FIELD DEPLOYMENT AND INTEGRATION OF WIRELESS COMMUNICATION & OPERATION SUPPORT SYSTEM FOR THE LANDSCAPE IRRIGATION RUNOFF MITIGATION SYSTEM

A Thesis

by

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ABSTRACT

The study of water conservation technologies is critically important due to the rapid growth in urban population leading to a shortage in potable water supplies throughout the world. Current water supplies are not expected to meet the water demand in the coming decades; this could seriously affect human lives and socio-economic stability.

About 30 percent of the current municipal supplies are being used for outdoor irrigation such as gardening and landscaping. These numbers are increasing due to the increase in urban population. Due to the current inefficient or improper landscape irrigation practices, substantial amounts of water are lost in the form of runoff or due to evaporation. Runoff occurs when the irrigation precipitation rate exceeds the infiltration rate of the soil, which depends on the soil and site characteristics such as soil type and the slope of the site. Runoff being an obvious water wastage, it also poses a great problem to the environment with its potential for transporting fertilizers and pesticides into storm sewers and, eventually, surface waters. Thus, this study focuses on designing a smart operational support system for landscape irrigation that has the potential to reduce runoff and also decrease water losses in the form of evaporation.

The system consists of two main units, the landscape irrigation runoff mitigation system (LIRMS) and an operational support system (OSS). The combined system is referred to as the second-generation LIRMS. The LIRMS is installed at the border of a field/lawn. The LIRMS consists of a central controller unit and a runoff sensor. Based on the feedback from the runoff sensor, the controller unit pauses and resumes irrigation as needed in order to reduce runoff. The main purpose of OSS is to automate the scheduling of the irrigation process. A multilayer perceptron based OSS was designed and implemented on a dedicated web-server. The OSS processes historical irrigation data and the environmen-

tal/weather data to choose an optimal schedule to irrigate on a given day. The OSS aims to reduce irrigation water losses due to natural environmental factors such as evaporation and rain. A wireless communication link is established between LIRMS and OSS for monitoring and analyzing irrigation events.

The second-generation LIRMS was installed in the Texas A&M Turfgrass Research Field Laboratoy, College Station, TX for performing irrigation tests. The preliminary results show that the average soil wetting efficiency has increased with the use of the operational support system when compared to previous tests performed without the operational support system. Also the results suggest that the second generation LIRMS has comparable runoff reductions when compared to the first-generation LIRMS. Yet, more tests are required to quantify the overall water savings.

CONTRIBUTORS AND FUNDING SOURCES

Contributors

This work was supported by a thesis committee consisting of Dr. Jean-Francois Chamberland [advisor] of the Department of Electrical and Computer Engineering and Dr. Jorge Alvarado [co-advisor] of the Department of Engineering Technology and Industrial Distribution and also Dr. Benjamin Wherley of the Department of Soil and Crop Sciences and Dr. Gregory Huff and Dr. Srinivas Shakkottai of Department of Electrical and Computer Engineering.

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NOMENCLATURE

LIRMS	Landscape Irrigation Runoff Mitigation System
ET	Evapotranspiration
ET0	Evapotranspiration
SMS	Soil Moisture Sensor
SM	Soil Moisture
EIT	Effective Irrigation Time
AIW	Allowable Irrigation Window
SWEI	Soil Wetting Efficiency Index
PCB	Printed Circuit Board
ANN	Artificial Neural Network
MPC	Model Predictive Control
WSN	Wireless Sensor Network
ZC	Zigbee Coordinator
ZR	Zigbee Router
ZED	Zigbee End Device
RF	Radio Frequency
GSM	Global System for Mobile communication
JSON	JavaScript Object Notation
URL	Uniform Resource Locator
HTTP	Hypertext Transfer Protocol
HTML	HyperText Markup Language

SQL	Structured Query Language
REST	Representational State Transfer
API	Application Programming Interface
NUC	Next Unit of Computing
GUI	Graphical User Interface
MLP	Multilayer Perceptron

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1. INTRODUCTION

1.1 Background

All living organisms need water to sustain their lives. Almost 71 percent of earth's surface is covered by water. However, only one percent of that is available for our day-to-day use in the form of ground and surface water [3]. In today's world, where the population is increasing day-by-day, the need for efficient management and use of such a critical resource is as important as the resource itself. Agricultural water uses account to 80 percent of total consumptive water from ground and surface water sources [4]. Furthermore, a significant amount of this water is used in urban-municipal uses like maintaining gardens and landscapes [5].

In Texas, urban-municipal water uses are the second largest component of water use, which occupies around 27 percent of the total water demand [6]. Given a rapid pace of urban growth in the state, the need for efficient municipal water supplies has become critical. It is anticipated that by 2060, the demand for municipal water will grow by 436 percent due to the increase in population [7]. Catering to the demands at such an alarming rate of increase places great strains on the current water supplies. Hence, greater stewardship of municipal water supplies has become critical in Texas and throughout the United States.

In the residential setup, about 30 percent of residential water usage is devoted to outdoor uses. More than 50 percent of that outdoor water is used for watering lawns and gardens [8]. Depending on the geographic location and season water usage varies greatly. In the drier regions like Texas and other Southwest states, where the population growth is often greatest, water withdrawals for irrigation and landscaping are highest.

According to the Environmental Protection Agency, more than 50 percent of water used in commercial and residential irrigation is wasted due to evaporation, wind, overwatering or improper system design [8]. Overwatering is the major cause for water wastage among the other reasons. Most people water their lawns more than required, oversaturating the lawns, which leads to the excess water running off the lawns and into the streets, this is referred to as *runoff*.

Runoff occurs when the irrigation precipitation rate exceeds the infiltration rate of the soil. Both the soil and site characteristics such as the soil type and the slope of the site affects runoff. It is obvious that runoff causes water wastage. In addition, runoff also poses great problem to the environment because of its potential for transporting fertilizers and pesticides into the storm sewers and eventually the surface waters [9]. Also, runoff causes the depletion of nutrients from soil. In many municipalities, restrictions are imposed on the landscape irrigation water such as limiting the irrigation to once a week. Instead of solving the problem, such measures taken to save water by the municipalities has only resulted in a tendency of homeowners to irrigate excessively on their given watering day. This has amplified the problem. Therefore, such negative effects of runoff increase the need for developing better irrigation strategies by employing efficient irrigation systems.

Current commercial products used to improve the efficiency of irrigation are already available in the market. Many of the commercial products are sold with 'add-on' features for improving irrigation efficiency. However, the available products are usually expensive. Some of the add-ons such as rain sensor simply stops irrigating when it is raining but cannot prevent excess irrigation when scheduled by the user. Another such add-on feature is the soil-moisture sensor, which stops irrigation if a threshold soil moisture is achieved. The disadvantage of soil-moisture sensor as an add-on is its dependency on the soil permeability that changes the sensitivity of the sensor and routinely cannot prevent runoff because of its slow response time characteristics. In addition, the price of these products increases as the efficiency increases. Thus, an add-on with the feature to control the irrigation based on runoff detection should lead to higher or better irrigation efficiency.

To address the issues with commercially available products, a first-generation of Landscape Irrigation Runoff Mitigation System (LIRMS) was designed by a team of researchers with Texas A&M Agrilife Research and Texas Engineering Experiment Station [1][2]. LIRMS has the capacity to mitigate landscape runoff by using a float-switch sensor, which is a low-cost and durable sensor that senses when runoff begins. The first-generation LIRMS was capable of offering greater landscape irrigation efficiency and reduced runoff.

1.2 First Generation LIRMS

LIRMS was designed to work on the principle or activation mechanism based on runoff. The first-generation LIRMS consists of two main units, a float-switch sensor and a central control unit. The float-switch sensor can detect the existence of runoff in the field and the central control unit controls the valves, which provide water to the sprinklers based on the feedback from the float-switch sensor. In the first-generation LIRMS, the whole system is hard-wired. Based on the runoff signal from the float-switch sensor, the controller allows the irrigation process to pause for a given period of time before restarting to finish the irrigation cycle. Upon restarting the irrigation, if the sensor detects a runoff still, then the controller unit pauses the irrigation again. This pause-restart cycle continues until one of the terminating criteria is satisfied. This pause-restart cycle can be described as a smart cycle-soak irrigation mechanism.

A durable, reliable and low-cost LIRMS was designed, built and field-tested for minimizing irrigation water losses from landscapes by Junfeng Men [1]. It was designed to be installed at either the construction phase or as an add-on to the existing irrigation systems. A 45 percent reduction in runoff was achieved during the field-testing of LIRMS with a float-switch sensor.

1.3 Motivation for Current Work

Urban population growth and the decrease in potable water supplies throughout the world have increased the need for studies on water saving technologies. Also, the current water sources are not expected to meet the water demand in a few decades. This scarcity of water could have serious consequences on socio-economic stability [7]. However, even with such a need for water conservation, much water is being waster every year for urban household and commercial applications. This is caused by inefficient or improper irrigation practices [8]. Thus, designing an efficient strategy is important. A device that can mitigate runoff has the potential to save water and improve the quality of waterbodies and, ultimately, address the future water crisis.

The first-generation LIRMS, which was designed and field-tested, has shown the potential to improve efficiency of landscape irrigation and decrease water losses from runoff. However, the first-generation LIRMS did not have the features to remotely control and monitor the irrigation process. Furthermore, the whole system was hard-wired, which limits its applicability in remotely located lawns and fields. Also, when the user lacks expertise in the landscape irrigation requirements the lack of information can affect the benefits of using LIRMS to decrease water losses. The soil will become oversaturated if the user schedules an irrigation cycle for more than the prescribed time, which could lead to increase in water losses from runoff [8]. Irrigating for less than the prescribed time, could affect the health of the lawn. Thus, manual control of the irrigation process by users can potentially decrease the irrigation efficiency.

This thesis addresses the Wireless Communication and Operation Support for the LIRMS and its additional functionalities. The second-generation wireless LIRMS has the capacity to work in remote irrigation fields. The system can autonomously function in terms of power and controllability without user intervention.

2. LITERATURE REVIEW

This section highlights many of the current irrigation issues and problems that motivated the development of the first and second generations LIRMS. The section has been divided into six parts. The first part focuses on the effects of urban runoffs. The second part discusses current water conservation techniques in urban areas. The third and fourth parts discuss available commercial irrigation products and current mitigation strategies. The fifth part focuses on design, built and field-test of first generation LIRMS. Finally, the sixth part discusses about the current research in Machine Learning based smart water conservation strategies.

2.1 Effects of Urban Runoff

Runoff being an obvious source of water loss, many researcher have been investigating the effects of urban runoff on the environment. In the study conducted by Weibel et al. [10], the authors have investigated the role of urban runoff in polluting the surface water sources. For the study, a residential area that has family homes, stores, restaurants and other public buildings was selected. The sample area was equipped with grassed or gravel gutters for sewage. The study showed that runoff has increased the amount of pollutants in nearby waterbodies. By examining these waterbodies, the results showed an increase in suspended solids (SS) by 140 percent; volatile suspended solids (VSS) by 44 percent; biochemical oxygen demand (BOD) by 6 percent; chemical oxygen demand (COD) by 25 percent; nitrogen by 11 percent and phosphate by 9 percent. The authors conclude that urban runoff is one of the factors of pollution.

Gromaire-Mertz et al. [11] shows that the growth in urban population increases the pollution levels in surface water sources caused from urban runoff. For this study, three types of urban runoffs were considered: runoff from streets, runoff from courtyards and runoff from roofs in public areas. The authors concluded that the water exceeded level-2 water quality standards, containing high concentrations of heavy metals. In the case of metals such as Zinc and Lead, the concentration levels exceeded the limits of industrial discharge water. These tests conclude that runoff has high potential in affecting the water quality in the surface water sources.

In another study conducted by Kimbrough et al. [12], investigated pesticide concentrations in nearby streams. For this study, water sources within the urban and agricultural areas in Colorado were considered. The study compares the pesticide levels between these two areas. A total of 47 pesticides were tested in water samples obtained from the water sources. The results show that 30 pesticides were detected in the agricultural areas and 22 pesticides were detected in the urban areas. These results show that both the agricultural and urban areas contribute to the pollution of nearby streams.

Another study focusing on the spread of pyrethroid pesticides due to the residential runoff was conducted by Weston et al. [13]. From the tests conducted, the levels of pyrethroid pesticides were exceeding the toxicity thresholds in the water streams of California. The authors believe that this same situation prevails throughout the United States of America. From an early research conducted by Weston et al., the drain outfalls contained the highest concentrations of this pesticide, thus concluding that the storm drains are the major source of pollution in California.Therefore, storm runoff is a major cause of transporting pesticides into local water sources. The study discusses the harmful effects of this pollutant to the aquatic life.

Finally, Gross et al. [14] investigated the effects of runoff on nutrient loss from turfgrass. For this study, two separate plots were identified. An unfertilized plot known as a control plot and a second experimental plot was treated with granular and liquid fertilizers. The runoff from both the plots were analyzed, with results showing that the runoff from the experimental plot contained significantly higher concentrations of Percolate Nitrate-N when compared to the control plot. This proved that the runoff is a signigicant source of nutrient loss from turfgrass. In addition to the depletion of soil nutrients, this runoff becomes a potential source of surface water pollutant which can stimulate eutrophication [15].

2.2 Water Conservation Techniques/Methods in Urban Areas

With the growing water demand and the shrinking supply throughout the world, water conservation has become highly important. According to the 2017 Texas Water Plan [7], water demand is predicted to increase by 436 percent due to the increase in population over the next 50 years. This increase in demand will cause a shortage in water, making water conservation a high priority throughout the state.

Ferguson focused on investigating possible solutions for achieving water conservation in urban areas in [16]. According to the study, an estimation of 10 to 50 inches of water is used for irrigating lawns in the USA every year. These estimations are even greater in the arid western states. He points out the difference between the agriculture and urban irrigation techniques. Ferguson has identified three main factors that impact water conservation: landscape maintenance, urban landscape design and irrigation hardware. Landscape maintenance include practices such as reprogramming the irrigation controller frequently to match the changing water requirements of the lawns in different seasons. For urban landscape design, based on the geographic location and its moisture levels, different plants that minimize water usage should be used. Recycling of waste water and runoff from irrigation and rainfall should be used for irrigation in urban areas. In the case of irrigation hardware, new improved products such as programmable controllers and drip irrigation systems should be used for minimizing the runoff.

In the study conducted by Allen et al. [17], the authors designed a method of irrigation based on the net evapotranspiration. The study also investigated the benefits of using water saving plants and designing the ecogeographical region intelligently for water conservation. Precision landscape irrigation is another method that was discussed by the authors, highlighting that it could improve the efficiency of irrigation. The study suggests that designing an irrigation system specifically for a field taking into consideration the soil type, plant type, and using sensors that could feedback the characteristics of the field can help in conserving water. Also, the importance of using recycled water for irrigation is discussed.

2.3 Commercial Products for Landscape Irrigation

In recent years, many commercial products were developed to improve irrigation efficiency. Among which, smart irrigation controllers are widely popular for conserving water and optimizing the irrigation process. According to Swanson et al. [18], the term smart irrigation controller refers to various types of controllers that have the capability to automatically calculates and schedules irrigation without human intervention. Most smart controllers are designed based on information obtained from the irrigation fields to schedule the irrigation that closely matches the day-to-day water requirement of the grass. In recent years, many manufacturers have introduced smart irrigation technology, that is being promoted for use in both residential and commercial landscape applications.

Among the most widely used smart irrigation controllers, most of them are based on evapotranspiration (ET), rain sensors and soil moisture sensors. However, these weather-based smart controllers perform better than the traditional controllers in terms of water savings, but the commercially available smart controllers are usually expensive. According to the researcher at the Irrigation Technology Center at Texas A&M University [18], ET based controllers that have on-site weather stations show better performance across different weather conditions. However, controllers that use off-site weather data, historical ET data, or limited data from on-site sensors do not have the capacity to account the varying water requirements accurately. The results suggest that in real-world conditions, most ET based controllers do not save water.

Most commercially available rain sensors are divided into two types based on the working principle: water weight and electrical conductivity of water and expansion disks. Bernard Cardenas-Lailhacar et al. [19] investigated the performances and potential water savings of rains sensors based on expanding disk. For this study, mini-click and wireless rain-click rain sensors are used. For the experiments, the mini-click based rain sensors were divided into three groups with different operating thresholds and only one group of wireless rain-click rain sensor were used. During the tests, rain occurred on 62 percent of the tested days. The results show that the rain-click rain sensor saved a total of 44 percent of water and the mini-click rain sensor groups have saved somewhere between 3 percent to 30 percent of water based on the thresholds selected.

In another study conducted by McCready et al. [20], the performance of existing smart irrigation controller based on ET, rain sensors and soil moisture sensors was investigated. In the study, the results showed that the rain sensor could reduce the irrigation water consumption by 7 percent - 30 percent, while SMS sensor could reduce by up to 74 percent, and ET sensor could lead to 25 percent - 62 percent reduction in water consumption. The research suggests that the irrigation water consumption can be efficiently reduced with proper smart irrigation controllers without harming the quality of the lawns and plants.

It has been shown by the studies conducted by Bernard Cardenas-Lailhacar et al. [19] and McCready et al. [20] that both Soil moisture sensors and ET controllers have the potential to save water. However, there are drawbacks in the implementation of these technologies. Due to the presence of plant debris and disk malfunctioning, the rain sensors were identified to be faulty sometimes. The report [21] lists the advantages and disadvantages of each type of rain sensor. For example, one type of rain sensor determines when to stop irrigation based on the amount of water collected in a bucket. The main drawback with this type of a operating principle is the noise caused by natural things such as the leaves or stones that might trigger false positive to the sensor. In the other type of rain sensor, electrodes are used in the measurement. The salts present in the soil can eventually corrode these electrodes causing malfunctioning sensor. In the other type of sensor that operates using a disk, disk malfunction is a very common problem.

On the other hand, there are certain limitations of the soil moisture sensor even though it was demonstrated that it is capable of saving water. One of the main limitation of the soil moisture sensor is that it cannot be a useful tool to know the water needs when the landscape has different plant types with different root depths [21]. Also, the soil moisture sensor is supposed to be calibrated and adjusted to the type of soil before it is installed. Soil factors such as soil salinity, fertilizer contents and temperatures affect the moisture measurements [22]. There are four types of soil moisture sensors based on their working principle [23]. The first type is based on the measurement of resistance between two electrical resistance blocks. The drawback with this type is that it needs good knowledge of calibration for installing the sensor. The second type is based on tensiometer. This type has a poor performance in coarse sand and the gauges that are used for the measurement are easily damaged. The third type is a neutron probe which uses a radioactive source to measure soil moisture. The fourth type is a di-electric sensor which measures the soil moisture by measuring the di-electric constant of the soil. The drawback of the last two types is their high cost.

ET controllers are one of the most widely used systems in irrigation systems. These controllers use several methods to calculate the amount of water needed [18]. The main drawbacks of the ET method is that it cannot account for unusual weather conditions. Also, the ET calculation method is subject to bias because it relies a lot on the weather information obtained from the Internet. The most efficient ET controllers use on-site weather stations, which are very expensive.

2.4 Current Runoff Mitigation Strategies

Many studies have concluded that apart from being a source of water wastage, runoff is harmful to the environment. The effects of runoff have attracted various scientists to do research on developing strategies for mitigating runoff. Daniel et al. [24] have developed a strategy to use green roof to mitigate storm runoff in urban areas. A green roof was designed and tested and the results were compared with the conventional roof. The results show that the green roof has the capacity to reduce storm runoff by up to 70 percent when compared to the conventional roofs.

Fassman-Beck et al. [25] have focused on the effects of different specifications of the extensive green roofs on runoff mitigation. For the study, four extensive green roofs and three conventional roofs were used. The results show that the green roofs have the potential to reduce peak flow rate by 62 to 90 percent when compared to the conventional roofs. The roof characteristics such as the flow path length, drainage layer roughness and materials used can affect the performance of green roofs.

In another study on mitigation of urban runoff by Fassman et al. [26], the benefits and effectiveness of using a permeable pavement system over an impermeable pavement were investigated. The working principle behind the permeable pavement system is that both the precipitation and runoff water flows over a permeable surface and infiltrates into a storage reservoir. Afterwards, the collected water in the storage reservoir slowly infiltrates into the adjacent soil. During the experiments, a $200m^2$ permeable pavement system was constructed and tested. The results were compared with a conventional asphalt section acting as a control site. The results suggest that the pavement system designed with the permeable material has the potential to mitigate the peak runoff flow-rate by up to 70 percent. The authors believe that a low impact runoff control system can be designed using permeable pavement system.

In their study, Betty et al. [27] focused on the effects of parking lot design on reducing urban runoff. For this study, four different kinds of experimental sites were designed based on the design and material used for the construction. The sites were divided based on whether a site it is an impervious pavement or a basin that was built with or without swales. Results showed that swales could reduce runoff by 30 percent while the basin could add another 10 percent runoff reduction.

Many other useful methods and strategies have been studied by other scientists to reduce runoff. However, very few methods that were developed have based their control strategies on the volume of runoff. Thus, there is space for improvement in urban runoff mitigating strategies based on runoff volume.

2.5 Design, Built and Field-Testing of First-Generation LIRMS

The objective of the study conducted by Junfeng Men [1] was to design a LIRMS. LIRMS is equipped with a reliable, durable and low-cost irrigation runoff sensor which is used for minimizing irrigation water losses from residential or commercial landscapes.

The LIRMS consists of two main units, the central control unit and the float-switch irrigation runoff sensor. If the float-switch sensor shown in 2.3, detects runoff above a defined threshold, it communicates back to the central control unit. After that, the central control unit pauses the irrigation for a given amount of time (Wait Time or Pause Time is adjustable, depending on environmental and field parameters such as soil texture, infiltration rate, soil moisture, slope, etc.) before resuming the irrigation. Upon resuming the irrigation, if the sensor still senses runoff, the irrigation is paused again. The cycle continues until the total run time (Effective Irrigation Time) has been satisfied or the allowable irrigation window (or Total Irrigation Time) has expired. The algorithm implemented by LIRMS can be described as shown in the figure 2.1

The irrigation runoff sensor and the central control unit are hardwired for communi-

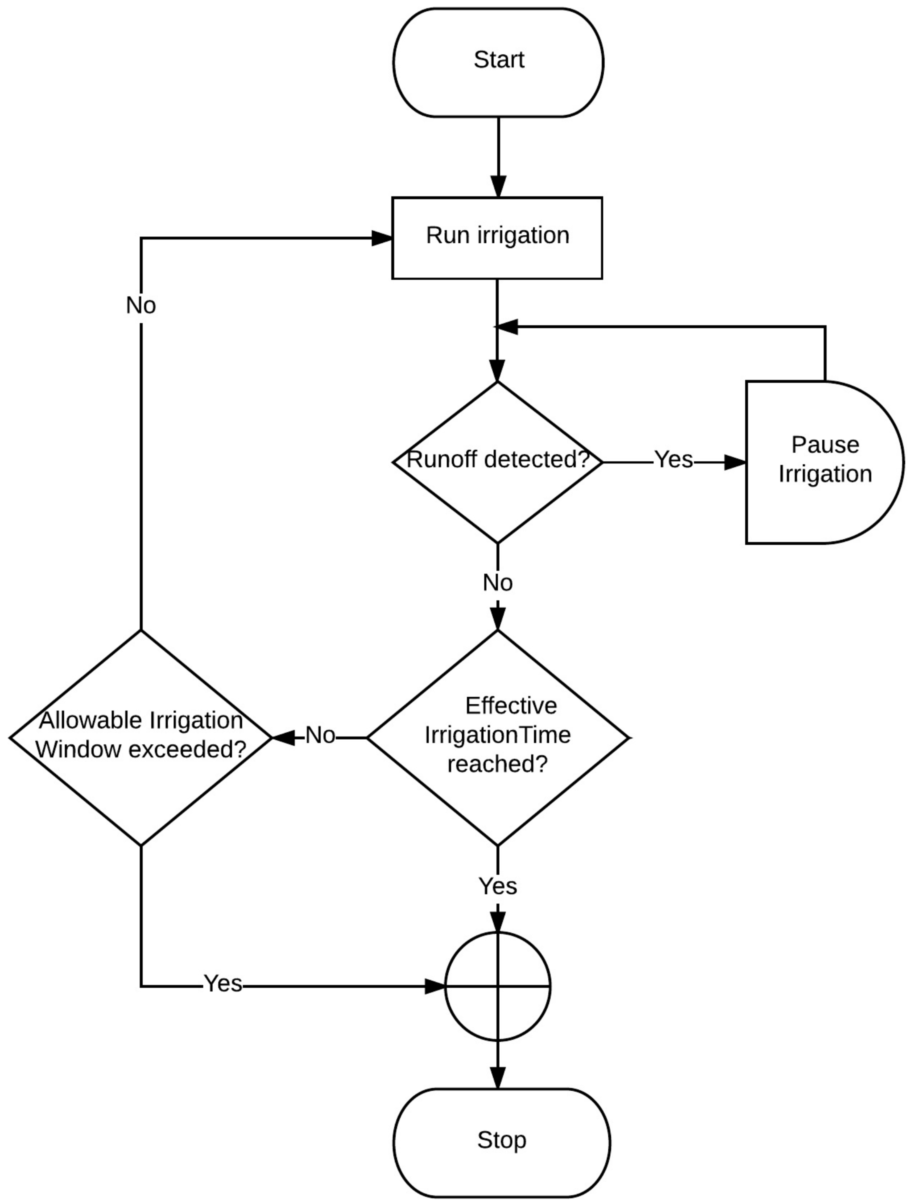

Figure 2.1: Operating principle of first-generation Landscape Irrigation Runoff Mitigation System designed by Junfeng [1].

cation and power delivery purposes. A dedicated PCB was designed and developed for the central control unit. An AT-Mega microcontroller chip was installed on the PCB to control the irrigation logic. Other electronic components such as relays (used to control the irrigation valves), an RTC timer (to track current time) and an SD card holder (used for SD card based programming of the control unit) were mounted on the PCB as shown in 2.2. Irrigation settings for operating the LIRMS were programmed using an SD card. The settings such as the Start Time, Pause Time, Effective Irrigation Time and Total Irrigation Time were all manually loaded onto the SD card. Once the settings were loaded, the SD card was manually inserted into the control unit. The control unit records all irrigation activities into a SD card. Then, to visualize the irrigation cycle, the user had to upload the contents of the SD card manually in a web-interface.

LIRMS was installed and field-tested at the Texas A&M Turfgrass Field Research Laboratory Runoff Facility as shown in 2.4. The LIRMS was programmed for 30 min Effective Irrigation Time and 6 hours of Total Irrigation Time during the field-tests in the year of 2015. For this study, a float-switch irrigation runoff sensor was used with LIRMS. The results from the field-testing showed that a 30-40 percent decrease in the amount of runoff was achieved along with a 10-30 percent increase in water absorption by the soil.

Although, a significant decrease in runoff was achieved by the first generation LIRMS, there are many drawbacks associated with it. The need for manual programming and visualizing an irrigation cycle limits the expansion of deploying the system in remote locations. Being hardwired for both the communication and power supply to the sensor only increases the system's limitations. Furthermore, the irrigation logic on the central control unit cannot be modified since its operating system was uploaded and fixed permanently.

This thesis addresses the limitations of first generation LIRMS. A robust wireless communication and remote operational support features were designed and developed to enhance its current capabilities. The second-generation wireless LIRMS has the capacity to

Figure 2.2: Controller unit used in First-generation LIRMS. The operational logic discussed in 2.1 is implemented on the controller unit.

Figure 2.3: First-generation irrigation Runoff Sensor

Figure 2.4: Turfgrass Field Research Laboratory Runoff Facility

work in remote locations autonomously both in terms of power and controllability without user intervention.

2.6 Smart Water Conservation Strategies

With the availability of enormous open source software for Machine Learning, it is possible to build a smart system that can make smart decisions autonomously [28][29][30]. Powerful Machine Learning tools have been recently adapted to irrigation applications to improve the robustness and efficiency of water conservation strategies [31]. This section discusses smart strategies that are being used in various forms of irrigation systems.

In the study conducted by Karasekreter et al. [31], an Artificial Neural Networks (ANN) based system was developed for irrigation purposes. This system predicts the irrigation ratios and time intervals. The study used soil moisture, plant type, soil type, and time interval data as inputs to the ANN. Levenberg-Marquardt learning algorithm [32] was used for training the network. The output of the model predicted water requirement of the plant and determined the time intervals for irrigation. The study aims to save water by reducing the evaporation of irrigation water that occurs during daytime. The study suggests that, to reduce water losses from evaporation, the optimal time for irrigation is during night. In addition, the study also aimed to save energy. The authors tried to save energy and water by irrigating during the night when the water requirement is lesser than during the day. The irrigation system was installed and tested in a strawberry orchard of 1000 m^2 in the Serik district of Antalya, Turkey. The system achieved water saving upto 20 percent and also saved 23.9 percent of energy.

Another study conducted by Umair et al. [33], designed a new irrigation schedule using an ANN. The study used soil moisture, air moisture, wind speed, external environmental temperature, radiation and soil salinity as input parameters. The authors calculated evapotranspiration rates using the input parameters and transferred the results to the ANN model. The output of the model determined the required humidity and estimated the amount of water needed for irrigation. The controller achieves the estimated water needs by controlling the valves.

In the study conducted by Xiaohong et al. [34], the authors designed an irrigation system to save water by using wireless sensor network (WSN) and fuzzy control. The WSN consists of a cluster of sensors and irrigation controller nodes. The sensor nodes measure soil moisture and regularly transmitting the measurements to the controller node. A fuzzy controller embedded in the coordinator node takes the rate of change in the soil moisture as its input. It then calculates water demand for crops based on change in soil moisture by using the fuzzy inference and fuzzy decision. The calculated water demand is loaded into the irrigation controller node, which controls the irrigation. The study reports that the designed system saved water by irrigating according to the water demand of the crops.

Capraro et al. [35] designed an autonomous irrigation neuro-controller for precision agriculture. The main aim of the irrigation neuro-controller is to regulate the soil moisture level in the agricultural field by controlling the valves of the irrigation system. The controller uses soil moisture in the root zone. The changes in the moisture level in the root zone has been modeled as a non-linear differential function based on the factors such as the amount of water supplied, water consumed by the crop, and characteristics of the soil. In their study, ANN was used to model the dynamic system. After training the network, it was used within the control algorithm as a prediction logic. The control algorithm then determined the irrigation time necessary to achieve the user desired moisture level. At the same time, a new and improved model of the soil moisture is obtained by retraining the ANN. This retraining enabled the system to account the changing crop requirements and soil characteristics. The study compares closed-loop adaptive irrigation methods to open-loop traditional irrigation methods (such as timed irrigation control), concluding that the close-loop control gives higher performance.

Zhang Li et al. [36] have predicted the water requirement of crops in the Donggang region. The study analyzed the impact of different meteorological factors on reference crop evapotranspiration (ET0). A three-layered ANN model was developed to predict ET0. The predictions were based on the conventional meteorological data in the years of 1999 and 2000. The inputs to the neural network were daily average relative humidity, daily net radiation and daily average wind speed. The output of the model was ET0, which was calculated by the Penman-Monteith formula [37]. By conducting recursive tests, an optimal network model was determined. The authors reported that the best neural network constructed has 11 neural nodes in the hidden layer, employed `tansig` function as the transfer function and used `trainlm` function to train the network. The results showed that the average relative error between predicted ET0 values and target ET0 values was under 9 percent.

Another study conducted by Zhang Bing et al. [38] also designed an ANN model for predicting crop water requirements. The authors have designed the model by using the L-M optimization algorithm with back propagation neural network. The neural network was trained by experimental meteorological data of 100 days measured in the Tennessee Plateau Experiment Station. The simulated results showed that the back propagation neural network can solve the uncertainty and non-linearity of multi-dimensional climate date. The results showed that the model has achieved high prediction precision.

Prakashgoud Patil et al. [39] designed a fuzzy logic based intelligent irrigation control system by employing wireless sensor network (WSN) for precision agriculture. In this system, desired soil moisture level is achieved by controlling the irrigation valves using an irrigation controller. The proposed methodology uses a WSN equipped with SMS and temperature sensors. The controller uses fuzzy logic for making irrigation decisions. The fuzzy controller then monitors moisture level in soil, leaf wetness, temperature, humidity and other field parameters like plant root depth, soil texture and water storage capacity of soil. The authors claim that such a system can be effectively adapted to different types of agricultural terrains. The simulation results showed that the system has the potential to predict the water requirement accurately.

Mousa et al. [40] designed an efficient irrigation system by predicting the water requirement for irrigation based on evapotranspiration (ET). Fuzzy inference methodology was employed in the study. The system aims to schedule irrigation based on the requirements of a crop. The changes in various climatic parameters were taken into account by system. The results demonstrate that the fuzzy model is a quick and accurate tool for calculating evapotranspiration as well as predicting the irrigation water requirement. The system starts the irrigation when the depletion ratio of soil moisture reaches 50 percent of total desired soil moisture. The proposed algorithm calculates the irrigation time for both micro-irrigation methods such as sprinkler and drip irrigation. The authors reported that the proposed system had the power to schedule irrigation automatically and achieve the desired water requirements of plants.

Camilo Lozoya et al. [41] present a Model Predictive Control (MPC) designed for an irrigation system. The MPC determines that water requirement of the crop by using soil moisture and evapotranspiration. The process dynamics for the irrigation system was described using an hydrological balance model and is evaluated against a traditional irrigation system. The MPC was used to minimize the effective irrigation time while maintaining soil moisture under desired threshold to avoid runoff. The model also considers external parameters such as reference evapotranspiration to predict the process dynamics. For validation purposes, the proposed model was simulated and compared against measurements from a traditional irrigation system. Simulation results show that higher control efficiency and reduction in water losses can be achieved by using a MPC in an irrigation system.

Renato Ribeiro [42] focused on the application of fuzzy logic and neural networks to design an automatic irrigation system by estimating evapotranspiration. The fuzzy logic system was used to simultaneously manage numerical data and linguistic statements, mimicking human reasoning. An automated irrigation control system was developed using the fuzzy logic approach. The system has the ability to schedule and control irrigation in real-time. Data from an in-field weather station and from soil moisture sensors were used as input to the system. A fuzzy logic estimation system was designed to map solar radiation and relative humidity into evapotranspiration. The fuzzy control processes the estimated evapotranspiration and soil moisture using linguistic knowledge to automatically control the irrigation valve. The system showed robust response to the variations in climatic and soil moisture. Neural networks were then used to process the system inputs and output data for redefining the membership functions as to optimize the system.

Jianbing Zhang et al. [43] presented a methodology to use genetic algorithms based on the Takagi-Surgeon Fuzzy Logic System for generating fuzzy rules. A dataset based on multi-dimension weather data and crop water requirement was used for building the fuzzy model to predict crop water requirements. The dataset contains continuous water requirement data that was observed during the growth process of green peppers. The data was filtered by regression analysis. The proposed model was established based on the mappings between the crop water requirement and weather parameters. The model predicted the irrigation requirements based on nine simple fuzzy rules. The study shows that complex agricultural problems can be solved by designing fuzzy model based on simple fuzzy rules.

Finally, Olutobi Adeyemi et al. [44] discusses the benefits of using adaptive decision support (ADS) systems into precision irrigation management. The study highlights the benefits of using precision irrigation to achieve environmental and economic goals. The study discusses the time-varying nature of the soil-plant-atmosphere system. The ADS systems based on model predictive control (MPC) have the potential to adequately account for this time-varying nature. The authors report that a significant improvement in crop yield and water savings was achieved by using MPC into precision irrigation decision support tools. Also, they highlight the need for deficit irrigation management system in water savings.

In the studies discussed so far, most of the smart irrigation systems depend on high cost sensors. An irrigation system based on a WSN need a large network of sensors. Such a WSN-based approach involves high cost of deployment and maintainability of the system. To obtain data at high spatial resolution it becomes a constraint in commercial applications because of the requirement for dense deployment of costly sensor units. Also, most of the systems discussed develop a model to predict the water requirement of plants. Moreover, most of the irrigation controllers are used for irrigating continuously for the predicted amount of time without any real time feedback mechanisms for the soil response.

This thesis addresses the drawbacks of previous studies done by other scientists in developing smart water conservation techniques. A low cost LIRMS was designed and developed for that purpose. An irrigation algorithm has been implemented based on a robust and durable irrigation runoff sensor. The irrigation runoff sensor gives real-time feedback on the soil response to the irrigation controller. The following chapters discuss the design, construction and field-testing results of LIRMS using a smart controller.

3. DESIGN AND IMPLEMENTATION OF WIRELESS COMMUNICATION AND OPERATION SUPPORT FOR THE LANDSCAPE IRRIGATION RUNOFF MITIGATION SYSTEM

3.1 Aim and Objectives

Although, the first generation LIRMS designed by Junfeng [1] has shown significant decrease in runoff, it has its own drawbacks. The main drawbacks with the Junfeng's system are:

1) The system is manually programmed.

2) The system runs until it achieves the total irrigation time or the effective irrigation time before it stops the irrigation-this could cause more runoff after the soil become saturated.

3) The runoff sensor is hardwired to the central control unit for communication and power.

4) Clogging issues with the irrigation runoff sensor.

5) Too much direct user involvement needed for the operation of the system.

The main objective of this study is to build a wireless autonomous system. The major improvements compared to the first generation LIRMS are wireless communication between the central control unit and the server, wireless communication between the runoff sensor and the central control unit, solar based self-powered runoff sensor, and a machine learning based smart operation support system.

3.2 Second-Generation Landscape Irrigation Runoff Mitigation System

3.2.1 Sensor Reconstruction

To eliminate the clogging issues with the first generation sensor, a new design with an improved flushing mechanism was constructed. It is a float-switch based irrigation runoff sensor. The structure and alignment of the outlet pipe as shown in figure 3.1 was designed to flush all the collected water. The sensor flushes out water based on the syphon effect. Also, the mechanical side has been reconfigured to increase system sensitivity. A mesh was built to filter out the mud and debris as shown in figure 3.2. The new design has addressed the main drawbacks of the first generation irrigation runoff sensor.

Figure 3.1: Second-generation runoff sensor installed in the turfgrass field laboratory for field-testing.

3.2.2 Solar Powered Wireless Sensor

One of the main drawbacks of first-generation LIRMS is that the runoff sensor is hard-wired to the controller for both communication and power. To eliminate the restrictions

Figure 3.2: Second-generation runoff sensor is equipped with a mesh like filter to filter out mud and debris.

caused due to hardwiring of the runoff sensor, the second-generation runoff sensor comes with zigbee modules and solar powered batteries. Zigbee modules are used for wireless communication. A zigbee module is a low-power, low data rate wireless digital radio used for close proximity (example, Personal Area Network) wireless applications. Solar panels and rechargeable batteries are used as a power source for the runoff sensor.

The wireless communication between the runoff sensor and the central control unit will expand the applications of using LIRMS to large remote irrigation fields. With a wireless range of 50-500 meters, zigbees are the best wireless options for this project. Building a sensor network using zigbee protocol is straightforward. Zigbee devices are classified as follows:

a) Zigbee Coordinator (ZC): The coordinator is the root of the network. Other networks can be bridged using ZC. There is only one ZC in each network. All the network information is stored in the ZC.

b) Zigbee Router (ZR): A ZR acts as an intermediate node, transferring data between devices. Router can also run an intermediate application logic and control the data flow. Routers are used to increase the range of the WSN.

c) Zigbee End Device (ZED): The only functionality of these nodes is to transmit the data to a parent node (either the coordinator or a router). ZED do not have the capacity to relay data like the ZR. This hierarchal relationship of ZEDs with the WSN allows them to be in power-saving mode (asleep) for a significant amount of the time. A ZED requires the least amount of memory and, therefore, can be less expensive to manufacture than a ZR or ZC.

A simple first-level sensor network was built with the central control unit acting as a zigbee coordinator (ZC) and the runoff sensors as the zigbee end device (ZED). The flow of data is from the runoff sensor to the central control unit. On the runoff sensor, a low power microcontroller is used for driving the zigbee. Once the microcontroller detects runoff, it activates the zigbee to send the runoff information to the central control unit. When the central control unit receives the runoff signal from the runoff sensor, the control unit controls the irrigation valve. Each ZC can connect to many ZED nodes in a zigbee network, this expands the scope of using multiple sensor units in a large field with multiple zones to irrigate.

Digi International ZigBee RF Modules were used in this project. Table 3.1 shows the specifications of these modules.

Table 3.1: Technical specifications of Zigbee modules (Mfg part # XB24CZ7WIT-OO4) used in this study.

Operating Frequency	2.4 GHz
Range	4000 ft
Data Rate	250 kbps
Operating Supply Voltage	2.1-3.6 V
Maximum Operating Temperature	+ 85 C
Minimum Operating Temperature	- 40 C
Interface Type	SPI, UART
Antenna Connector Type	Integrated

The autonomous power supply module consisting of solar panels and rechargeable batteries was designed to provide the sensor with needed power. During daytime, the solar panels provide the energy required for recharging the batteries. During the time without sunlight, the rechargeable batteries provide the runoff sensor with the power required for sending and receiving signals from the main controller. The runoff sensor with the addition of these two features has expanded the potential applications of LIRMS to large turf-fields. The add-on circuit for the irrigation runoff sensor is shown in the figure 3.3.

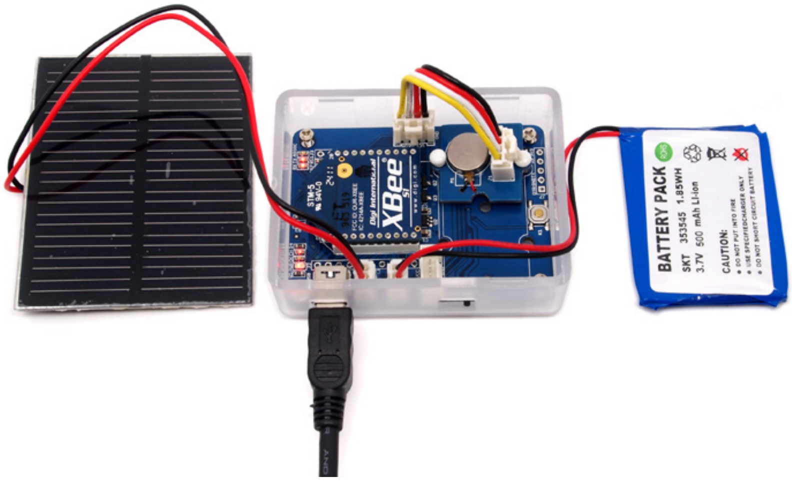

Figure 3.3: Add-on circuit for designing solar powered wireless sensor.

3.2.3 Soil Moisture Sensor

The soil moisture level in the field varies with the depletion and refill of water in the soil. The level of soil moisture can be used to understand and monitor water use and the level of water content in the field. It is important to irrigate with right amount of water to have healthy turf. However, grass is prone to fungal infections when too much water is used for irrigation. On the other hand, when less water is used, it could dry up the grass. Therefore, for irrigation scheduling and managing, soil moisture can be useful.

The second generation LIRMS has a soil moisture sensor hardwired to the central controller. The controller reads the soil moisture values every 30 minutes. The soil moisture readings enable the system to acquire the moisture content of the soil before and after each irrigation event.

A traditional 7.6 cm (3 inch) handheld soil moisture reader was used to calibrate the soil moisture sensor. Table 3.2 shows the calibration results. The following equation is used for calculating the soil moisture values obtained from the sensor.

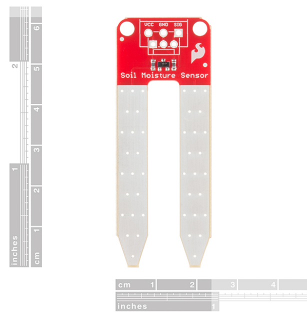

Figure 3.4: Soil moisture sensor used in this study.

Table 3.2: Comparison of soil moisture sensor reading with traditional soil moisture reader for calibration

Moisture Meter (%)	Soil Moisture Sensor (mV)
30	170
32	185
34	198
35	206
36	222
37	250
39	286
40	304
42	346
44	372
45	387
46	401
100	800

$$MoistureMeter(\%) = 1.0929 * Soil\_Moisture\_Sensor\_Reading(mV) - 0.7857$$

A soil moisture sensor has been installed in the center of the irrigation plot to determine moisture content. The sensor is placed at a depth of 5.1 cm (2 inches) from the surface of the soil. To compare the Soil Wetting Efficiency Index of each plot, both plots have a soil moisture sensor installed.

Figure 3.5: Soil moisture sensor installed in the field for acquiring soil moisture content data.

3.2.4 Central Controller Unit

In this study, Intel Galileo development boards were used for building the central control units. Intel Galileo is designed using Intel processor technology. A low-power, small-core Intel Quark SoC X1000 processor is used. It is also provided with the support for Arduino compatible hardware expansion cards (called *shields*) and the Arduino software development environment. The Galileo development board runs on open source Linux operating system with the Arduino software libraries. This Arduino software is called *sketches*. A sketch runs every time the board is powered. Operating at a clock speed of 400 MHz, with 256 Mb of DDR3 RAM and 8 Mb flash memory, the Galileo development board is more powerful than standard Arduino development boards.

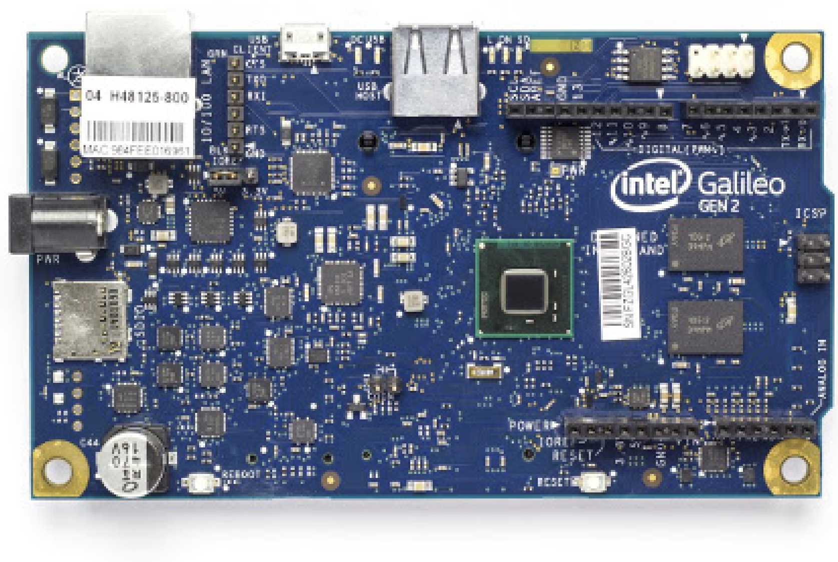

Figure 3.6: Intel Galileo Gen-2 Development board used for designing central control unit.

Galileo development boards support the Arduino shield ecosystem. Unlike most Arduino boards, the Intel boards support both 3.3V and 5V shields. The Galileo development board comes with several industry standard I/O interfaces. WiFi, Bluetooth or GSM cards can be plugged in to the board using PCI Express. Galileo has 20 Digital I/O pins and 6 Analog pins. The board has a built-in RTC clock, which is used for tracking current time. It has a SD card for backup. The following are the specifications for of Intel Galileo development board.

Table 3.3: Important technical specifications of Intel Galileo Gen-2 Development board

Specification Name	Specification Description
Processor	Intel Quark SoC X1000 (16K Cache, 400 MHz)
PCI Support	Yes. mini-PCI Express
# of Serial Ports	1
Package Size	123.8mm x 72.0mm
Digital I/O	20
Analog Pins	6
Power	Input 7V - 15V DC
Arduino Compatibility	Uno R3 / Arduino 1.0 pinout (both 3.3V or 5V Shield Support)

3.2.5 Communication between Central Controller and Runoff Sensor

The central controller unit and the runoff sensor communicates using zigbee modules. The controller is the ZC and the runoff sensor is a ZED. When a runoff is detected, the runoff sensor transmits a signal to the controller unit through the zigbee protocol. This data flow hierarchically between the runoff sensor and the controller, allows the runoff sensor to be in power-saving mode (asleep) for a significant amount of the time, thereby consuming less energy.

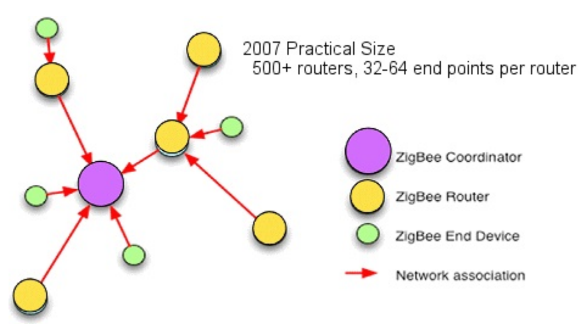

Figure 3.7: General Zigbee mesh topological structure. The data flows from a Zigbee End Device to a Zigbee Coordinator.

3.2.6 Communication between Central Controller and Server

One of the main objectives of this study is to eliminate the human intervention needed for using the first generation LIRMS. During the development of the initial LIRMS, both programming and analyzing irrigation events were accomplished manually. This limits the application of using first generation LIRMS in remote or large fields. To solve this limitation, a GSM modem is used. The GSM modem provides Internet connectivity to the controller unit. Using the Internet connection, the controller can communicate with the server in real time. The T-mobile network is used as the Internet service provider and the modem uses AT commands to connect and interact with the internet.

The user can program and send irrigation instructions to the controller unit over the Internet using the server. Similarly, the user can visualize the irrigation activity using the user-interface provided on the server. The controller unit can be programmed and monitored over the Internet using the server as well. The controller logs all the irrigation activity on a server database for bookkeeping purposes. Since a private IP address was not provided with the GSM modem, the communication is one-way, i.e., the controller unit is the active agent that establishes the communication and the server is a passive agent that responds to the requests.

On the server side, the user programs the irrigation instructions using the web interface provided in the LIRMS website (`http://lirms.tamu.edu/program`). Once the user submits the irrigation settings, the server logs the instructions in an SQLite database. The instructions are made available in a JSON format for the controller to download. The controller uses the URL (`http://lirms.tamu.edu/data/cs/settingdown`) to download the instructions. Similarly, when there is an irrigation activity, the controller logs the activity using the URL (`http://lirms.tamu.edu/data/dblogger`). The controller uses HTTP GET method to log the irrigation activity on the server. Once the server receives a log request, it parses the information into the SQLite database.

The controller checks for new instructions every 30 minute. If the instructions are updated, the controller downloads and parses the instructions into the corresponding irrigation settings. The irrigation settings include start-time, pause-time, effective irrigation time, total irrigation time and number of cycle-soak cycles. Once these irrigation settings are loaded, the controller waits to begin the irrigation. Once the controller unit starts an irrigation cycle, it stops checking for new instructions on the server until the end of the current irrigation cycle. When the runoff sensor detects a runoff, the controller uses the URL (`http://lirms.tamu.edu/data/dblogger`) to log the runoff activity. Apart from the runoff activity, the controller also logs the soil-moisture sensor data for 30 minutes to the server. Figure 3.8 summarizes the communication between central controller unit and server.

3.3 Server

3.3.1 Overview

A dedicated server has been designed and implemented for the second generation LIRMS. The server-side logic is used for control and monitoring of LIRMS. The main features of the server-side logic are programming LIRMS, storing and visualizing irrigation activity and analyzing irrigation performance metrics.

The server-side logic and client-side user interface is implemented on an Apache web server (Version 2.4.7-Ubuntu Distribution). The server runs on an embedded Intel NUC mini-PC deployed in Dr. Huff's Laboratory. The server-side logic is implemented in Python (Version 2.6.4) and structured using the Django framework (Version 1.9). The Django framework ensures customizable solutions by enforcing the code to follow a design pattern that separates the user interface from the functionality of the application. The server-side logic uses Structured Query Language (SQL) to maintain databases. SQL is

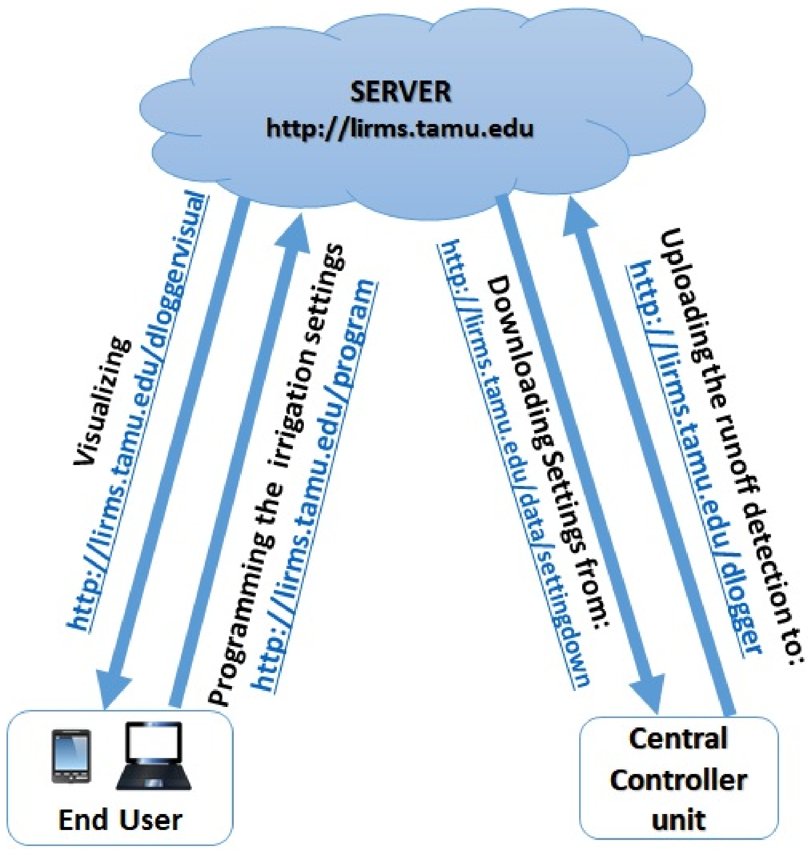

Figure 3.8: Block diagram representation of communication between central controller unit and Server.The controller unit is the active agent initiating the communication link with the server. User can program and visualize irrigation cycle using a web-interface.

used to communicate with the database to extract and add the irrigation data. This data is then used in generating the client-side user interface. SQLite databases are used as databases. SQLite is an open-source embedded SQL relational database management system. Unlike most other SQL databases, SQLite do not need a separate server process for functioning. SQLite reads and writes directly to ordinary disk files. A complete SQL database with multiple tables, indices, triggers, and view is contained in a single disk file. The Django framework supports the use of HyperText Markup Language (HTML) templates to create the client-side user interface. These HTML templates are generated on request using the relevant data stored in the databases. Templates are designed using HTML and JavaScript. The user interface uses the JQuery library (`http://jquery.com/`) and Google Visualization API (`https://developers.google.com/chart/`) to support additional graphical elements, such as interactive charts. To further enhance user experience, the client-side user interface enables the user to make dynamic requests to the server using Representational State Transfer (REST). The REST based requests prevent web-pages from having to be completely re-downloaded and instead it just updates the relevant sections of a page.

3.3.2 Specification and Features

Hardware Specifications

The server runs on an embedded Intel NUC mini-PC. Table 3.4 describes the important hardware specification for the Server. The two main purposes of building a dedicated server is to remotely control (programming the LIRMS with desired irrigation instructions) and monitor (visualizing the irrigation activity during field-tests) of the LIRMS. These are the two main drawbacks with the first-generation LIRMS, which are addressed in the second-generation LIRMS.

Two independent web-interfaces are designed for programming and visualizing. The

Table 3.4: Hardware and Software specifications of Server

Specification Name	Specification Description
Processor	Intel Core i7-5557U Processor (4M Cache, up to 3.40 GHz)
Memory	8GB DDR3L
RAID Configuration	2.5" HDD/SSD + M.2 SATA/PCIe SSD (RAID-0 RAID-1)
Hard Drive	512GB SSD
Operating System	Ubuntu 16.04 LTS
Power	Input Voltage 12-19 V DC

following describes the overview of the web-interface for these two features.

Programming the LIRMS

Programming the controller unit can be achieved using the web-interface accessed at the URL (`http://lirms.tamu.edu/program`). The User Interface for programming is shown in the figure 3.9. Each LIRMS systems (currently deployed in College Station and Dallas) has a unique ID. Using this unique ID, each corresponding controller unit can be programmed individually. The controller can be programmed using two options. The first option is to manually choose the irrigation settings and the second option is to let the operational support system to choose the irrigation settings.

Visualizing

A web-based user interface (UI) is designed for visualizing and analyzing an irrigation cycle as shown in the figure 3.10. The UI can be accessed using the URL (`http://lirms.tamu.edu/dloggervisual`). The visualizing interface is powered using Google chart API (`https://developers.google.com/chart/`). Google chart API is an interactive web service that creates graphical charts from data.

A python logic is implemented to create graphical charts on-the-fly using the corresponding or relevant data. A date based visualizing UI has been developed. The graphical charts can be created with the click of a button. In the backend, the python script retrieves

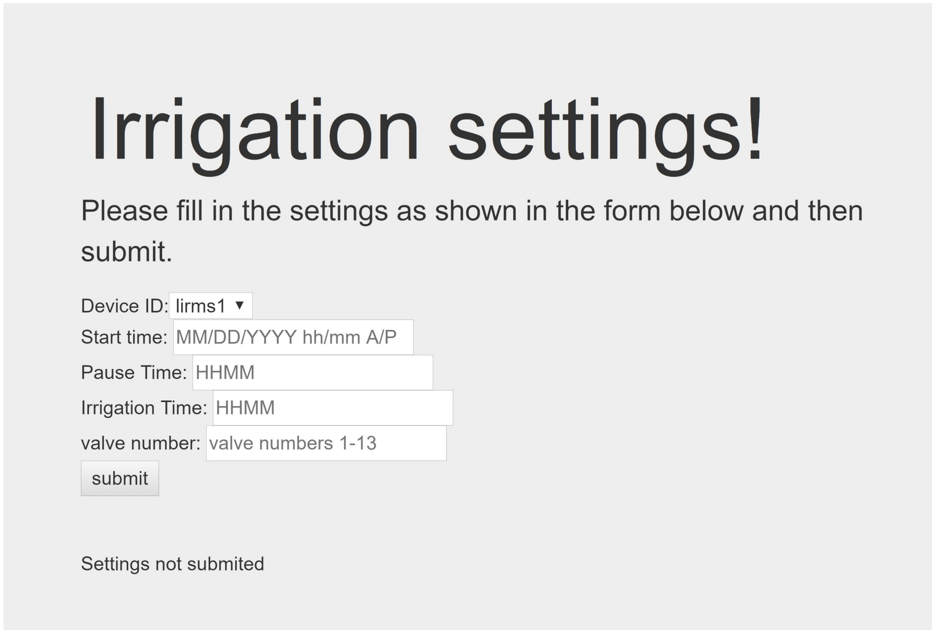

Figure 3.9: Web-based User Interface for programming irrigation settings/instructions for an irrigation cycle. Once the user submits the irrigation instructions, the controller unit downloads the instructions and proceed to irrigate accordingly.

the necessary data for the selected date and creates graphical charts using the Google chart API.

3.4 Databases: Data Acquisition and Storing

Two main databases were built in this study for the second-generation LIRMS. One of the database contains the irrigation activity observed during the field tests. The irrigation activity is obtained directly from the central controller unit deployed in the field. During an irrigation test, the controller unit uploads the observed irrigation activity to the server. The second database contains the local weather readings obtained from an online weather service.

Both the irrigation activity data and weather data are used for setting up (training and controlling) the smart operational support system for the second-generation LIRMS. The

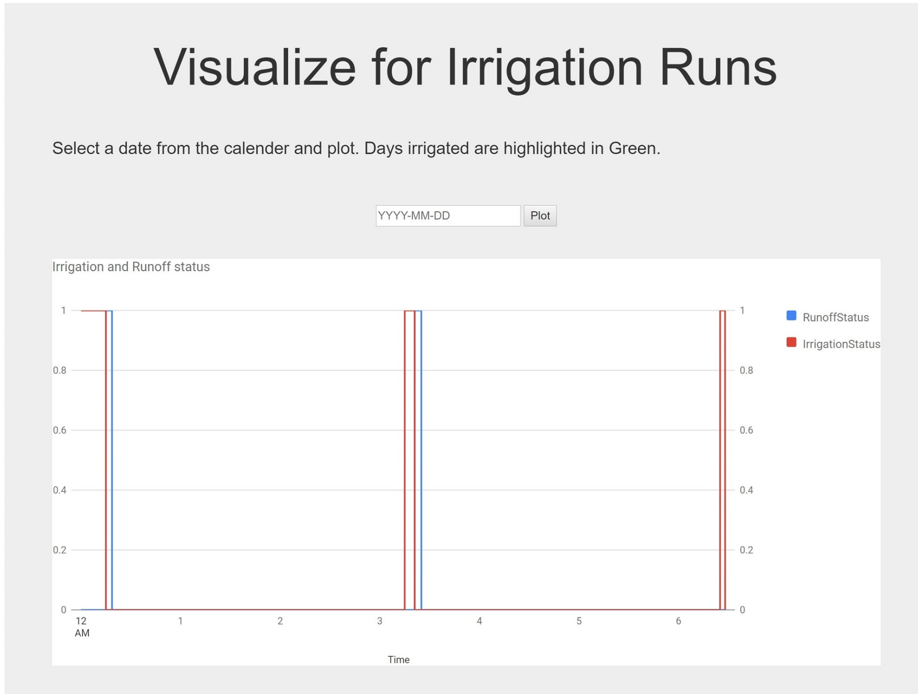

Figure 3.10: Web-based User Interface for visualizing irrigation activity. User can plot the irrigation activity for each irrigation cycle.

following describes the process involved in the acquisition and storing the data.

3.4.1 Irrigation Activity

The controller unit uses the HTTP GET method to log all the irrigation activity to the server. All the irrigation activity is stored in an SQLite database named *irrigation.db*. Table 3.5 describes all the irrigation parameters that are collected from an irrigation cycle.

3.4.2 Weather Data

One of the main goals of this study is to build a smart operational support for LIRMS. To build such a smart support system, environmental conditions are needed to ensure proper operation. Therefore, continuous monitoring and storing of the weather parameters is an important step in achieving this goal. To continuously monitor and store the

Table 3.5: Irrigation parameters that are saved in the database

Parameter	Description
Time stamp	Current time at which the activity was observed
Date	Date at which the activity was logged
Device ID	LIRMS system ID
Runoff Status	Current status of runoff in the plot/field
Valve Status	Current status of the irrigation valves
Irrigation Status	Current status of the system (Irrigating or Not)

weather parameters, a python script has been implemented on the server. The script downloads the current and forecast weather data using the Open Weather Map API (`http://www.openweathermap.com/api`).

The weather data is collected every fifteen minutes. Tables 3.6 3.7 describe the parameters provided by the API. The script downloads the weather data using the API in the form of a JSON object, which is parsed and stored in an SQLite database named *weather.db*.

Table 3.6: Current weather parameters downloaded and stored in the weather database.

Parameter Name	Parameter Description	Units
C_Temp	Current Temperature.	Kelvin
C_Humidity	Current Humidity	%
C_Pressure	Current Atmospheric Pressure	hPa
C_Temp_min	Minimum Temperature at the moment	Kelvin
C_Temp_max	Maximum Temperature at the moment	Kelvin
C_Wind_speed	Current Wind Speed	meter/sec
C_Wind_deg	Current Wind Direction	degrees
C_Clouds	Current Cloudiness	%
C_Rain	Rain volume for the last 3 hours	inches
C_Snow	Snow volume for the last 3 hours	inches

Starting from October 2016, more than 11K weather readings have been downloaded and stored in the database. The weather data can be displayed using the URL (`http:`

Table 3.7: Weather forecast parameters downloaded and stored in the weather database.

Parameter	Description	Units
Average Temperature Max	Maximum Average Temperature forecast	Kelvin
Average Temperature Min	Minimum Average Temperature forecast	Kelvin
Average Pressure	Average Pressure forecast	hPa
Average Humidity	Average Humidity forecast	%
Average Rain	Average Rain forecase	Inches
Average Wind	Average Wind speed forecase	meters/sec
Average Clouds	Average Cloudiness forecast	%

`//lirms.tamu.edu/weatherplots).`

3.5 Machine Learning based Operational Support System

In this study, the Machine Learning based smart operational support system (OSS) used to automate the working of LIRMS is presented. The OSS enables second-generation LIRMS with the capacity to function autonomously without human intervention. The OSS is implemented as a part of server-side logic.

The main objectives of the OSS are to automate the irrigation cycle and minimize the water loss. As discussed in the literature review, many research studies show that irrigation strategies based on proper irrigation schedules [33] [40] [42] and knowledge of water requirement for each system [17] [40] [43] can reduce irrigation water loss. Karasekreter et al. [31] reported that their approach could lead to 20 percent in water saving. Other researchers have reported that scheduling the irrigation based on soil and plant characteristics can improve water saving as well [45]. Apart from soil and plant characteristics, some researchers used many other weather-based parameters to build smart irrigation systems and save water. In this study, the OSS reduces the overall water loss by optimizing the irrigation schedule and the water requirement of the lawns.

The remainder of the section explains the design and implementation aspects of the Operational Support System.

3.5.1 Features

Based on the data acquired in this study, 36 features were identified and used initially. The features are classified into four main classes: 1) Current weather, 2) Past weather, 3) Forecasted weather and 4) Irrigation based activities including runoff events and soil moisture content.

Current Weather Features

Current weather parameters are included in this class of features. These features determine the immediate effects of weather conditions on irrigation. Effects of windy conditions, high ambient temperature and rain forecast can determine the effectiveness of an irrigation cycle. It is a good practice to avoid irrigating when the conditions are too windy because of the high rate of evaporation and water loss. In addition, it is not advised to irrigate on a hot sunny day when the ambient temperatures are high. Similarly, irrigating right before or after a rainfall is futile.

Therefore, knowledge of current weather conditions play an important role in programming irrigation events. Table 3.8 presents the features that were used by the operational support system to optimize the irrigation schedule.

Table 3.8: Current weather parameters that are used as features.

Parameter Name	Parameter Description	Units
C_Temp	Current Temperature.	Kelvin
C_Humidity	Current Humidity	%
C_Pressure	Current Atmospheric Pressure	hPa
C_Temp_min	Minimum Temperature at the moment	Kelvin
C_Temp_max	Maximum Temperature at the moment	Kelvin
C_Wind_speed	Current Wind Speed	meter/sec
C_Wind_deg	Current Wind Direction	degrees
C_Clouds	Current Cloudiness	%
C_Rain	Rain volume for the last 3 hours	inches
C_Snow	Snow volume for the last 3 hours	inches

Past Weather Features

Past weather parameters are included in this class of features. These features determine the effects of past weather conditions on the irrigation. Weather conditions from last few days can also affect the irrigation process. For example, if it rained for the last few days, it would be a good practice to avoid irrigation, as the soils might already be wet. Similarly, in summer when the weather is usually dry, it is advised to increase the amount of irrigation to satisfy the increased water requirement.

Therefore, knowledge of past weather conditions play an important role in irrigation. Table 3.9 presents the features that were used by the operational support system to optimize the irrigation schedule and determine the water requirements of the grass.

Table 3.9: Past weather parameters that are used as features.

Parameter Name	Parameter Description	Units
PAvg_Humidity	Average Humidity for the last three days	%
PAvg_Pressure	Average Pressure for the last three days	hPa
PAvg_Temp_min	Average Minimum Temperature for the last three days	Kelvin
PAvg_Temp_max	Average Maximum Temperature for the last three days	Kelvin
PAvg_Wind_speed	Average wind speed for the last three days	meter/sec
PAvg_Clouds	Average cloudiness for the last three days	%
P_Rain	Rain volume for the last three days	inches
P_Snow	Snow volume for the last three days	inches
Numday_last_rain	Number of days it was from last recorded rain event	Number
Numday_last_irrigated	Number of days it was from the last irrigation event	Number

Forecasted Weather Features

Weather forecast parameters are included in this class of features. Forecast also plays an important role in irrigation. For example, postponing irrigation can be a useful step in saving water when the forecast for the next day suggests rain. Therefore, knowledge of the weather forecast can play an important role in irrigation. Table 3.10 presents the weather forecast features that were used by the operational support system to optimize the irrigation schedule and determine the water requirements of the grass.

Table 3.10: Forecast weather parameters that are used as features.

Parameter Name	Parameter Description	Units
F_Humidity	Average Humidity forecast for the next day	%
F_Pressure	Average Pressure forecast for the next day	hPa
F_Temp_min	Minimum Temperature forecast for the next day	Kelvin
F_Temp_max	Maximum Temperature forecast for the next day	Kelvin
F_Wind_speed	Average wind speed forecast for the next day	meter/sec
F_Clouds	Average cloudiness forecast for the next day	%
F_Rain	Rain forecast for the next one day	%
F_Snow	Snow forecast for the next one day	%

Irrigation Activity Based Features

Historical irrigation parameters are included in this class of features. These parameters help in scheduling an irrigation cycle. For example, irrigating more often than required might harm the health of the lawns. In addition, irrigating too often increases the chance of runoff, which is a main source of urban water loss. Similarly, irrigating less than required can also affect the lawns [46]. Knowledge of the historical irrigation activity can play an important role in scheduling an irrigation event. Table 3.11 presents features based on historical irrigation activity that were used by the operational support system to optimize the irrigation schedule and determine the water requirements of the grass.

3.5.2 Approach and Implementation of the Operational Support System

Approach

The irrigation-scheduling task by the operational support system (OSS) can be treated as a Machine Learning classification problem. The OSS schedules an irrigation cycle

Table 3.11: Irrigation parameters that are used as features.

Parameter	Description
Effective Irrigation Time	Effective Irrigation time achieved on the last irrigation cycle
Number_Runoffs	Total Number of runoffs detected before irrigation is completed
Total_runoff_time	Total runoff time observed in the irrigation cycle
Time_to_First_Runoff	Irrigation time taken for the system to trigger the first runoff
Time_to_Second_Runoff	Irrigation time taken for the system to trigger the second runoff
First_Runoff_Interval	Time between start and end of the first runoff
Second_Runoff_Interval	Time between start and end of the second runoff
Soil Moisture	Soil Moisture readings taken before the start of irrigation

based on the irrigation and weather features discussed earlier. The variance in water requirement by the grass within a season is assumed to be negligible. Therefore, irrigation templates and rules can be designed for each season. These rules can be used as a references for irrigation.

Based on the observations made from previous field tests and with the help of Dr. Wherley, two different sets of empirical irrigation rules were formulated. Prescribed irrigation rules for the Spring (March - May) and Fall (October - November) seasons are shown in Table 3.12. During this period, the climatic conditions are moderately dry with regular spells of rain during this period. The water requirement of the grass is roughly around 0.75 inch per week. To achieve this water requirement in the turfgrass field laboratory, LIRMS requires 25 to 30 minutes of effective irrigation time.

Table 3.13 shows the prescribed irrigation rules for the Summer (June-September) season, when the climatic conditions are mostly dry. The overall water requirement increases. This increase in water requirement is satisfied by increasing the effective irrigation time reflected in the irrigation rules. A minimum of one inch of water per week is needed for the grass. To achieve this water requirement in the turfgrass field laboratory, LIRMS requires 30 to 35 minutes of effective irrigation time.

The irrigation scheduling based on the features (irrigation and weather features) can

Table 3.12: Prescribed Irrigation rules for Spring and Fall seasons

Irrigation settings code	Start Time	Pause Time	Maximum-Operational Time	Effective-Irrigation Time	Suitable for Lawn/Weather Condition
M0	0	0	0	0	No Irrigation needed
M1	12:00 AM	3 hours	6 hours	15 min	Too Wet
M2	12:00 AM	3 hours	10 hours	20 min	Wet
M3	7:00 PM	3 hours	12 hours	20 min	Wet
M4	12:00 AM	2 hours	8 hours	25 min	Moderate/Normal
M5	10:00 PM	3 hours	8 hours	25 min	Moderate/Normal
M6	12:00 AM	2 hours	8 hours	30 min	Dry
M7	12:00 AM	2 hours	6 hours	30 min	Dry

Table 3.13: Prescribed Irrigation rules for Summer season

Irrigation settings code	Start Time	Pause Time	Maximum-Operational Time	Effective-Irrigation Time	Suitable for Lawn/Weather Condition
M0	0	0	0	0	No Irrigation needed
M1	7:00 PM	3 hours	12 hours	30 min	Wet
M2	12:00 AM	3 hours	10 hours	30 min	Wet
M3	10:00 PM	3 hours	8 hours	35 min	Moderate/Normal
M4	12:00 AM	2 hours	8 hours	35 min	Moderate/Normal
M5	12:00 AM	2 hours	6 hours	35 min	Dry
M6	12:00 AM	2 hours	8 hours	40 min	Too Dry

be formulated as a classifying problem. The irrigation rules are used as the outputs of a classification algorithm [47]. Hence, the problem can be described as a multiclass classification [48], with each class corresponding to one irrigation rule. The classifier algorithm chooses one of the irrigation rules to schedule the irrigation based on the feature vectors. The seasonal factor is taken into account to distinguish between the two sets of irrigation rules (Table 3.12 and Table 3.13).

Implementation

With the development of open-source tools and libraries for Machine Learning, prototyping any complex learning algorithm has become easier. The open-source library called `scikit-learn` is one of the most popular python library available for machine learning. For initial validation of the approach, classifier algorithms from `scikit-learn` library have been used.

Synthetic data sets have been created to validate the classification approach. Multinomial Logistic regression, Multilayer Perceptron and SVM classification schemes have been implemented on synthesized feature vectors. The synthetic data sets have been carefully formulated using previous irrigation (irrigation activity recorded during 2015 and 2016 field-tests) data and their corresponding weather parameters. The data sets consist of 400 feature vectors. Each feature vector is mapped to one irrigation rule based on expert knowledge. These curated data sets are used for training, validation and testing the classifier.

The data sets have been normalized before training the classifiers. After normalization, 75 percent of the data was randomly chosen for training and validation of the classifier, and the rest 25 percent of the data was used for testing and validation. Table 3.14 compares the performance of each classifier.

The classification results using the synthetic data sets indicate that the approach described above can be used for addressing the scheduling problem. The results show that

Multilayer Perceptron has higher classification accuracy, suggesting that it is a better classifier than the other two classifiers (Logistic regression and SVM) in this scheduling problem.

Table 3.14: Comparison of the classification accuracy for different classifiers

Classifier	Classification accuracy
Multinomial Logistic regression	83%
SVM classification	85%
Multilayer Perceptron	94.5%

The trained Multilayer Perceptron classifier has been used to design the operational support system, which has been implemented on the server-side logic. The server-side logic is implemented in python and structured using Django framework. The `mod_wsgi` package is used to host the python logic in Apache server based on Python Web Server Gateway Interface (WSGI) specification. This configuration can be achieved by installing `mod_wsgi` package from the `PyPi` Python library. Once configured, the Python application can be hosted on the Apache server. A web-interface is designed to use the operational support system.

The following subsection describes the Multilayer Perceptron classification scheme.

3.5.3 Multilayer Perceptron

The artificial neural network (ANN) is a widely used soft computational model for simulating various non-linear systems. The ANNs are composed of small micro-computational units called *neurons*. These neurons are arranged in groups called *layers* and connected with each other through weights. Three types of layers are used in building any neural network structure: the input layer, the hidden layer and the output layer. The input layer receives the input data or the input feature vectors, which then passes the data through the hidden layer(s) until an output is obtained at the output layer. The input layer does no have any computational role in the network. It just passes the input data to other layers of the network. Except the neurons in the input layer, every other neuron receives inputs from other neurons through weighted connections. These weighted inputs are summed to form arguments. These arguments are used by a transfer function to produce the final output of the neurons. The ANN does not require detailed information regarding the physical process that govern the working of a system. This feature of ANN increases its scope to effectively model various non-linear processes [49].

A multilayer perceptron (MLP) is a feedforward ANN model. The MLP maps multiple sets of input data onto a set of appropriate outputs. Like a simple ANN structure, MLP consists of a system of simple interconnected neurons grouped in layers as shown in figure 3.11. These simple neurons are called perceptron. The perceptrons are connected by weights. The output signal of a perceptron is a simple function obtained from the sum of its inputs transformed by a simple nonlinear transfer or activation function. This superposition of multiple non-linear transfer functions, enable the MLP to model complex non-linear systems. Transfer functions such as linear, logistic or hyperbolic tangent functions are used routinely. With a linear transfer function, the MLP can only model linear systems.

By identifying a suitable set of initial weights and transfer /activation function, MLP can approximate any smooth and measurable function between the any inputs and output vectors [50]. MLP are trained using supervised learning. In the training process, a set of training data is required. The training data is built using a series of inputs and associated output vectors. During the training, MLP updates its connection weights based on the error feedback obtained by repeatedly presented with the training data sets. This loop is repeated until the network identifies a desired input-output mapping. The output of a perceptron can be represented as:

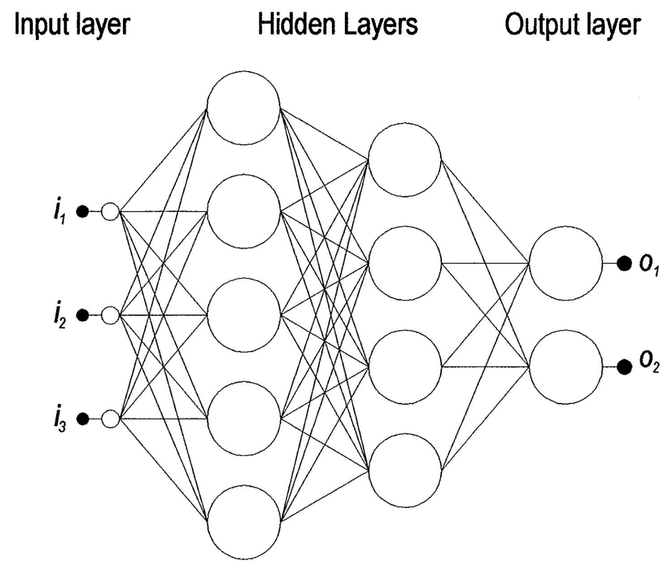

Figure 3.11: A simple representation of multilayer perceptron structure.

$$O = f\left(\sum_{j=1}^{n} w_j i_j + b\right)$$

where w_j is the weight vector, i_j is the input vector $(j = 1, 2..., n)$, b is the bias, f is the transfer function (or activation function), and O is the output. The transfer function used in this validation is the logistic sigmoid function,

$$f(x) = \frac{1}{1 + e^{-x}}$$

The main steps involved in designing an MLP model are a) Proper selection of input and output parameters and b) Finding optimal MLP structure specified by the type of transfer (or activation) function, number of hidden layers, number of neurons, initial weights and the learning factor. To achieve this, the input data is transmitted through the network, layer after layer, and a set of output data was obtained. The output from the MLP, for a given input set, may not be equal to the desired output. Therefore, an error variable is defined as the difference between the desired and calculated output of the network. This error is then used in back-propagation training to adjust the weights so that the overall error of the MLP is reduced. The learning is an iterative process. This learning process continues until the error variable is within an acceptable level (threshold).

Table 3.15: Parameters used for developing operational support system based on multi-layer perceptron

Activation function	logistic sigmoid function
Hidden layer size	100 neurons
Learning strategy	Stochastic gradient descent
Learning rate	Adaptive learning rate
Number of epochs	200

The training is repeated over several times with a combination of different initial conditions until an optimal model is obtained. The classifier with parameters shown in table 3.15 has produced the highest classification performance. These parameters, obtained from the training, are used in the operational support system.

4. RESULTS AND DISCUSSION

4.1 Experimental Setup

All results presented in this thesis were obtained from the tests performed at the Texas A&M Turfgrass Research Field Laboratory, College Station, TX. Tests were performed during 2016 and 2017 on two 4.06 m x 8.44 m (13'x 27') test plots within the urban landscape runoff facility. The two plots were selected from the 24 plots at the facility based on proximity to one another and similar runoff flow characteristics, as seen in earlier research. Plots consisted of 3-year old *Raleigh* St. Augustine grass of good quality and appearance. Plots were designed to simulate a typical front lawn of a home landscape. Underlying soil at the facility was a Boonville series fine-sandy loam on a 3.5 percent slope. Each plot was independently irrigated with an identical in-ground irrigation system design, with precipitation rate of 2" per hour. Runoff water from plots drained into collection gutters, which then flowed through H-flumes equipped with bubble flow meters for continuous measurement of runoff flow volumes from plots.

Two irrigation approaches were used in the tests. The first is an industry standard with single irrigation application. This approach is referred to as *Control*. The plot that uses this approach is referred to as the *Control plot*. In this Control approach, if a 30-minute irrigation application was programmed, the *Control plot* would be irrigated for a period of 30-minutes without breaks.

The second irrigation approach utilized LIRMS. To sense runoff, an irrigation runoff sensor was installed at the outflow from the plot. Once the runoff sensor detected runoff, it communicated with the central control unit to pause the irrigation. If an equal (30-minute) amount of irrigation was programmed for LIRMS plot, the irrigation event would often be paused and resumed based on feedback from the runoff sensor. Thus, for periods

Figure 4.1: Flowmeter setup in the runoff field laboratory to collect the runoff flow data which is further used for analysis purposes.

when soil was very wet at the initiation of the irrigation test, the LIRMS would enter into numerous (3-4) pause-restart cycles until one of the termination criteria was met. The second-generation LIRMS terminated an irrigation based on the following three criteria:

a) The Effective Irrigation Time is achieved,

b) The allowable irrigation window (AIW) was exceeded or

c) The mean residence time for runoff is less than the prescribed threshold.

The first-generation LIRMS only uses the first two termination criteria. However, the drawback with the first generation LIRMS approach was observed when the soil was very wet at the initiation of the irrigation test. In such a situation, the LIRMS would enter into numerous pause-restart cycles until one of the two termination criteria were met. As the soil was wet in the initial condition, it could take very little time to saturate the soil. Therefore, multiple runoffs were observed during the test. In the figure 4.2, shows the irrigation cycle with multiple runoff events during the test conducted on 7-9-2016. The figure 4.3 shows that the Mean residence time (MRT) decreases from 28 minutes to 2 minutes after 6 runoffs. By analyzing the runoff flow data obtained from the flowmeters, it is observed that after the first two or three runoffs, the mean residence time for runoff decreased and became constant. This pattern in mean residence time shows that any further irrigation would not benefit the soil and would only result in additional water loss due to runoff. To overcome the above drawback a mean residence time based termination criteria was implemented in the second-generation LIRMS. Based on the irrigation tests conducted at Turfgrass Research Field Laboratory, the mean residence time decreased and became constant after two to three pause-restart cycles. The second-generation LIRMS logic is represented in the form of a flow chart shown in figure 4.4.

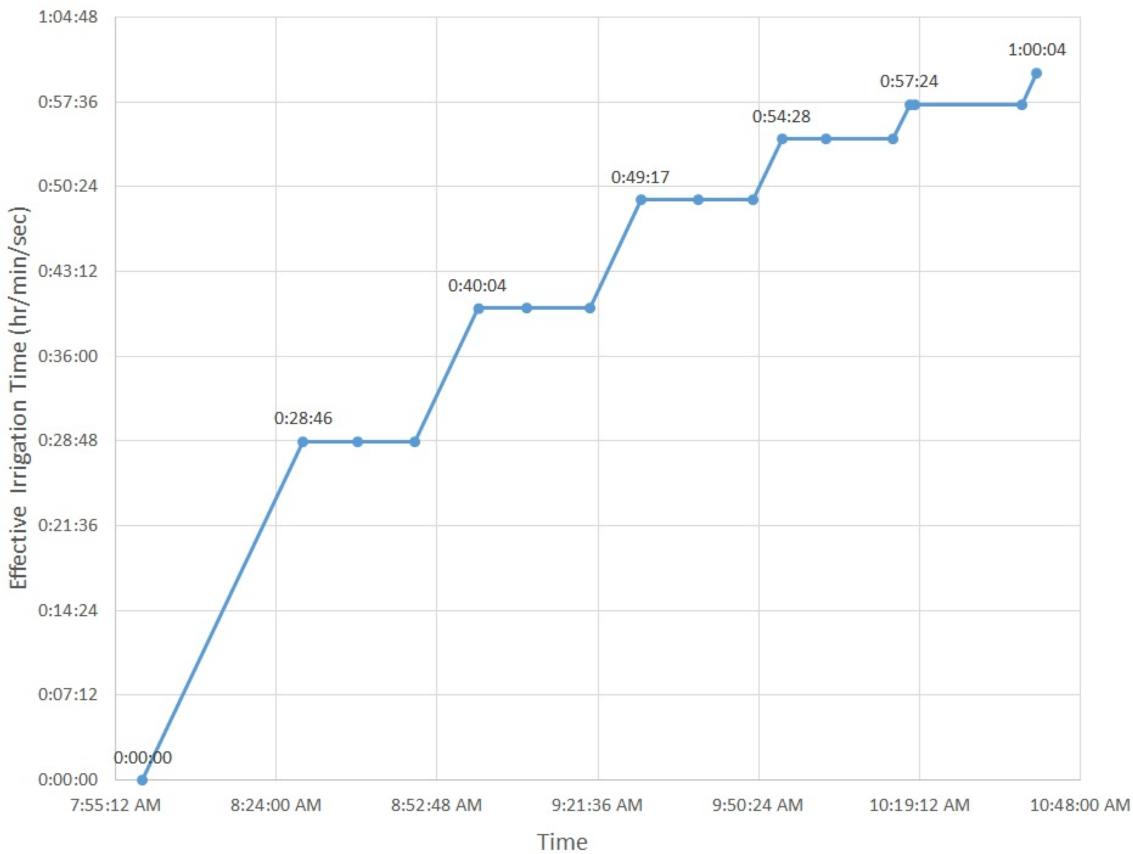

Figure 4.2: Irrigation pause-restart cycles shown for the irrigation test conducted in field during 7-9-2016. The graph shows step-like increment of the effective irrigation time achieved during the test. The horizontal lines shows the *pause* state of irrigation after detecting a runoff. The inclined line shows the *resume* or irrigating state of the system. The length of the inclined line or the irrigating state measures the Mean Residence Time.

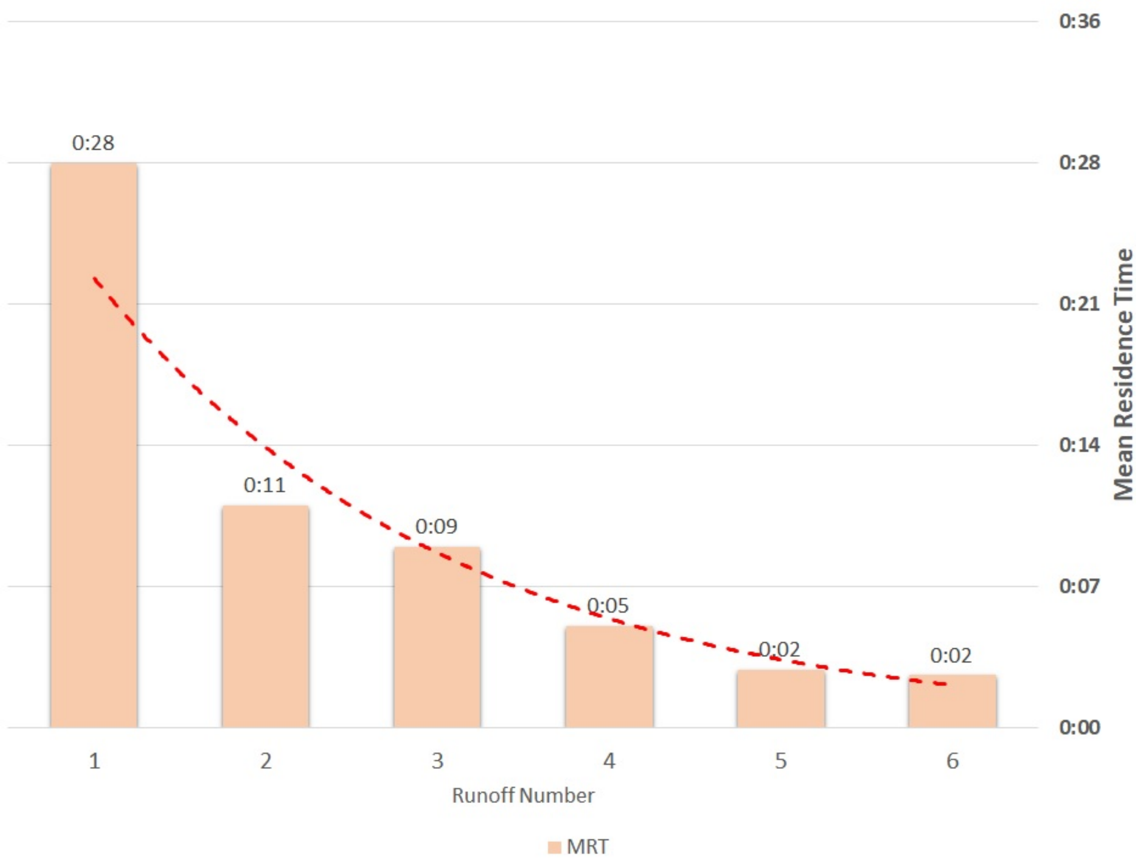

Figure 4.3: The graph shows the decrease in Mean Residence Time during the irrigation cycle. The MRT decreases from 28 minutes to 2 minutes.

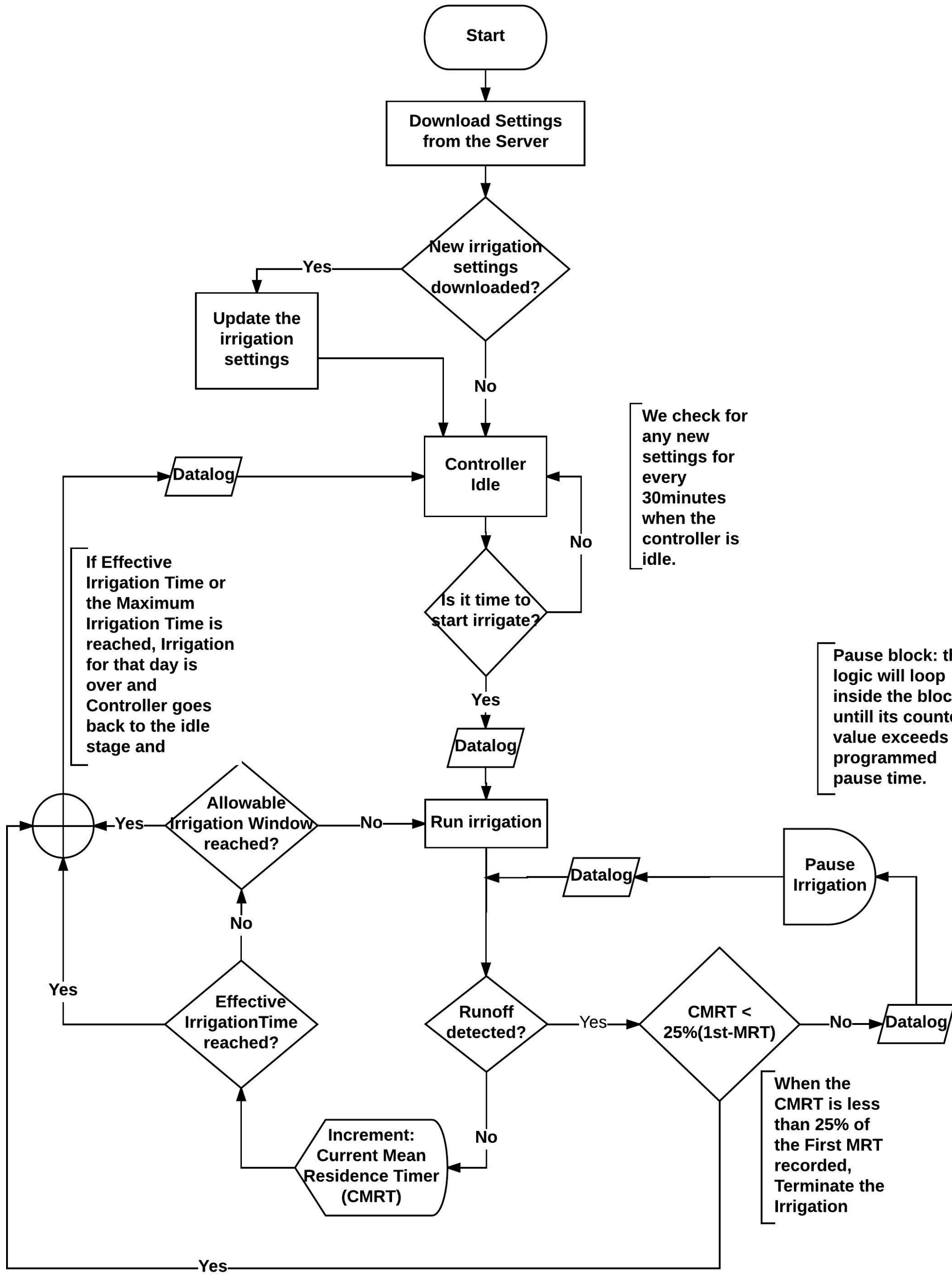

Figure 4.4: Operating principle of Second Generation LIRMS. The logic includes a Mean residence time based terminating criteria.

4.2 Performance Metrics

In this study, two parameters were defined for quantifying the efficiency of an irrigation cycle/test. One is the Soil Wetting Efficiency Index and the second one is the Runoff Reduction.

4.2.1 Soil Wetting Efficiency Index

A Soil Wetting Efficiency Index (*SWEI*) is used to compare relative wetting efficiencies of *LIRMS plot* vs. of the *Control plot* irrigation approach. Compared to a standard single application, LIRMS detection of runoff and irrigation control resulted in much greater soil wetting efficiency (increase in soil moisture per gallon of water applied). The following formula is used to calculating *SWEI*.

$$SWEI = \frac{\left[\frac{(SM_{post} - SM_{pre})}{SM_{pre}} \times 10000\right]}{(IV)}$$

Where *SM* is soil moisture readings obtained *pre* and *post* irrigation cycle. *IV* is total irrigation volume in gallons. Based on the *SWEI*, use of LIRMS resulted in an overall average 63 percent greater soil wetting efficiency during 2016 field-testing. Greater soil wetting efficiency should ultimately result in higher quality lawns and landscapes requiring less frequent irrigation events

4.2.2 Runoff Reduction

This is a more direct parameter used for quantifying the amount of water saved using the LIRMS. With both the plots irrigated with the same initial conditions, this parameter will give us an idea of how much water can be potentially saved by using the sensor (LIRMS) that can more precisely and effectively allocate water to plots through industry standard practice.

$$Runoff\ Reduction(\%) = \frac{Runoff_{Control} - Runoff_{LIRMS}}{RunoffControl} \times 100$$

Where *Runoff*$_{Control}$ and *Runoff*$_{LIRMS}$ are the runoff volumes measured by the flowmeters installed on the *Control* and *LIRMS plots*.

4.3 Irrigation Tests with First-Generation LIRMS

During the Spring and Summer season of 2016, the LIRMS system was tested using the irrigation logic of first-generation LIRMS. For these irrigation tests, both the controlled and LIRMS plots were programmed to irrigate for an effective irrigation time of 30-minutes. The termination criteria employed for these tests are:

a) If the Effective Irrigation Time is achieved, or

b) If the Allowable Irrigation Window (AIW) was exceeded.

The LIRMS plot would be irrigated until one of the two terminating criteria were met. A first-generation runoff sensor was used. Performance analysis of selected irrigation tests are presented in Table 4.1.

Table 4.1: Performance analysis of irrigation tests performed during the Spring and Summer of 2016. The data is received from Wherley et al. [2].

TEST DATE	IRRIGATION VOLUME		RUNOFF VOLUME		RUNOFF REDUCTION BY LIRMS (%)
	LIRMS (gal)	CONTROL (gal)	LIRMS (gal)	CONTROL (gal)	
3/25/2016	137	234	45	103	56
4/8/2016	240	225	22	26	13
4/15/2016	207	231	87	97	11
4/22/2016	200	229	83	124	33
5/6/2016	250	227	49	63	23
5/13/2016	245	212	45	62	27
5/20/2016	120	239	57	116	51

4.3.1 Observations from First-Generation LIRMS Tests

The following are key insights observed from these tests:

a) Testing data demonstrate that LIRMS is effective at reducing landscape runoff. An average runoff reduction of 31 percent was achieved by LIRMS in the February through May 2016 testing.

b) The two termination criteria, although resulting in runoff reductions, could be improved upon. A more robust termination criterion that takes into account the field-characteristics could lead to greater runoff reductions.

c) Intermittent clogging issues with the first-generation runoff sensor were found.

4.4 Irrigation Tests with Manual Termination Criteria

During Fall of 2016, the second-generation LIRMS was tested with a new manual termination criteria. The second-generation runoff sensor was used during these field tests. Soil moisture readings from *pre* and *post* irrigation were collected and analyzed. Soil wetting efficiency index was calculated to understand the soil wetting characteristics of the LIRMS. To quantify the efficiency of LIRMS, both the *Control* and *LIRMS plots* were programmed to irrigate for an effective irrigation time of 30 minutes. The LIRMS terminated irrigation after it sensed the first runoff i.e., the pause-restart cycle was not allowed.

This new termination criterion was employed to understand the impact of peak flow mitigation on the runoff reduction. During a typical irrigation test (30 minutes effective irrigation time), runoff from both *LIRMS* and *Control plots* begin to occur 14-16 minutes into the irritation. LIRMS detected and responded to this runoff flow early on, minimizing peak flows during the runoff. On the other hand, peak flow occurring from the *Control plot* rapidly approached maximum flow rates. The main objective of these tests was to understand the impact of peak flow mitigation on the runoff reduction and soil wetting efficiency. Performance analysis of selected irrigation tests are presented in the table 4.2

Table 4.2: Performance analysis of irrigation tests performed during the Fall of 2016.

TEST DATE	IRRIGATION VOLUME		RUNOFF VOLUME		RUNOFF REDUCTION BY LIRMS (%)	SOIL WETTING EFFICIENCY INDEX	
	LIRMS (gal)	CONTROL (gal)	LIRMS (gal)	CONTROL (gal)		LIRMS	CONTROL
8/13/2016	159	253	15	81	71	13	9
8/26/2016	126	254	20	75	45	19	9
9/2/2016	135	253	14	85	70	27	16
9/9/2016	129	251	25	63	22	13	10
9/23/2016	163	253	19	50	42	20	14
9/30/2016	146	251	33	101	45	18	13
10/14/2016	139	253	25	62	25	22	13
10/21/2016	162	250	22	45	23	13	10
11/18/2016	146	253	33	93	39	18	11

4.4.1 Observations from Testing Manual Termination Criterion

The following are key insights observed from these tests:

a) The Soil Wetting Efficiency Index was noticeably greater in LIRMS than *Control plot*. It should be noted that the amount of irrigation time achieved by LIRMS was almost 50 percent to that of the *Control plot*. This indicates that the soil had reached saturation levels following the first runoff. Figure 4.5 shows a comparison of soil wetting efficiencies between *LIRMS* and *Control plots* for all the tests performed during the year 2016.

b) Testing data demonstrate that LIRMS was effective at reducing landscape runoff without compromising on the soil wetting efficiency index. An average runoff reduction of 47 percent and soil wetting efficiency index of 20 was achieved by LIRMS. It was observed that an average of 140 gallons of water was irrigated on the LIRMS plot.

c) The mean residence time based on the terminating criteria was derived based on the above conclusion.

d) The second generation runoff sensor eliminated the drawbacks of its predecessor.

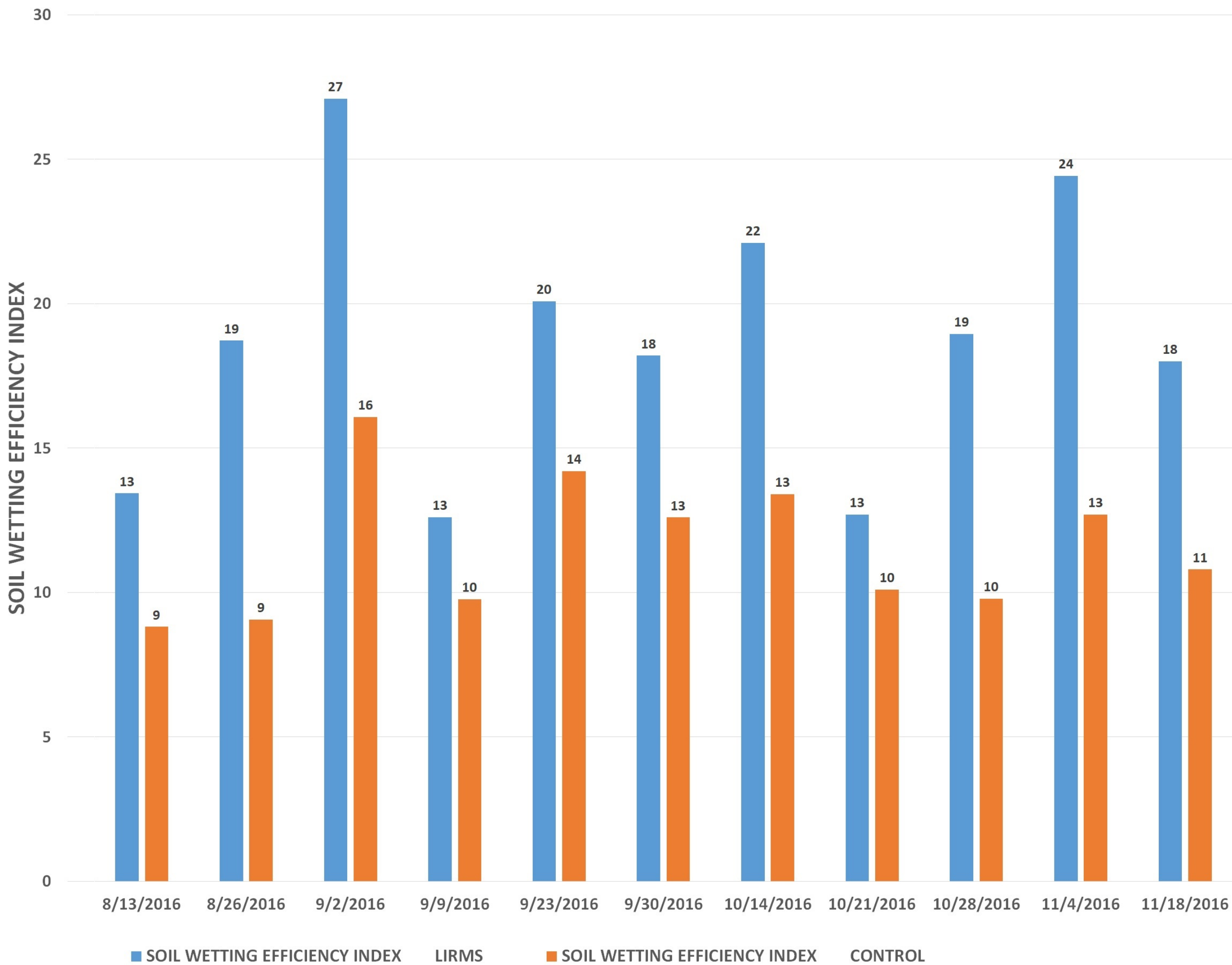

Figure 4.5: Comparison of SWEI for between the LIRMS and Control plots during the tests performed in the year 2016.

4.5 Field Testing of Operational Support System

The second-generation LIRMS was designed and installed for these irrigation tests. The operational support system was validated using simulated data sets as shown in Table 3.14. With positive results from the simulation tests, the fully trained operational support system was integrated into the server to conduct field tests. In addition, the controller unit was reprogrammed to add the termination criteria based on mean residence time.

Starting in Spring of 2017, a fully functional second-generation LIRMS was deployed for field testing. The operational support system is expected to irrigate once a week. The irrigation schedule is decided based on the output of the multilayer perceptron classifier. The classifier uses the weather and irrigation features to schedule the irrigation.

The results from irrigation tests performed so far have shown comparable results, if not better than the first-generation LIRMS. The overall soil wetting efficiency is significantly increased when compared to the previous tests. Performance analysis of irrigation tests are presented in Table 4.3.

Table 4.3: Irrigation test results using second-generation LIRMS. Operational support system is used for irrigation programing.

TEST DATE	IRRIGATION RULE	IRRIGATION VOLUME		RUNOFF VOLUME		PERCENT RUNOFF (%)	
		LIRMS (gal)	CONTROL (gal)	LIRMS (gal)	CONTROL (gal)	LIRMS	CONTROL
4/15/2017	M7	245	235	40	60	16	26
4/28/2017	M4	225	219	44	68	19	31
5/5/2017	M6	242	234	36	54	15	23
5/12/2017	M4	229	224	46	65	20	29
5/20/2017	M7	253	240	45	70	18	29
5/26/2017	M6	245	235	44	65	18	28

Table 4.3: Continued

TEST DATE	SOIL MOISTURE		RUNOFF REDUCTION BY LIRMS (%)	SOIL WETTING EFFICIENCY INDEX		WEATHER CONDITION
	LIRMS Pre/ Post (%)	CONTROL Pre/Post (%)		LIRMS	CONTROL	
4/15/2017	30/47	33/44	38	22	15	Dry
4/28/2017	36/45	37/45	39	11	10	Moderate weather
5/5/2017	27/43	28/43	35	26	24	Dry
5/12/2017	35/45	34/46	31	13	15	Moderate weather
5/20/2017	24/46	25/45	38	35	31	Dry
5/26/2017	28/45	28/44	36	25	24	Dry

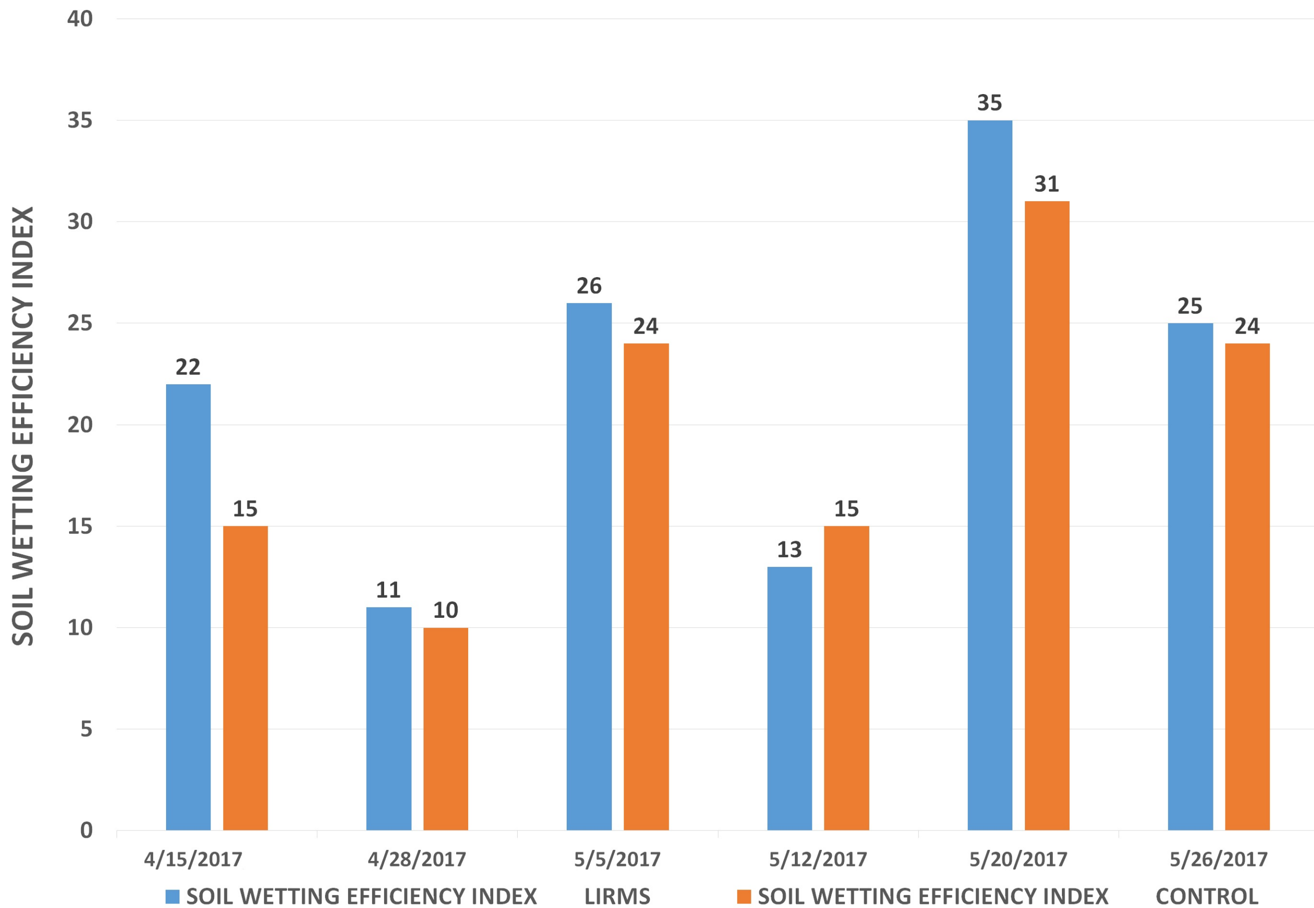

Figure 4.6: Comparison of SWEI the *LIRMS plot* and *Control plot* during the field-testing performed with OSS. The pause-resume cycles increase the absorption of the soil.

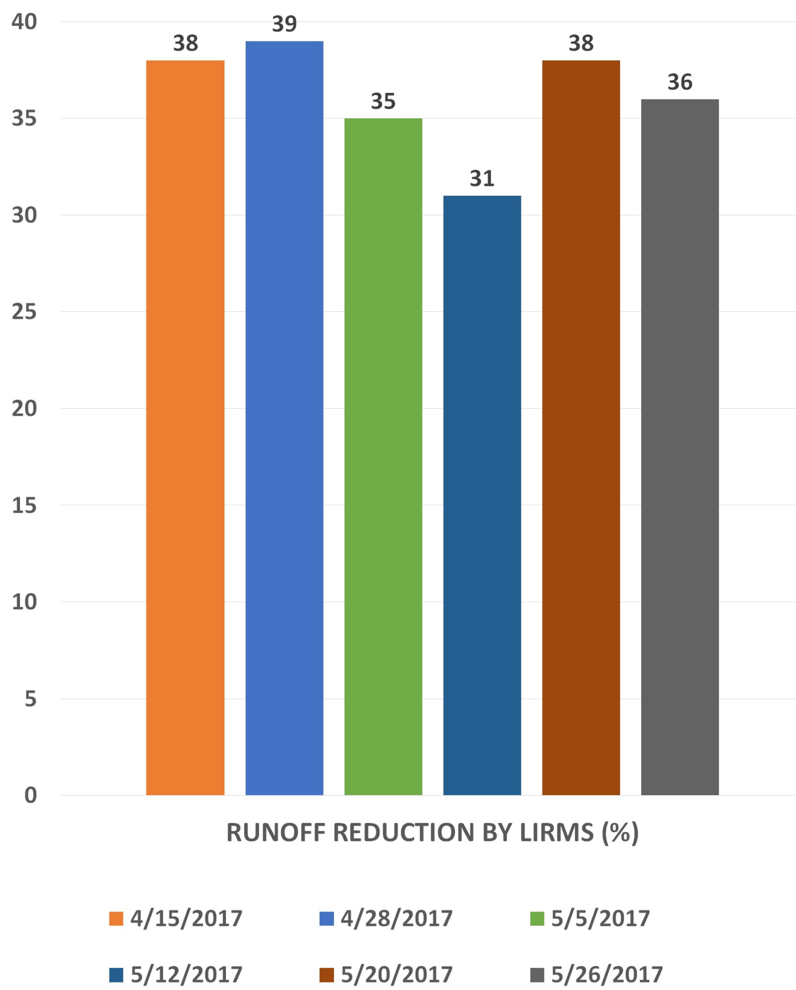

Figure 4.7: Runoff Reduction (%) achieved by *LIRMS* during the field-testing performed with OSS.

4.5.1 Observations from Field Testing of LIRMS with Operational Support System

The following are key observations from these tests:

a) The LIRMS has better soil wetting efficiency, when compared to the *Control plot*. The comparison is shown in the figure 4.6.

b) The average runoff achieved during the irrigation tests with OSS is 36. The figure 4.7 shows the graphical representation of the runoff reduction achieved during these

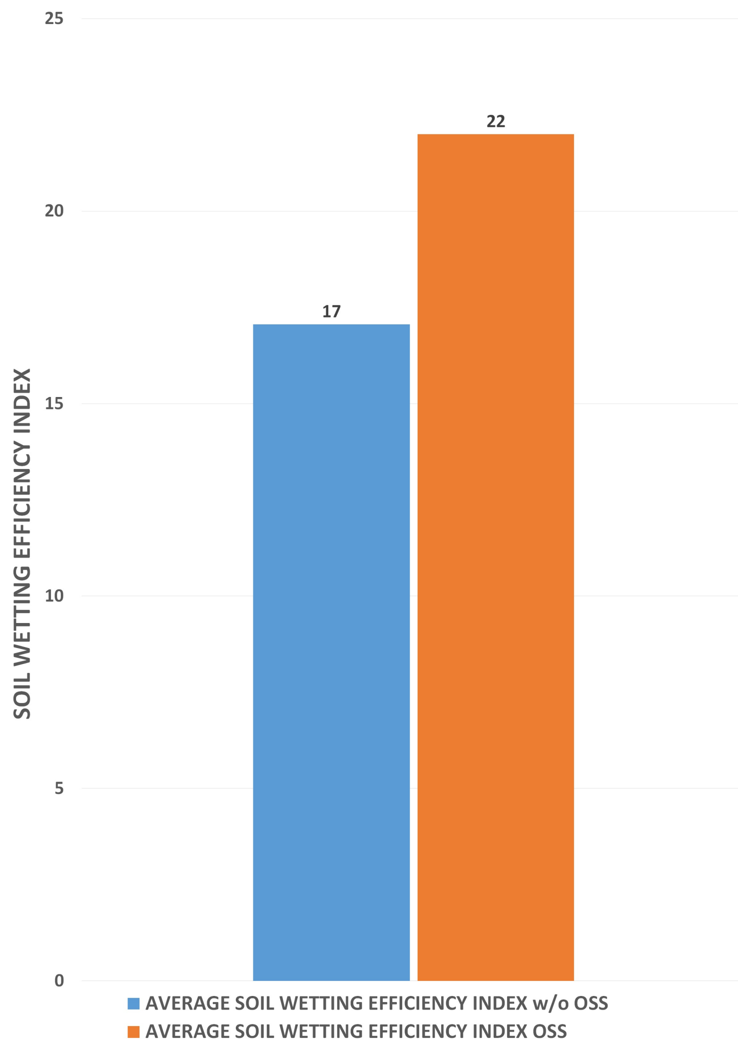

Figure 4.8: Comparison of Average SWEI achieved for *LIRMS plot* during the tests performed with and without operational support system. The results show that Average SWEI increases with the use of OSS, improving the water absorption of the soil

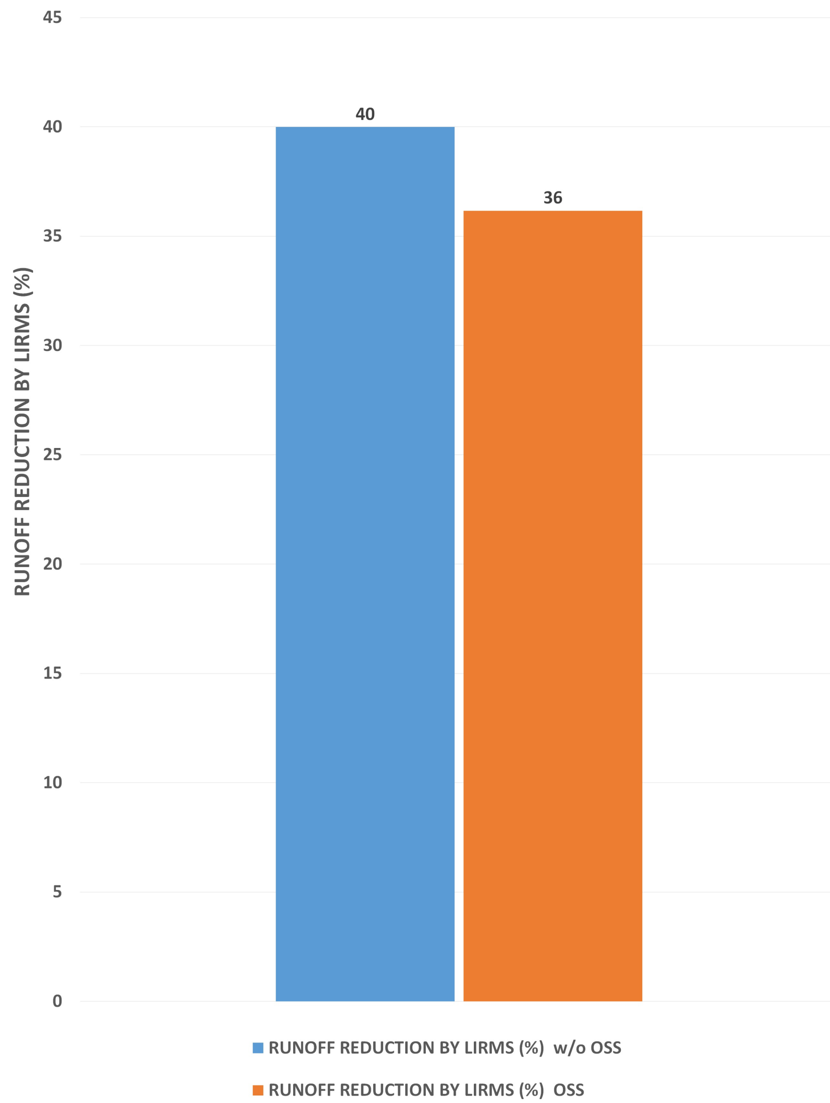

Figure 4.9: Comparison of Average Runoff Reduction achieved by *LIRMS plot* during the tests performed with and without operational support system.

tests.

b) The Average soil wetting efficiency has increased with the use of OSS when compared to previous tests performed without OSS. The comparison is shown in figure 4.8.

c) The Average runoff reduction by LIRMS with OSS is comparable to the results obtained in previous irrigation tests performed without using OSS. The comparison is shown in figure 4.9.

d) The preliminary results suggest that the termination criteria based on the mean residence time has the potential to reduce runoff. When the initial soil condition is relatively wet, the LIRMS show significant increase in runoff reduction.

e) Based on the preliminary results, the operational support system has the potential to decrease the runoff. This reduction can be significantly noticed in the long run. The runoff reductions obtained from the past few tests are shown in Table **??**. Flow meter readings were estimated using the past irrigation tests conducted during 2016. A linear approximation between irrigation volume, irrigation time and initial & final soil moisture readings are assumed for the estimation.

f) However, more tests are clearly required to quantify the overall water savings. The testing will continue during summer 2017. For gathering more irrigation data for quantifying the irrigation efficiency of LIRMS with OSS, two additional plots will be used for installing and testing LIRMS.

g) We plan to implement the new testing methodology for quantifying long term water savings by scheduling LIRMS based on operational support system. The results will be compared against the industrial standard (*Control plot* will be scheduled to irrigate weekly on a fixed day for fixed amount of time) scheduling.

5. SUMMARY AND CONCLUSIONS

5.1 Conclusion

This work evaluates the performance of the two proposed approaches that attempts to minimize the water wastage in landscape irrigation. The LIRMS with adaptive cycle-soak mechanism based on the float-switch irrigation runoff sensor was tested and evaluated to show that it has the potential to decrease the runoff by almost 60-70 percent. The tests were performed in the Texas A&M Turfgrass Research Field Laboratoy, which is well equipped to quantify the observations. Being a sandy loam soil topsoil at the research facility, a mean residence time based trend was observed that shows that the soil at the site was saturated after the third or fourth pause-restart cycle. The system has been recently installed at the Texas A&M Agrilife Research and Extension Service located in Dallas on blackland clay soil to verify the saturation patterns observed for different soil types. Since the termination criteria is based on the relative decrease in the amount of irrigation time(mean residence time), it is believed to function more or less in the same way.

The web-server based operational support system that schedules the irrigation has been trained and tested on synthetic data. The accuracy of the classification using MLP was between 90-95 percent. The trained classifier has been used to schedule irrigation on the runoff facility plots. Only few irrigation cycles were scheduled so far and experimental data is being collected from the facility. Preliminary results suggest that irrigating using LIRMS with the operational support system has the capacity to improve the soil wetting efficiency and increase the runoff reduction.

5.2 Further Study

Based on the preliminary results obtained from limited number of tests, it can be validated that the system has the potential to save water. However, more tests are required to quantify the overall water savings. The testing will continue for the next few months. Two more plots (in the research facility) are planned to be used with LIRMS to collect more data.

With the current irrigation methodology, short-term water savings in the form of runoff reduction can be observer. However, with the use of operational support system to schedule the irrigation test, the short-term water savings do not capture the entire water saving capabilities of the second-generation LIRMS.

Therefore, to quantify the long-term water savings by the second-generation LIRMS, a new testing methodology is planned to be implemented. This is done by scheduling the *LIRMS plot* to irrigate based on operational support system and these results will be compared to the *Control plot* which is operated based on the industrial standard (i.e., the *Control plot* will be scheduled to irrigated weekly on a fixed day for a fixed amount of time) scheduling. By following this methodology, the long-term benefits of second-generation LIRMS can be quantified.

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