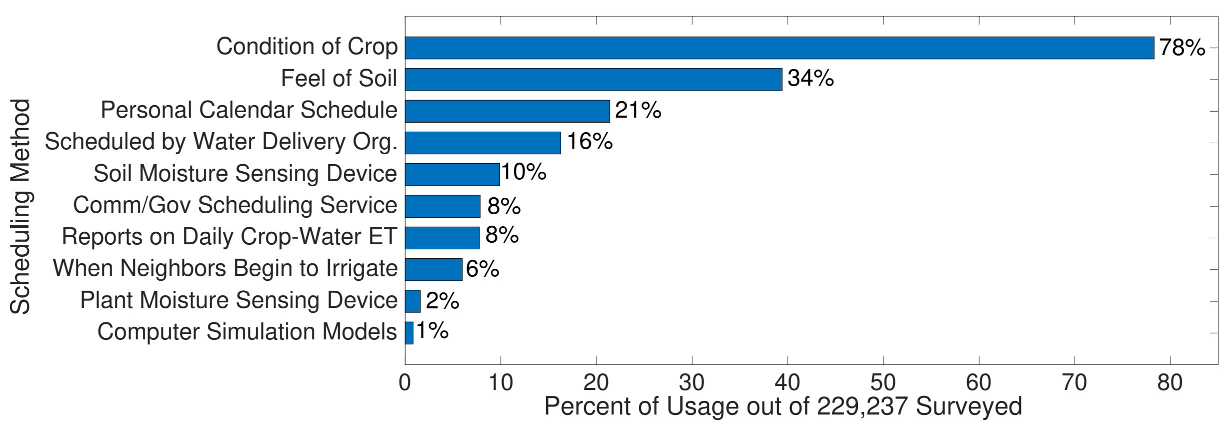


Figure 1.5: Irrigation 2013 USGS Survey on Methods Used for Irrigation

Although demand for water saving global deficit of fresh water poses challenges just like energy, but it has not been addressed with the same intellectual investment. Particularly, the expected deficit in electrical energy has been successfully addressed by computer aided design and design automation tools empowering energy saving circuit design and development, as well as solar energy harvesting. Water deficit demands must be treated with the same level of emphasis as other main stream domains. Thus, to move towards new level of rigor in irrigation systems, new engineering tools and infrastructure need to be used.

Until recently, this was not easy to achieve, because smart irrigation devices were complex, expensive and prone to failures. The proliferation of new IoT components and devices that have gone through numerous improvements in cost, size, performance, power and overall capabilities are starting to drive a paradigm shift towards the new desired goals.

In order to be successful and garner adoption of advanced precision irrigation systems, the end devices must be affordable, scalable and dependable. An affordable design utilizes high volumes of production by limiting design variations. A scalable device in the context of irrigation systems, would efficiently handle variable watering demands without failures. Moreover, a dependable irrigation system would be one that is easy to use, maintain and replace.

The next generation of devices will have integrated configurable or "plug and play" sensors, actuators, valves, micro-controllers, battery and redundant energy supply/harvesting options. This integration results in reduced overall production cost, and more importantly, makes it possible to scale the number of devices to be deployed while reducing the time, effort and complexity of deployment as one does not have to worry about the communication of multitudes of devices (e..g connecting sensors and actuators separately to a central controller). Maintaining the deployed infrastructure is also simplified since there is only one component type.

1.0.3 Dissertation Contribution and Outline

These proposed methods allow for a complete rework of current stagnating irrigation practices, with the use of circuit inspired models for irrigation systems, IoT multi-depth tensiometer monitoring studies in Temecula Valley with RCWD, self powered scalable IoT controller and sensor wireless networks.

Chapter 2

Lack of rigorously designed models that can provide actionable intelligence to the user motivated us to start our irrigation studies journey through circuit inspired modeling. This chapter proposes the integration of circuit-inspired modeling of natural phenomena and man-made artifacts to generate end-to-end irrigation system circuit models as described in Figure 1.6. Such models can take advantage of existing circuit design and simulation tools that have been perfected over the past decades to efficiently process large input sets. We show that circuit-inspired models are indeed qualitatively sound and quantitatively accurate in capturing both natural phenomena and engineered physical irrigation systems.

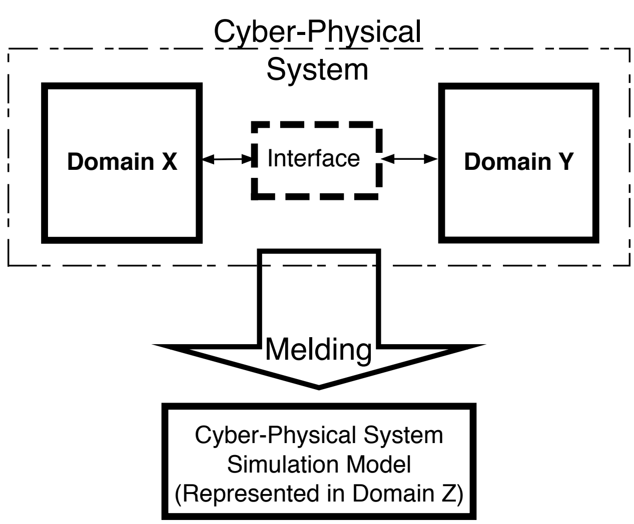


Figure 1.6: Melding of Multiple Domains to a Single Domain Simulation Model

Chapter 3

No control system can be stable if there is no appropriate feedback; thus, with that in mind, we then delved into developing state of the art scalable data collection and monitoring system design research inspired by Internet of Things (IoT). IoT integration with Precision Irrigation practices brings Internet enabled Irrigation Monitoring, while fully monitoring Irrigation systems entails monitoring key performance indicators from water source to applicator and all the way to the plant. These indicators could be the flow speed, soil water content, water tension, leaft uptake, pressure regulation, pressure settling time and many other parameters. In this chapter are presented our observation on a multi-year case study conducted in vineyard irrigation setting. During this study, we aimed to understand and expose modern challenges of precision vineyard irrigation systems and how to use existing technologies such as Internet of Things to empower vineyard management in terms of water productivity. We have learned that precision monitoring tools are an effective method for preventing over-watering and under-watering. In fact, our results show that IoT using monitoring tools with 87% confidence reduces water usage, and in some cases saves up to 33.8% of water usage, while improving overall performance.

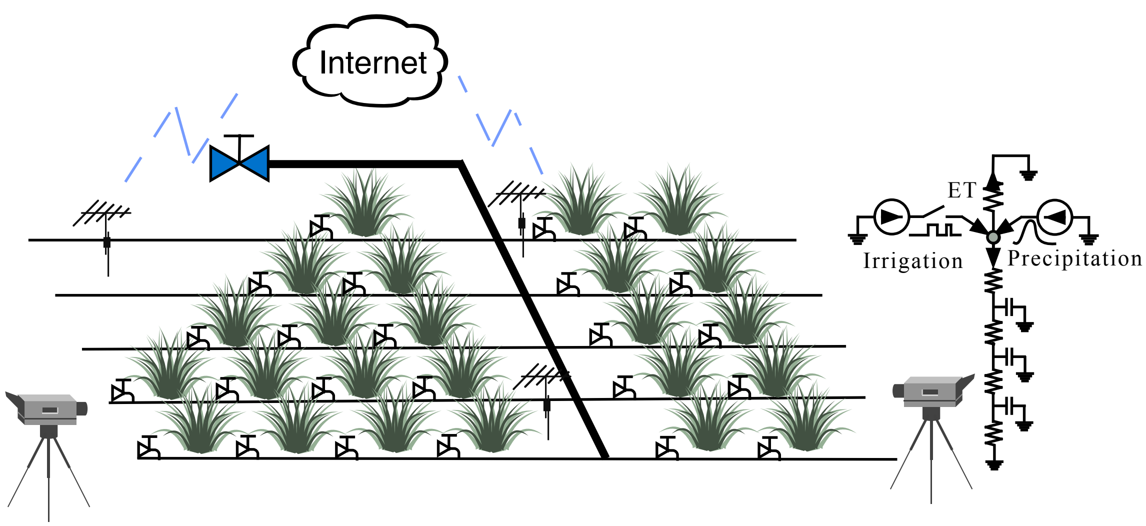


Figure 1.7: Future of Irrigation Systems

Chapter 4

As we have covered models and monitoring, the next most important subject to cover is to make sure that scheduling algorithms based on models can actually be implemented. Indeed, there is a significant unrealized potential in developing state of the art electronics for agriculture. Thus in this chapter, we discuss design challenges of next generation crop monitoring and water flow control systems, in particular, designing IoT Stations with localization and energy harvesting in mind. Our studies show that it is possible to have self-powered, self-configurable and highly functional water flow stations that will transform and free Micro-Irrigation from centralized control as visualized in Figure 1.8. In this chapter is covered design methodology, strengths and weaknesses, topology aware localization multi-graph technique as well as lessons learned from prior experiments, which will ultimately help to fulfill the next generation of CPS-IoT Precision Irrigation Systems.

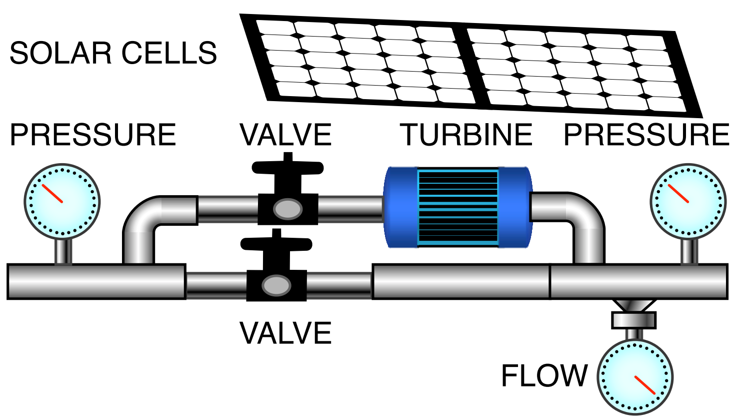


Figure 1.8: Proposed Redesign of the Irrigation Controller

Chapter 5

In hindsight, the previous chapters paint a pretty clear picture of how to approach irrigation with state of the art models, controllers and scalable monitoring/feedback systems. However, what we have missed is the essence of irrigation the crop centric nature of it. Thus, in final Chapter 5, the final set of contributions which relate to imaging and image processing of crops are presented for development of health and growth feedback - an essential tool that confirms and validates irrigation schedules.

Continuous monitoring of crops is an essential task of agricultural practices for the detection of diseases or pests, precision irrigation and fertilization. State of the art monitoring and imaging systems use aerial imaging to obtain visual feedback as well as multi-spectral imagery to determine crop growth factors. Our findings indicate that plant health and growth assessment could be moved from lab and expensive monitoring tools to ubiquitous silicon technology based cost effective solutions without much loss of accuracy. This if done properly, will entail that additional hierarchical loops of control can be added on top of the irrigation period and intensity control to fit the crop needs, to notify for human intervention or targeted pesticide control as depicted in Figure 1.9.

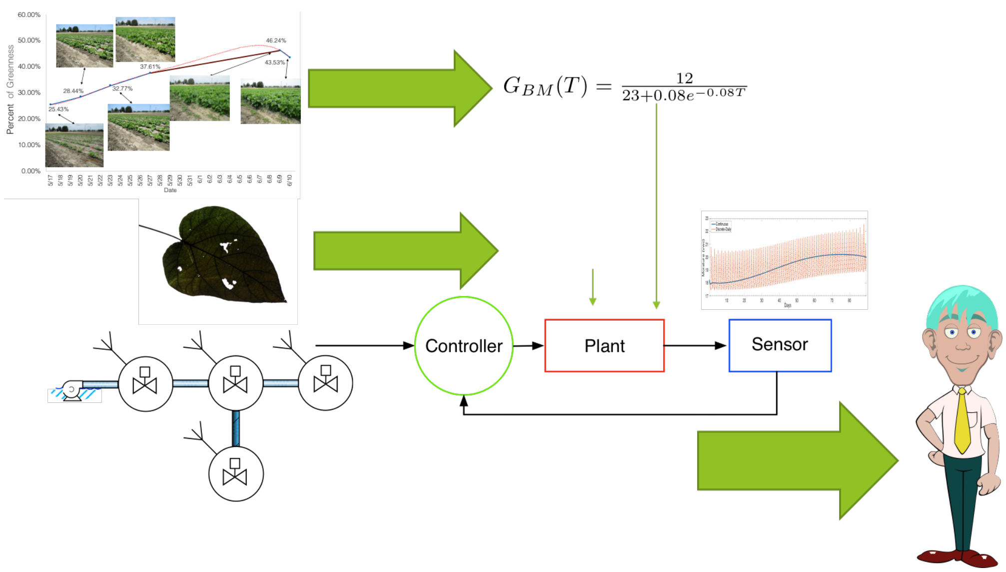


Figure 1.9: Hierarchical Control View of the Proposed Irrigation System

Chapter 6

Finally, Chapter 6 presents the conclusions and implication of this dissertation.

Chapter 2

Models for Irrigation: Circuit Inspired Modeling Method for Irrigation

2.1 Abstract

Precision irrigation systems promise to bring significant improvement in resource efficiency and crop yield by providing analytics and smart tools for the growers. While significant amounts of data can be collected in a sensor-rich system, there are no rigorously designed models that can provide actionable intelligence to the user. This paper proposes the integration of circuit-inspired modeling of natural phenomena and man-made artifacts to generate end-to-end irrigation system circuit models. Such models can take advantage of existing circuit design and simulation tools that have been perfected over the past decades to efficiently process large input sets. We show that circuit-inspired models are indeed qualitatively sound and quantitatively accurate in capturing both natural phenomena and engineered physical irrigation systems.

2.2 Introduction

Irrigation is a man-made phenomena to compensate for lack of rain, to increase productivity in terms of agricultural yield, and to support aesthetically pleasing turfs. Over 38% of all fresh water resources go into irrigation [52] which uses \$2.67B worth of electricity annually in the United States [130]. Fresh water is a resource soon to be in global scarcity as it is expected that by 2030 a massive 40% deficit [125] in water will happen. In order to avoid this expected deficit, current highly inefficient [50] irrigation practices must be optimized to improve yield and reduce water consumption. This paper proposes the use of circuit based modeling for irrigation systems for design time and run time irrigation management by providing representation, by qualitative and quantitative description.

Irrigation systems are Cyber-Physical Systems (CPS) composed of computing, actuating and sensing systems, as well as multiple physical domains comprised of natural phenomena and man-made artifacts. The integration of man-made and natural systems is inherently difficult to accomplish. The cyber-physical subsystems of cyber-natural systems must be designed and operated with real world constraints in mind, which can only be accomplished if all of the system components are rigorously modeled and studied.

Current state of the art Irrigation Systems are designed with trial-error and are not done by use of system models. To advance CPS modeling rigor, this work purposes use of circuit analogy based modeling substrate atop of which natural and man-made systems can be seamlessly integrated. Specifically, the main contributions of this work are in: "*analogy based modeling method for development for man-made and natural systems model as a circuit for irrigation systems*".

2.2.1 Motivation

Electronic Design Automation (EDA) has developed a wide repertoire of modeling, simulation and evaluation approaches to deal with the increased complexity of stochastic systems as one might expect in a complex system of this nature [30] [69] [68]. Lessons from development of these tools can be used to develop domain independent simulation environments. For example, at an abstract level one can consider the water cycle as a circuit, where water is transported (via resistors) from one storage medium to another (capacitors), due to the impact of different physical processes such as precipitation, run-off, and irrigation, as shown in Figure 2.1. These processes exhibit spatial-temporal variability [9], but can be analyzed using EDA tools such as those that encapsulates phenomena such as capacitive coupling, thermal impacts, and aging.

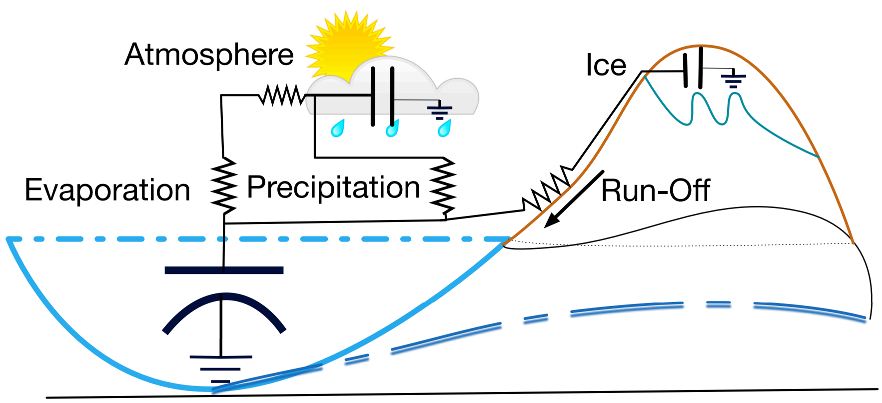


Figure 2.1: Circuit Representation of Water Cycle

The main motivation to use circuit inspired modeling for irrigation systems is that every aspect of the water cycle can be modeled in varying levels of details as an RC-based system, ranging from minute details regarding water uptake by plants [148], to large-scale water cycles [136]. Studies dating back to the 1960s [24] have studied in scrupulous mathematical detail how certain aspects of plant models (e.g. root systems etc.) could be constructed using RC circuit analogs. However, larger scale unified studies do not exist because circuit simulation and available computational resources were not mature enough at the time. Since then, major advances in circuit simulators such as (SPICE) [90] or similar tools became the corner stone of electrical circuit simulation. Faster computers, sophisticated modeling and simulation techniques have allowed the analysis of larger circuits under uncertainty in system parameters, as well as other circuit components such as transistors, diodes, inductances etc.

2.2.2 Central Challenge

Existing modeling approaches produce compartmentalized and complex system simulation models. Cyber-physical system modeling challenges span from practice to theory. Indeed, researchers have identified modeling distributed behaviors as one of the central cyber-physical system modeling challenges [28]. In particular, irrigation systems are centrally controlled as there are no practical distributed models to be used for developing distributed control. Moreover, the most common practices use simple apply-when-dry principal and cannot be considered precise methods. This is an end result of lack of scalable models within a single framework: a circuit.

2.2.3 Background

Natural hydrological and meteorological phenomena, as illustrated in Figure 2.2, affect irrigation systems as part of a greater soil-plant-atmosphere system [39], [42], [24]. Yet, crop yield is a function of the moisture content of soil [84] [118] [137], which changes due to in-flow and out-flow. Irrigation, run-in and precipitation increase the moisture content; meanwhile, evaporation, transpiration, run-off, and percolation reduce the moisture content of the soil. Unlike irrigation, which is a man-made phenomenon of fulfilling water deficit, the laws of physics govern evaporation, transpiration, run-off, and percolation [117].

Thus, the moisture content of a single grid cell of soil is described by the following equation

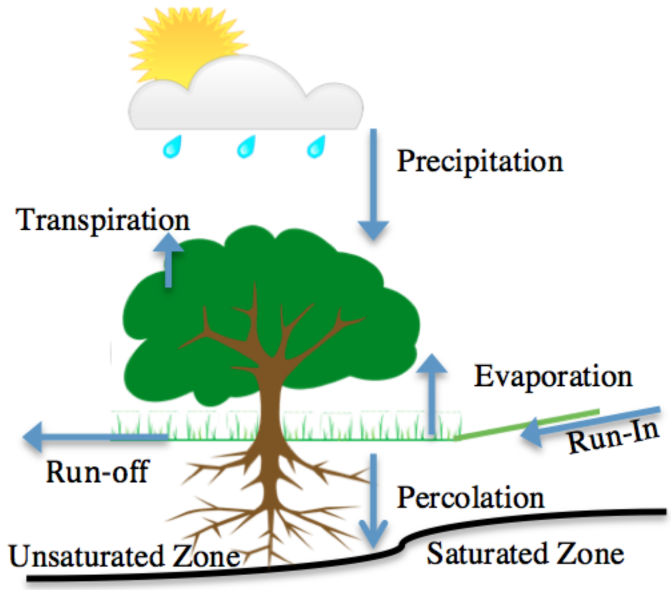


Figure 2.2: Hydrology of Irrigation: Processes and Soil Zones

[117]:

$$\frac{\partial m}{\partial t} = P - E - T - R - D \tag{2.1}$$

Soil

The principal ingredients of soil are clay, sand and silt; hence, soils are categorized by the percentage amount of the soil's principal components. The soil composition triangle is also used for identifying and mapping of soil types see Figure 2.3.

Soil is usually abstracted into two zones: saturated and unsaturated. Unsaturated is the zone where water content is much lower the water holding capacity of the soil, whereas saturated is the zone where water is more than the holding capacity and soil is acting like a permeable material in the water flow, this zone is usually in the lower layers as Depicted in Figure 2.2. Darcy's law and Richard's equation describe the flow of water in permeable materials such as

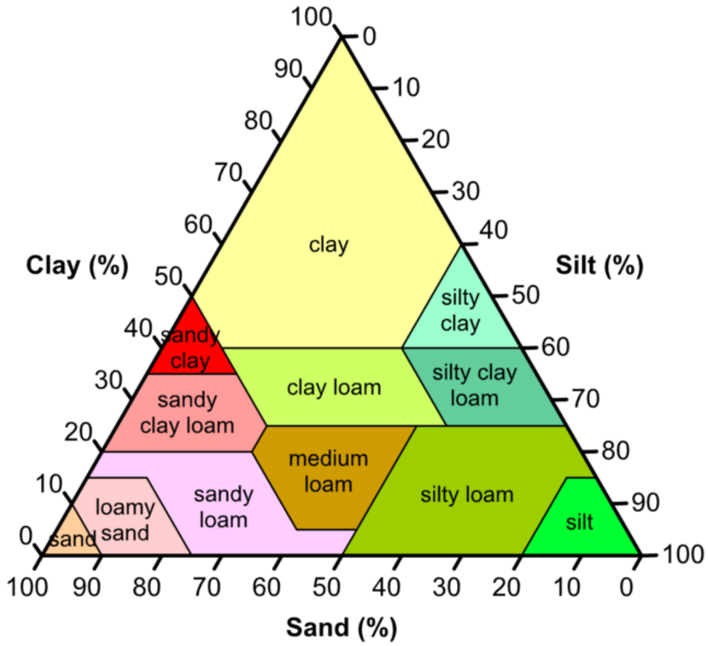


Figure 2.3: Triangle of Soil Composition [141]

soil, respectively, for saturated and unsaturated soil. According to Darcy's law, water flux $q(m/s)$ is proportional to the gradient of water potential and the coefficient of proportionality is the water conductivity coefficient.

According to [81], Darcys Law states:

$$q = K(\psi)\nabla\psi \tag{2.2}$$

This can also be rewritten in the analogous form:

$$q = \frac{KA(\psi_2 - \psi_1)}{L} \tag{2.3}$$

of Ohm's Law [61]:

$$I = -\sigma A(V_2 - V_1)/L = V/R \tag{2.4}$$

On the other hand, Richard's Equation (2.5)[60] represents the flow of water in unsaturated soils.

$$\frac{\partial\theta}{\partial t} = \frac{\partial\theta}{\partial z}[K(\theta)(\frac{\partial\theta}{\partial z} + 1)][60] \tag{2.5}$$

This nonlinear partial differential relation does not have a closed-form analytic solution, but can be expressed as:

$$\theta(z,t) = \textstyle\sum_n^\infty (A_n e^{-\alpha_n^2 Dt} cos\alpha_n z + B_n e^{-\alpha_n^2 Dt} sin\alpha_n z) \tag{2.6}$$

and approximated as [60]

$$Q(t) = Q_0(1 - \frac{8}{\pi^2} e^{-(\frac{\pi}{2L})^2 Dt}) \tag{2.7}$$

Infiltration

Infiltration of water to soil also doesn't happen instantaneously and depends on the soil type. Infiltration is important for understanding heavy storm-water capacity that can be stored in soil without overflow and designing appropriate discharge infrastructures. Among many empirical equations notable ones are the Kostiakov's and Horton's equations.

One of the earliest, equations is the Green and Ampt (1911) equation:

$$i = i_s + \frac{b}{I} \tag{2.8}$$

Whereas Kostiakov's (1932) equation says [60]:

$$i(t) = Bt^{-n} \tag{2.9}$$

According to Horton's (1940) equation [60], infiltration is described in soil physics literature as:

$$i(t) = i_c + (i_c - i_0)e^{-kt} \tag{2.10}$$

Philips equation (1957):

$$i(t) = i_c + \frac{s}{2t^{0.5}} \tag{2.11}$$

Holtan's equation (1961) [61]:

$$i = i_c + a(C - I)^n \tag{2.12}$$

Evapotranspiration

Evapotranspiration (ET) is the combined measure representing evaporated water from soil and transpired water from plants. It can be calculated with Penmon-Monteith method [34] ET_0 (see equation 2.13) and has been adapted by UN for estimation of reference ET. In this method, ET_0 is periodically updated and remotely calculated measure of evapotranspiration for the turf and is used to estimate crop factor for evapotranspiration ET_c by using developed crop constants (see equation 2.14), e.g. for wine grapes it is 0.35 initially, mid season 0.7, and ends with 0.4 at harvest [34].

The Penman-Montheith Combination Method, see Figure 2.4, uses information such as wind speed at 2m, grass length of 12cm and analytical equations 2.13 to estimate a reference value of ET namely ET_0 for estimating crop specific ET factor (ET_c, see Equation 2.14).

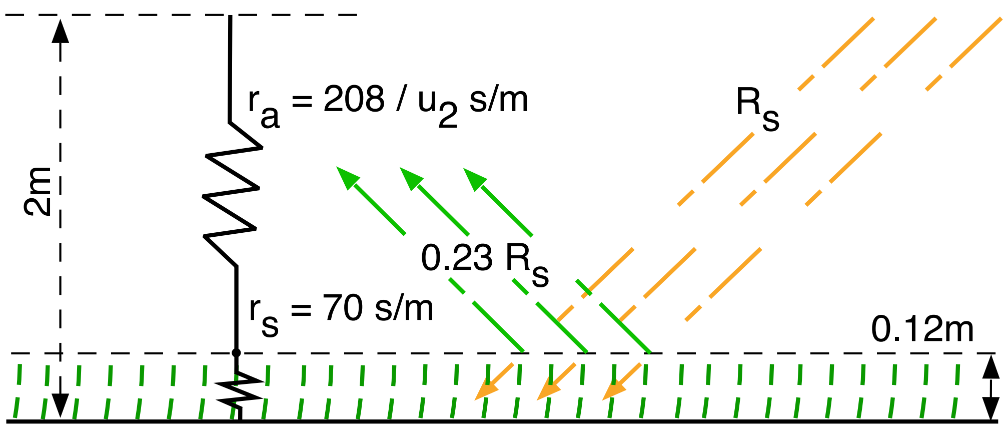


Figure 2.4: Penman-Monteith combination method

The California Irrigation Management Information System, CIMIS [20], web service that utilizes sensor stations deployed in California provides periodic estimates of ET_0 by zip code. Similar services exist around the United States, however, due to low resolution, estimates can significantly vary in field. Hence, the ET_0 measurements are intended as reference points and cannot be the sole measure for irrigation decision calculations.

$$ET_0 = \frac{0.408\Delta(R_n - G) + \gamma\frac{900}{T+273}u_2(e_s - e_a)}{\Delta + \gamma(1 + 0.34u_2)} \tag{2.13}$$

$$ET_c = K_c ET_0 \tag{2.14}$$

2.2.4 Related Work

While multi-domain, multi-physics modeling approaches and tools could in principle be used for modeling both man-made and natural systems, the scale of most irrigation systems limits the usability of such tools. For example, the work in [143] describes how complex system analysis can be adopted to the irrigation system at a scale that is not captured by available tools, such as Hydrus [113] and Comsol multi-physics [23]. Nevertheless, the work offers a turf simulation model with 60000 mathematical equations and 900 constraints.

On the other hand, circuit inspired models are not new and have been used in the past to address research challenges associated with heating and hydrological modeling. For example, researchers have used the event based scheduling of radiant systems by using circuit inspired thermal models. This model used electro-thermal analogy to model heat storage and exchange between water in the radiant system and the building zones [13]. Moreover, researchers have used another analogy, the hydro-electric analogy, to develop groundwater hydrologic models [144].

2.3 Materials and Methods

To properly explore and demonstrate the circuit-inspired modeling method, we share our work on man-made and natural/physical phenomena to demonstrate the robustness of the modeling framework. Generally, when modeling physical systems and processes, it is difficult to bridge qualitative description with quantitative evaluation. However, it is easy to notice the similarities between different domains, which express knowledge. We illustrate this task through two examples: water transport in the soil (a natural phenomenon) and irrigation valve (a man-made artifact). To validate the domain fusion translation and fusion approach, we conducted a series of experiments from in-lab to field.

2.3.1 Proposed Approach

In some simulation environments, such as Ptolemy, domains are differentiated by regions, which are governed by a single director. Moreover, hierarchical compositions use continues time models with domains such as finite state machines and (partial) differential equations for modeling hybrid system models. Thus, by conventional approach each domain is assigned to a single model of computation which are implemented by directors [28].

In applications, such as irrigation systems, modelling of the entire system is challenging as all physical processes are interacting with one another across the entire space. This is due to complexity associated within physical models, which are heterogeneous: multi-domain and multi-physics. One of objectives of the simulation models is to hint about the current state of the system given the initial conditions and time passed. In particular, irrigation system simulation models would hint to make optimized decisions: when to irrigate and by how much.

We believe that melding multiple domains into a single substrate will avoid complexity explosions in Cyber-Physical Systems model development. Unlike multi-domain multi-physics models, an equivalent single domain model will avoid inter-domain complexity explosions by complexity reduction prior to simulation without significant losses of fidelity, see Figure 2.5.

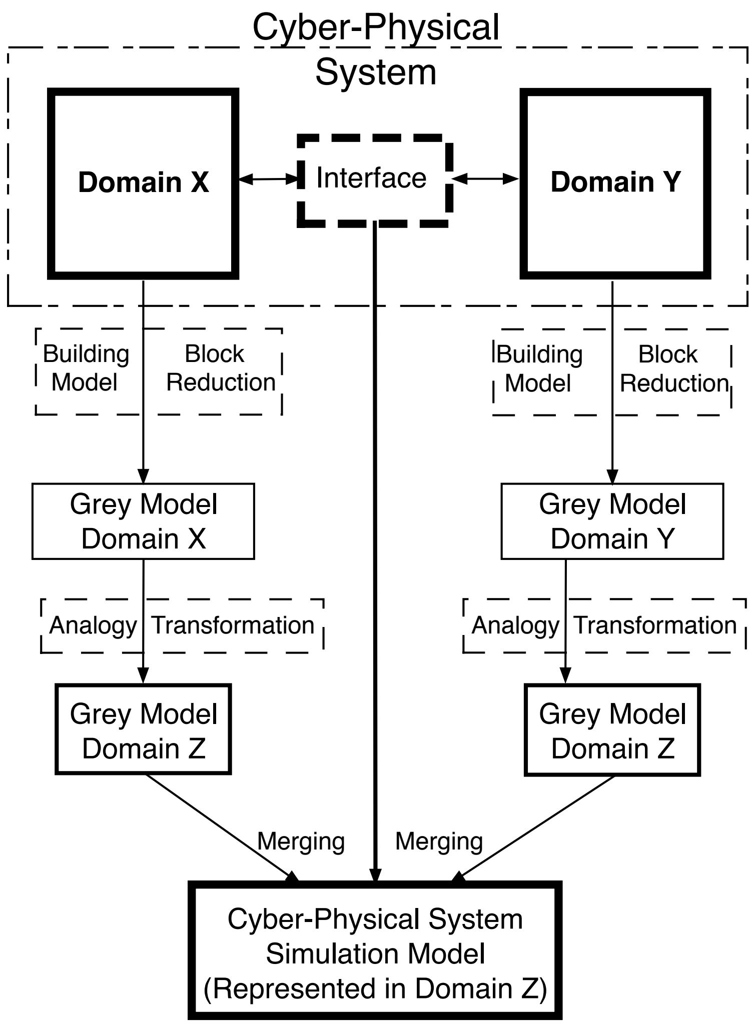


Figure 2.5: Melding of Multiple Domains to a Single Domain Simulation Model in Detail

Analogies of fundamental scientific modeling approaches are found in thermal, electrical, mechanical, hydraulic and acoustic domains. These analogies, e.g. Table 2.1, have congruent mathematical representations [110][106][124], thus, allowing researchers to use representation of one domain's physics in another domain's model. In past, cross-domain analogies were applied to model different physical processes by one mathematical model (see Figure 2.6) [60]. This idea of equivalencies or similarities, can be used to convert multiple simulation processes

Electric	Hydraulic	Thermal	Mechanical
Charge	Water Volume/Mass	Vibration	Mass
Current	Discharge	Rate of Heat Conductance	Force
Potential Difference	Potential Difference	Temperature Difference	Velocity Difference
Capacitance	Storage Heat	Capacitance	Inertance
Resistance	Transfer	Resistance	Resistance
Earth	Sea	Atmosphere	Immobile
Generator Element	Pump	Heat Source	Generator

Table 2.1: Analogies Between Electric, Hydraulic, Thermal and Mechanical [110]

into a single domain simulation with use of the mathematical models. Thus, we propose the following framework where domains with their physical processes is to be transformed into a single-domain simulation model, which encompasses multi-physics nature of all domains, and conform or integrates interfaces of the original domains (Figure 2.4).

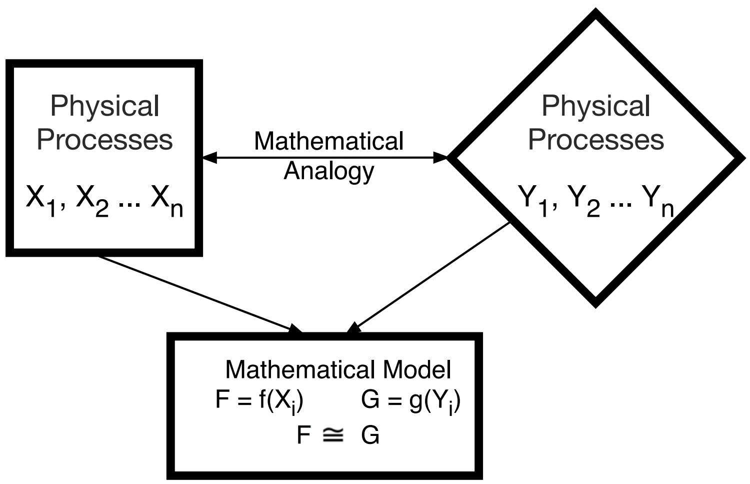
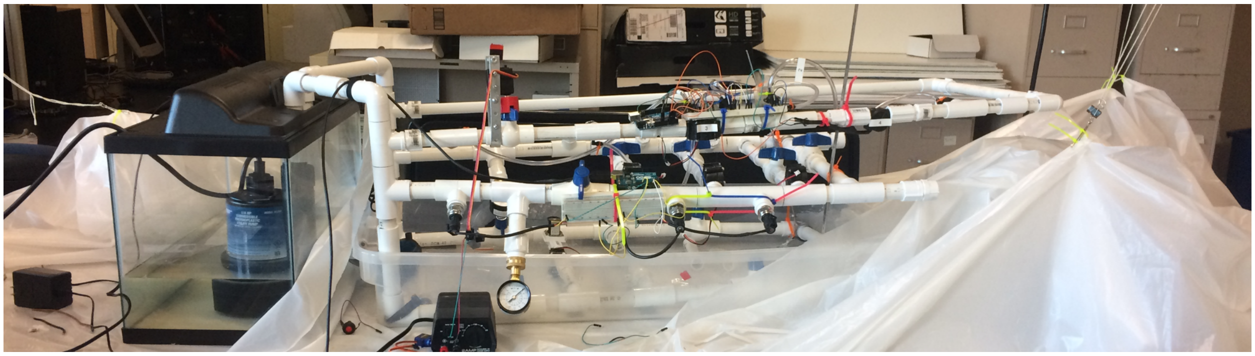


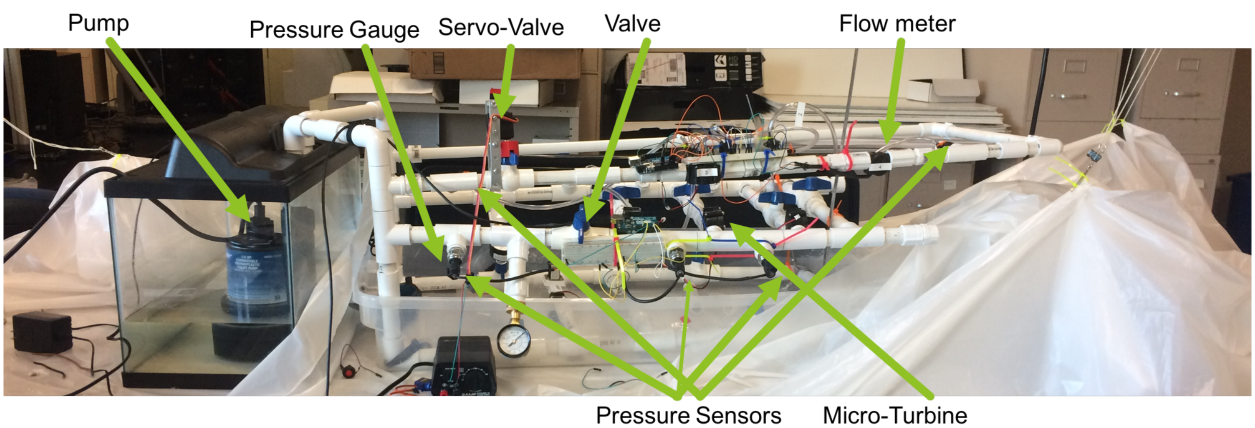
Figure 2.6: Analog models: Same mathematical model is used to describe two completely different physical processes

2.3.2 Experimental Setups

In our hydroponic laboratory setup, we used different components to study their hydraulic properties. This is where we devised the hydro-electric analog switch model as depicted in Figure 2.12 with resistive capabilities to allow conforming with characterization of different types of hydraulic valves. This setup has different pressure and flow meters as analogous to current and voltage sensors in an electrical circuit, see Figures 2.7a and 2.7b.



(a) System Setup



(b) System Breakdown

Figure 2.7: Hydroponic Experimentation Setup (a) and System Breakdown (b)

We have conducted our final experiments in the field, where sensors monitored moisture changes in the soil. Throughout the study, there were 6 irrigation events and 1 precipitation event. A data set gathered from outdoor soil moisture sensor in a 16-day duration with 15 min sampling period.

2.4 Model Development

Although the goals of irrigation practices depend on specific needs, such as greenness of the turf or sweetness of grapes, all irrigation systems are affected by physical phenomena. The science behind these phenomena is not new and is quite well studied, however, quantitative models that can be integrated with other systems do not exist.

2.4.1 Circuit Inspired Physical Modeling

Our approach to modeling physical processes is to use existing hydroelectric analogies [144], which have been developed to model complex systems nature of hydrological processes (see table 2.1). In this work, we show how to use this circuit inspired method for irrigation systems modeling.

Equation 2.1 demonstrates how one would approach studying hydrological systems with respect to soil. Moreover, if we add irrigation to the picture, as in Equation 2.15, the result changes by the addition of I, the irrigation component. These equations are similar to Kirchhoff's laws of conservation of charge in the circuit, where current at any junction can be accounted for by all components. Hence, on the surface we can visualize every soil segment as a junction of conductors and in this junction current will flow in the direction as appropriate to the phenomena.

$$\frac{\partial m}{\partial t} = P - E - T - R - D + I \tag{2.15}$$

In fact, these phenomena can be reduced to a single junction of a soil segment in the unsaturated zone as illustrated in Figure 2.8 under the assumption that to prevent run-

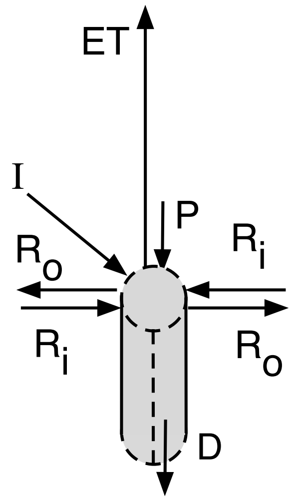
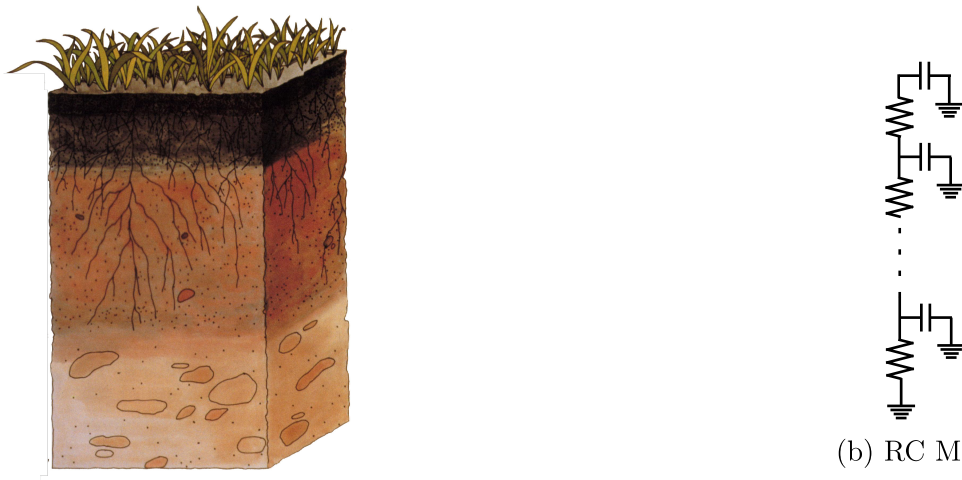


Figure 2.8: Hydrologic Processes on Single Segment of Soil

off/run-in have been taken by users/farmers. Otherwise, the development of the model would integrate the segments of soil by surface connections in a 2D plane, which can be done by using transfer components such as resistors. The interconnected circuit then would represent the entire field as opposed to a single lot.

To model water transport in soil, we note that Darcy's law and Richard's equation do not have closed form solutions; thus, we chose to model and simulate the phenomena using electrical circuit components. To expose the underlying soil physics, we modeled vertical segments of soil as layers of water storage (capacitive), and transport (resistive) components. Thus, water transport in soil can theoretically be modeled as an infinite series of resistors and capacitors. Depending on the granularity of the modeling, the circuit in Figure 2.9 can be expanded vertically to model the different soil layers. Although we cannot know exactly the values of the resistances and capacitance of the infinite series at every instance in time, we will describe a lumped estimation method, which is known in the electromagnetic transmission line model, or mathematical cable theory.

In a similar manner, evapotranspiration can also be modeled as a resistor whose value depends on factors such as temperature, wind and other phenomena as reflected in Equation 2.13. It



(a) Soil Layers

(b) RC Model

Figure 2.9: Soil Layers and Analog RC Model

can also be learned and inferred using historical data for simplicity.

Optimization

In order to find the best model structure and parameter values we used mixed approaches from design parameter tuning using Mean Squared Error (MSE) as the loss function and Machine Learning approach of differentiating data into training and testing data sets. While design parameters were being tuned on train data, test data was used to pick the best model order, in the presented findings, for example, model order of 3 was the best one (see Figure 2.10). An example of the design space tuning is presented graphically in Figure 2.11.

2.4.2 Man-made Systems Characterization

The circuit models can factor in man-made artifacts using design characteristics. Specifically, we looked at the typical infrastructure of irrigation systems. The system is composed of pipes, valves and emitters. We can think of a water pipe as conductive connection, but valves, header and emitters are not as simple. The most commonly used ball valves are essentially

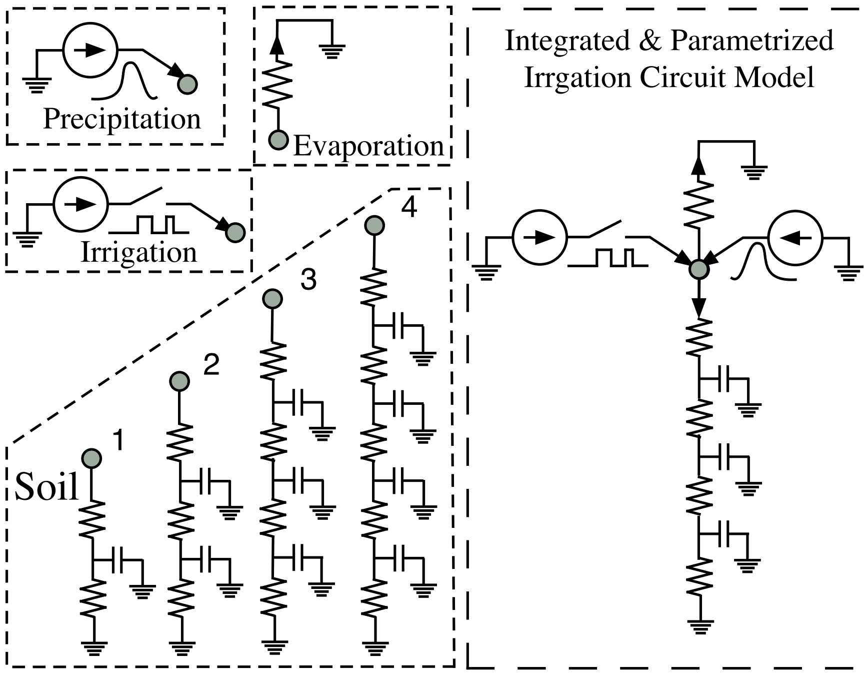


Figure 2.10: Irrigation and Soil Lumped Model Evolution

binomial state objects with open and close states. However, the process of switching between open and close states can create a resistance to water flow. Thus, if the switching is slow or uses perforation diameter changes between different open states, a variable resistance must be used to capture this flow resistance as depicted in the Figure 2.12a.

2.5 Results

To turn these analogous representations into models, we conducted several experiments and studies. To show predictive accuracy, we utilize existing techniques, optimization and time series decomposition, respectively, for natural systems (soil) and man-made systems (pump, valve).

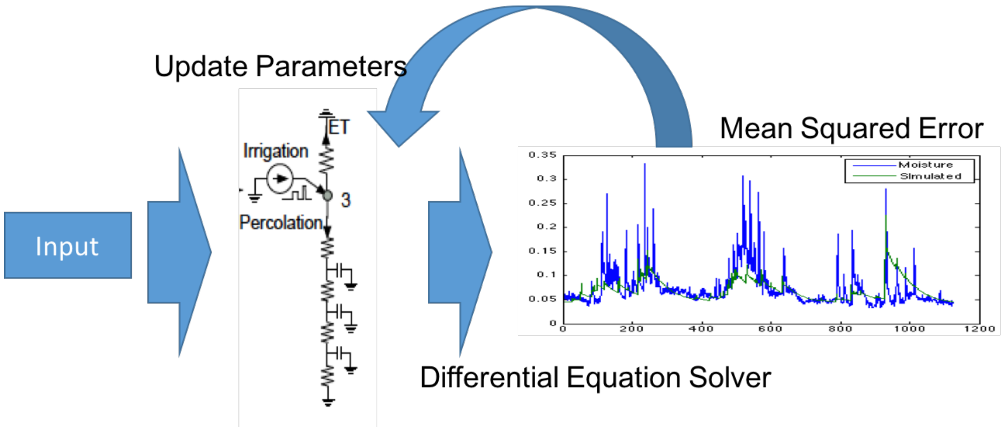
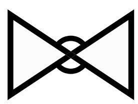
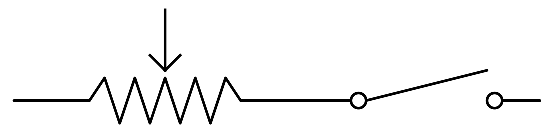


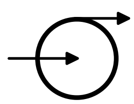
Figure 2.11: Single Optimization Step



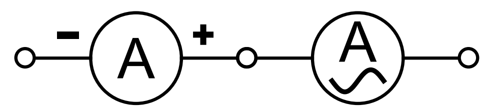
(a) Hydraulic Valve



(b) Electric Valve



(c) Hydraulic Pump



(d) Electric Pump

Figure 2.12: Hydroelectric Analog Models

2.5.1 Manmade - Pump and Valve

Parameter estimation approaches differ by models. Man-made artifacts can usually be characterized. Indeed, data-sheets of irrigation components can be used as a starting point. Augmented with characterization experiments as many of these models and evaluation tools are already developed by the institutes such as the Center for Irrigation Technology [100]. Thus, it is possible to derive accurate and stable electrical analog models of such components.

For example, we experimented with a 1/4 horse power water pump. In the experiment, we collected data over different resistance to the flow obtained by opening and closing a ball valve. We see in Figure 2.13 how flow rate changes over time, yet, pressure has a very steady response. This observation means that we can model a pump as composition of a DC and an

AC source. Thus, by looking into pressure frequency response the signal can be decomposed into the DC, which is the mean over time, and AC series, which are sinusoidal parts of the signal; and the remaining fits a Normal Distribution. Thus, we can effectively think of this man-made water pump as a combinational composition of electrical power sources as depicted in Figure 2.12d. Of course, in many cases such as the presented model, AC part may be small in comparison to the DC, and so it can be further simplified as just a DC source.

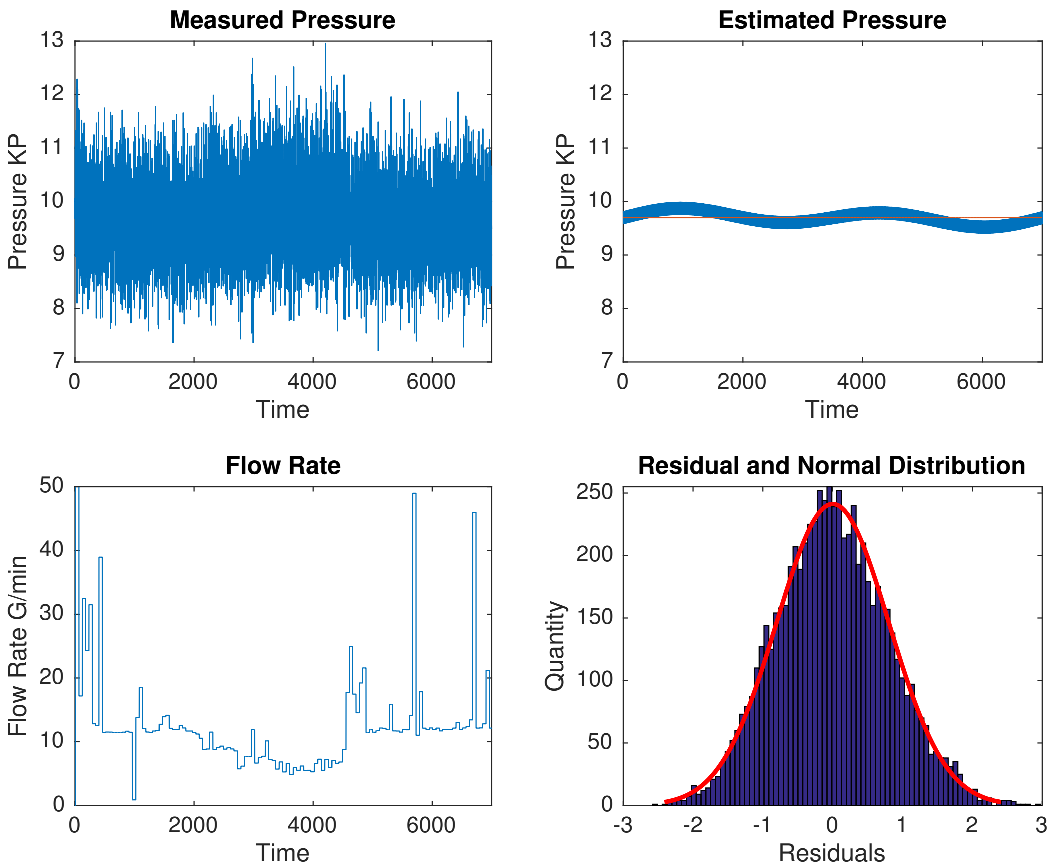


Figure 2.13: Pump Experiment Outcomes

2.5.2 Nature Made - Soil

Natural phenomena, on the other hand are much harder to characterize due to the fact that their physics are much more complex and they are also influenced by many other phenomena that are themselves much harder to predict. Furthermore, these phenomena are also time varying with a multitude of epoch due to daily, monthly or seasonal fluctuations for instance. For example, the soil water transport phenomena is possible to model using different levels of RC circuits as shown in Figure 2.10. In essence, all these circuits are low pass filters of different orders. It becomes a matter of choosing which filter and what parameters to pick for the different RC values. In order to accomplish that, we use a learning algorithm, which uses past precipitation and soil moisture data to tune and evolve the model complexity starting with a single layer of storage. First, the simplest form of a circuit is chosen with a pair resistive and capacitive elements as the basic building cell, which represent transport and storage moisture in storage, connected to a current source. we can think of addition of water to soil surface as analog to addition of current in electrical circuit, hence, the current source and not a voltage source is used. This qualitative model is then randomly initialized and optimized for fitness with respect to target or observed moisture data. If the result fits the desired outcome, then this process ends, otherwise a new set of resistors and capacitors is added and evaluated following previous steps until results fit desired criteria.

The data presented in Figure 2.14 shows the soil moisture measurements, where spikes indicate irrigation events and the last (smaller) spike is due to a precipitation (rainfall) event. In the modeling phase data was split into training and validation sets, where the training data was used to (1) determine which soil model in Figure 2.10 is best fit, and (2) estimate the corresponding R and C values of that model. Validation results show that model order 3 (Figure 2.10) has the best fit of experimental data with $R^2 = 0.923$(Figure 2.14). Thus, this ODE based simulation methodology describes transient behavior of vertical moisture transport in soil.

As irrigation and precipitation have similar impact on soil, they increase the water content. Similarly, in electrical circuits, current source adds a predetermined amount of charge per unit time just like the sprinklers, furrows and sprayers do. Hence, irrigation events can be modeled with the current source (Figure 2.19a) with controllable impulse train.

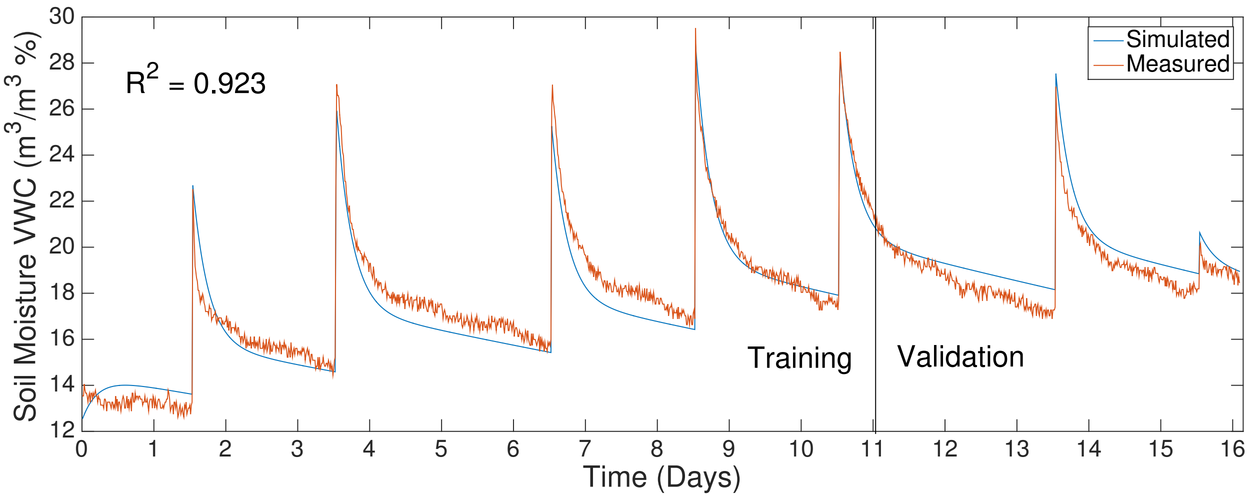


Figure 2.14: Soil Moisture Simulation Training and Validation Data

2.6 Qualitative Implications of the Method

In this section, we will introduce some of the future directions in further melding of domains related to irrigation systems. The presented ideas will have mostly qualitative nature, but is envisioned that the presented method could as well apply to quantitatively evaluate these as well.

2.6.1 Hydraulic Microturbines

The future irrigation systems will include more exotic parts such as microturbines to power distributed irrigation systems. One of the reasons that turbines are particularly important for the study of hydroelectric analogy is that turbines are devices that convert the hydro energy into an electric energy. In theory, this transfer of energy can indeed be captured by circuit components, as the water flow through a turbine can be qualified as a flow of electrons in an inductor. If this is true, and we can fit this complex process of flow and energy conversion into a single parametric circuit, then the opportunities for design space exploration of irrigation systems can be even further studied.

To that end, we have studied how a conventional micro-turbines operate and are structured as depicted in Figure 2.15. The essential mechanical components of any micro-turbine are turbine, shaft, rotor and the enclosure. Rotor includes the magnet that interacts with airfoils to generate electrical alternating current due to the rotation or the changing magnetic field. These coupled coils than are connected with an electrical circuit that converts into the desired output.

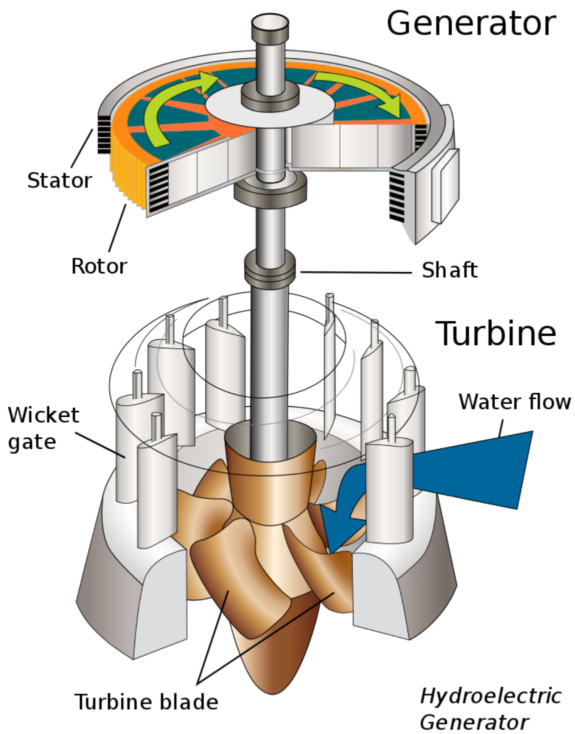


Figure 2.15: Micro-turbine Skeleton [127]

In our experimental micro-turbine, the converter circuit delivers Direct Current (DC) power. To achieve this, we present a basic buck converter schematic in the Figure 2.16, which is connected on one side to the rectifier and on the other side to a load. Therefore, rest of the circuit is well known and studied and can be now even further analyzed within the irrigation setting.

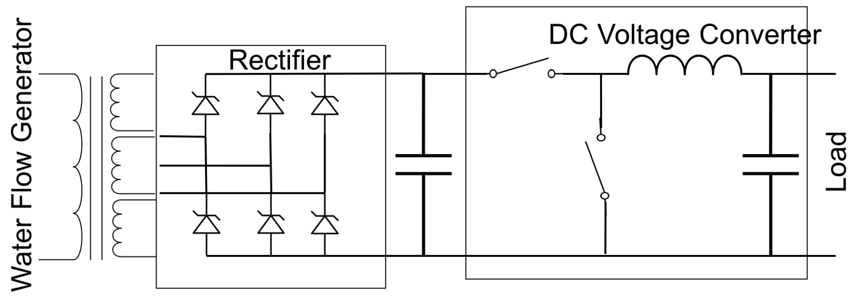


Figure 2.16: Micro-turbine Electrical Circuit of DC Power Supply with Hydrological Inductive Component

2.6.2 Flow in Pipes

Although, we have so far assumed that the water flow in pipes is much like the electron flow in ideal conductors, it is not without resistance to flow. In fact, Hagen-Poiseuille Equation 2.16 describes the relation of the pressure drop across its length and width of the pipes diameter. This is indeed something can be parameterized as non-ideal resistors utilizing Ohm's Law and can be omitted in calculation when it is insignificant much like in other electrical circuits. We will see more on the use of this in Chapter 4.

$$\Delta P = \frac{8\mu LQ}{\pi R^4} \tag{2.16}$$

2.6.3 Electromagnetic Wave Propagation in Wireless Communication Channels

Another interesting aspect of analog models is found in the electromagnetic domain, where we know that exists a method of effectively modeling propagation electromagnetic of waves through wireless channel [78]. One such model that is widely used is the transmission line modeling. The essential building block of the transmission line is made of the basic RLC circuit blocks as depicted in Figure 2.17.

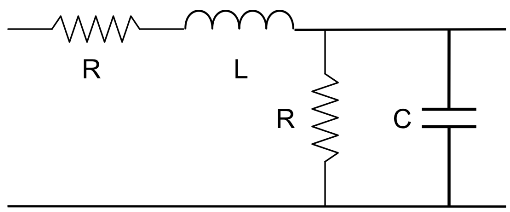


Figure 2.17: Transmission Line Cell Comprised of Series and Parallel Rs for Resistance, L for inductance and C for Capacitance.

Whats more fascinating is that transmission line model has again very similar infinite series of the cell component (see Figure 2.18). Although, this transmission model much like the soil model presented earlier is comprised of infinite series, but it can be approximated by using only few elements. There are extensive studies done to derive best approximation models for different medium and different signal properties [78].

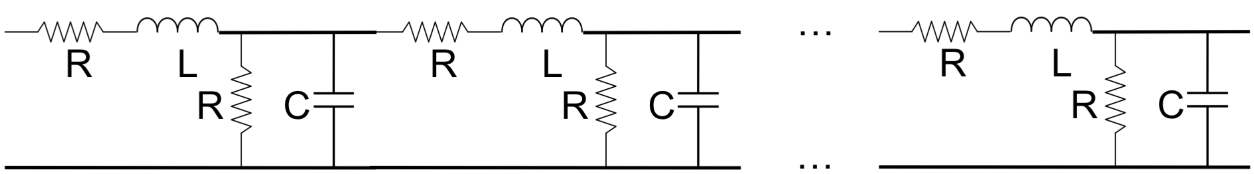


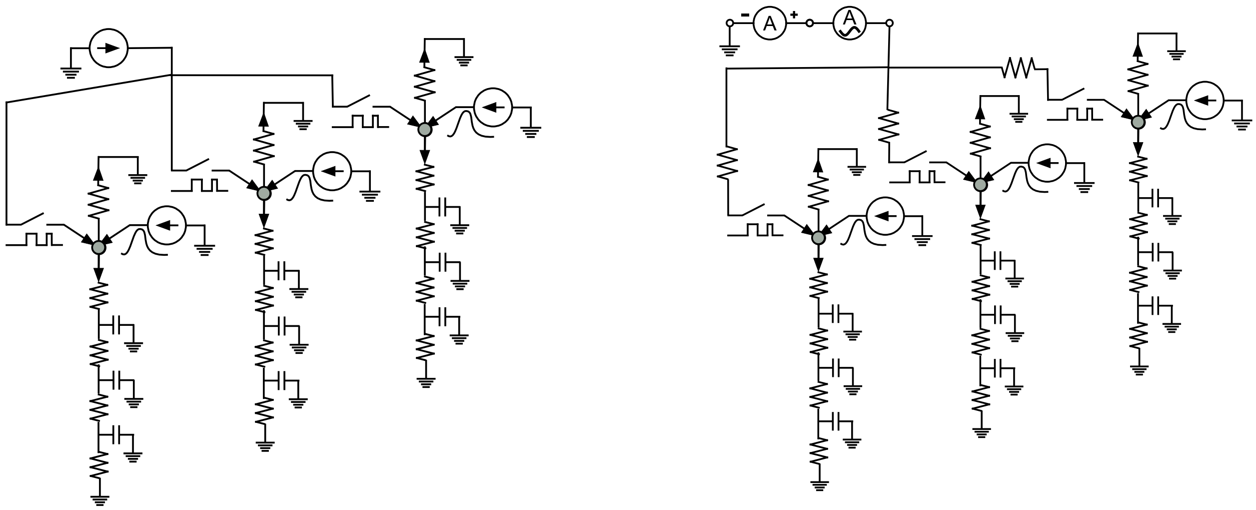
Figure 2.18: Transmission Line Model Comprise of Infinite Transmission Line Cells. One end is usually connected to the transmitter and the other connected to the receiver.

2.7 Discussion of the Method

Once models have been developed for all the relevant components, they must be integrated in one single model. There are several issues to be considered at this point. First, the granularity of the modeling must be decided. As in many different domains, one can trade-off accuracy of the model for computational efficiency (or memory footprint). The circuit-inspired modeling is ideally suited for this trade-off where one can represent different subsystems using lumped or distributed models. One of the determining factors is the nature, accuracy and resolution of sensing devices. Remote sensing, for example has a limited resolution (about 1km x 1km) and therefore components sensed by this method must be coarsely represented while *in-situ* sensors have a much finer resolution and would therefore be represented using more complex equivalent circuits. However, there may be a limited number of these sensors and that may limit the granularity of the equivalent circuit. In between these is *proximal sensing* which has a fine resolution (e.g. drone-mounted thermal imaging of canopies), but a limited sampling rate. All of these factors must be taken into consideration when building the equivalent circuit models. Figure 2.19 shows as an example, models of hydrology: evaporation, precipitation and soil water transport are integrated with pump and valve models to form a scalable electric irrigation circuit.

While this extensive analogy may be attractive at first sight, one must be cautious as there is some disconnect between the two domains (hydrology and electricity) : (1) Fields: water waves travel at the speed of sound while electrons travel much faster and drag other electrons, and (2) leakage in pipes results in change in water volume while charge remains mostly constant in an electric circuit. Thus, it may be wiser to keep the component repertoire to basic elements such as resistors and capacitors with only a few exceptions.

Variability is another key issue to be considered. Even when parameters are estimated, there is variability in those estimates, as well as in the input data. Variability awareness in these



(a) Multiblock Irrigation System (MIS)

(b) MIS with Added Valves and Pump Models

Figure 2.19: Irrigation System Model for Distributed Control

systems is similar to what electronic circuit simulation face today when component models are becoming more statistical in nature. Sophisticated Monte-Carlo methods have been developed and built into simulators such as SPICE to efficiently simulate large circuits with variability. In fact, SPICE allows most component parameters to be designated as random variables and will automatically spawn a user-specified Monte-Carlo sampling during simulation.

Unlike most Cyber-Physical Systems where software intermittent delays may be critical, irrigation systems have longer periods of control. That said, in future irrigation system models could use software and computational cost models as well.

2.8 Conclusions

In this paper, the objective was to demonstrate ways one can utilize circuit models and simulators for use in the water system such as irrigation system modeling. We hope that our results will be encouraging for practitioners to support circuit inspired modeling method for precision irrigation and will yield efficiency improvements in water use.

Chapter 3

Monitoring Vineyard Irrigation Performance with Internet of Things Enabled Multi-depth Tensiometer Sensor Stations

3.1 Abstract

Internet of Things integration with Precision Irrigation practices brings Internet enabled Irrigation Monitoring. Fully monitoring Irrigation systems entails monitoring from water source to applicator and even plant uptake. In this chapter are presented our observation on a multi-year case study conducted in vineyard irrigation setting. During this study, we aimed to understand and expose modern challenges of precision vineyard irrigation systems and how to use existing technologies such as Internet of Things to empower vineyard management in terms of water productivity. We have learned that precision monitoring tools are an effective

method for preventing over-watering and under-watering. In fact, our results show that IoT using monitoring tools with 87% confidence reduces water usage, and in some cases saves up to 33.8%, while improving overall performance.

3.2 Introduction

Limited water supply is the new norm for agricultural practice and it cannot be ignored. In the past, irrigation science was solving the water deficit in soil, but today global fresh water shortage is imminent and irrigation water supply is at a deficit [125]. To mitigate the impacts of imminent global water shortage and intermittent shortages such as droughts, water use needs to be monitored, appropriated and optimized. Therefore, there is an urgent need for science on how to irrigate under source-to-end water deficit from the water supply to the moisture in soil.

Water resources are managed by resource mandated organizations such as districts and are consumed by users such as farmers. Water suppliers are challenged to fulfill the demand under the infrastructure constraints, for example, regulating water pressure under intermittent water use, and applying pricing policies that are fair and encourage water conservation. However, water use optimization is also entrusted to the end users' judgment; however, the end user doesn't always have ability to gauge its own performance. For example, evapotranspiration (ET) reference estimate based irrigation is a widely accepted form of precision irrigation scheduling [34] which estimates the soil water balance deficit, but the ET reference of leaf area indexes is not enough to determine the best performance of the irrigation schedule for vineyard owners as ET has no relation with performance of irrigation, total cost of use and the return on water use investment.

Soil water balance is no more a "checkbook" problem as it was before [75] - soil is not a single "bank account", but a complex system. In a bank account, there are two processes, debits and credits, or respectively, deposits and withdrawals, similar to replenishment and loss of water content in the field. However, soil, weather and crop are not separate and independent variables: they are interlinked. The physical process linking water content changes is the tension: (widely accepted to be) a potential force that impacts water suction. State of the art complex system models use different techniques to represent and describe this physical process. With this in mind, water content management of large supply/demand constrained irrigation systems crosses boundaries of conventional models. Hence, novel contributions are required to deal with micro and macro irrigation management challenges.

In micro scale, quantitatively inferring gaps between demands of soil water tension and deficit water supply is needed, such as the amount and the frequency of irrigation, to fully take control of precision in irrigation systems. Conventional approaches to solving this in the past has brought about a circuit modeling approach to irrigation systems, which enables intertwining tension and content parameters in a single physical model [49]. However, even with a model in place, in order to apply precision irrigation, there must be a feedback loop guiding the control decisions.

In order to establish a feedback loop, the conventional approach to control systems uses sensing of parameters along side with models that make the system controllable and observable [80]. When it comes to irrigation systems, there are many different parameters from the infrastructure and environment to sense as the dynamic changes in the system are difficult to predict. There are two major source of parameters the infrastructure and the environment. For example, in the irrigation infrastructure parameters are water flow, supply line pressure [140], dripline emitter uniform flow rates [96], and many other parameters of interest. On the other hand, environmental parameters are ambient temperature, humidity, wind speed, solar radiation and etc [107]. Putting all of these metrics together one could make irrigation decisions. Thus, it is important to provide this information to the end users who is making the final decisions on irrigation schedules. The state of the art approach to providing access to data is by Internet enabled devices, which allow universal access to persistent data stored by remote computing services. This approach to monitoring is commonly referred as Internet of Things (IoT).

Although, the Internet can be utilized for precision of irrigation systems as a practice, the very existence of connectivity cannot be taken for granted in the rural and semi-rural settings. However, major internet service providers in the United States are moving to provide coverage for Internet of Things [120] [8] [135], which will fill an important gap between theory and practice.

3.2.1 Proposed Solution

In this work, study of Internet of Things based monitoring of Irrigation in Vineyards is presented. The central hypothesis of this work was trying to test whether Internet of Things based irrigation management can improve on key performance indicators such as water usage and whether this monitoring will have positive impact on irrigation usage productivity. In general, this work sheds light on multi-depth IoT monitoring impacts on irrigation practices. Presented here are findings and observations with regards to experiments conducted in Temecula Valley vineyards in collaboration with Rancho and Santa Rosa Water Districts and growers.

3.2.2 Prior Art

There are lots of empirical studies showing irrigation efficiency improvement by one or another technique, whether it is done by adding local evapotranspiration [101] or estimating targeted references [63, 6] as opposed to regional [20], improved control granularity control [143] or applicators with targeted watering patterns [89]. However, transition of these technologies into practice is hindered due to a number of factors, which is apparent from surveys conducted by USGS [102]. In fact, farmers are more inclined to trust their neighbors in making irrigation decisions than all advanced technologies already existing (Figure 3.1). On the other hand, with the turn of the past century the Internet went viral and enabled users to share even their personal information in virtual social networks. Similarly, irrigation could benefit from having larger shared ecosystem of users, who can proactively contribute and share their findings across geographies, crops/plants and practice norms. Something that users seem to be more inclined to do then install more advanced wetting front detector stations [119].

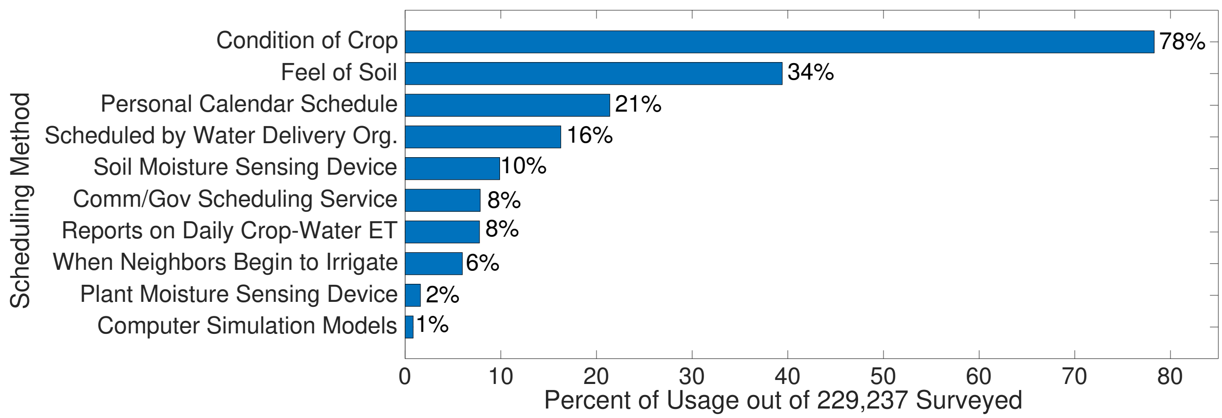
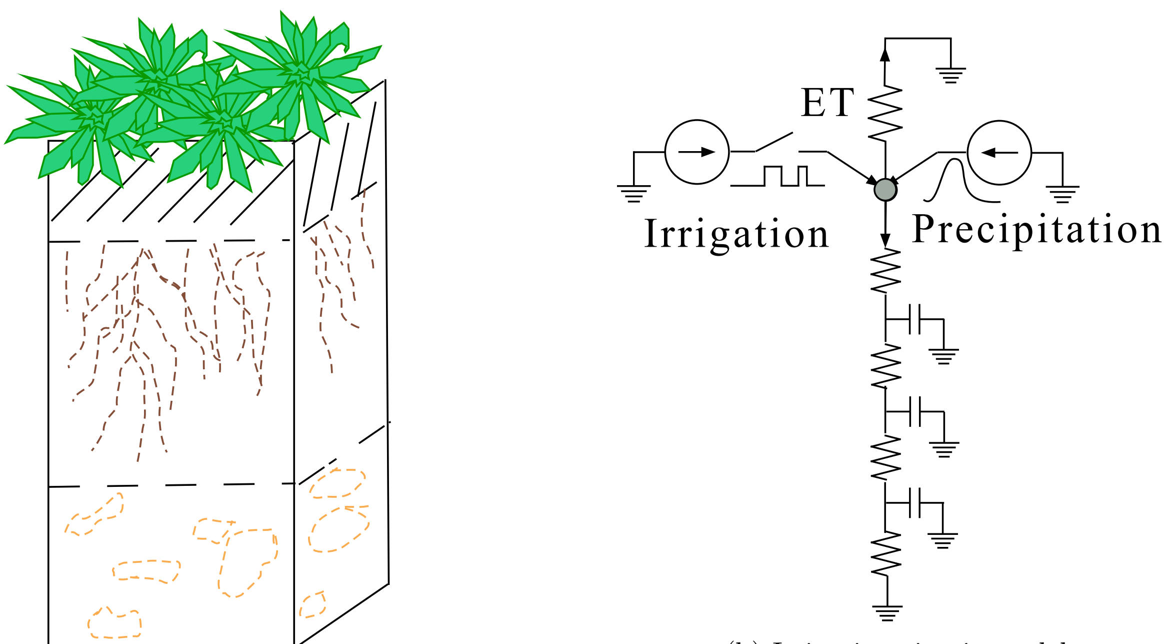


Figure 3.1: 2013 USGS Irrigation Survey on Methods Used for Irrigation [102]

Indeed, simulation show that site-specific adaptive control techniques can save significant water and improve the variability across fields [87]. However, to achieve this no study has been conducted to the best of our knowledge that shows that it is possible without using localized sensing techniques.

3.2.3 Prior Works: Circuit Models for Irrigation Systems

This experiment used multiple sensors around the active root zone to monitor the available water to the plants and below the root zone to detect percolation past the root zone as depicted in Figure 3.2a. This was motivated from the idea that by looking at the soil as a circuit model in Figure 3.2b starting from the ground level and moving down, a tension wave will pass down and can be controlled [49]. This is reflected in Figure 3.3, which was obtained using simulation of the soil water transport model in Figure 3.4 that shows that water moisture level is less varying at lower soil layers and at higher frequency of irrigation. This predicted behavior in simulation was verified by actual measurements at different soil levels shown in Figure 3.5, where higher resistance values stand for lower tension. The tension at deeper and shallower levels track reasonably well, and the deeper sensor tension levels looks like the moisture level at the shallower level.



(a) Soil

(b) Irrigation circuit model

Figure 3.2: Irrigation and Soil Circuit Model

In the design of Internet, every two computers are connected to routers, switches, hubs or base stations 3.6b. These base stations than route, hence the name, pockets of information to next station while effectively routing the shortest path between any 2 devices. This allows having low communication latency and elastic throughput. It is important to note that once devices are connected to the Internet via any base station, they are connected to each other.

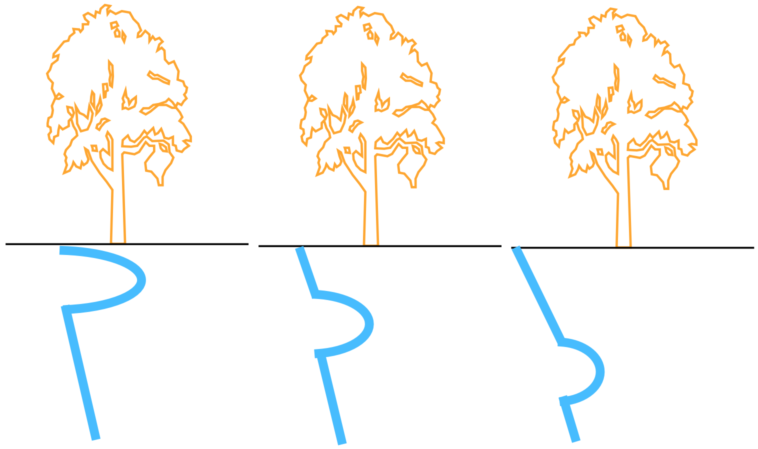


Figure 3.3: Soil Tension Wave Propagation Visualization

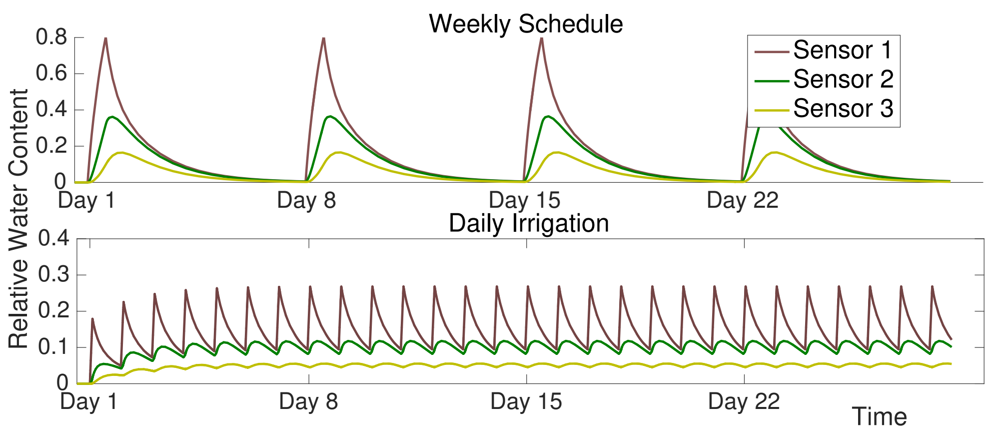


Figure 3.4: Irrigation SPICE Simulation

Thus, Internet of Things simplifies the inter-device communication, given that these devices can connect to any base station.

Originally, Internet was designed to be a wired network, where wires were the hard carriers of signal, but over time, it grew into mix of wired and wireless communication systems [147]. Wireless communication is one of the key components in our vision for the Internet of Things for Agriculture as large distance in fields require. In fact, significant work has been done in the science behind wireless sensor networks [95] and underground wireless sensor networks [138] to achieve the desired performance [55] while going as far as developing dedicated operating systems [67]. For example, there is significant work done to connect camera networks as a wireless sensor network

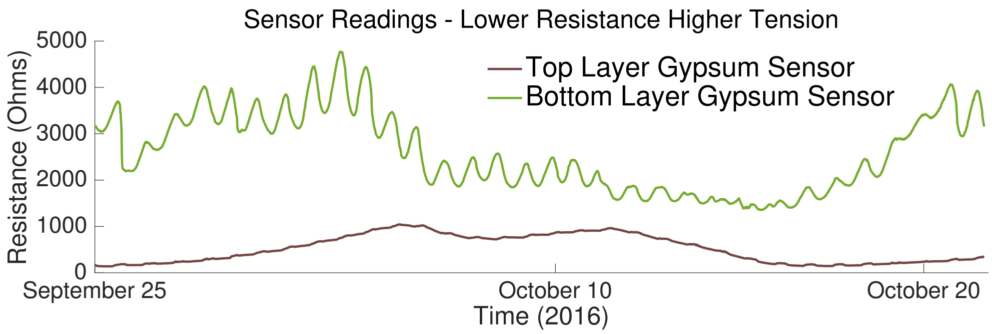
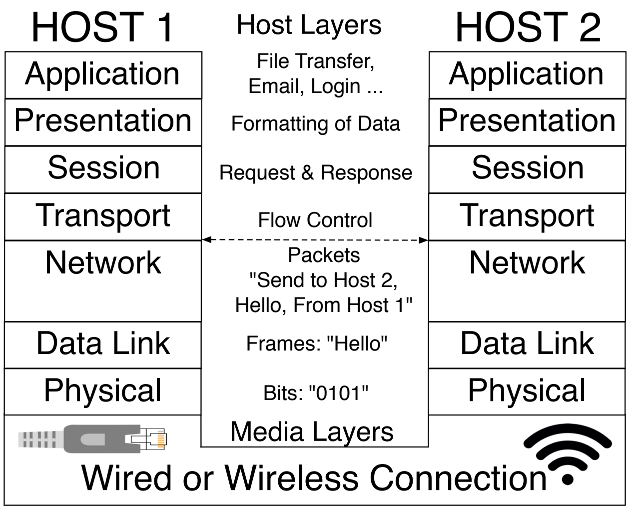


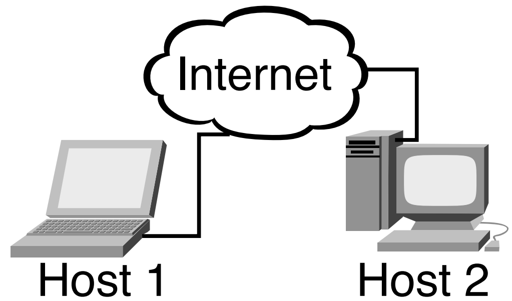
Figure 3.5: Sensor Measurements at 1 foot (Top) and 4 feet (Bottom)

[77] to detect pest control issues, damages and health risks. In fact, many communication protocols have been developed to address challenges associated with information flow in the networks, for example, Zigbee [73] and Bluetooth [59].

Internet is the magical tool that connects devices in a way that you can access information from anywhere. Everything is organized in layers of abstraction, which utilize rigorous scientific methodologies. Basic transmission of modulated signals is used to transfer bits of data from point A to B. This layer is called the physical layer (Figure 3.6a). On top of this layer, is the data link layer. Each pocket of information is communicated independently and in isolation in the physical layer. This is the layer that actually handles transmission of information. The layer above is the Network layer. In this layer, information exchange is handled between the nodes on the same network. However, it is in the Transport layer, that one of most important decisions was made, which allows devices to be far closer to each other. The approach was in a hierarchy that allows connection of different small networks to other networks by Internet Protocol Addressing, a unifying mechanism that allows to make logarithmic (with respect to the total count of devices) hopes between devices as depicted in Figure 3.6b. Up the ladder of these communication layers as depicted in the Figure 3.6a, information exchange is used for cohesion and unification of systems into the *network of networks*, the Internet.



(a) Internet Protocol Stack



(b) Internet

Figure 3.6: Internet of Things Foundamentals

3.3 Materials and Methods

The traditional irrigation practice for vineyards is a weekly long soak [114]. However, long irrigation drains deep in the soil, whereas short irrigation causes majority of irrigated water to stay at higher levels [145]. Thus, irrigating once a week, and replacing the weekly amount of water in one irrigation cycle, applies more water than what can be used in one or two days. The surplus of water will drain deeper and eventually become out of reach of the active roots. Unlike popular belief even for plants with long roots, like grapevines, most of the actual uptake of water takes place at shallow soil levels (up to 4 feet) [115]. Draining excessive water washes fertilizers away - reducing fertilizer efficiency and polluting aquifer [18] . Irrigating more frequently, e.g. daily, precision of irrigation can be improved to closely follow the (daily) evapotranspiration transient needs. The main goal is to supply the precise amount of water needed and have it delivered only to the soil layers with the active root system, where uptake is stronger.

Rancho California Water District is located in Southern California's Temecula valley, which is famous for its wineries and vineyards. The Temecula Valley climate is characterized by a

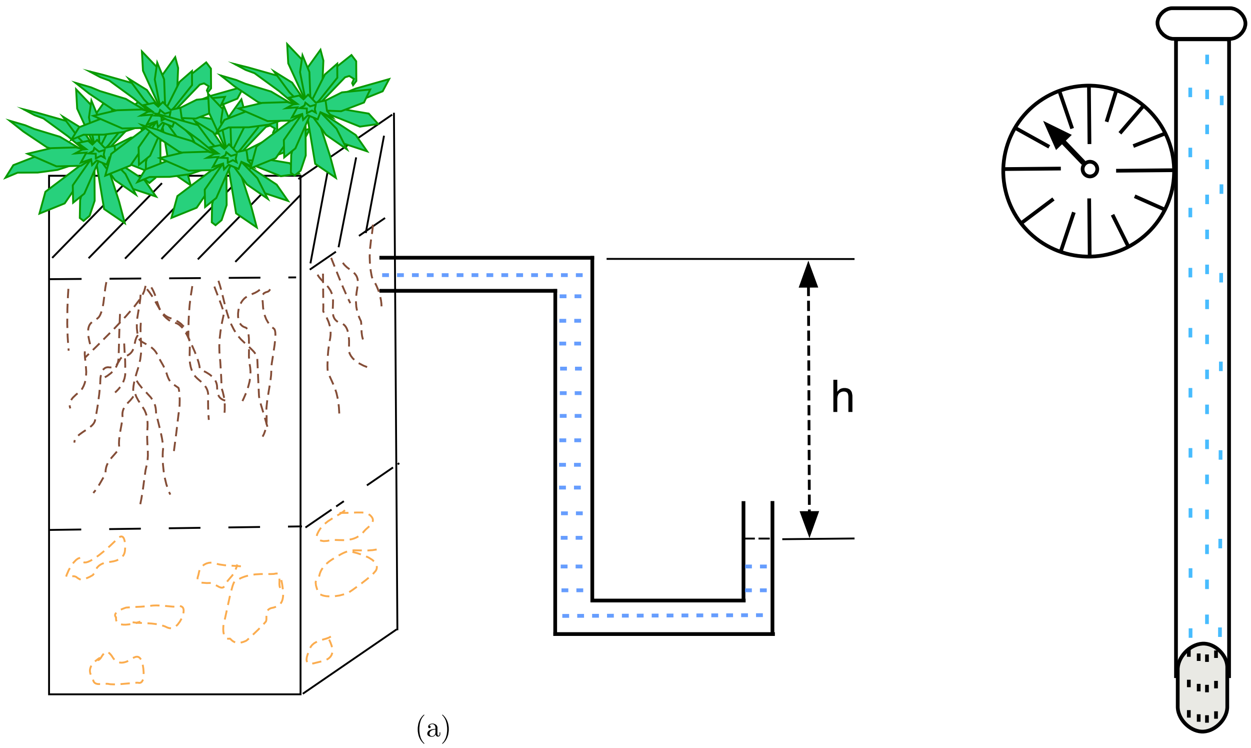
Mediterranean climate, with most of the rain occurring in the winter. Average annual rainfall is 12.6 inches, which is not enough to successfully grow winegrapes without the additional irrigation. Temecula, with $3,000 - 3,500°C$ degree days according, to the Winkler scale is in climate Region III [142]. The Winkler Scale is calculated as as the sum of degree days over $10°C$ from April 1 until October 31.

$$T = \sum_{i=April\ 1}^{October\ 31} max(T_{avg}^{i} - 10, 0) \tag{3.1}$$

In the region, the traditional irrigation practice for vineyards is a weekly good long soak. However, long irrigation drains deep in the soil, whereas short irrigation achieves majority of irrigated water staying at higher levels. Thus, irrigating once a week, and replacing the weekly amount of water in one irrigation cycle, applies more water than what can be used in one or two days. The surplus of water will drain deeper and eventually become out of reach of the active roots. Unlike popular belief, even for plants with long roots, like grapevines, most of the actual update of water takes place at shallow soil levels (up to 4 feet). Together with the draining water fertilizers also wash away, thus, reducing fertilizer efficiency and polluting aquifer. The ultimate goal is to supply the precise amount of water needed and have it delivered only to the soil layers with the active root system, where the plant uptakes it.

3.3.1 Sensor Calibration and Monitoring

A tensiometer is a measuring instrument used to determine the matric water potential (soil moisture tension) in the soil root area. The main idea behind soil tension is that dryness of soil and roots creates a negative pressure gradient. This negative difference in pressure can be observed by attaching a water probe as depicted in the Figure 3.7a, where the difference in water levels h estimates the soil tension. A better way to measure this tension is done by gauge tensiometer device that has a ceramic cap attached on one end and a pressure gauge on another as depicted in Figure 3.7b. Although gauge sensor significantly simplifies measurements, but it is still only available by eyesight. To improve this, we used electrical resistance based measuring soil tension devices that were connected to self powered IoT enabled devices, which were calibrated using the gauge sensors.



(a) (b)

Figure 3.7: Methods of measuring Soil Tension a) Water Suction Tensiometer, b) Ceramic Cap Gauge Tensiometer

The electrical equivalent sensing device that utilizes the resistive property of the water and gypsum mix was used to develop a low cost and high fidelity sensor. The design of the sensor is minimalistic as it uses only electrodes and a gypsum casing (see Figure 3.8). This case absorbs water when the tension is low and looses water content when the tension is high. Thus, it is possible to track the tension in other words sense it.

Sensors need about two seeks before they fully reach equilibrium with the surrounding soil and provide data, which are calibrated using a vacuum tensiometer and "sandbox" method. The tensiometer calibration is done on a terracotta container filled with soil which is then saturated with water and through evaporation gradually loses water content. In the soil a tensiometer and sensor under test are placed and readings are taken until the tensiometer is out of measurement range. To accelerate the calibration phase active calibration techniques were used which utilized vacuum pumping technology (see Figure 3.9).

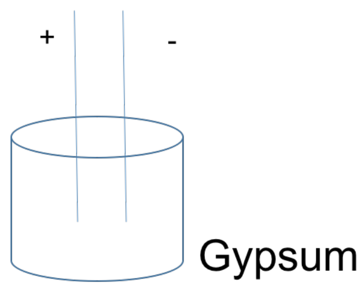
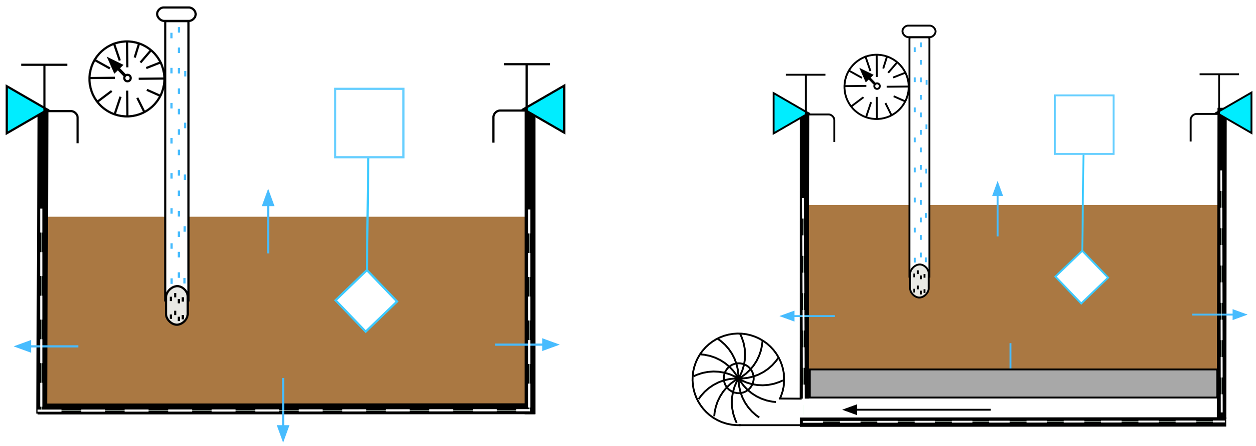


Figure 3.8: Sensor Structural Design

Even after calibration, sensors can deviate from their accuracy margins; thus, anomaly detection and secondary validation studies were performed alongside sensor deployment. Anomalies observed could be categorized into few groups such as event triggered, where a single sensor data was out of expected bounds, inconsistent, where 1 or 2 sensors were far off from the other station sensors, insensitive, which were sensors that did not detect controlled irrigation event and finally to quick to detect irrigation meaning probing effect was significant and required re-installation. Moreover, to further correct and replace defective units, manual checks were performed using leaf tensiometer devices.

3.3.2 Pressure Chamber Leaf Tensiometer

The idea behind leaf tensiometers is to evaluate pressure difference in the stem and leaf for the characterization of the plant stress. The belief is that the higher the stress on the plant,



(a) Passive Calibration

(b) Active Calibration

Figure 3.9: Calibration Setups, in a) and b) gauge tensiometer is depicted on left and sensor under calibration is depicted on right

the higher the pressure difference will be between the leaf and the stem. To measure this pressure, special chambers are made that allow pressure intake from the outside and release by the leaf stem. By carefully increasing the pressure, the visual observation establishes the pressure leaf tension as depicted in the Figure 3.10. The leaf tensiometer used in this project was PMS 615 [62] [103].

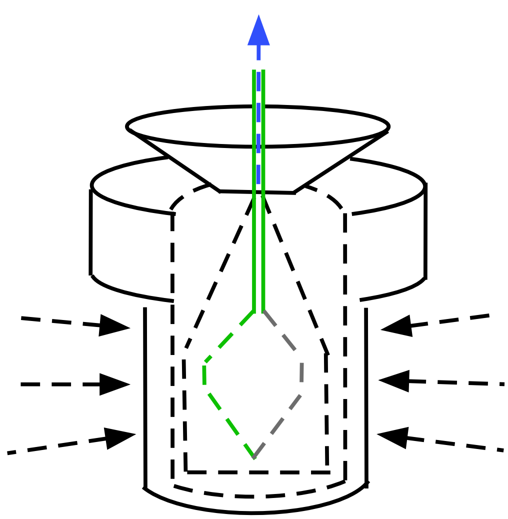


Figure 3.10: Pressure Chamber Leaf Tensiometer: As pressure in the chamber increases to the leaf water tension water escapes from the leaf xylem and can is observed visually

3.3.3 Soil Compositions in Experimental Sites

Experimental site soil compositions are predominantly sandy loam and rough broken land, with on average 8 percent slopes. Each site was studied using the USDA survey on soil make up [129]. We summarized the sites geo-images in the Figure 3.11 and the soil composition data here in Table 3.1.

Site	Symb	Description	Acres	Percent
1	ChD2	Cieneba sandy loam, 8-15% slopes, eroded	0.8	17.80%
	CkD2	Cieneba rocky sandy loam, 8-15% slopes, eroded	3.4	77.50%
	MmC2	Monserate sandy loam, 5-8% slopes, eroded	0.2	4.70%
2	GyD2	Greenfield sandy loam, 8-15% slopes, eroded	0.9	16.70%
	GzG	Gullied land	0.2	4.10%
	HcC	Hanford coarse sandy loam, 2-8% slopes	2.6	46.00%
	HcD2	Hanford coarse sandy loam, 8-15% slopes, eroded	1.1	19.70%
	RuF	Rough broken land	0.8	13.50%
	SeD2	San Emigdio fine sandy loam, 8-15% slopes, eroded	0	0.10%
3	GyD2	Greenfield sandy loam, 8-15% slopes, eroded	1.7	14.20%
	HcC	Hanford coarse sandy loam, 2-8% slopes	5.8	49.70%
	HcD2	Hanford coarse sandy loam, 8-15% slopes, eroded	0.9	7.80%
	RuF	Rough broken land	3.3	28.30%
4	HcD2	Hanford coarse sandy loam, 8-15% slopes, eroded	3.8	45.60%
	RuF	Rough broken land	4.5	54.40%
5	AtD2	Arlington and Greenfield fine sandy loams, 8-15% slopes	2.7	26.90%
	GzG	Gullied land	3.2	32.00%
	HcC	Hanford coarse sandy loam, 2-8% slopes	3.6	36.70%
	HcD2	Hanford coarse sandy loam, 8-15% slopes, eroded	0.2	1.80%
	TvC	Tujunga loamy sand, channeled, 0-8% slopes	0.3	2.60%
6	AtC2	Arlington and Greenfield fine sandy loams, 2-8% slopes	1.4	72.2%
	GzG	Gullied land	0.5	27.8%

Table 3.1: Soil Compositions by site and symbol

3.3.4 Network Structures

Network architecture for networks differs due to its physical connectivity range and type. Local connection by wired Ethernet create a different type of network than Wi-Fi connections. However, when thinking about agriculture and using sensors that are connected to one

(a) Research Site 1

(b) Research Site 2

(c) Research Site 3

(d) Research Site 4

(e) Research Site 5

(f) Research Site 6

Figure 3.11: Research Site Geo-imagery and Soil Composition [129]

another ranges can exceed a few hundred meters. Therefore, the conventional use cases are impractical and longer range solutions are needed.

Wi-Fi and Bluetooth, which are the two dominant consumer wireless communication protocols use a 2.4GHz band and can support devices up to 100m in unobstructed view. However, in practice this number is far lower considering that quality of communication efficiency tends to get lower causing multiple repeated transmissions, delays, and higher energy costs. Energy is an important metric particularly for wireless sensor networks which need to harvest their own energy. For this reason, lower frequency bands such as 400-900MHz were used. One of main consumer use drawbacks of lower frequencies is that receiver and transmitter antennas need be longer with respect to communication frequency, which is not a significant issue in agricultural settings where devices are stationary. Two dominant technologies in this domain are LoRa (Long Range) [112] and NB-IoT [1], [86]. For this study, LoRa networks were utilized to link the sensor stations to Internet.

3.3.5 Monitoring System Design

For test site recruitment the trial program was promoted in the Temecula Valley Winegrowers Association (TVWGA) and the Small Winegrowers Association Temecula (SWAT). The trial offer was free installation of sensor stations with 4 soil moisture sensors each and a smartphone application.

The standard sensor station is composed of 4 sensors, placed in the upper, mid and lower limits of the active root zones of winegrape plants. The current installation method was not an easy task and can be further enhanced, but it does allow for permanent and semi permanent placement of the sensors. In case of a hill location, the sensors were placed quarter way from the top of the hill. Each sensor is a solid state tensiometer design utilizing electrical resistance measurements for soil water tension (KPa). Sensor's internal design allowed for water tension to directly impact electrical resistance.

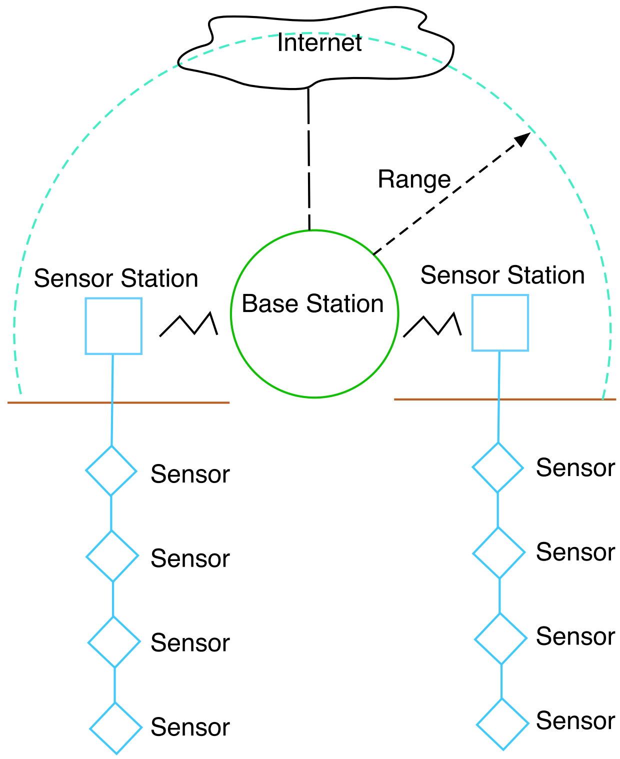


Figure 3.12: LoRa IoT Sensor Stations and Base Station based connection to Internet

To manually check the soil tension data, leaf water potential measurements using leaf tensiometer measurements were conducted using a leaf tensiometer. The data collected is presented in Table 3.2 which shows that electrical resistance soil tensiometer measurements were

mostly in agreement with leaf water tensiometer readings. High soil stress levels were observed at above 60KPa and low stress level at below 10KPa (absolute values here, in measurements they are negative), which respectively aligned with 9Bars and 16Bars of leaf tensiometer readings [116].

All of the selected sites used their conventional irrigation technique, which are mostly based on manual and arbitrary irrigation, or were left to management. Two of the six test sites (Site #1 and #4) used a controller for setting irrigation times, and the other 4 sites used manual irrigation valve control.

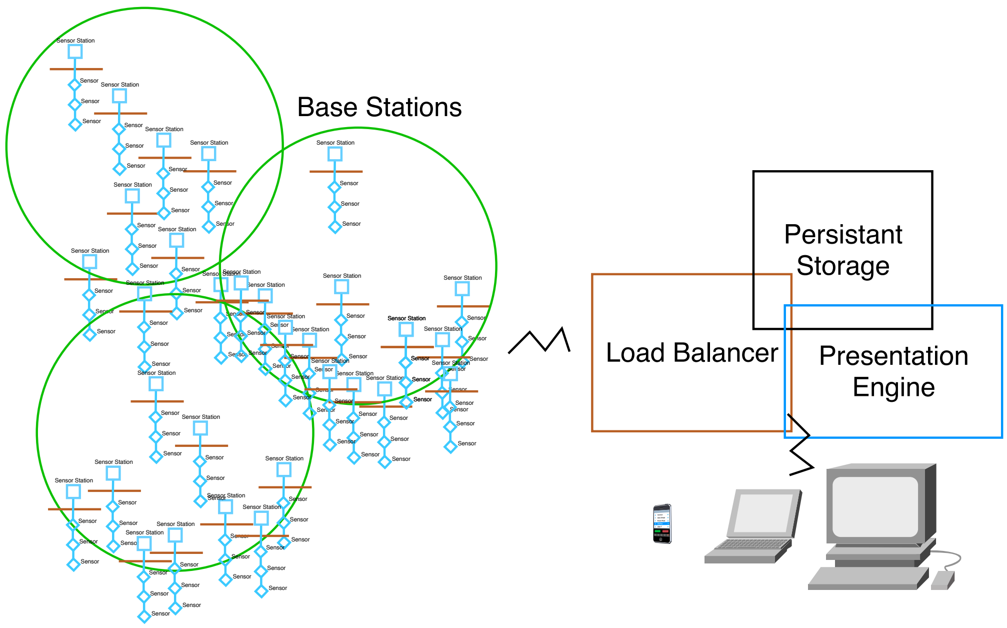


Figure 3.13: Complete IoT System Description

Site/Station	2/1/17	3/1/17	3/2/17	3/3/17	6/1/17	6/2/17	6/3/17
1 foot (KPa)	33	70	43	64	9	9	9
2 feet (KPa)	22	80	75	40	9	9	11
3 feet (KPa)	16	97	93	74	9	9	8
4 feet (KPa)	68	69	90	85	8	9	11
Leaf Tension* (Bar)	11, 13.5	16, 16	17, 15	18, 17.5	10, 10	9, 7.5	10, 9.5

Table 3.2: Soil tension and plant leaf tension relationship (*Two separate readings were performed and recorded)

Sensor installation was done with local winery support. Locations were selected in collaboration with the wineries. In case of a hill location, we placed the sensors quarter from the top of the hill.

3.4 Results - Data and Analysis

The Web based application calculates a daily irrigation recommendation time based on CIMIS ET data [20] and the specific vineyard properties (like vine spacing, canopy width, emitters, etc), and can be customized for the applied deficit level. This data is displayed in the application as a chart and table. It provides information and allows editing of reference daily intake (RDI), evapotranspiration (ET), crop factor (Kc), reference ET (ET_0), crop ET (ETc), and displays water use in hundred cubic feet (HCF).

3.4.1 Soil Tension data

The sensor system provided were in hourly measurements and were presented as charts and tables. In the trial, the sensor at 1 foot detected irrigation and rain events, as soil can be very dry in deficit irrigated vineyards. The sensors installed at 2 and 3 feet were used by users to determine under-watering events. The sensor at 4 foot acted as a drainage sensor as any significant changes in the sensor value would hint the user that they are over-watering.

During the 2015 and 2017 Rancho California District users have used all together about the same amount of water (see Figure 3.15) and was under very similar ET demands (3.14). In this same periods, the Research sites all together saved water although 1 of the research sites, and had to increase their usage due to underwatering practices while another had major leaks (see Figure 3.16). Altogether, results show with 87% confidence that multi-depth IoT monitoring of soil tension in the water use has improved water use efficiency with paired t score of 1.31 (see equations 3.2 and 3.3) for the research sites 2-6. Meanwhile, research site 1 had overall 33.8% savings (see Table 3.3 and Figure 3.17), and was an outlier and was excluded from the summary comparison of research sites. This is in part due to the fact that research site 1 has been using the stations prior to 2015 and is evidence that even more savings can be expected with prolonged use.

$$t = \frac{\frac{\sum_{i=1}^{n}(X_i - Y_i)}{n}}{\sqrt{\frac{\sum_{i=1}^{n}(X_i - Y_i)^2 - \frac{(\sum_{i=1}^{n}(X_i - Y_i))^2}{n}}{(n-1)(n)}}} = 1.31 \tag{3.2}$$

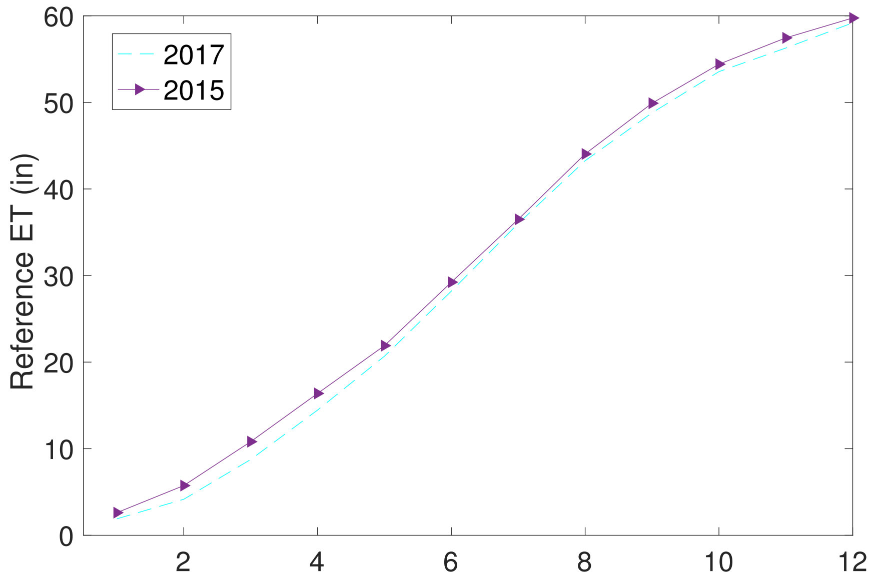


Figure 3.14: Monthly Cumulative ET of 2015 and 2017

Site/Year	2017	2015
1	1634(HCF)	2470(HCF)
2	2170(HCF)	2829(HCF)
3	3943(HCF)	4620(HCF)
4	6360(HCF)	5960(HCF)
5	4915(HCF)	5902(HCF)
6	9324(HCF)	9152(HCF)

Table 3.3: Usage Data in 5 Sites

$$df = n - 1 = 4 \tag{3.3}$$

3.4.2 Discussion

Having the ability to use IoT sensing can further improve water productivity methods already known to be effective, such as drip irrigation [37]. On the other hand techniques such partial root drying and regulated deficit irrigation require having effective tools for conducting such

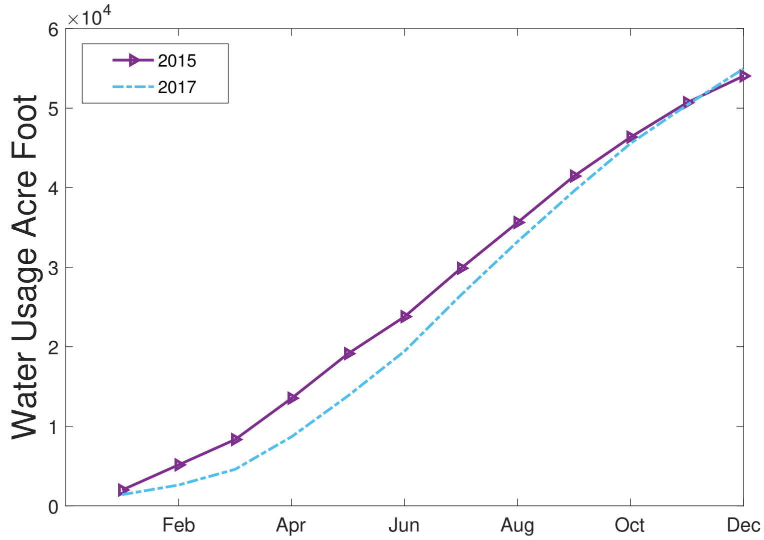


Figure 3.15: Cumulative Water Usage Date of the Water District

practices [3].

For successful deployment of the water saving system, having tight control over irrigation time is critical for success. This can be provided by using (battery operated) irrigation valve controllers, or by using the sensor stations with valve control capability [143]. That said, with all the great capabilities enabled by IoT solutions, large variability could be present in the ways these devices operate. However, variability in geophysical processes is a studied topic and there are existing tools to counter it such as wavelet transforms [94]. In fact, significant work has been done to improve uniformity of emitters performance [11].

Indeed, precision in irrigation systems can be interpreted differently, from wetting patterns of water to delivery of nutrients and conditioning. Automating precision irrigation requires not only advanced models, but also tools and infrastructure in place to operate by sensing and actuation. Most importantly, it reveals fortuitous business opportunity in the form of returns on investment, where users will be benefiting in every investment step towards the theoretical limit of precision and automation.

Irrigation systems are truly part of both the physical domain, such as precipitation and

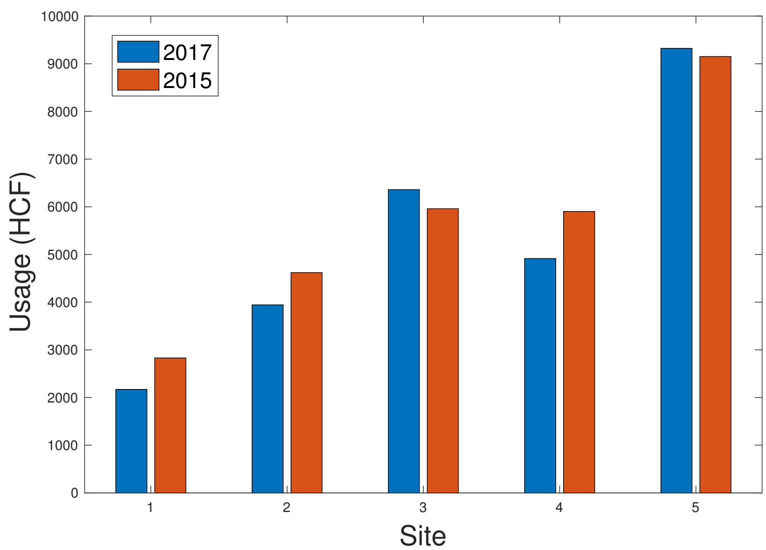


Figure 3.16: Research Centers 2-6 comparative Total usage between 2015 and 2017

cyber domains (controllers, sensors and applicators), yet, they are also often overlooked and under-appreciated for their significance in the whole scheme of engineering systems. It is possible that lack of such interest can also be attributed to the not so obvious complexity of water 'faucet' operation in the farmland. However, we should start thinking about irrigation scheduling automation more seriously to handle the ever increasing irrigation demand under declining water availability. Enabling better decision-making in farms and policies for water districts is opportune as upgrades to networks of irrigation systems pay off short and long term. This is where the phenomena of Internet of Things will be playing a critical role as we have observed in this work.

3.4.3 Opportunities

In parallel to our work with vineyards, Gallo Winery and IBM have been collaborating to bring Variable Rate Irrigation Control (VRIC) to fruition [109][54]. Their result indicate up to 25% water savings and up to 25% yield in quality improvement. This is very exciting as it entails that further research can be done to bring VRIC into IoT domain. However, to the

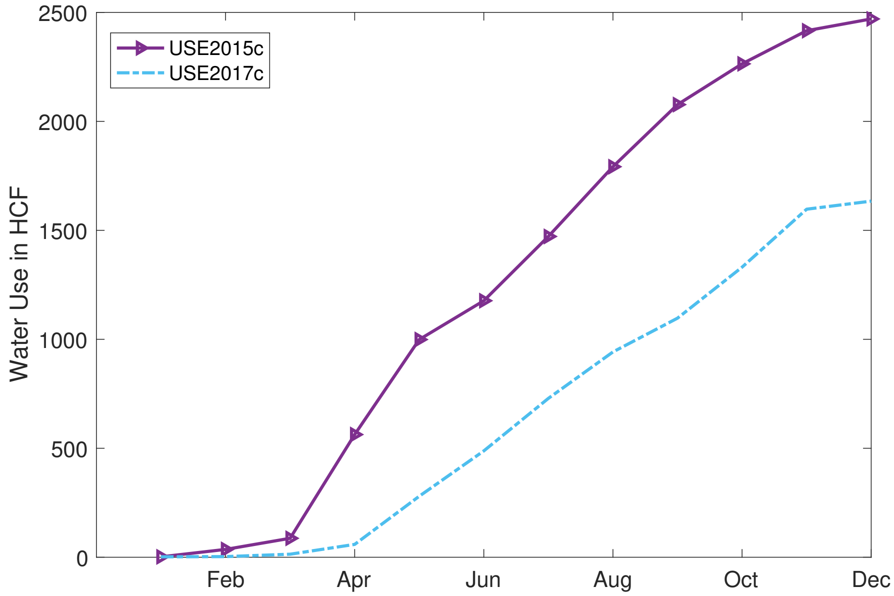


Figure 3.17: Research Site 1 Usage Data

best of our knowledge, there are no widespread affordable, self-contained and resilient systems to utilize in practice. To that end, in Chapter 4 we will discuss how that actually could be done with use of Cyber-Physical System Designed Controller Networks called Topology Adaptive, Resilient and Scalable (TARS) Controllers.

3.5 Conclusion

Indeed, IoT monitoring of Irrigation systems performance is a small, but an ambitious step towards global water savings. Moreover, a significant step can be made by closing the loop with remote controlled valves, which may further improve irrigation performance by cutting human error from irrigation actuation. That said, the study was limited to Southern Californian vineyards, thus, it is difficult to predict whether water savings can be expected in other geographies and crop choices, but with versatile IoT monitoring there may be other ways of improving the performance.

Chapter 4

Topology Adaptive, Resilient and Scalable (TARS) IoT for Irrigation CPS

4.1 Abstract

There is a significant unrealized potential in developing state of the art electronics for agriculture. This paper tries to lay down foundations for the vision in which we can use existing technologies of Internet of Things and Cyber-Physical Systems to enhance water infrastructure and precision in irrigation efficiency. We discuss design challenges of next generation crop monitoring and water flow control systems, in particular, designing IoT Stations with localization and energy harvesting in mind. Our studies show that it is possible to have self-powered, self-configurable and highly functional water flow stations that will transform and free Micro-Irrigation from centralized control. This chapter covers proposed design methodology, topology aware localization multi-graph technique as well as lessons learned from prior experiments, which will help to fulfill the next generation of CPS-IoT Precision Irrigation Systems.

4.2 Introduction

Cyber-physical systems approach to engineering enables design of highly complex engineering systems [47]. For example automotive [134], designs of silicon processors [35], medical devices [72], and smart manufacturing systems [19] utilize cyber-physical systems approach to shape novel, sophisticated and integrative solutions. An essential characteristic of cyber-physical systems approach is the underlying design methodology that supports scalability and complexity management through (1) modularity and composability, (2) synthesis, and (3) support of legacy systems.

This work demonstrates that CPS approach can also be applied to precision irrigation management by introducing novel design patterns that investigates both present and future irrigation needs and opportunities of modern technology in one plane. In particular, irrigation emitter operation, distributed control and system management can significantly benefit by utilizing topology adaptive, resilient and scalable (TARS) controllers. To this end, here are presented (1) design methodology capable of comparing Irrigation IoT controllers, (2) simulation tools and software capable of analyzing the distributed behavior of the TARS controllers, (3) topology adaptation technique that utilizes multi-graphs to mine the hydro-wireless topology of the IoT controllers, and (4) a TARS controller implementation with novel energy harvesting and low power operational support.

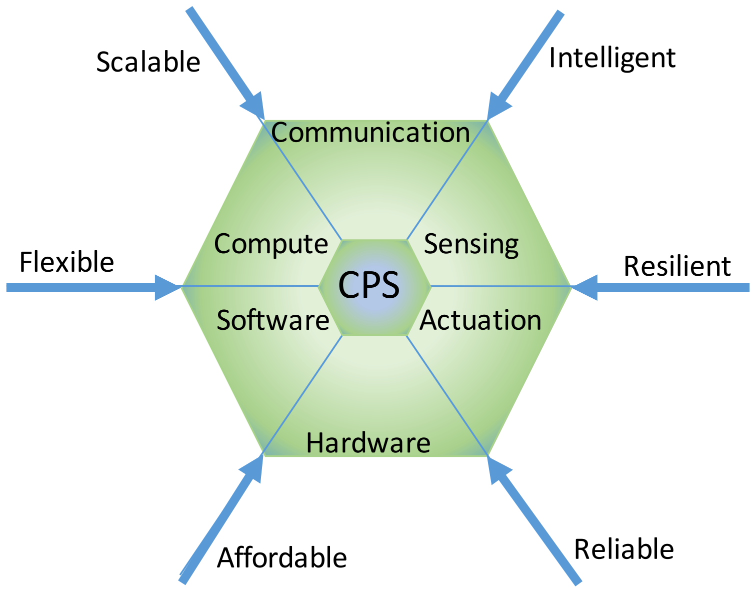
4.2.1 The CPS Design Pattern

The ultimate goal of any CPS designer is to develop delicate solutions that utilize key areas of computing, sensing, communication, hardware, software and actuation under the design space constraints and trade-offs. We define the design space as a medium of designs with vectored measures of intertwined bases, such that each base is not necessarily orthogonal to others, and is in technological balance with other bases. We introduce 6 such basis vectors as depicted in Figure 4.1a, e.g. flexibility, resilience and reliability. We combine all these pillars into the "design hexagon" of cyber physical systems as depicted in Figure 4.1a. However, these vectors are not the only ones - these have been chosen for brevity of discussion and importance to the irrigation subject. Nevertheless, we shall not forget the setting in which context implementations of design are utilized. Indeed in this paper, unique characteristics of the future needs of irrigation CPS are discussed, as well as how the CPS design pattern applies to Irrigation and where the shortcomings may be present. Before delving into irrigation system design needs some of the fundamental irrigation science needs to be understood because the design must be considered in the context of the hydro-meteorological setting (see Figure 4.1b).

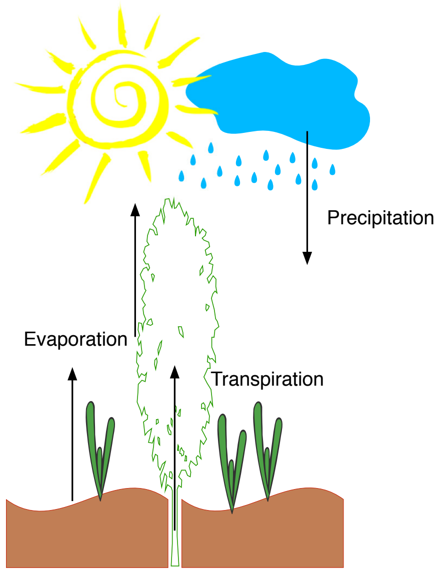
4.2.2 Background

Irrigation systems are cyber-physical systems, because they are composed of man-made systems: irrigation networks and their controllers, and physical world: soil, atmosphere and plants (see Figure 4.1b). The hydrological processes driven by solar radiation changes and climate either add or subtract water in soil-plant system. The main purpose of any irrigation system is to substitute for lack of precipitation in soil or in some cases to improve quality of agricultural yield in the plant. Irrigation systems are everywhere from non-constrained spaces such as urban and rural settings to constrained spaces like in warehouse, greenhouse or in home settings. Thus, the approaches to solving certain challenges may not universally be applied to all settings, although certain common characteristics are shared.

The state of the art drip irrigation systems are feedback control systems that depend on environmental factors such as air humidity, radiation and temperature, meteorological phenomena such as rain and also type of the plant, plants growth stage and etc. One can



(a) CPS Design

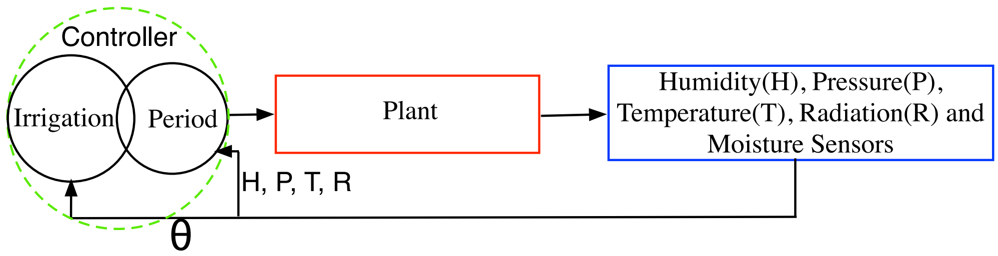


(b) Hydrological System

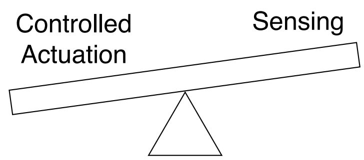
Figure 4.1: Design of CPS in the Context Irrigation Systems

visualize this in a block diagram as presented in the Figure 4.2a, where irrigation amount and scheduling periods are the control variables.

Conventionally, irrigation controllers are placed near main irrigation water source and are wired to control the valves of each group of irrigation drip lines. The most updated controllers are capable of having their own designated mobile internet connectivity for remote connection. However, most frequently these controllers are just stand alone devices that are capable of collecting some soil data as well as rain indicator data to shut off the valves during rain. On top of that, for control only simple decision trees are used for irrigation decisions and most commonly an interval based scheduling is used which must be determined by the irrigation managers. Some of these internet enabled irrigation controllers allow for remote reprogramming by hydrologists, who look at reference meteorological data, such as Evapotranspiration (ET), to adjust scheduling periods. To that end, some irrigation users place weather stations to more precisely measure the ET reference values or entering the ET estimates into the central controllers. However, as we are proposing this finer grain distributed actuation system, control decision can occasionally be made in the edge as well



(a) Control System



(b) Power Cost

Figure 4.2: Model of the Control System (in this figure "Plant" refers to the system under control, which comprised of the soil-atmosphere-plant)

as in the center, where *center* could be a centralized control system of a scale of a water district or larger. The reason for this type of aggregated thinking is first powered through the computational capabilities of modern computing systems, which can aggregate Terabytes of data and apply artificial intelligence for optimizing use for the entire system with the level of detail of each individual emitter. This may seem like a very ambitious goal, but we hope that with careful planning it can outweigh the initial costs.

Although there are some far fetched applications of modern technology in irrigation systems drip irrigation remains the most commonly adopted state of the art technology. For example, for soil moisture sensing there are quadcopter based soil sensing and sampling systems that utilize augmented reality [53], and robotic in row weed controllers for chemical reduced operations of weed control [132].

Conventional drip irrigation system has a single source and network with a single path to emitters as depicted in Figure 4.3. In the figure, we introduce two different types of control points, main block controller which usually is the only control point used, and emitters control point or valves. The reason for this distinction is that our central hypothesis states that by utilizing distributed control we can improve water distribution as many researchers have shown and ultimately improve irrigation precision and efficiency.

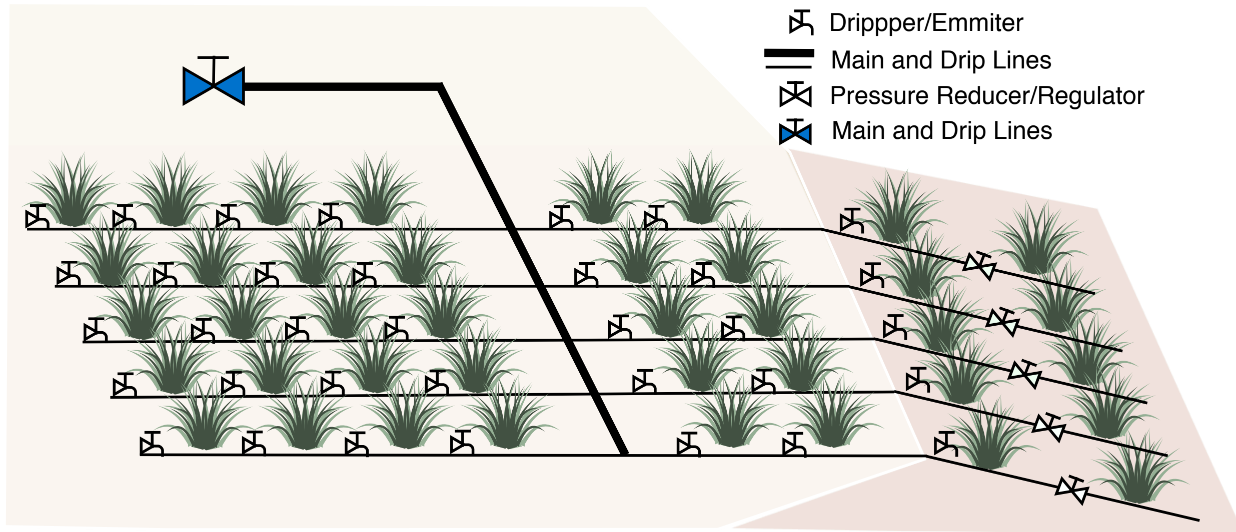


Figure 4.3: Drip Irrigation System

On the other hand, much like all cyber-physical systems, the drip irrigation system, is vulnerable to all kinds of attacks ranging from physical degradation to arbitrary leakages. These vulnerabilities are caused by animals chewing on drip lines or improper installations and intentional/adversarial attacks much like other CPS[7] [82] [79] [19]. Single source-path to delivery point systems, such as the drip tapes used for raw crops, are even more vulnerable as there is plurality of points of failure at any point in the drip line where each point causes a failure of the entire subsystem. This can be mitigated by adding more supply lines, duplicated routes and in some cases even utilizing new topology to further regulate pressure. However, even with the most precise pressure regulation a failure is inevitable which could cause a domino effect due to a single line failure. This is because there is no good way of figuring out a leak or breakage until it is observable by management.

In the past, irrigation research focused on developing models that can be used to deduce irrigation needs by estimating lost water due to evaporation and transpiration. However, new models and methods are present that can be used to model system, even as a circuit. With these models in mind, one can put together a circuit voltage controller like irrigation controllers as depicted in the Figure 4.4.

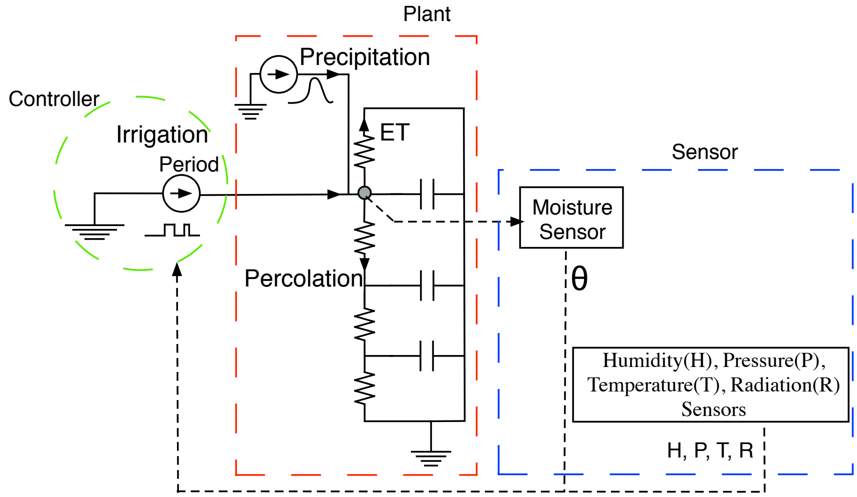


Figure 4.4: Circuit Control Representation

Wireless sensor networks as opposed to wireless controller networks have much lower energy and power demands as is depicted in Figure 4.2b. There is significant effort put forward in wireless sensor networks to localize [139], and to extend the communication protocols [45] along with the means for powering them [111]. However, there is little or no work done to utilize the same technologies for actuation networks such as IoT irrigation controllers [74].

One of the challenges of identifying absolute location or the relative location of two wireless devices is by using the Received Signal Strength Indicator (RSSI) measurements (per Equation 4.1) of the devices to use anchoring or relative distance measurements [12]. There is also significant research done to utilize path loss models for localization purposes [83]. In fact, customized models exist for specific use agricultural cases as described in Equation 4.2. On the other hand, when it comes to measuring or inferring the relative distance using water pipes by means of measuring the pressure drop (ΔP) per Hagen-Poiseuille Equation (see Equation 4.3). Thus, one can put together a circuit emulator for the hydraulic connections tuned using these equations.

$$\frac{P_r}{P_t} = G_r G_t \Big(\frac{\lambda}{4\pi R}\Big) \tag{4.1}$$

$$PL[dB] = PL_0 + 10nlog\Big(\frac{d}{d_0}\Big) + X_\sigma \tag{4.2}$$

$$\Delta P = \frac{8\mu LQ}{\pi R^4} \tag{4.3}$$

4.2.3 Motivation

Networked devices must operate without supervision. Thus, may need to be a priory, or statically, and dynamically configurable to adapt changes. However, this goal is not always achieved, and failures of devices can in many cases be only resolved by replacement. For example, to replace a failed device we have to first of all be able to identify and locate that device. However, a self-contained failure is a challenge to distinguish in a field of other devices, unless the rest of the devices can locate and hint the supervisory node of the failures. This and many other needs must be addressed to be able to have a fully distributed system of components that work independently of each other yet collaborate towards a common goal. In general, these systems can be described in a graph, where each vertex is the node that can sense, actuate and communicate, and each edge represents a connection. Usually, in a graph two vertices may be connected by a single undirected edge or a pair of directed edges.

However, in a graph that describes networked devices in irrigation settings, this might not be true. First of all, there may be different types communication links that connect nodes to each other. Moreover, irrigation controller valves are also connected by the water network too. Thus, to fully capture the system description we have to use multi-graphs, which are general forms of graphs that allow same vertices to be shared in topology multiple graphs as depicted in Figure 4.5 with colors of edges representing different planes of graphs or types of dependencies. Another concept that can be utilized with graphs, is the weights of the edges. A graph in a multi-graph representing the water irrigation water network may have a different weight depending on the distance and diameter; or, it may be split into two parallel graphs each represented with weights of edges as the parameters of the plane.

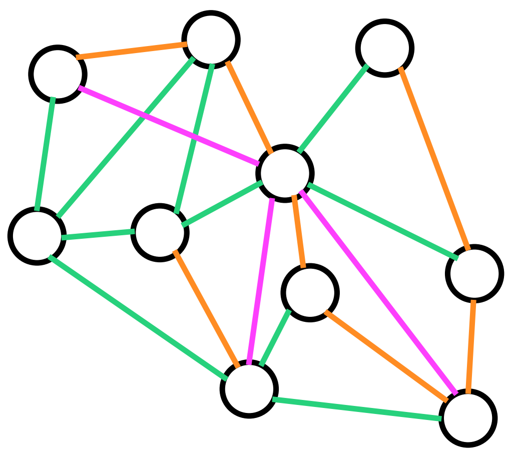


Figure 4.5: A Multi-Graph Representation, where Vertices are the Irrigation IoT Nodes and Edges are Communication, Water, or any other type connection (or relation) each on its own plane or individual graph representation.

One application of multi-graphs is that the graph representation allows to deduce minimum spanning trees, shortest paths and critical points of failure for communication message passing and/or water routing in case of emergencies.

4.2.4 Purpose

The Purpose of this work is to define the future direction of IoT enabled distributed irrigation networks that can be easily proliferated to bring maximum water savings and quality of yield. Projections on water budget are only derived from empirical studies, which result in ranges of needs with large variations (see [33]) between 50-100%. For example, grain is reported to have 400-800 gal/season and carrots 1200-1900 gal/season. Indeed, demands of plants can be different, furthermore, their demands change over their growth stages. In the past researchers have been able to fit the growth patterns of different crop to different mathematical functions. For example, it is known that the rate of growth of the maize crop has the function described in Equation 4.4, where BM is biomass in $t\ Ha^{-1}$ and T is time in days [88].

$$G_{BM}(T) = \frac{12}{23 + 0.08e^{-0.08T}} \tag{4.4}$$

The function derived requires the continuous application of a very little amount of water soil throughout the farming practice. In some cases this may be possible. As in some greenhouse or hydroponic farming practices precision of irrigation can be tuned very accurately, however, in open field farming, which has the majority stake in farming and is mostly irrigated through furrows, is difficult to achieve. That said, sprinkler based irrigation system can be tuned to provide certain amount water [87]; yet, given intrinsic variability it cannot be used for continuous control. On the other hand, this may be plausible for drip irrigation systems while being very complicated to implement as the entire farmland would require homogeneous precision irrigation system control. Thus, it is important to consider other forms of control, which do not require such costly methods. For example, discrete control with predictive power may be able to alleviate this by stacking the needed water demands in discrete irrigation periodic events.

For example, Figure 4.6 represents the control signal for daily irrigation events of 15 minutes. Moreover, by adding the control signal magnitudes relative budgets can be computed. Thus, one can then use this graph to choose an optimal water saving scheduling scheme or water saving plant much like by using advanced crop models [27] [85] [88] [38] [122] [16]. This would be possible given that all scheduling schemes are possible to implement, while trading off accuracy or efficiency of irrigation as with longer periods there will be more over and under irrigation events.

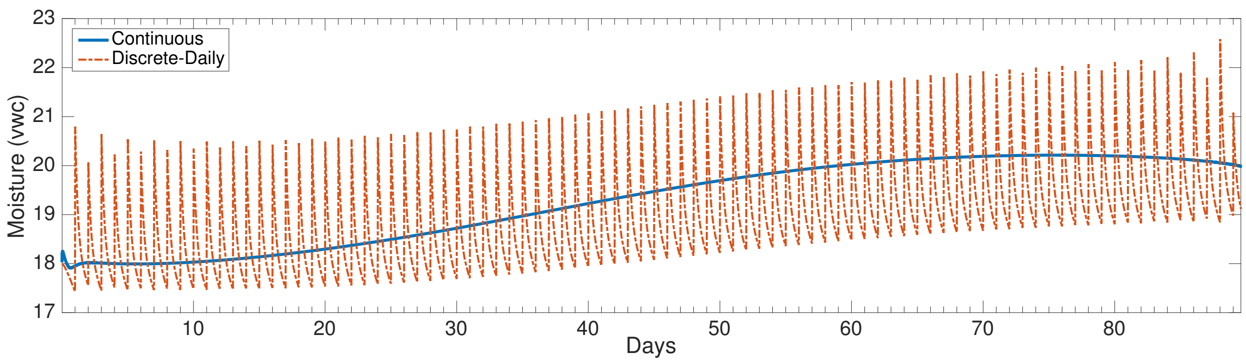


Figure 4.6: Comparison of continuous and discrete control moisture variations. Continuous control tightly follows growth demand curve after initial settling while discrete control significantly varies over time.

With control needs in mind, we came up with a design of next generation controllers, which are equipped with intelligent flow and pressure sensors, reliable network connectivity and resilient energy harvesting. These design requirements are essential for resilient long lasting operation that are worthy of investment as they each have a necessary application for the modern irrigation systems. First, we would like to discuss localization of networked nodes, which is part of studies in wireless sensor networks. Second, we will discuss energy harvesting functions of irrigation controllers which can generate enough power to be able to handle not just sensing but also actuation functions for servo-valve functions or solenoid valves. Finally, we will discuss image processing opportunities for growth feedback and health monitoring. We studied these applications in laboratory setup.

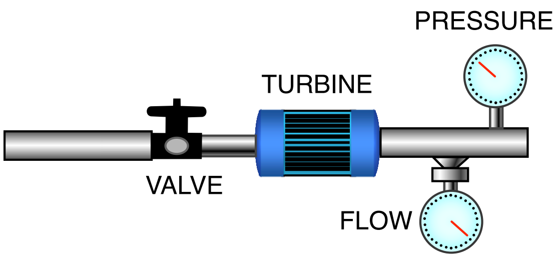
4.3 Material and Methods

The methods of designing next generation Irrigation CPS must adhere to the overall CPS design pattern (see Figure 4.1a). With this in mind, refinement of needs in distributed irrigation CPS conforms to following directives:

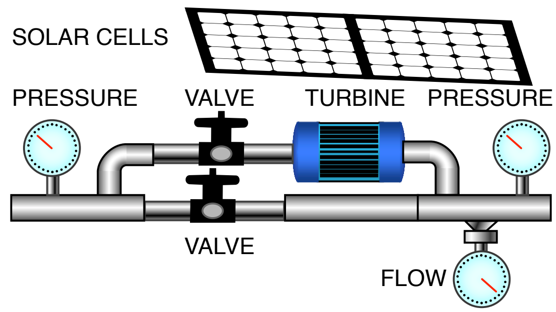
- Resilience: Essentials of Resilient Design are its ability to support its energy and power needs, and be secure from physical and environmental attacks and risks. There has been significant effort to bring about design methods for cross layer resilience [121].
- Scalability: Fundamentally, scalability in distributed CPS entails having ability to add and subtract units in the network with constant effort. This means that we can add and take out components without disturbing every part of the system. An integral part of any solution is its ability to handle more workload in a manner that does not significantly reduce its performance or accuracy. Such systems are said to have elastic scalability, an example of this are cloud virtualized workloads. However, when it comes to distributed irrigation control, we have to realize that the challenges associated with scaling may be due to lack of water availability. Further we need to also consider the complexity associated with interactions of different units and coherent operation of the distributed system as a single entity.
- Flexibility: In the context of modular design and support of legacy systems, we can think of degree of flexibility as the designs ability to conform, plug and played in the existing system as by increasing reuse.
- Reliability: Reliability in the irrigation context really means an ability to give guarantees on environmental adversities associated with material or physical performance. This can be observed from biochemical changes of the plastic drip tapes to salt build ups in valves and emitters. There has been some work done on CPS systems by utilizing machine learning as well [64].
- Affordability: Any design needs to be affordable and realizable. Of coarse having gold

wires is great, but it costs much less with copper, and maybe much less without having any wiring.

- Intelligence: Intelligence is a new paradigm that has shifted the focus of many embedded and Cyber-physical systems. It can be interpreted as the means of optimizing operation to meeting stringent deadlines and having predictive power in the system as a whole.



(a) Simple



(b) Modified

To this end, the design space exploration that test and validate different patterns can be done analytically using simulation environments that capture a multi-domain nature. One approach to the communication and water connectivity is to use graph coloring techniques, that said, a single graph cannot represent multiple domains, but multiplicities of graphs can. Once we abstract a node that is shared in the plane of communication and water network we will obtain a multi-graph. Thus, the approach is based on Graph Theory algorithm, where the Nodes and pipes are respectively modeled by the vertices and edges of an undiscovered graph. Using a graph node search DFS algorithm, we let the water flow through the pipes network discovering each and every node and pipe in the setup. Our method is based on the Depth-First Search recursive algorithm, and generates an ordered list of instructions to the Nodes, indicating which valve should open or close during the whole discovery phase. This algorithm minimizes the number of valve switching in the network as each and every node is open and closed only once. We have, therefore, for V nodes and E edges an $O(V+E)$ complexity algorithm, which is both scalable and energy efficient because switching a valve requires a non-negligible amount of power.

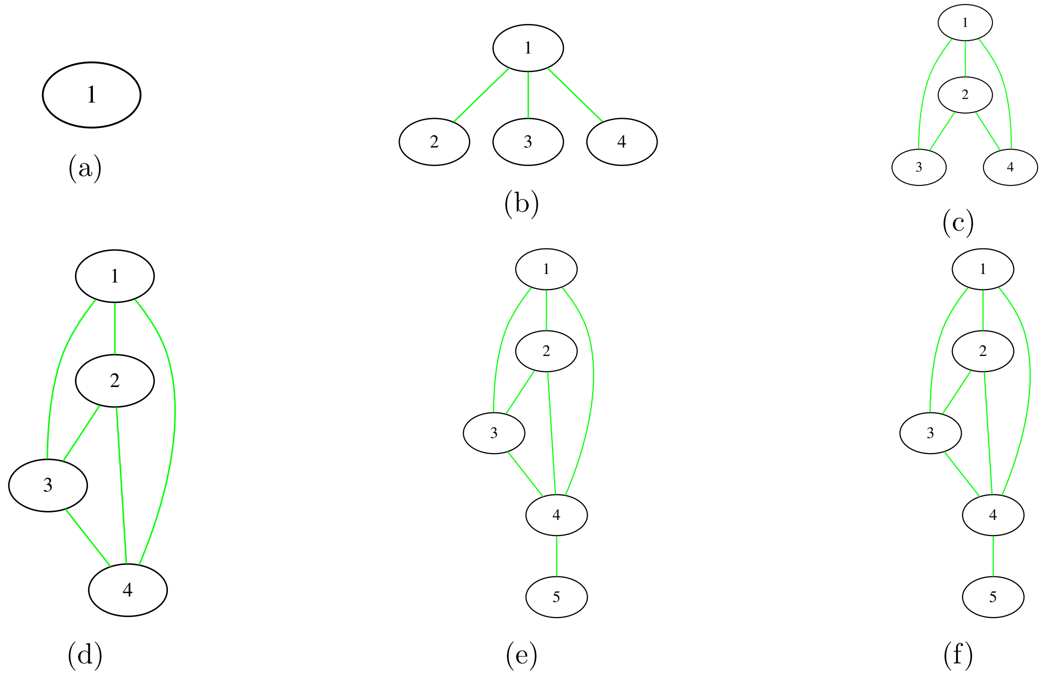
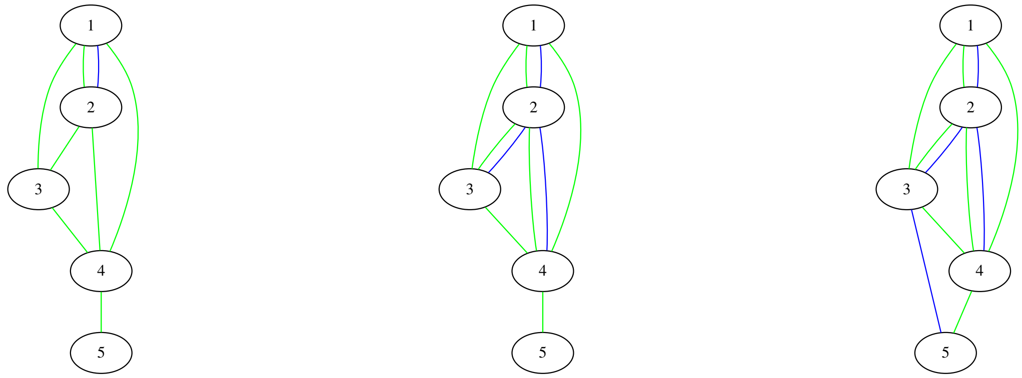


Figure 4.8: Communication Network Topology Discovery

This algorithm is supposed to run chronologically after a first stage of network discovery, where all the wireless sensors advertise themselves to the network. Our proposed algorithm is then executed, discovering all the physical neighbors of every Node so that a proper water delivery algorithm can be executed as a subsequent stage. A sate machine describing each individual nodes behavior can be visualized as in Figure 4.10.

One drawback of that algorithm is that if new nodes need to be added at a later stage, after all the nodes have been registered to the network, the algorithm will have to be executed and ran from scratch, which can be very inefficient in case of very large scale sensor networks. We can improve the topology adaptation by making it resilient to unit failures and dynamic changes in the system structure. We can define the failure of a need as failure of its essential parts, for example, failure of sensing, computing, and communication. If we can communicate, seems like the problem can be simplified down to letting others know that a particular node is missing and there is either a need to redo the topology discovery algorithm or let the centralized system deduce a better path. If the failure also includes the communication cost



(a) (b) (c) , (d) and (e)

Figure 4.9: Water Network Topology Discovery

then we can expect two behaviors, either the device failed before closing its valve or after. Knowing the difference between these two cases is important as it determines the severity of the situation; for example, an open valve is potentially leaking.

Thus, we propose having handshake procedures after every operation with a neighboring node. In other words, every node has a supervisor node, which means that although there is one Master node all across that manages the main water supply, but all nodes have a corresponding peer supervisor to introduce a redundancy and avoid single points of failure. This is similar to the Neighbor Discovery Protocol [92] link layer protocol stack and can be embedded in the physical layer of IoT networks.

Indeed, it seems that in the future TARS controllers will solve many future irrigation challenges including self-awareness conceptualization, which is hot topic at the moment [32]. However, our analysis was limited to a single water supply plot whereas the future may require having multiple water supply sources for additional resilience to failure to mitigate failures from source of water supply. Towards further understanding and developing methods of analysis, simulation tools are in development to study behaviors of multi input self structuring algorithms.

In order to further test our algorithms, we have designed a MATLAB based Graphical User

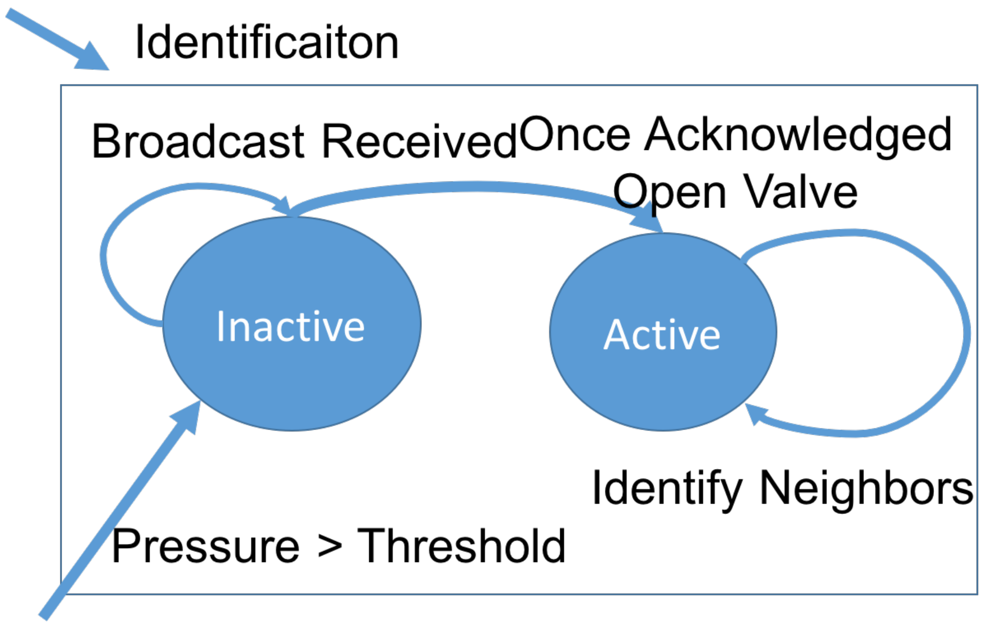
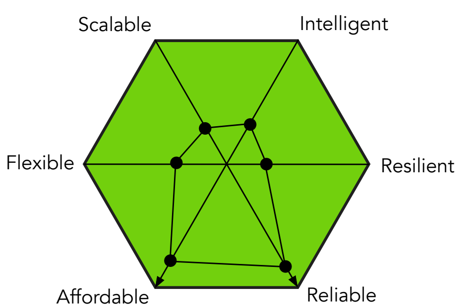
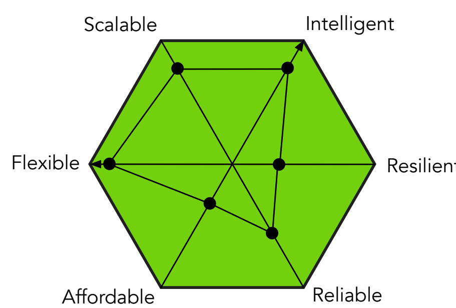


Figure 4.10: State Machine Describing the Topology Identification Process



(a) Centralized Controller [31]



(b) Generic IoT Node

Interface enabling the user to build a graph and run virtually the algorithms previously developed on the interface instead of running them directly on the physical system. That interface is also a good tool for future algorithm developers to easily compare different alternatives. It is meant to be user friendly so that anyone can build a graph easily and visualize the different steps of the discovery phase, even without having any background in MATLAB programming. Graphs can also be saved and loaded in a subsequent session.

Whenever the user presses on the 'Start' button, the algorithm runs and generates a list of instructions based on the graph previously built using the interface. The program then reads the list of instructions and highlights on the graph the specific Node that is being open or

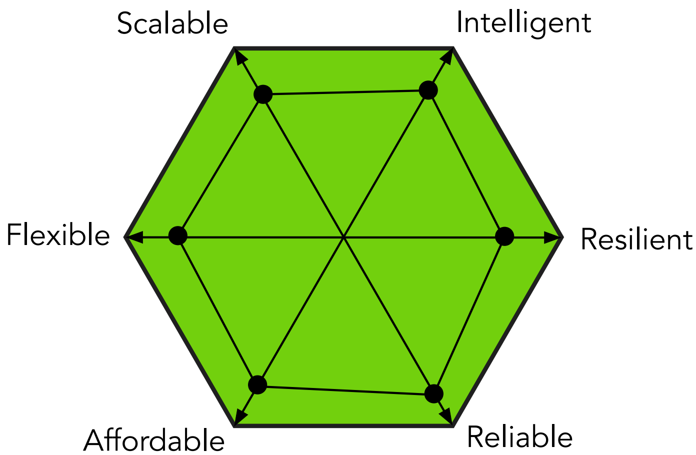


Figure 4.12: Envisioned TARS Controller Characteristics

closed, as well as the neighbor Nodes discovered at that step and the edges/pipes flooded with water according to the legend below.

Nonetheless, we have also developed a Python version of this software which was also used to make the Figures 4.9 and others by utilizing open source Python code [40].

4.3.1 Powering TARS Controllers

In order to properly discuss powering IoT system needs, here is formal perspective to needs vs demands. It may be intuitive and simple however it is worth to cover fundamentals of any responsible power system designs.

We can formulate power constraint in the design of any irrigaiton CPS system as follows:

- Power Balance: $P_D = P_C + P_A + P_S + P_N + P_0$ at every t

where

- P_S, P_A, P_C and P_N, respectively, stand for the power required for Sensing, Actuation, Communication, Computation

- P_0 is power needed for the remaining system parts, e.g. power supply.
- P_D is the power demand.

This means that energy gathered by the energy providing sources (e.g. photovoltaics, turbines, grid ...) should not be less than the energy needed within any period of time. Indeed, for non intermittent powering of services, we may have to go beyond conventional harvesting techniques such as photovoltaics and use others such as micro-turbines. To that end, we have experimented with powering our nodes using only micro-turbine energy and we demonstrate that in some cases, it can not only be an alternative but also a main power supply. For example, in underground networks or with plants that quickly grow over the field, it would cost enormous man power to maintain a solar panel.

To properly validate our irrigation system design ideas we introduce an in-lab testbench comprised of a water reservoir, pump and PVC pipes circulating water as depicted in Figure 4.13, which instead of electrical circuit now used pressure/flow sensory.

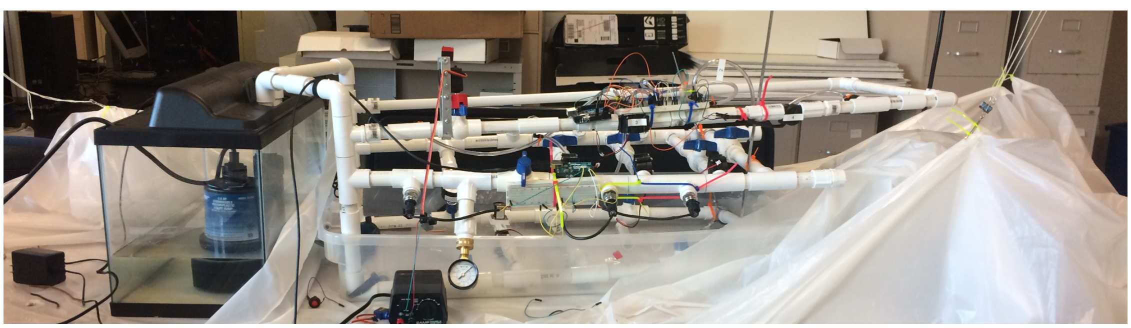


Figure 4.13: Laboratory Setup where hydraulic pressure sensors were used to detect incoming pressure and open close the operations

In an experiment to test and validate that micro-turbine as an energy source meeting the above mentioned requirement we compared conventional basic valve controllers with valves to our servo-valve design. First, we measured how much energy the conventional valve alone without controller uses, then measured the setup with valve On state and valve Off state to deduce the power consumption of the valve alone as depicted in the Figure 4.15. We also measured the amount of power/and energy it would take to operate the servo valve

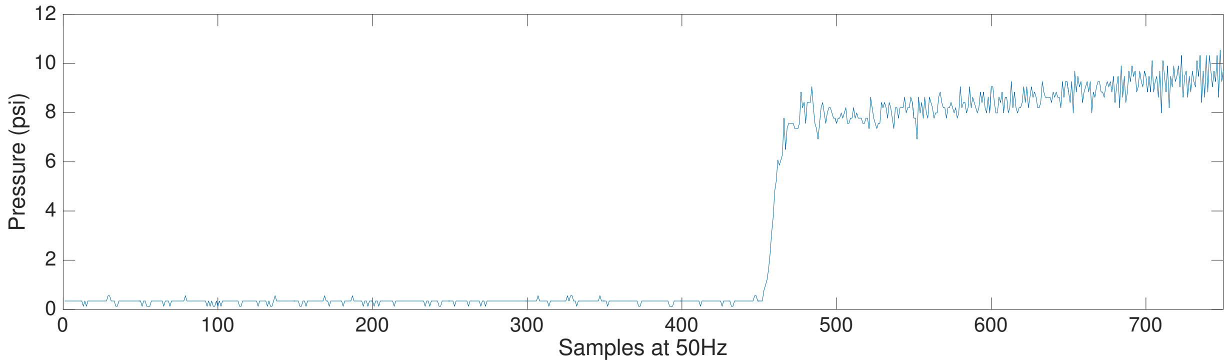


Figure 4.14: Pressure Edge detected at above set threshold

as depicted in the Figure 4.16 and the amount of power our micro-turbine would normally generate. Although, the generated power was adequate for operating the servo valve, but it was not high enough for the solenoid valve due to on power consumption, which in the case of the servo-valve is negligible. That said, there are designs of latching solenoid valves that may well be within power range generated by a micro-turbine.

In the experiments described in the Figure 4.15, the AC Power Meter was used for measuring power consumption of the irrigation controller [97] [98]. In the case of the experiment described in the Figure 4.16, the USB data acquisition device [93] was used for measuring the DC power usage.

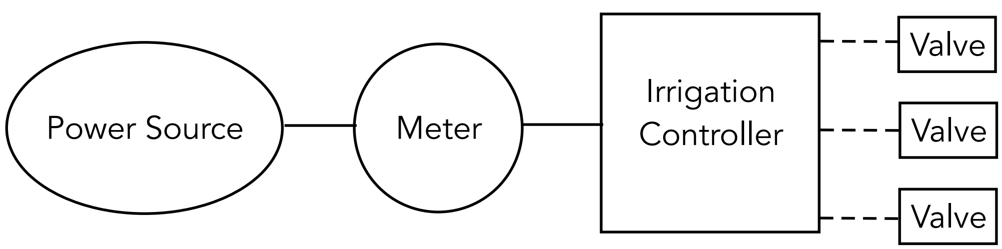


Figure 4.15: Controller Power Metering of Conventional Wired Valve Controller

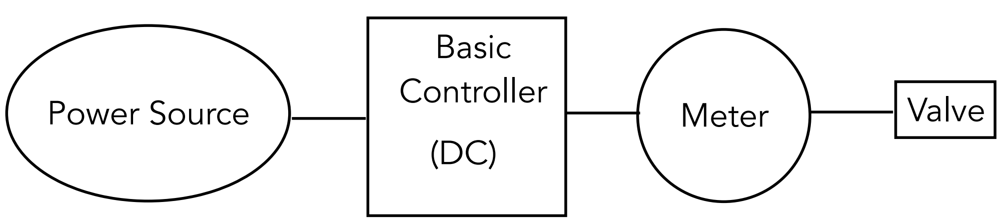
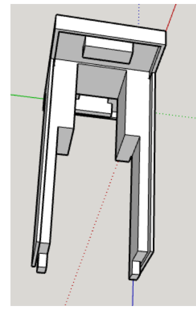


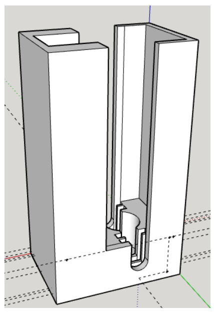
Figure 4.16: Controller Power Metering of Designed Servo-Valve

4.4 Results

(a) Original Micro-Valve [31]



(b) Top Cover



(c) Bottom Base

(d) Partially Assembled Model

Figure 4.17: Modular Design of the Micro Enclosure Drawings and Assembled Model with Motor Attachment and Drip Tubes

Networked devices must operate without supervision; thus, this need to be a priory and dynamically configurable to adapt changes. However, it is not always the case and failures of devices can in many cases be only resolved by replacement. For example, to replace a failed device we have to first of all be able to identify and locate that device. However, a self-contained failure is not really obvious to distinguish in a field of other devices, unless the rest of the devices can locate and hint the supervisory node of the failures. This and many other needs must be addressed to be able to have a fully distributed system of components that work independently of each other yet collaborate towards a common goal. In general, these system can be described in a graph, where each vertex is the node that can sense, actuate and communicate, and each edge represents a connection. Generally, in a graph, two vertices may be connected by a single undirected edge or a pair of directed edges, however, in a graph that describes networked devices in an irrigation setting this might not be true. First of all, there may be different types of communication links that connect nodes to each other. Moreover, irrigation controller valves are also connected by the water network too. Thus, to fully capture the system description, we have to use multi-graphs, which are general forms of graphs that allow same vertices to be shared in topology, or multiple graphs as depicted in Figure 4.5 with colors of edges representing different planes of graphs. Another concept that can be utilized with graphs, is the weights of the edges. A graph in a multi-graph representing the water irrigation water network may have different weight depending on the distance and diameter, or may be split into two parallel graphs each one representing the weights of the edges as the parameters of the subgraph.

We have also developed a Servo Valve that is capable of turning standard 1/2" ball valve using 35n*m toque servo with metal shaft. The assembly utilizes both bent metal rods and $3D$ printed enclosures, see Figure 4.18.

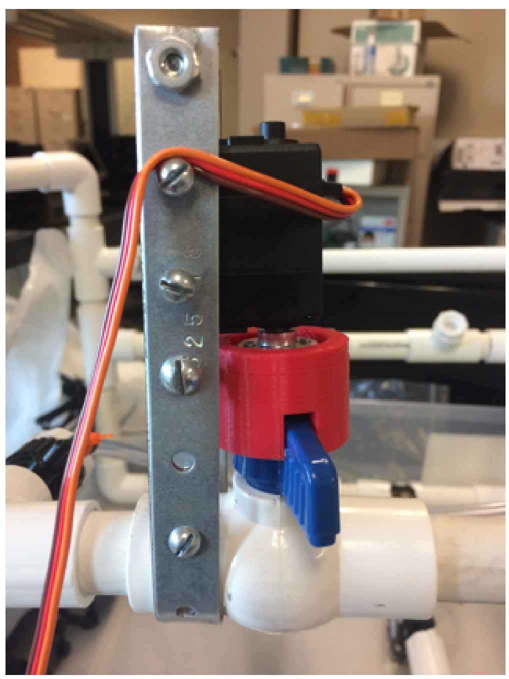


Figure 4.18: Modular servo-valve design for block line operation fits on top of a legacy PVC ball valve

4.4.1 Validation

With use of software using a circuit analog model of the irrigation system, the software simulation results were validated. The experimental setup utilized Bluetooth enabled nodes, such as CSR1010 and CSR1011 Bluetooth LE modules [104]. In the Figure 4.20a, a breadboard circuit that stands for irrigation networks functionally demonstrated the simulated algorithm with wireless communication enabled. Although, this type of analog test-bed based validation is not a formal verification technique of the design, however, it shows an initial integration testing of algorithms and communication plane. The next experiment further validated this on a smaller setup of the hydroponic test-bed, see Figure 4.20b.

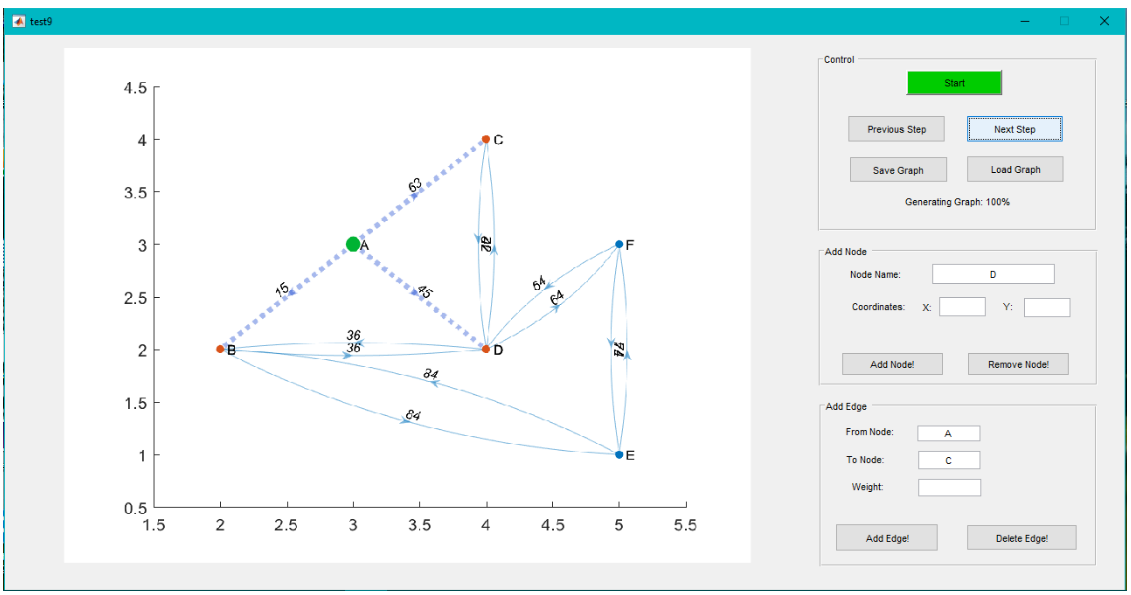
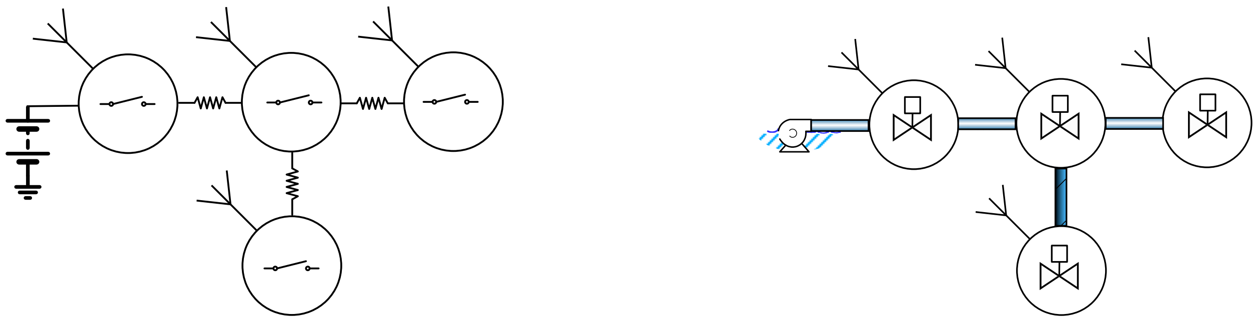


Figure 4.19: MATLAB based IoT Topology Adaptation Simulator

4.5 Discussion

Irrigation is itself not just a science but also a business practice. Thus, we shall also look into it from the entrepreneurial stand point. It is indeed difficult entering the market as there are not many IoT controllers used in field, which means that there are many legacy system that



(a) Electrical IoT (b) Hydraulic IoT

Figure 4.20: Irrigation IoT System Testing with Circuits - Electrical circuit used for validation of the topology adaptive communication plane.

need to be taken into account. That is why interfacing with legacy systems will help support challenges associated with market barriers.

Increased costs from added sensors and communication circuits reduces usability of the tools, but can lower installation costs. The complexity of installation of these units will depend on the precision of location and quantity needed to be installed, tracked separately, and maintained. However, when supply feature that enable wireless network to self manage and provide actionable insight one can expect reduced recurring costs. Moreover, installation expertise would be reduced in terms of needed specialization, for instance, only plumbing experience would be required as opposed to high/low voltage expertise.

Nevertheless, security concerns such as side channel attacks [2] [4], which can be used to manipulate irrigation schedules, are valid and will play a critical role in the future research of irrigation CPS.

Current drip irrigation practices use emitters that are manufactured to output nominal flow rates, however, we know that these flow rates are inconsistent across drip lines and are sources of variations in irrigation. To reduces these variations in flow, drip system designers would use pressure regulators, which within their design limitations, reduce the pressure in areas with high pressure - ultimately normalizing the pressure across different segments of drip system. In an ideal world this would be enough, but we know that even identifying these pressure build up zones takes practice and in many cases ruptures to identify them. In one hand, we can blame the emitters for not being perfect; on the other hand, can blame drip lines, or even the designers. However, there is a fundamental flaw in the practice, which is that these components are all passive - not active or aware of the operational mode they are in.

The other fundamental element of control is the feedback. Feedback enables control to be more resilient to uncertainties in design and practice. For example, active pressure step down regulation would allow to maintain the pressure across a range of high inputs, and active step up pressure regulation would enable increasing pressure. In electronics, these devices are called DC-DC (or AC-DC) step up, or step down converters which use the feedback of voltage output response for the control. One electronic design that enables this control is the famous buck converter. The principal of operation can be fundamentally applied to water as well, although in many cases realizations maybe unnecessarily costly. However, what the power conversion science does teach is that pressure regulation can be fine tuned with feedback control.

Fundamentally, feedback relies on sensing, which in context of an irrigation setting is extracted/evaluated from water flow, water pressure, soil water tension, humidity, temperature and etc. For example, in the case of pipe pressure regulation sensing, the pressure at the output and passing this information for control to refine internal operation makes up the foundation of the feedback control which stabilizes the system. In the example of the pressure regulators, pressure sensing becomes essential. Unlike flow sensing, pressure sensing is actually a lot easier with current semiconductor pressure transducers, whose costs are reducing as the technology is evolving.

Going back to emitters, with finer pressure regulation at the emitter input, we can then guarantee finer output. However, note that the emitters don't have a feedback of their own.

They take the water in and out put the flow rate needed, but where the water goes and how much should go is on only controlled by the main controller of the drip line. These emitters are also passive devices, and require yet another feedback that tell them to stop per application needs. Not every emitter emits to the same identical plants. In fact, drip emitters provide not to the plant, but to the soil - exposing it to uncertainties in the soil, environment and climate. Thus, feedback from the soil, or the plant is required to adjust each individual emitters total output.

The irrigation control feedback from soil can be either from the water content in it, in terms of volume or mass, or tension, respectively, by using a moisture sensing device or tensiometer. However, unlike pressure regulation in the drip line, where feedback is instantaneous (assuming fluid flow is incompressible), we know that infiltration delays in soils. This depends on soil type and depth of interest, where the roots are located, because they are significantly large in both magnitude and variation.

Traditionally, we are used to building electrical circuits or systems by linking input power to all components by wiring around the system or circuit. However, currently technology allows us to harvest and generate our own electrical energy and we can generate power right where it is needed. For example, solar power photo-voltaic cells require small footprints for energy generation and can be used for various applications from control to sensing, and communication. PV arrays heavily rely on sun and weather conditions and thus its considered to be intermittent and prone to variations in power generation. Another form of power generation is from water flow in hydropower systems to small micro-turbines that can generate as high as 1W power with high efficiency - taking very little kinetic energy from the water line (as opposed to 750W input power of the Pump). Also, a hybrid approach to power generation can be applied in an electrical circuit to generate power from both water flow and ambient light for all purposes of irrigation system. Results of pressure and power generated is summarized in the Figure 4.21.

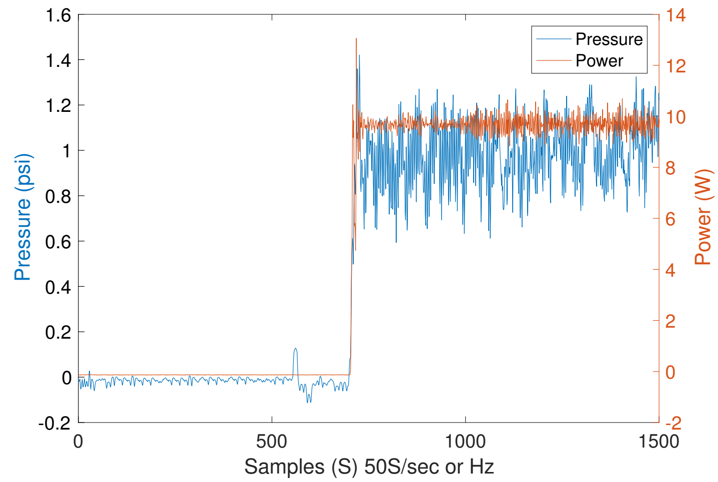


Figure 4.21: MATLAB based IoT Topology Adaptation Simulator

If we can generate power, then we can also implement this distributed control mechanism using valves with minimal energy demands. In the market currently, there are solenoid small valves that can be turned on and off with a few watts of power. These valves can be further improved for energy consumption by having mechanical locks; in other words, having low power or shut down modes.

On the other hand, we see a great potential in using valves that have finer control applications. For example, valves instead of having binary, on/off, operational modes could also have flow control features, as in opening the perfusion to enable partial, but known flow mechanisms as well as fully open and closed operations. For this purpose, currently there exist low cost servo motors which can fine-tune control ball valves even with modular design. We have used a modular design approach to demonstrate this for valve sizes for common drip lines and $\frac{3}{4}$" pipes. We expect finer integration of servo-valves to have much higher efficiency in terms of energy and power consumption.

4.6 Conclusion

In irrigation CPS, all the involved elements must be carefully weighted because in some cases irrigation must be designed once but used for decades. Moreover, a complete solution to irrigation systems must incorporate every step from design and development to deployment. In other words, there should be means to make design decisions *a priori*, to re-calibrate system settings during or after the final stages of installation and to use the current knowledge to engineer tailored or standardized solutions in the farm.

By putting the puzzle together, we can deduce that the next generation of precision irrigation requires new devices for control that can handle many different tasks from energy harvesting to regulation of pressure/flow, thus, requiring sensing for feedback operation. Although there are many self regulating mechanical applications, it is more common and convenient to make electrical, electronic or digital smart devices. Moreover, micro-irrigation systems can be enhanced with CPS approach by cost reductions, automation and improved monitoring.

4.6.1 Future Work

In future works, we intend to improve the modularity of the design of the servo valve to support attachment to more legacy components. Additionally, it would be a good idea to redesign controller valves with more sensitive flow sensors and active pressure regulation features. To further validate our current findings we would need new field experiments with IoT controllers that automate and improve irrigation efficiency.

Chapter 5

Multi-Modal Imaging Feedback For Health and Growth Monitoring

5.1 Abstract

Continuous monitoring of crops is an essential task of agricultural practices for the detection of diseases or pests, precision irrigation and fertilization. State of the art monitoring and imaging systems use aerial imaging to obtain visual feedback and multi-spectral imagery to determine crop growth factors. The main idea is that the features can be automatically calculated and assessed after pre-processing the images. After pre-processing, the parameters can then be computed using image processing techniques. For example, key leaf function traits like leaf life span and leaf mass per area can be calculated. Our findings indicate that plant health and growth assessment can be moved from lab and expensive monitoring tools to ubiquitous silicon technology based cost effect solutions without much loss of accuracy. The covered contributions in this chapter are: (1) leafsnap dataset based feasibility study of leaf venation based health assessment, (2) experimental case study of growth tracking using

pigmentation, on site measurements and derivation of a fidelity model for growth tracking; (3) a thresholding-overlapping technique for recognizing plants between frames of overhead images; (4) a dataset that was labeled for plant recognition and pest identification; and (5) a Deep Learning architecture that can identify pest infected images bounding rectangles of the bush bean plants.

5.2 Introduction

Continuous monitoring of crop is an essential task of agricultural practices for detection of diseases or pests, precision irrigation and fertilization. The state of the art monitoring and imaging systems use aerial imaging to obtain visual feedback and multi-spectral imagery to determine crop growth factors. These are in most cases coarse tools and do not focus on providing close up information, such as particular plant health assessment. Moreover, most of the time detected diseases are already advanced to the point that nothing can be done to isolate, countermeasure and reverse the spread. On the other hand, studies show that it is possible to visually determine plant health characteristics by looking at individual leaf internals such as distances between veins at etc [15]. In this work, we show that it is possible to use computer vision algorithms to automate the health assessment process and enable further assistance to overhead imaging based monitoring.

This work will describe image processing methods that can be applied to agricultural image processing settings and will provide a few novel contributions in the application area. The main motivation being for this thrust is to close the feedback loop at different modalities of imaging and processing. The main contributions presented here are: (1) a novel health assessment technique that automates an existing technique and utilizes dataset, that was previously used for plant identification only; (2) an experimental case study of growth tracking using pigmentation, *in situ* measurements and derivation of fidelity model for growth tracking;

(3) a thresholding-overlapping technique for recognizing plants between frames of overhead images; (4) dataset that was labeled for plant recognition and pest identification; and (5) a Deep learning architecture that can identify pest infected images bounding rectangles of the bush bean plants.

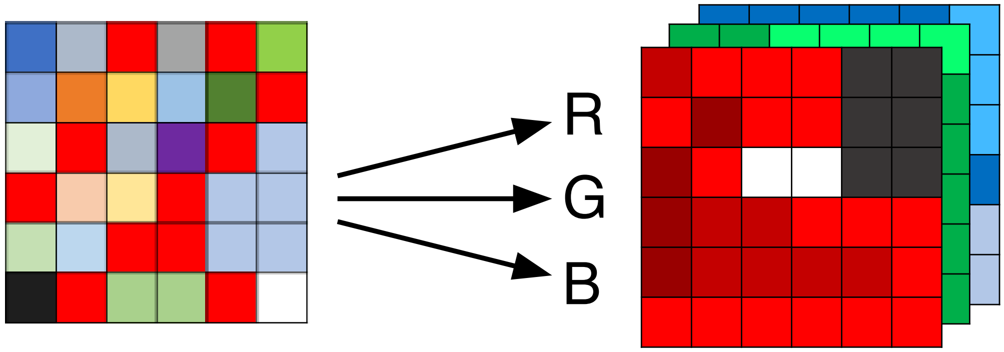
5.2.1 Background

In computer vision, image segmentation is the process of partitioning a digital image into multiple segments. The goal of segmentation is to simplify and even change the representation of an image into something that is more meaningful and easier to analyze. Image segmentation is typically used to localize objects and their boundaries. More precisely, image segmentation is the process of assigning a label to every pixel in an image such that pixels with the same label share patterns. One of the common unsupervised techniques for doing so is the super-pixelation technique that looks at each pixel and its neighbors' and determines whether these pixels can be clustered into a single entity.

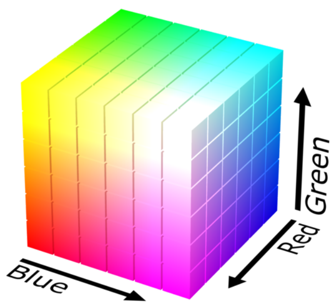
Modern agriculture is driving agricultural production towards intelligent automation by applying scientific and technological achievements. Providing more precise information using image processing and machine-vision techniques can be an effective substitute to naked eye based judgment on irrigation/water stress, fertilizers, pesticides and quality of yield. Thus, it is important to discuss areas that show the potential of machine vision techniques in the agriculture field as they can be extremely cost effective, quick and automated.

Morphological Image Processing

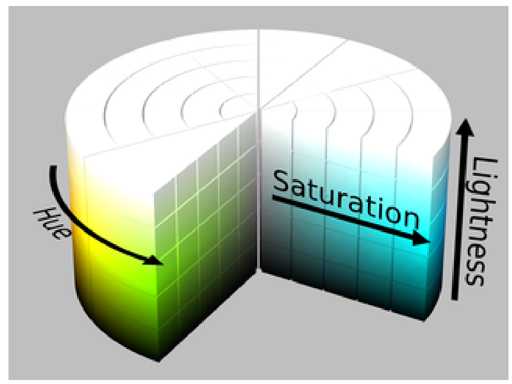
There are several fundamental morphological processing techniques used in image processing. Some of the fundamental morphological processing methods are Translation, Reflection,



(a) Image to 3 component decomposition



(b) RGB Model



(c) HSL Model

Figure 5.1: Color Representation RGB and HSL Models

Erosion, Dilation, Opening, Closing and etc, and are summarized in Table 5.1. These operation in their essence are bitwise operations, which are processing either once per each individual pixel such as in the case of complimentary operation, or by window which is moved around the image. Some of these are region growing operators, while all of them are also called filters. These filters are said to be convolving around the 2D space, which is a fundamental utility of Convolutional Deep Learning, where learnable filters are used to produce desired feature extraction and supervisory learning (a visual description is available in Figure 5.2).

These operations in their essence are bitwise operations, which are processing either once per each individual pixel such as in the case of complimentary operation, or by window which is moved around the image (see more in Appendix B Chapter 8). Some of these are region growing operators, while all of them are also called filters. These filters are said to

Compliment	$A^c = \{c \mid \notin A\}$
Translation	$A_z = \{b \mid b = a + z, a \in A \text{ and } z = (z_1, z_2)\}$
Reflection	$\hat{A} = \{b \mid b = -a, a \in A\}$
Erosion	$A \ominus B = \{z \mid (B)_z \subseteq A\}$
Dilation	$A \oplus B = \{z \mid (\hat{B})_z \cap A \neq \oslash\}\}$
Opening	$A \circ B = (A \ominus B) \oplus B$
Closing	$A \bullet B = (A \oplus B) \ominus B\}$

Table 5.1: Morphological Image Processing Fundamental Operations

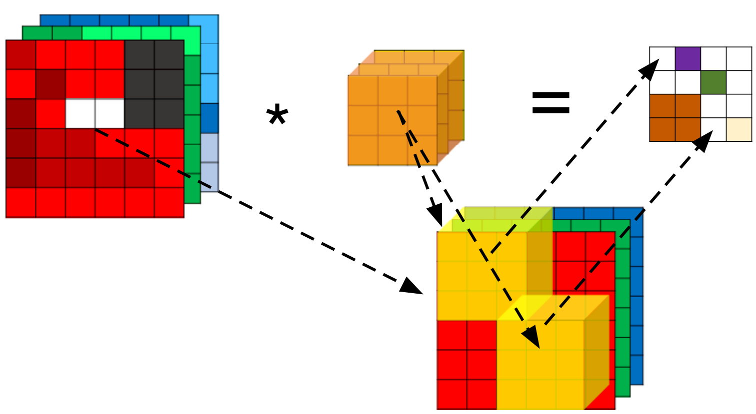


Figure 5.2: Graphical Visualization of 3D Convolution. The overlapping areas are then elementwise multiplied and added.

be convolving around the 2D input space, which is the foundation of Convolutional Deep Learning where the input is passed through consecutive learnable filters that produce desired feature extraction. Learning in the context of Deep Learning is the process of optimization of parameters by the means of matching and optimizing set of input and output pairs.

Deep Convolutional Learning

Indeed, Deep Convolutional Learning has come a long way with tools enabled to provide means for modeling the most complex phenomena such as taste [133] [44] [56], objects [65] and even artistic style transfer [36]. That said, there is little work done to apply deep learning techniques to agricultural practice although there are several efforts to do so in the forms of studies on using deep learning for certain tasks. For example, plant phenotyping has been studied with improvement of segmentation quality on the previously tradition computer vision heuristic method of leaf edge curvature estimation. However, we shall acknowledge and review much of intuition that is utilized in deep learning as it has been extensively studied in the past.

Most conventional Deep Learning models are constructed as tensor layers where input is passed from one layer to next chaining the data flow from input to output. However, there are certain architectures that have additional features such ResNet that allows data in between layers to skip and pass forward through skip connections [43]. Although, some of the architectures have different unique characteristics, most of them share many common utilities. Utilities that are universally used to connect the layers of modern deep learning computer vision architectures include Convolutional Filters, Pooling and Activation Functions.

- **Convolutional Filters** are filters much like in conventional signal processing, but in 2 or 3 dimensions. Usually they are used in multiplicity allowing to filter out different features or signals. A basic filter operation can be described by convolution operation

Average pooling	$(x, y) \rightarrow \frac{(}{x}, y)$
Max pooling	$(x, y) \rightarrow max(x, y)$
L1 Norm	$(x, y) \rightarrow \lvert x + y \rvert$
L2 Norm	$(x, y) \rightarrow \sqrt{x^2 + y^2}$

Table 5.2: Pooling Methods and definitions

that passes through an input signal. When applying convolutional filters to the input image there are three considerations: number of filters used at that layer, strides to be taken when moving the filter window around the input and padding or zero-padding added to the image constraints. The intuition is to take as much locality information while lowering overall dimensionality.

- **Pooling** is a technique that maps many values to a single value. It is usually a very coarse decision model that picks a single value out of many or some kind of simple operation. That said, much work can be done to improve pooling techniques. However, there are already known and widely used different pooling techniques such as:

- **Activation Functions**: ReLU (Rectifier Linear Unit), ELU (Exponential Linear Unit) Saturating hyperbolic tangent, Sigmoid and Softmax. The main Recursive Formula describing Fully Connected Networks is following: $Z^{n+1} = W^{n+1}A^n + B^{n+1}, A^{n+1} = Activation(Z^{n+1})$

  - ReLU - $max(x, \alpha)$, where α is usually 0.

    * Leaky Relu - $\begin{cases} \alpha x & x \leq 0 \alpha < 1 \\ x & x > 0 \end{cases}$

    * ELU - $\begin{cases} \alpha(e^x - 1) & x \leq 0 \\ x & x > 0 \end{cases}$

  - Saturating hyperbolic tangent - $tanh(x)$

  - Sigmoid - $\frac{1}{1+e^{-x}}$

  - Softplus $log(1 + e^x)$

– Softmax - $\frac{e^x}{\Sigma e^x}$ is usually used for distinguishing between classes of classification. It is considered a loss function as it determines how far off the predictions are from intended target training and is usually placed at the last layer.

– Others -

  * $erf(\frac{\sqrt{\pi}}{2}x)$

  * $\frac{x}{\sqrt{1+x^2}}$

  * $\frac{2}{\pi}gbd(\frac{\pi}{2}x)$

  * $\frac{x}{1+|x|}$

– Loss Functions - These are functions that are present in the last layer of the network where predictions and the estimates are compared.

  * Absolute Loss - absolute difference between predictions and estimates. $|X-Y|$

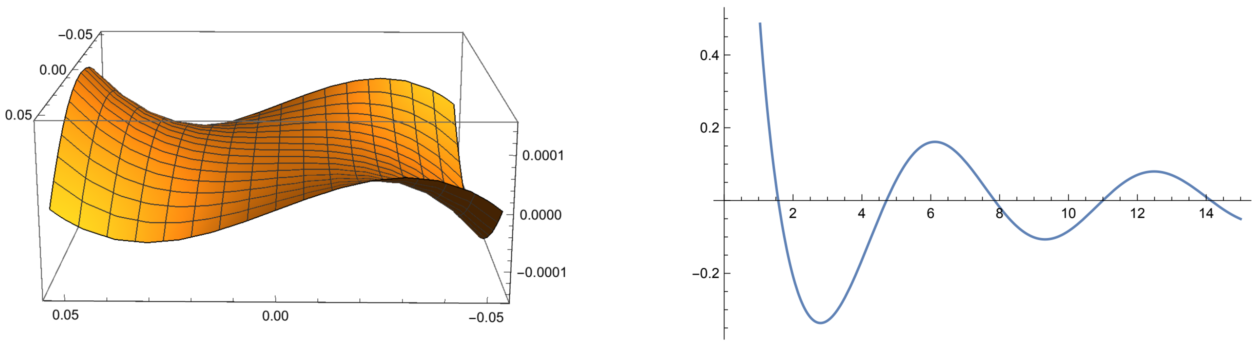
  * Squared/Mean Squared/Mean Squared Error loss - squared difference between predictions and estimates.$(X-Y)^2$

  * Kullback-Leibler/Cross Entropy - Entropy based function $\Sigma(X-Y)\log{(X-Y)}$

  * Hubert loss -$\begin{cases} \frac{1}{2}(X-Y)^2 & |x-Y|<\delta \\ \delta(|X-Y|-\frac{1}{2}\delta) & otherwise \end{cases}$

  * Hinge loss - $max(0, 1-X.Y)$ where Y is -1, $+1$.

For optimization of the model parameters, the most commonly used technique in networked models such as neural networks and deep learning is the back-propagation. That said, back-propagation utilizes optimization catalyzing techniques to speed up the optimization. The most common catalyzers are Adam, AdaBoost, Ridge regularization, general boosting and bagging, which speed up the optimization process and help to reach the global optima. In the very high dimensional functions under optimization usually the optimization target moves from between local minima and global minima (see Figure 5.3b), to between lots of saddle points and the global minima. Saddle points are points where the function has more than one curvature much like a saddle, where in one projection its a convex function, while on another projection it is not. An example of a function that has a saddle point is $F(x, y) = x^3 - xy^2$ as depicted in Figure 5.3a.



(a) Saddle $f(x, y) = x^3 - xy^2$

(b) Convex Function $f(x) = \frac{cos(x)}{x}$

Figure 5.3: Optimization Challenges Low-Dimensional Local Minima and High Dimensional Saddle

Optimization Methods

The gradient descent method utilizes linearized learning rate:

$$\theta_t = \theta_{t-1} - \eta \Delta J(\theta) \tag{5.1}$$

One of the known disadvantages of gradient descent method is that it tends to converge upon local minimas and may even oscillate between values and never reach a minimum. To avoid this a more robust, momentum optimization is used:

$$\begin{aligned} \mu_t &= \alpha \mu_{t-1} - \eta \Delta J(\theta) \\ \theta_t &= \theta_{t-1} + \mu_t \end{aligned} \tag{5.2}$$

Momentum optimizer is generally faster than gradient descent, and there are some different ways similar idea is used to accelerate the step by adding extra momentum on step size. However, it applies the same learning rate to very parameter, thus, an improved algorithm has been proposed, Adagrad:

$$\begin{aligned}
\eta_{t,i} &= \frac{\eta}{\sqrt{G_{t,ii}}} \\
\theta_{t,i} &= \theta_{t-1,i} - \eta_{t,i} g_t
\end{aligned} \tag{5.3}$$

Although Adagrad personalizes learning rates it also lowers the magnitude of learning rates the the converge closer to the desired objective, thus, it makes it difficult to quickly reach the minima. To avoid this, the most widely used algorithm has been proposed Adam, which utilizes both momentum and scaling of learning rates:

$$\begin{aligned}
m_t &= \beta_1 m_{t-1} + (1 - \beta_1)\Delta J(\theta) \\
\mu_t &= \beta_2 \mu_{t-1} - (1 - \beta_2)[\Delta J(\theta)]^2 \\
\eta_t &= \frac{\eta\sqrt{(1 - \beta_2^t)}}{(1 - \beta_1^t)} \\
\theta_t &= \theta_{t-1} - \frac{\eta_t m_t}{\sqrt{\mu_t} + \epsilon}
\end{aligned} \tag{5.4}$$

Thus, in our optimization techniques we used Adam method, which adds few more hyper-parameters as evident in the Equation 5.4, but significantly cuts on optimization time and improves convergence likelyhood.

Convolutional Models

Some of the most successful Convolutional Networks are LN5 (see Figure 5.4), AlexNet3 (see Figure 5.5) and VGG16 (see Figure 5.6). They have been utilized for MNIST [71] and other datasets for predicting handwritten digits and etc. These architectures of convolutional networks provide insight into the anthropological development of deep learning. Chronologically, going from earliest LN5 to somewhat new VGG16 (there many more complicated and improved models) how the depth and the width of the architecture expands. This is no surprise as over time more computational power has been available as there is a certain length of time that any researcher is willing to spend on waiting for simulations to complete. Thus, it is important to notice that fast simulations have a catalyzing impact on machine learning domain and may have much similar impact on irrigation and agricultural sciences.

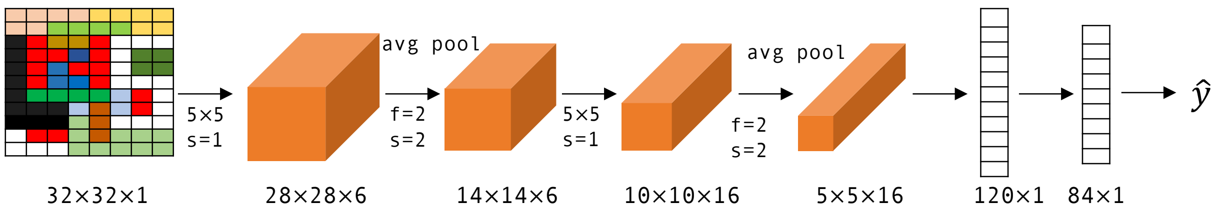


Figure 5.4: LN5 Network (S stands for Stride of the filters)

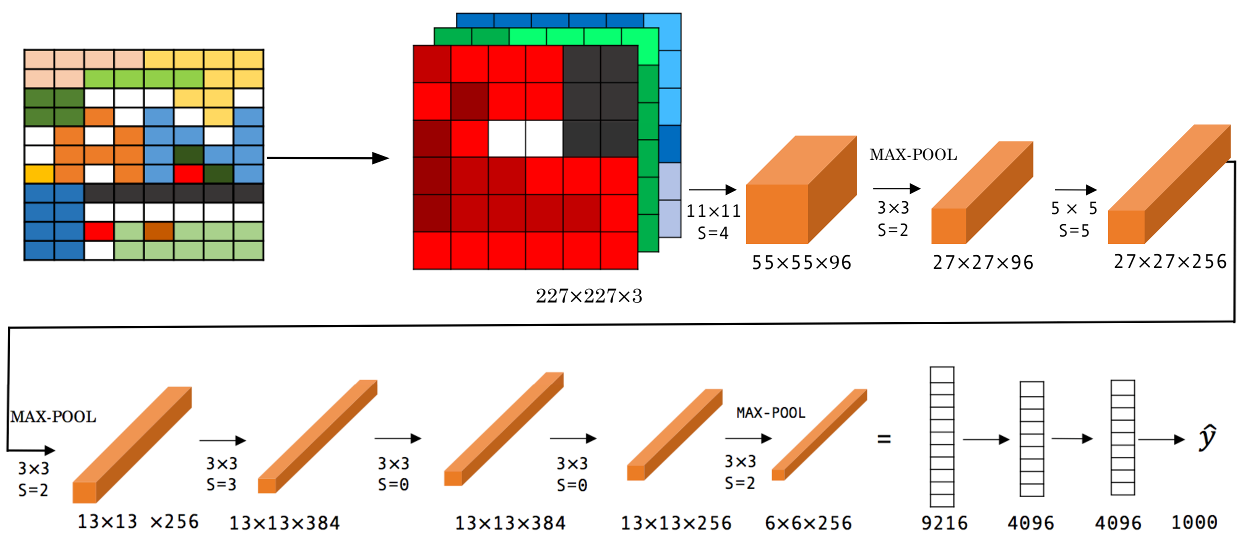


Figure 5.5: AlexNet Network (S stands for Stride of the filters)

5.3 Materials and Methods

In this section are presented materials and methods used for feasibility analysis of health and growth monitoring using machine vision techniques.

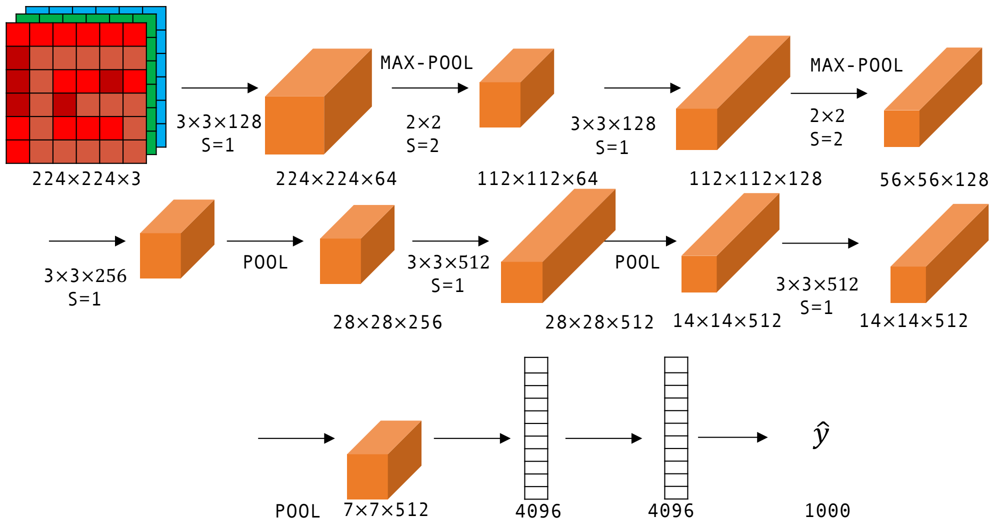


Figure 5.6: VGG Network (S stands for Stride of the filters)

5.3.1 Leaf Venation Networks

Leaf venation networks are the skeleton connection of the leaf. They determine how much water or nutrients have to go to the plant how it will react to environmental factors such heat, humidity and solar radiation. In the past, researchers have identified features that capture plant health [15]. Some of the parameters to be estimated are:

- Density (σ) is the total path length of veins in a region of interest (ROI) divided by the ROI area.
- Distance (d) is the mean diameter of the largest circular masks that fit in each areole (closed loop).
- Loopiness (ξ) is the number of areoles in the ROI divided by the ROI area.

The main idea is that the features can be automatically calculated and assessed after pre-processing the images. After pre-processing, the parameters can then be computed using image processing techniques.

$$LL = k_1 d \tag{5.5}$$

$$LMA = \pi r_V^2(\rho_V - \rho_L)\sigma + \frac{2\rho L}{k_0} d \tag{5.6}$$

$$N_m = k_2 A_m + \frac{k_3}{k_0}\frac{2d - k_0 \pi r_V^2 \sigma}{LMA} \tag{5.7}$$

For example, key leaf function traits leaf life span (LL) and leaf mass per area (LMA) can be calculated, respectively, using Equations 5.5 and 5.6 by determining the d and σ.

To study this, a dataset of over 185 tree species called leafsnap [66] was used which has over 30,000 images. The dataset consisted of lab and field images of the leafs. The original work extracts the leaf contour curvatures as features to identify plants from leafs. However, it is not limited in use, as our method demonstrates that it can be used for health assessment as well.

In order to extract the needed venation diagrams we used ridge filtering, binarization and skeletonization technqiues [76] [25]. These techniques utilize ridge filter transformation method to identify ridges which closely follow the venation networks. To that end, we have extensively experimented with leaf snap dataset. The process can be repeated using Mathematica code published in Github [48].

Generally, a Gaussian function is defined as in Eq. 5.8, however, for an image there are two direction or variables x, y as in Eq. 5.9. That said, we know that the image can be approximated using second order approximation as in Eq. 5.10 (where $H_g, the Hessian, is defined in Eq. 5.11$). Note, in the Eq. 5.8 and 5.9 σ is the standard deviation and not the vein density.

$$G(x) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(x-\mu)^2}{2\sigma^2}} \tag{5.8}$$

$$G(x, y) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{x^2+y^2}{2\sigma^2}} \tag{5.9}$$

$$g(x, y) = \frac{1}{2} \begin{bmatrix} x \\ y \end{bmatrix} H_g [x \quad y] + \begin{bmatrix} x \\ y \end{bmatrix} \begin{bmatrix} \frac{\partial g}{\partial x} & \frac{\partial g}{\partial y} \end{bmatrix} \tag{5.10}$$

$$H_g = \begin{bmatrix} \frac{\partial^2 g}{\partial x^2} & \frac{\partial^2 g}{\partial x \partial y} \\ \frac{\partial^2 g}{\partial y \partial x} & \frac{\partial^2 g}{\partial y^2} \end{bmatrix} \tag{5.11}$$

In fact, to calculate the ridges, only the eigenvalues of Hessian need to be computed, as it is the second order derivative and eigenvalues only determine whether it is a ridge or not. In the following steps, skeletonization uses the erosion process to narrow these into a single line.

After preprocessing into a binary images as presented in the Figure 5.15 we used the following methods for calculating the parameters. To calculate σ we used the semi perimeter divided by the area; in other words, we counted the non black pixels and divide the result by the considered area. On the other hand, computing d was a very tedious process. To find d we first have to calculate minimal cycles - the cycles that don't contain subcycles in them. After that, we can find the largest inscribable circle's diameter in each cycle utilizing Voronoi Regions and Chebyshev Center.

5.3.2 Case Study: Practice of Drip Irrigation on Bush Beans

In this subsection, the experimental case study of growth tracking using pigmentation is covered using *in situ* measurements and derivation of fidelity model for growth tracking is presented.

To study this growth based crop demand model for control as well as other irrigation scheduling techniques, an experiment was conducted at the University of California Agricultural and Natural Resource South Coast Research Center on Bush (Green) Beans. In the experiment, 12 rows of seeds were planted, then sprinkled with water during the germination week and followed with drip tape irrigation (See Figure 5.7). To easily track field growth progress, the field was randomly sampled with 7 samples from every other row as depicted in Figure 5.8. Field growth parameters such as plant height and largest leaf dimensions were recorded on a weekly basis (see 3-Week Summary of results Figure 5.9).

5.3.3 Thresholding

In this Subsection we present a thresholding-overlapping technique for recognizing plants between frames of overhead images for use in application such as relative localization, plant tracking or plant counting. Our method to determine the threshold is, firstly, to convert the plant image into binary image, and then segment every single plant into a Region of

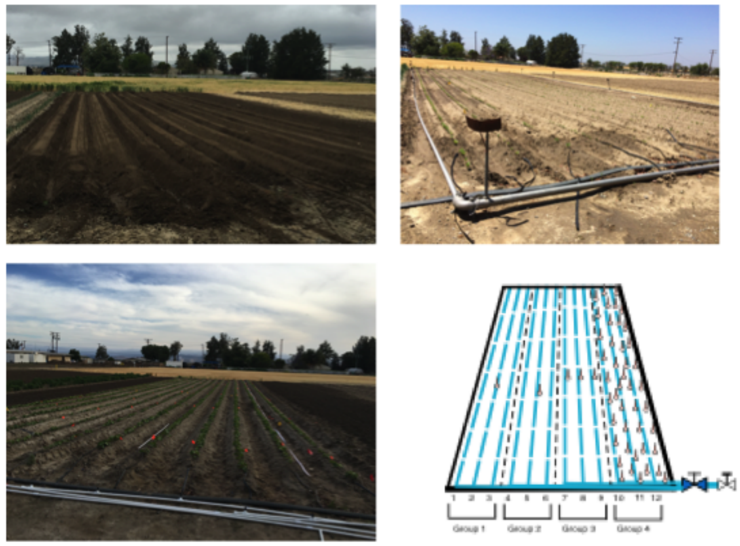


Figure 5.7: Experimental Field and Setup.

Interest (ROI) box, so they become separated, independent components. By overlapping the components in different images one by one, we can get the percentage of their overlapping area.

The next step is to look for identical plants in original images by hand, record the least overlapping percent of the identical plant pair where the upper threshold and the lower threshold are the largest overlapping area percent of any other plants which do not match with each other.

5.3.4 Labeled Dataset

In the field experiment, a dataset of about 200 images was collected from $1m$ above ground by using a reference rod. Later, the dataset that was labeled for plant recognition and pest identification. Plants were marked with their ROI rectangles, and labeled with size: small, medium and large; health as healthy or not, and three options for the plants occlusion level: separate, overlapping and partial. For labeling commercial tools, we used LabelBox [70] and Dataloop [26] (see Figure 5.13).

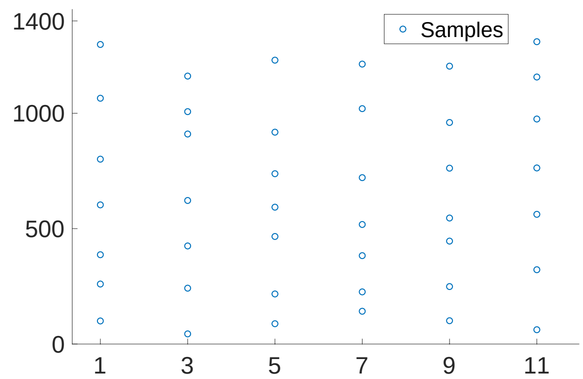


Figure 5.8: Every other row was randomly sampled at 7 points. Horizontal Axis are the row numbers, vertical axis is the distance from beginning of row in ft. The position were randomly generated.

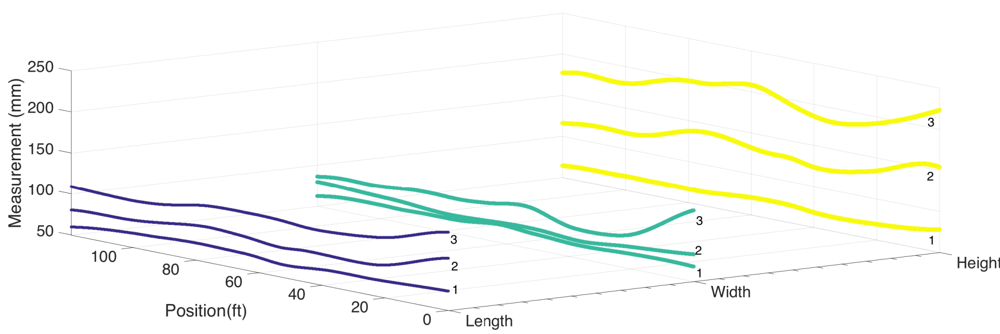


Figure 5.9: 3 Week Sampled Data of Plant Leaf Height, Largest Leaf Length and Width as metrics of growth

The dataset contains a series of row plant images, and in any two continuous images, there are some repeating plants. Our initial goal was to count the number of plants through finding these same components and recognition of unique plants.

At first, we planned to distinguish every plant by principle component analysis, so that we can find the distance of different plants in dimension-reduced coordinate, and classify them by k-means clustering. But we only have 2 or 3 samples for each plant; thus, lack of samples makes us unable to run an accurate PCA on these images. Hence, we changed the method into direct morphological operation and comparison, which is to compare the overlapping area percent of two plants. If the overlapping percent is larger than a certain threshold, we can say they are identical, otherwise they are not.

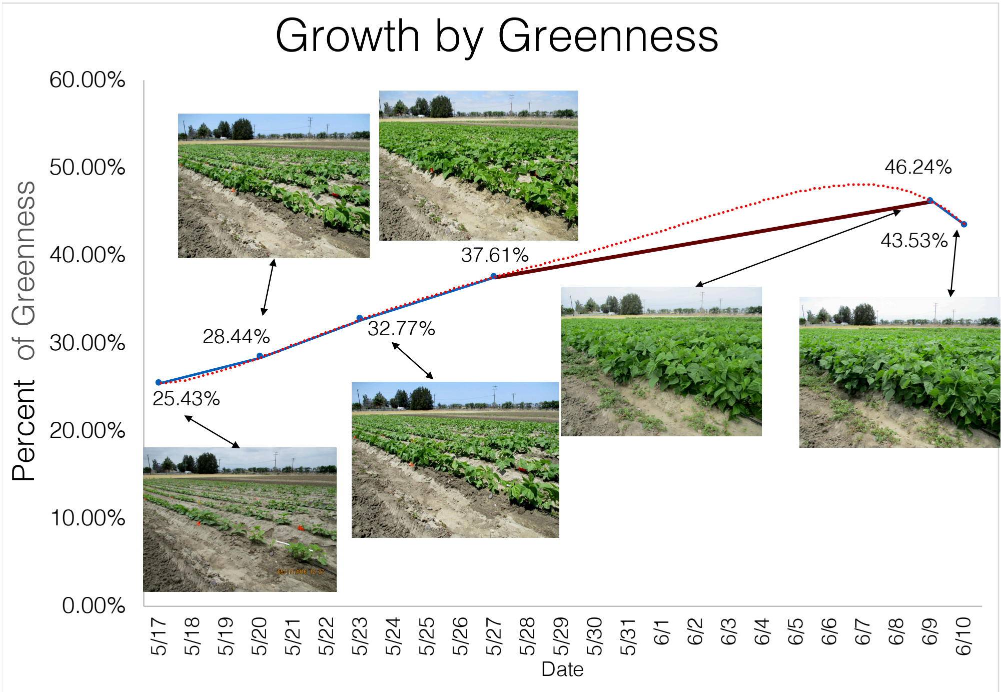


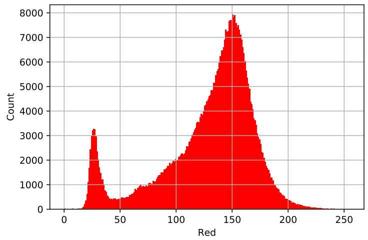
Figure 5.10: Pigmentation based growth Tracking

5.3.5 Deep Learning Architecture

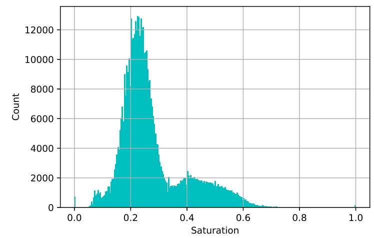
In this subsection, a new deep learning architecture is presented that can identify pest infected images bounding rectangles of the bush bean plants and other labels as described in the data (see Figure 5.23).

5.4 Results

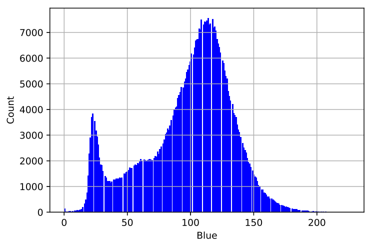
In this section, the discussion of results of experiments are covered within respective subsections where there was quantitative data present.



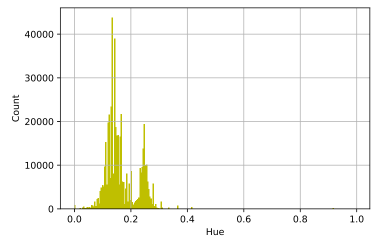
(a) Histogram of Red



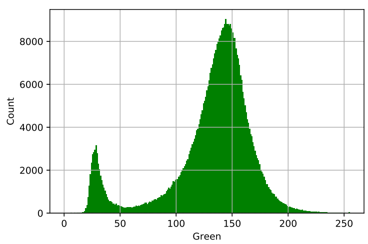
(b) Histogram of Saturation



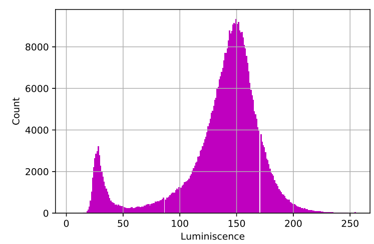
(c) Histogram of Blue



(d) Histogram of Hue



(e) Histogram of Green



(f) Histogram of Luminescence

Figure 5.11: Histograms of Sample 1 Image in RGB and HSL

5.4.1 Health Assessment using Leaf Venetian Networks

In the Fig. 5.15, 3 different preprocessed results are presented. These results demonstrate that indeed, there is a significant potential to utilize simple camera imaging. To finally complete the d, σ calculations, we present an image with shaded regions for the respective calcualtions in the Fig. 5.16.

In order to demonstrate the lighting impact on final results we present 4 different lighting situations observed for one of the leaves of Acer Palmatum plant in Fig. 5.17.

Our results indicated close to 80% results of successful estimation of the parameters; however, a much lower rate of 38% is observed on the images from field settings or in not so well lit

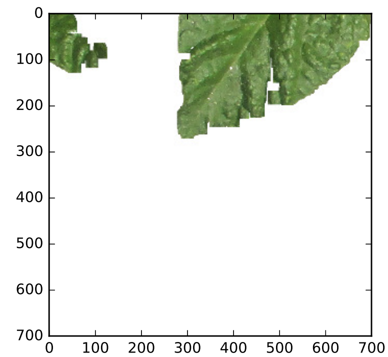


Figure 5.12: Segmented Image Small Sample

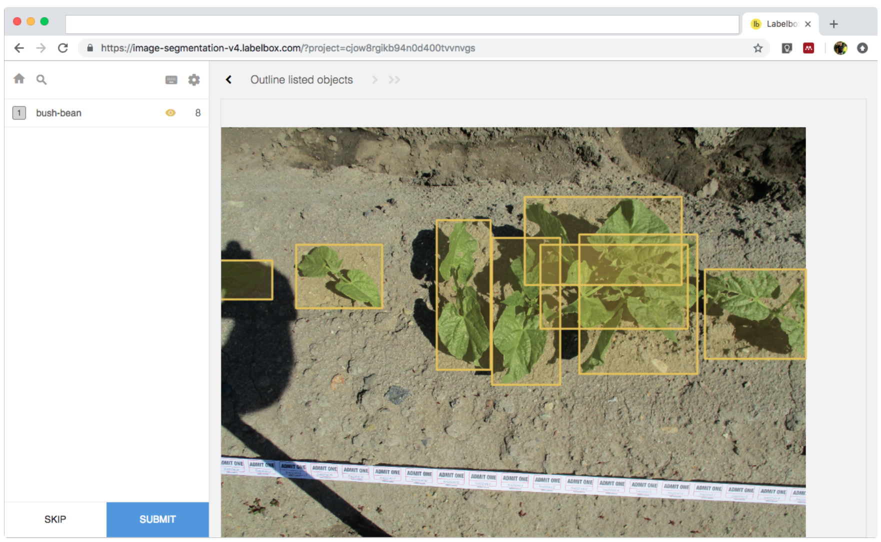


Figure 5.13: Label Sample

samples (See more details in Figure 5.18).

5.4.2 Thresholding

For the thresholding experiment, we examined 74 images in total. The objective was to identify repeated images of the same plant, which means that the same plant that appears in any of the 74 images would have to compared to others. However, this can be simplified, as we know that the images taken are in sequence, thus, only comparing pairs of images, for repeated plants is required - only 73 pairs of comparison. When there are no wrong matching

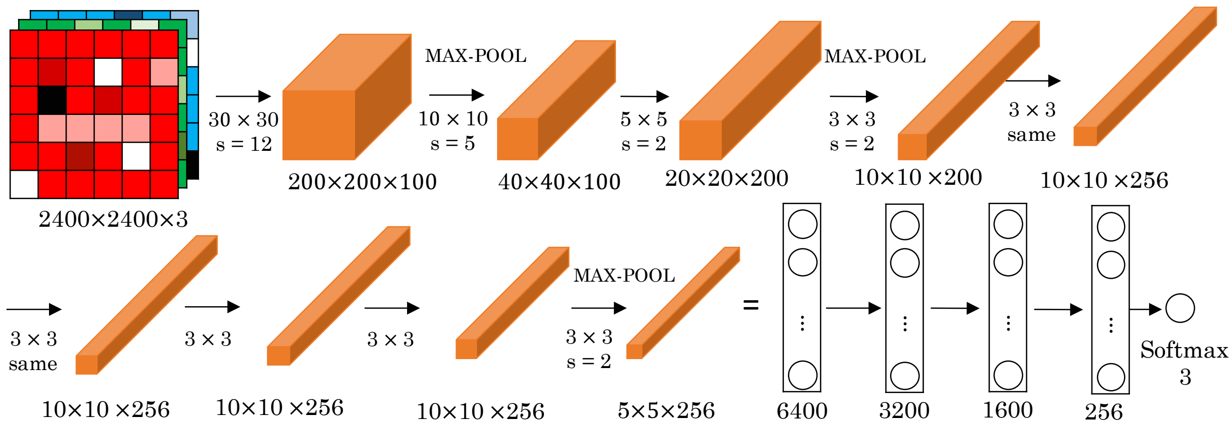
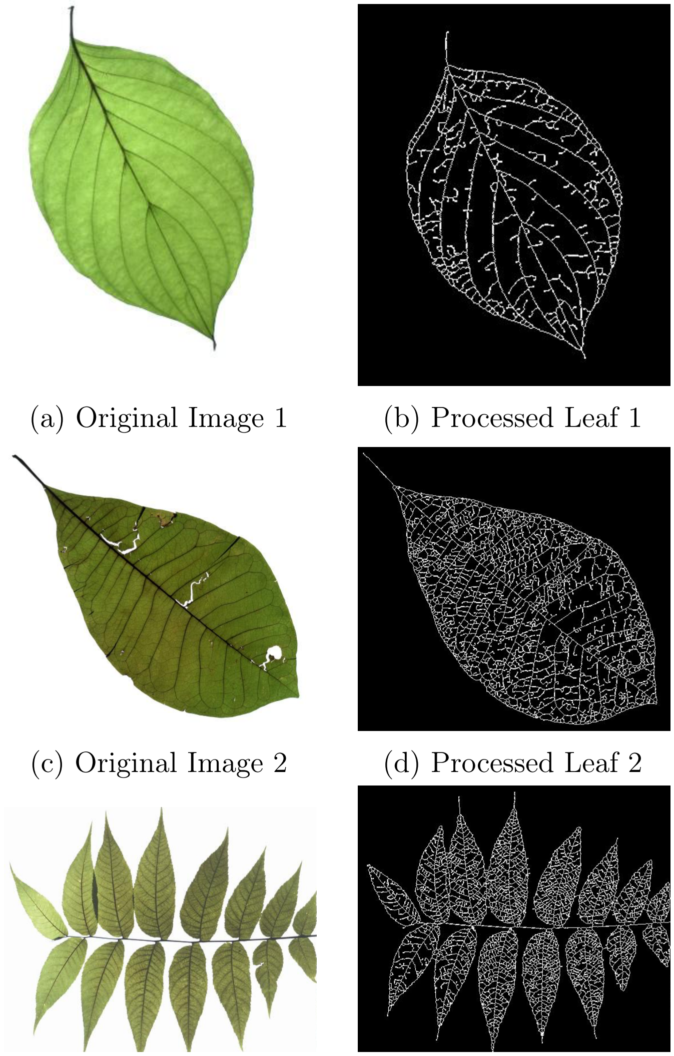


Figure 5.14: Our Network Architecture (S stands for Stride of the filters)

plants in the images - the upper threshold is less than lower threshold, we record it as positive matching. Through drawing the histogram of upper and lower threshold, we got the result of optimal threshold, [0.438, 0.46], which can satisfy the 58/62 images, so the actual matching rate after determining the threshold was 59/73, which is good but there is really not much space for improvement. A sample of the overlapping process is demonstrated in the Figure 5.19. However, findings show that it is impossible to have a threshold which can meet the need of all the images.

After an examination of 10 images, the counting result by hand is 23, while the number generated by computer is 18, it is smaller because of failure of recognizing the linked or overlapping plants. Sometimes two or more plants are close to each other and have overlapping leaves, thus they are linked together. We may know that they are different plants by naked eyes, but the computer doesn't. And the cause of wrong matching is mainly because of linked plants, too. Take Figure 8 for an example, in the first line leaf 6 and 7 are separated, but in another image taken in another view, they become one (leaf 3 in the second line), and that is why wrong matching happens. The biggest uncertainty results from binarization and the image opening operation. Large sized filters when applied on image opening will damage the integrity of leaf edge, but if it is too small, the linked area of different plants can not be deleted. Therefore, we need to think beyond the simple morphological operation to



(a) Original Image 1 (b) Processed Leaf 1

(c) Original Image 2 (d) Processed Leaf 2

(e) Original Image 3 (f) Processed Leaf 3

Figure 5.15: In Lab Leaf Segmentation using Ridge Filtering

improve the binarization results or we can eliminate it by planting with a larger gap between individual plants. For one, Deep Learning Convolutional Networks can be used.

5.4.3 Row Crop Images and Deep Convolution Network Result

Our architecture demonstrates 78% accuracy in the training set and 65% accuracy in the test set. Most of the inaccuracies can be contributed to the occluded images, which indeed is

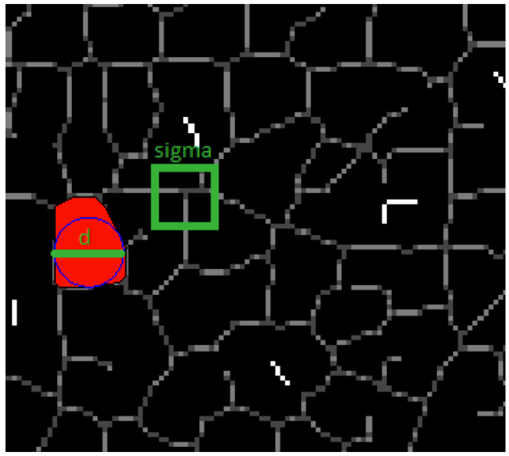


Figure 5.16: Demonstration of calculated d, σ

an open ended research challenge. On the other hand, even human error rates of marking the occlusions were very high as the data set was marked and corrected for occlusions with 6x more likelihood than the separate plants. This means that one can expect a significant human error rate present in the labeled data (even after twice repeated labeling process) that contributes to the overall performance.

5.5 Discussion

Our findings show that these calculations can be done with high fidelity as further research may be needed to compensate for quantization errors and other assumptions done by the process. The presented method has certain pitfalls such as lack of flexibility to lighting changes, which can be improved by introducing the adaptive techniques such as cost function that determines quality of the transformation.

However, in this work we did not calculate the exact parameters as the Leaf size as it is not determined directly from the image. Although the results are only relativistic, but we believe it provides means for tracking the progression of health for every leaf by σ and d, which implies that calculating LMA, LL, Am and Nm may be bypassed.

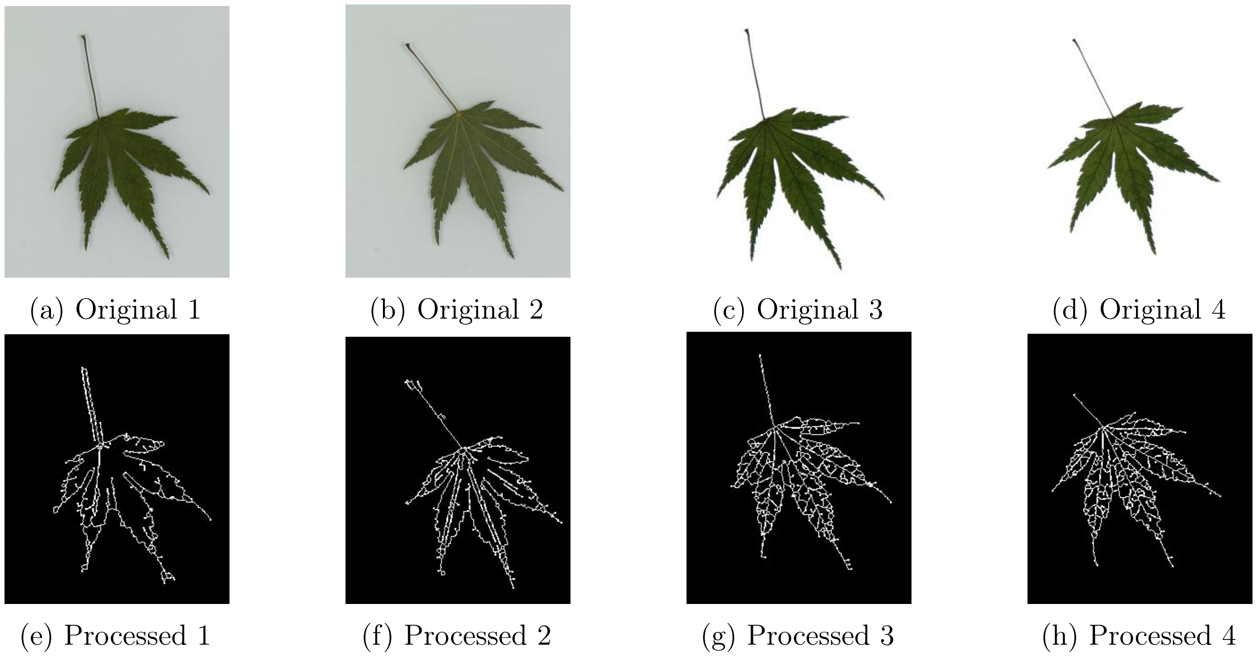


Figure 5.17: Lighting impact on processing: left original, right processes.

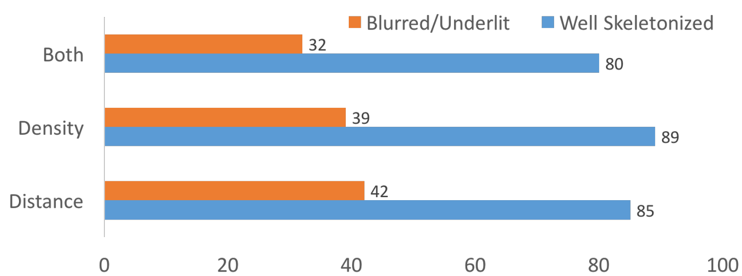
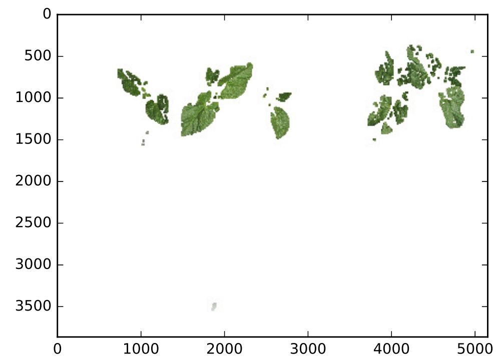


Figure 5.18: Health Estimation Results

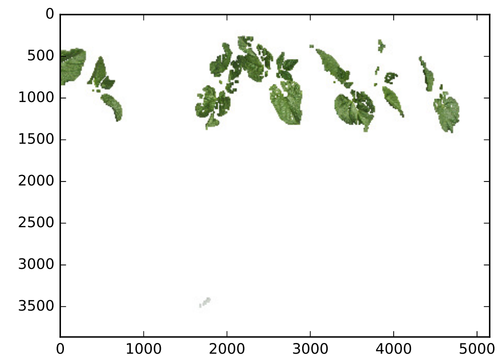
On the other hand, there were issues associated with the data set as well. many of the images were taken of the same plant under different lighting conditions, however, the files were saved in JPG compression format which is a lossy compression method which can compress images up to 10:1 without significant loss of quality [41].

Histogram-based methods are very efficient compared to other image segmentation methods because they typically require only one pass through the pixels. In this technique, a histogram is computed from all of the pixels in the image, and the peaks and valleys in the histogram are used to locate the clusters in the image. Color or intensity can be used as the measure.

Figure 5.19: Overlapped Images



(a) Image Sample 1



(b) Image Sample 2

Figure 5.20: Segmented Image Samples

A refinement of this technique is to recursively apply the histogram-seeking method to clusters in the image in order to divide them into smaller clusters. This operation is repeated with smaller and smaller clusters until no more clusters are formed. However, a disadvantage of the histogram-seeking method is that it may be difficult to identify significant peaks and valleys in the image.

Histogram-based approaches can also be quickly adapted for application to multiple frames while maintaining their single pass efficiency. The histogram can be done in multiple fashions when multiple frames are considered. The same approach that is taken with one frame can be applied to multiple, and after the results are merged, peaks and valleys that were previously difficult to identify are more likely to be distinguishable. The histogram can also be applied on a per-pixel basis where the resulting information is used to determine the most frequent color for the pixel location. This approach segments based on active objects and a static environment, resulting in a different type of segmentation useful in video tracking.

There are some interesting issues to be considered further. We can compare morning and night images to eliminate the shadow or use information of shadow/sun position for perspective

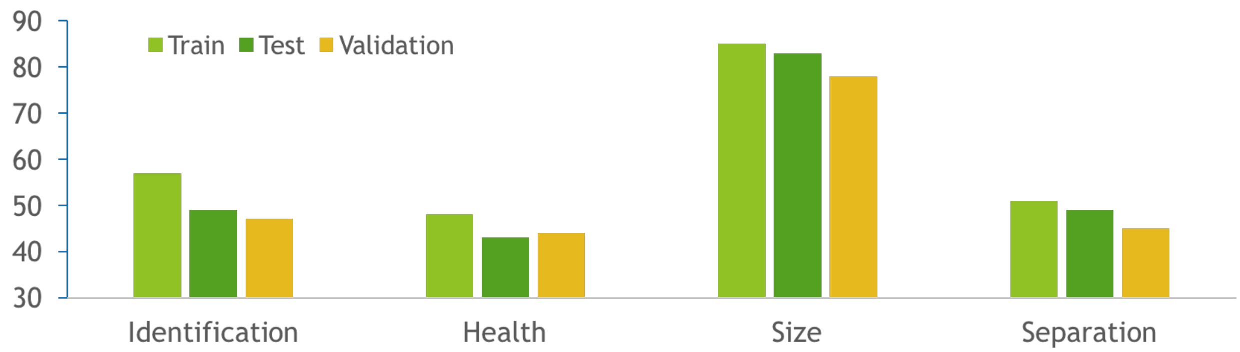


Figure 5.21: Training, Testing and Validation Results of DCN

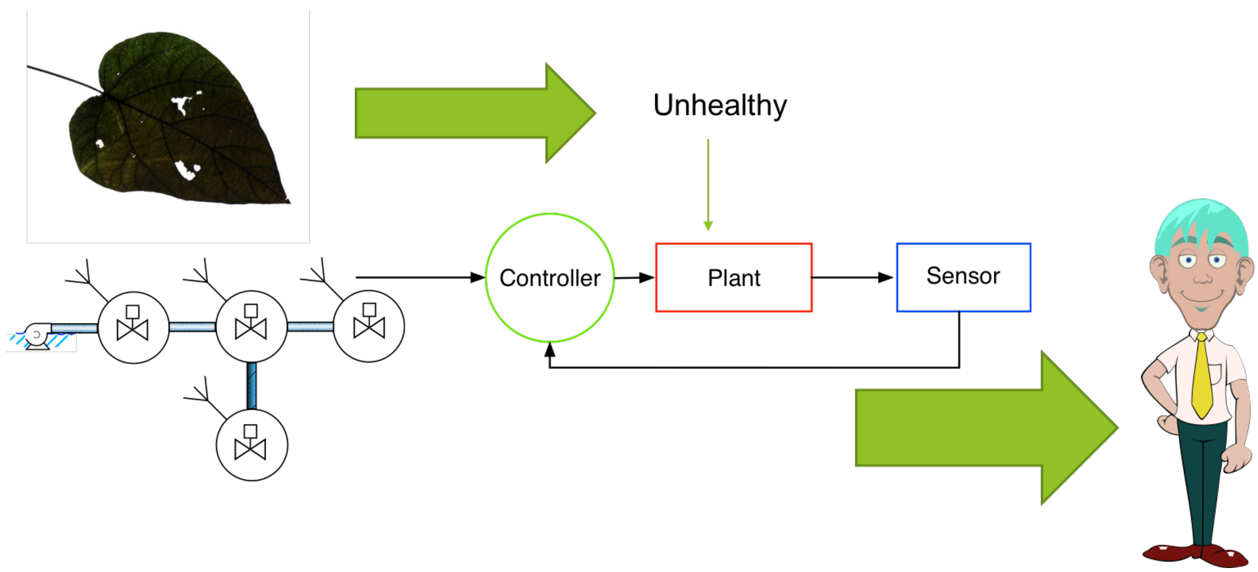


Figure 5.22: Health in the Control Loop

registration for better area calculation. The thresholding method is not adaptive and it would require, human intervention for situations when results don't make sense, or are out of expected bounds. The satisfiability criteria calculation is a very lengthy and tedious process, but with unsupervised learning techniques, perhaps one can adjust the threshold automatically.

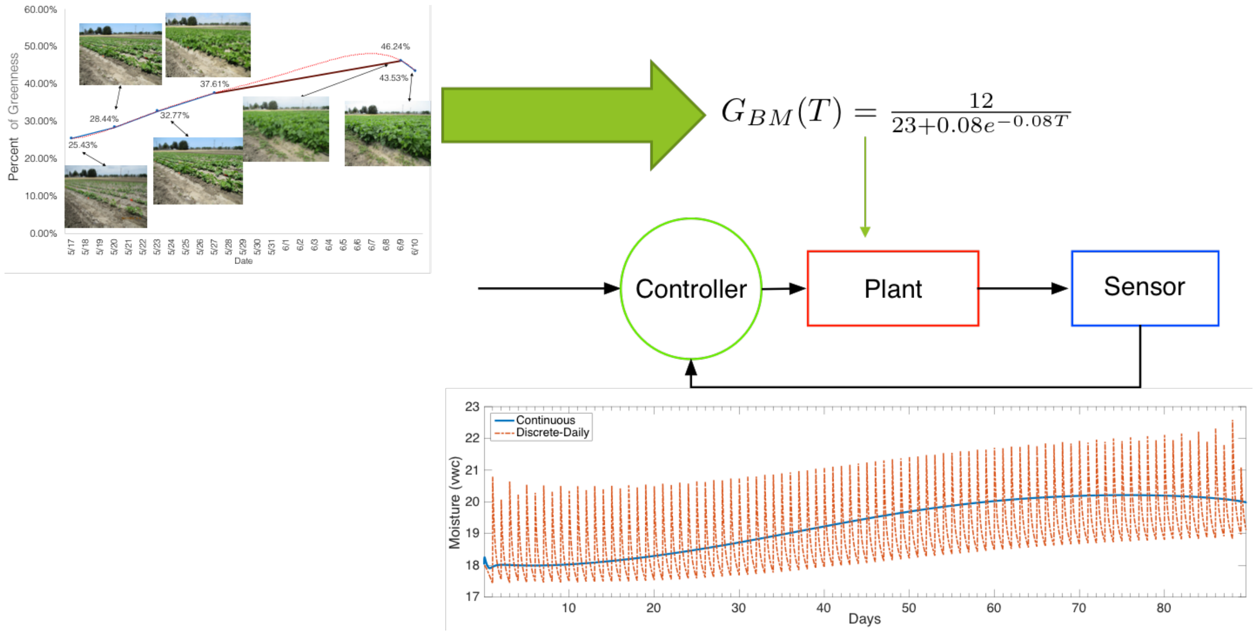


Figure 5.23: Growth in the Control Loop

5.6 Conclusion

Results show that quad-copter based overhead imaging could be an effective method for tracking growth parameters. Unfortunately, this method does not do well on overlapping images, which are intended to be improved in the future works.

On the other hand, the findings indicate that plant health assessments could be moved from lab and expensive monitoring tools to ubiquitous silicon technology based cost effective solutions without much loss of accuracy. In fact, these parameters can also be computed on a mobile device. This work used ridge filters to identify a skeleton for distance and density to quantify traits such as LL and LMA, but that does not mean that other parameters cannot be estimated as only these parameters were attempted for their simplicity of computation.

5.6.1 Future Works

That said, we see a significant drop in quality of processing due to luminescence changes. Moreover, our method of using conventional image processing techniques is light-weight. However, by using deep learning techniques we hope to obtain improved results. This can also be done on a mobile device by using neural accelerators.

Although we ended this Chapter with introduction to our Deep Learning results, the study itself has just started and is promising to yield far better results than observed in the presented study.

We are also interested in building apparatuses that have fixed background lighting to allow improved imaging as well markings to determine the exact size of the plant. In this work we have not found/presented effective ways of calculating the σ, d. However, utilizing the method described in [105] for computing inscribed radius may be useful or again maybe trying some of the more advanced Deep Learning techniques could be worthy.

Chapter 6

Conclusions

This dissertation addressed the open ended research challenges in the domain of irrigation systems, a man-made practice that is often wasteful and has global implications such as food and water security. Although this work addressed parts of the not well understood pitfalls, there are other aspects to irrigation science that still need thorough investigation. That said, the results indicate that significant progress can be made towards improvement of irrigation practice by utilizing state of the Cyber-Physical Systems approaches to modeling, monitoring, design, sensing and control of irrigation systems.

Our initial contributions presented here were in the field of model development. In particular, our initial contribution was novel modeling substrate that enables circuit simulation software to simulate real world irrigation scenarios as covered in Chapter 2. The significance of this work is not just in the result that enables simulation of irrigation phenomena specifically but also in the method of the development of hydroelectric analogy inspired models, which are developed using non conventional optimization techniques on a transfer medium, an electric circuit modeling substrate.

Thereafter, this work presented and delved into the actual practice of irrigation to establish a monitoring and sensing strategy that can be utilized towards water improvement by human management (see more in Chapter 3). That said, even better practices can be established with a quantum leap improvement in design/development of connected, communicating and self reconfigurable controllers such as the presented design methodology and TARS controllers in Chapter 4.

Finally, any system, no matter how sophisticated, needs to be surveyed from end point for yet another layer of scrutiny. Moreover as presented in Chapter 5, overhead imaging can achieve this with machine vision to track health and growth of plants in the ultimate product of the irrigation agricultural system.

In summary, here we introduced contributions in modeling, monitoring, control, design, machine vision. These contribution are small pieces of a bigger puzzle that irrigation science attempts to answer. I have hope that this work can improve irrigation practices from vineyards to row crops and indoor farms. Indeed, advancements in silicon technology enable a great deal integration of computational tools at fraction of production cost.

6.1 Implications

We have explored the circuit inspired modeling approach which utilized both continuous differential models and machine learning principals and optimization techniques. We utilized these models to devise control mechanisms and designed infrastructure to support such controls.

Thank You for reading! That's it.

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