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**INNOVATIVE HYDROPONIC CONTROL USING HYBRID
INTELLIGENT ALGORITHMS: A CASE STUDY IN
BOTSWANA**

by

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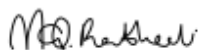
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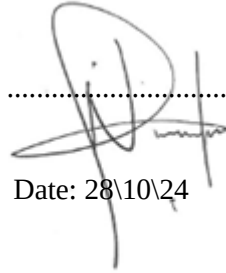
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Abstract

This work evaluates various control algorithms in hydroponics farming, to analyse the performance of the algorithms with the aim to design an intelligent controller which can improve resource efficiency and crop yield by leveraging their ability to handle non linear systems more effectively than conventional controllers. The focus is on the nutrient solution section of the hydroponics farm, specifically monitoring and controlling pH, water level, and water temperature. To achieve this, both simulation and prototyping approaches are adopted. First, mathematical models for each environmental parameter are developed using first-order differential equations in the MATLAB Simulink platform. Conventional PID control, as well as intelligent controllers such as PID-Fuzzy Logic Control (PID-FLC), Fuzzy Logic Control (FLC), are designed and applied to the developed transfer functions. The performance of these algorithms are then evaluated using transient performance parameters: steady- state error, overshoot, settling time, and rise time. These metrics are used to compare the control systems against practical requirements set by farmers or users. Based on a systematic approach, the best-performing algorithm is selected for further evaluation in a prototype system together with a data driven control algorithm . The prototype consists of a 24-plant nutrient film technique (NFT) hydroponic system. Data collected from this setup are used to implement a data-driven Long Short Term Memory-Artificial Neural Network (LSTM-ANN) controller, which is then compared against the selected control algorithm from the simulation stage. The research showed that PID-FLC performed better in terms of responsiveness recording lower rise times and setting times. Specifically, the PID-FLC recorded rise times of 60 seconds for pH increase and 70 seconds for pH decrease, compared to the ANN's 230 seconds and 120 seconds, respectively. For settling times pH up for PID-FLC 119.38 seconds ANN 320 seconds. In terms of steady-state error, all algorithms showed capabilities in maintaining required levels as they recorded low values close to 0 or range close to the setpoint. As for overshoot, the controllers were able to maintain overshoots of less than 2.5%. The study further analyses the financial viability of the use of an intelligent controller analysing the cost savings, net present value, and payback period of the project.

Publications

A. Journal Papers

Part of the work in this thesis documentation has been submitted to international journals.

1. Maemo Rathedi, Oduetse Matsebe, and Nonofu Ditshego, Performance Evaluation of Hydroponics Control Systems for pH, Temperature, and Water Level Control, International Journal of Engineering Research in Africa (Published).

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List of Abbreviations

FLC	Fuzzy logic control.
PID	Proportional Integral Derivative Controller.
PID-FLC	Proportional Integral Derivative and fuzzy logic controller.
LSTM	Long Short Term Memory
ANN	Artificial Neural Networks.
IoT	Internet Of Things.
ANFIS	Adaptive Network-based Fuzzy Inference System.
DL	Deep Learning.
CNN	Convolutational Neural Networks.
DNN	Deep Neural Networks.
KNN	K- Neirest Neighbor.
EC	Electric conductivity.
pH	Potential of Hydrogen.
NFT	Nutrient film technique.
DWC	Deep water culture.
UOD	Universal of Discourse.
SVR	Support Vector Regression.
COG	Center of gravity.
MOM	Mean of Maximum.
MSE	Mean Squared Error.
RMSE	Root Mean Squared Error.
VLT	Very low temperature.
LT	Low temperature.
C	Center zero.

HT	High temperature.
VHT	Very high temperature.
VHP	Very high pressure.
HP	High pressure.
M/No	No difference.
LP	Low pressure.
VLP	Very low pressure.
MLP	Multi Layer Perceptron.
PWM	Pulse with modulation
TDS	Total dissolvable solution
NPV	Net Present Value

1 Introduction

1.1 Background

In 2020, Botswana faced a significant need for more local agricultural produce due to border lockdowns caused by the worldwide pandemic. This situation highlighted the country's necessity to find ways to increase agricultural yields, particularly in horticultural products. Hannes Borgwardt's thesis on the conception of a vertical farm in Botswana underscored the increasing demand for food driven by population growth and the substantial impact of climate change on agricultural supply [1]. This is further supported by a report by Chantal Le Mouél and Agneta Forslund [2], which states that the world's population will require alternative farming methods due to the rapid increase in urbanization. As such, several alternatives have been considered, with one of the most promising being hydroponics, which this study has found particularly interesting. Hydroponics is a soil-less farming method where the nutrients required by plants are delivered directly to their roots [3]. It is considered one of the best solutions for improving crop yields and quality [4], [5]. Additionally, it is a sustainable method that minimizes water usage and space while reducing the need for chemicals and pesticides [6].

Hydroponic systems comprise several components: the growing area, growing medium, nutrient solution tank, lights, and crops. Each component is vital to the cultivation process and affects it in different ways. This study, however, focuses on the reservoir or nutrient solution tank, which supplies the crops with adequate nutrients and creates a conducive environment for root growth and crop development [7]. To ensure a good supply of nutrients, the reservoir should be monitored to maintain proper pH levels, ideal water temperatures, and sufficient water levels.

pH is a critical parameter because the optimal level for a specific crop facilitates easier nutrient absorption [8], [6]. Likewise, maintaining optimal temperatures ensures optimal root growth rates, enhances water uptake by roots, and reduces high microbial activity that can be detrimental to the plants [9], [10]. Whereas maintaining the water level ensures a balance of all the parameters. Therefore, these parameters must always be monitored to ensure optimal crop growth. This necessity is evident in the increasing

use of smart hydroponics technologies, which help maintain ideal conditions for plant growth.

Hydroponic control was introduced over the years and has continued to evolve. With the introduction of new technologies, new advancements are being made to improve hydroponics control [11]. Hydroponics control can be done in one of two ways: open or closed model. In the open model, only the water nutrient solution's potential hydrogen(pH), electrical conductivity (EC), water level, and water temperature are maintained which the study will be focusing on as stated above. For the closed model, also known as the greenhouse model, the environmental conditions are monitored and regulated, i.e., intensity and duration of light, humidity, and surrounding temperature, along with the water nutrient solution. The main aim is to fully automate the entire process (maintaining and controlling the process variables, room temperature, light intensity, carbon dioxide, etc.) without the presence of the farmer. It is seen that much more can be improved to save energy and also come up with a cost-effective system.

Various algorithms are implemented in control systems, ranging from conventional PID algorithms to artificial intelligence algorithms, and these are increasingly being applied in the field of hydroponics. There is also a significant interest in designing hybrid controllers that complement each other in real-life applications. Some examples include neural networks, which are machine learning algorithms that mimic the functioning of the human brain by studying and recognizing patterns in data sets [12]. Another example is fuzzy logic control, which operates on the principle of mimicking human decision-making processes to determine system outputs [13].

Additionally, hybrid controllers, such as PID-Fuzzy Logic Controllers (which combine FLC and PID controllers) and Neuro-Fuzzy controllers (which combine ANN and FLC), are being developed. This study aims to develop a hydroponics controller to implement the best-performing intelligent algorithm to enhance crop yields, improve energy efficiency, and create a cost-effective system.

1.2 Problem Statement

Botswana is faced with low produce in the agricultural sector currently at 71% mainly in the horticulture sector. A large amount of horticultural produce is exported from

neighboring countries. Most hydroponics farmers still operate their farms manually, hence low yields are produced due to failure to monitor fields efficiently as . This leads to farmers providing wrong control measures which provide incorrect conditions for plants. For farmers who have managed to install automated systems, these setups often lack the precision adaptability needed to adjust to the specific requirements of plant growth. As a result, these systems may still provide inconsistent growing conditions, limiting the potential yield improvements that full automation could bring to hydroponic farms. It is against this background that this research work proposes to design and implement an intelligent hydroponics control system based on intelligent control techniques(algorithms). It is envisaged that the designed system will automate the hydroponic farming processes and hence improve food production in Botswana.

1.3 Objectives

Aim

To design, implement, and evaluate intelligent control algorithms for a hydroponic farming system.

Objectives

- Objective 1: Mathematical modeling of the hydroponics control process.
 - Develop models for water level, temperature level, and pH dynamics.
- Objective 2: Design and simulation of various control algorithms to monitor and control pH, water temperature, and water level.
 - Select the best-performing control algorithm based on simulation results.
- Objective 3: Implement the selected control algorithm in the physical hydroponic system.
- Objective 4: Implement, evaluate, and validate the best-performing control algorithm in a physical hydroponic system.
- Objective 5: Conduct an economic analysis of the intelligent control system.

1.4 Hypothesis

The use of intelligent and hybrid controllers could enhance controller performance by improving set-point tracking, rise time, and settling time, thus increasing the overall precision of the system.

1.5 Significance of Study

This study conducts a comparative analysis of different intelligent controllers for a hydroponics system, evaluating transient parameters such as overshoot, settling time, rise time, and steady-state error. It then identifies the optimal controller which is crucial in maximizing crop yield and resource efficiency in hydroponic farming. The study will also provide practical insights into the physical implementation of the proposed algorithm, offering valuable information on its strengths and weaknesses for local researchers and engineers. This knowledge will enable them to deploy effective control strategies in agricultural automation.

1.6 Scope

The study focuses on monitoring and controlling environmental parameters in the nutrient solution tank of a hydroponics system, specifically pH, water level, and water temperature. The study will conduct simulation models and develop a prototype to test the proposed intelligent controller.

1.7 Thesis Structure

The thesis is organized as follows:

- Chapter 2 focuses on presenting in-depth knowledge of the existing control systems in hydroponics control. It shows related works from conventional controllers to the use of intelligent controllers and other emerging hybrid control algorithms.
- Chapter 3 shows the steps followed to achieve our objectives, along with a description of the control algorithms designed in the study.

- Chapter 4 presents the research findings, including the evaluation of the control algorithms in simulation and physical implementation.
- Chapter 5 concludes by highlighting key findings and insights achieved in the research. Additionally, it provides recommendations that could improve the research study.

2 Literature Review

2.1 Related works

The chapter describes the work that has been done in the hydroponics control field and the chapter focuses on the conventional most used control algorithm and the emerging most used AI control algorithms, together with new emerging hybrid controllers.

2.1.1 PID Algorithms

PID control is one of the most commonly used controllers in industries, and many authors have implemented it in their work. Tandil, et al. [14] developed a hydroponic nutrient mixing system aimed at delivering the required fertilizer concentrates for specific plants. The system calculates the nutrient needs of a particular plant, which are then sent to the system to deliver the fertilizer concentrates. It consists of two main parts: the user interface and the mixing controller. The mixing controller was developed using an STM32 F44RE microcontroller, while the user interface was used to collect data for the target nutrient or type of fertilizers required. The system incorporates dosing pumps and a DC motor water pump, commanded by the microcontroller, along with an HC-SR04 ultrasonic sensor. In the study, a proportional (P) controller was employed to control the volume of water in a particular tank, which is necessary for the operation of the DC motor pump. This volume of water is used in the calculation of the correct concentration from the various required fertilizers, hence the use of dosing pumps. The error from the controlled DC motor pump was found to be a steady-state error of 2.5%.

Adhau [15] aimed to develop a low-cost controller with present technology to utilize real-time data to monitor and automate the hydroponic systems, also incorporating IoT applications. The study focused on controlling humidity, temperature, pH, and light, using sensors such as DHT11, LM325, electrodes, and ambient light sensors respectively. Data collected from these sensors is sent to an Atmega 3238P microcontroller interfaced with LabView on a computer. The LabView handles real-time data processing and provides the user interface, and also runs the PID control algorithm used in the system. The controller compares set points with recorded readings and adjusts PWM outputs to actuators such as fans, blowers, halogen light bulbs, pumps,

and motors. The paper demonstrates stable and smooth control actions.

Nurmahaludin [16] developed the PID algorithm to improve errors associated with on-off control. The study focused on controlling nutrient concentration in the solution for a NFT system. The sensors used were the TDS sensor and the data collected was sent to the NodeMCU microcontroller, which sends command instructions to the actuators; servo motors that open and close the water valves. The PID algorithm compares the concentration value in the nutrient solution with the system input or set point then its output will be sent to servo motors to adjust their angles. Through using the trial and error method in adjusting the PID parameters, they tested the PID constants which can give them the smallest error, and finally reached a conclusion at $K_p=0.8$, $K_i=0.5$, and $K_d=0.5$ which gave them a 3.92% error.

2.1.2 Fuzzy Logic Control Algorithms

Indra Agustian et al.(2022) [17] developed a Mamdani fuzzy logic system for an NFT hydroponic system to also reduce active times for pH and nutrient pumps. To carry out the research they developed the NFT system and were primarily focused on monitoring the number of dissolved particles, the pH, and the water level of the system. There they used TDS sensors SEN0244, pH sensors SEN0161, and ultrasonic sensors HC-SR04 to monitor the parameters stipulated above respectively. The sensors served as inputs to the Arduino Mega 25600 which sends out instructions to the pumps. Within the study, they also incorporated IoT through the use of a Blynk application which helped provide a user interface for the farmers. The input to the Mamdani system was pH level and TDS level outputting the active duration of the pumps. The study produced results from both simulation and the physical system that compared the two results for each parameter and showed that the maximum error in pH active duration is 91.86ms, the RMSE is 225ms and the normalized RMSE is 0.4083. While the maximum error of nutrient pumps active duration is 400.69 with an RMSE of 224ms and a normalized RMSE of 0.5083. With a settling time of 150s for both pH up and down.

Chen.Hung Chen [18] focused on adjusting the working time of the solution pumped through the fuzzy logic controller, the study showed that it can effectively reduce the measurement burden and complicated calculations by farmers by adjusting nutrient solutions. The study used Raspberry Pi3 to receive sensory data from the environ-

ments. It collected EC and pH readings which were processed by the FLC control algorithm. The output-controlled relays were interfaced with actuator pumps. The authors carried out four experiments firstly the preparation of mixing solutions value to confirm all the initial values for the mixing solutions. Secondly automatic control adjustments without the plants to test mixing solutions to reach the required EC and pH setpoint. Thirdly cultivation of 3 different plants was carried out lettuce, broccoli, and strawberry were grown under the FLC control conditions while the final test was carried out by cultivating the above plants without FLC control. Throughout the cultivation number of plants, average number of leaves, and average length of plants were also observed and compared between the conditions. From the study, the following was recorded in the lettuce FLC control the settling time recorded was 1200s for EC and 1000s for pH control, for strawberry the EC and pH settling times were 400s and 250s respectively whereas for broccoli 430s settling time for EC and 300s for pH.

Khudoyberdiev, et al.(2020) [19] aimed at providing efficient energy consumption in a hydroponics environment by using an optimization scheme. The project is an automated hydroponics system that implements the Internet of Things (IoT) in the system. IoT platform helps in monitoring and provides data capture, storage, and communication within the system. The project has an optimization scheme that uses FLC as the control platform. It is divided into three layers, the environment layer, the IoT layer, and the optimization layer. With the environmental layer inclusive of the hydroponics system, i.e., the plants and the structure, the IoT layer is inclusive of the sensors and the actuators with the last layer having the optimization algorithm and the FLC algorithm. The optimization algorithm aims at providing ideal parameters for the system to improve the energy consumption of the system. The system monitors two parameters, namely, the water level and humidity using sensors that transmit data to the controller and from the controller to the actuators, the dehumidifier, fogging system, overflow, and water pump. The FLC being the controller in the project sends out the working duration and power levels of the actuators. The FLC algorithm was of the Mamdani type with 4 inputs, optimized level, and current levels for the respective parameters being monitored, and 2 outputs being working level and working duration for each actuator. Membership functions used for input parameters were trapezoidal with the output being triangle membership functions. Finally, the paper showed an

18% decrease in energy consumption changing from 915 kWh to 752 kWh.

Bacalla, A.C, et al. (2019) [20] focused on researching and designing an algorithm that monitors a hydroponics farm in a real-time and stable way through data fusion. Data is being applied by collecting various information from the sensors and using the collected data to make robust and accurate outputs. The paper also aimed to conduct tests for the performance levels of a FLC algorithm in hydroponics farming. In the study, they used the prototype modeling method to analyse their data. The model is comprised of a water reservoir, water pumps, an air pump nutrient pumps, sensors, a wastewater reservoir, and a fuzzy logic controller. Within the FLC algorithm, they used a dosing pattern [8] that is they formulated a mathematical algorithm to calculate the amount of dosage needed or required to maintain the controlled parameters for example pH and water level, this also enhances the stability of the above-stated parameters. In conclusion, the authors used a grading system to evaluate the performance, functionality, and robustness of the control system. A panel of individuals was invited and graded the system above 90/100 in all criteria, showing the system's quality in terms of tracking the system changes.

Fuangthong, M & Pramokchon,P (2018) [21] also proposed the use of FLC algorithm of the Mamdani type. The study focused only on EC and pH parameters as they mostly affect the water solution condition. Therefore, the algorithm was developed of two inputs the pH and EC parameters with four outputs being the four solutions used for adjusting both acid and alkali conditions. It carried out a test to evaluate the performance between the FLC algorithm, an experienced farmer manual control, and an inexperienced farmer control. The test was carried out in a DRFT hydroponics farming system. The experiment was carried out in a 120-liter tank and the experiment showed the addition of alkaline to the water tank showed pH changes of ± 0.5 , with the addition of 5ml of pH down solution, decreasing the pH by ± 0.1 . Whereas for EC addition of 50ml solution showed an increase in the EC by ± 0.05 . With the setup above manual control by both an experienced and inexperienced farmer showed a settling time of 105 minutes whereas FLC showed a settling time of 100 minutes to reach the desired pH and EC.

Muhammad Daud, et al.(2018) [22] looked to improve the efficiency of the actuator pumps by monitoring the air temperature and moisture of the planting medium, this

aimed to improve the absorption of the nutrient solution by the crops. The study carried out a systematic prototype and used the ebb and flow hydroponic system. FL was used as the control algorithm and the sugeno method was implemented. The input variables were the air temperature and plant medium moisture with the output variable being pump flow in the form of PWM. The performance testing and analysis were done by growing the green bean as the sample plant and observing the height of the plant and the number of leaves it produces in a 28-day period. Which resulted in an average height of 22 cm and 14 strands of leaves. Desta Yolanda et al.(2018) [23] carried out the cultivation prototype in an NFT system, for the FLC system the input variables for the Mamadani method were the EC level and the water solution level in the reservoir with the output being the pump solutions for a nutrient solution mixture and water. The aim of the study was to maintain the EC level in the required range and also integrate the IoT platform by using Android. The performance testing and analysis done was by using the settling time for different conditions 1 being when the EC actual value is further than the set point and secondly when the EC actual value is closest to the set point. The results were ± 101 seconds for the first condition and ± 89 seconds for the second condition.

Herman, et al.(2019) [24] compared the traditional planting method for a hydroponics system with smart control farming using the FLC algorithm. The input variables to the FLC algorithm were pH, EC, and water level. The inputs were rather paired with pH being paired with water level and the output is the duration of the pumps. Whereas EC was also paired with water level. To measure the performance of the two farming methods they measured, observed, and compared the leaf length and width of the plants that is the lettuce and bok choy plants over a 4 week period. From the study it showed that smart control has higher differences from traditional hydroponics farming. Similarly Fakhurroja's study [8] observed the growth rate of water spinach was also observed over a 30-day period, using the Sugeno FLC algorithm with pH and humidity as input variables. The performance of the controller was tested by observing its capabilities of being able to maintain the required pH and humidity values. The author concluded that the FLC system can indeed be able to maintain the set pH and humidity values. Other studies that employed the FLC algorithm include [25], [26], and Sudana [27], [28] all of which demonstrated the effectiveness of the FLC algo-

rithm. Additionally, Mashumar [29], added a layer of prediction to the FLC algorithm by using a HSV histogram. The histogram was used to predict the age of the plant and maintaining the required EC according to the age of the plant resulted in an error rate of 8.9%.

Kaewwiset and Yooyativong [30] carried out a study to estimate the relation of EC and pH when adjusting either variable. The study discovered that by adding an EC-adjusting mixture to the nutrient solution, there is no direct correlation between EC and pH. However, when adding or increasing pH using nitric acid there is an increase in the EC value of the solution. They further designed an automatic control system for adjusting EC and pH in NFT system [31] by using linear regression. The cultivated plant was Green Oak and the system control accuracy was 80.8% while for pH it was 95%. [32] also used the linear regression method in the NFT system and had an accuracy level of 87.84%.

2.1.3 Neural Networks and Machine Learning Algorithms

Data-driven control algorithms are also considered in the hydroponics field, with a few authors being able to execute the models Abdoulaye Sidibe et al, [33] experimented by growing out Ballard greens in NFT hydroponics system. The study aimed to develop a model that prevents nutrient deficiencies by predicting EC, and pH values. To predict these values, the study used environmental parameters that directly affect plant growth: air temperature, humidity liquid flow rate, and water temperature. Data values were collected over 15 days, resulting in 3950 data points after preprocessing. A Nonlinear Auto-regressive network with an exogenous input(NARX) model was developed and run on an Arduino Mega. The model was able to predict with 99% accuracy while the pH values showed error deviations of 0.1.

Mokhtar, et al.(2022) [34] aimed to predict crop yield in a greenhouse setup. Lettuce plants were cultivated in hydroponics systems, and data was collected from the setup and used to model different AI models including support vector machines(SVR), extreme gradient boosting(XGB), random forest, and Deep Neural Network(DNN). The collected input variables were the number of leaves, water consumption, dry weight, stem length, and stem diameter. These variables were used in different combinations to model the algorithms, ranging from using all variables to a minimum of

2. The performance of the models was evaluated using a Taylor diagram to display the statistical comparison of the applied models. The results showed that SVR and DNN were the best-performing models. However, the study concluded, that DNN was preferred because it showed better performance with fewer variables.

Ahsan et al.(2021) [35] used deep learning(DL) models and computer vision models to determine the nutrient concentration of grown crops. The DL method was a Convolutional Neural Network (CNN), and the visual geometry group models were VGG16 and VGG19. The study cultivated four different lettuce species (black seed, Rex Flandria, Tacitus) in a hydroponics system. The species were grown under four types of nutrient concentrations 0, 59, 200, and 300ppm. The data collection method in the study was Red, green, and blue (RGB) images, which were used in the modeling of the 3 models. The computer vision models VGG16 and VGG19 outperformed the CNN model with 88% to 100%.

Ramakrishnam et al.(2022) [36] used deep learning CNN to predict nutrient levels and detect plant diseases. Data was collected in real-time collection using a Raspberry Pi microcontroller. The collected parameters included water temperature, water pH, air temperature, humidity, sunlight, and turbidity sensor. Additionally, a camera was used for plant images for the disease classification. The prediction model resulted in 99.3% prediction and classification.

Rizkiana et al.(2021) [37] developed an ANN algorithm(backpropagation) to predict the height of lettuce growth. The input to the algorithm was air temperature, air relative humidity, light intensity, and EC these data variables were collected over a 45-day period. The study used 36 training data samples and a testing data sample of 9. To develop the ANN architecture different configurations were used through trial and error while maintaining the 4 input nodes and the output variable height. The hidden layer nodes varied from 1 to 7. The optimal architecture was 4-7-1, showing the best results with an RMSE error of 0.032.

Arora et al.(2021) [38] also developed an ANN backpropagation algorithm, using a trial and error method to determine the architecture. The input variables For the study were sunlight radiation, air temperature, humidity, nutrient levels, water temperature, and carbon dioxide. The outputs were the amounts of water and nutrients needed to be supplied to the plants.

Ferentinos [39] developed an ANN algorithm to predict future ec and pH values in a deep trough hydroponic system. The study used 9 inputs pH, nutrient solution temperature, air temperature, relative humidity, light intensity, plant age, amount of added acid, and amount of added acid to predict the 2 outputs. The data for these variables was collected over a month, with values recorded every 10 seconds and later averaged over 20-minute periods. This resulted in a total data set of 3600 columns. The dataset was trained using the backpropagation algorithm, achieving 90% accuracy for predicting pH values and 82% for EC values. It should be noted that the study did not have any control measures to adjust the EC, or pH values it just provided the prediction algorithm.

Mehra, M, et al. (2018) [40] applied deep neural networks (DNN) to automate a hydroponics system, integrating IoT for controlling and monitoring the system. The parameters measured and controlled in the system were water level, water temperature, humidity, and light intensity, using a water level sensor, DHT11 sensor, and a photoresistor were used respectively. For actuators two propellers for humidity control and a water pump were used, all being operated by DC motors. The system included an Arduino microcontroller and a Raspberry Pi. The Arduino handled data capture whereas the Raspberry Pi managed the neural network fitting model trained using the collected data. The Raspberry Pi was also responsible for sending instructions to the actuators to execute their respective actions. The DNN was used to predict correct/appropriate actuator actions from the monitored data, which improved the level of accuracy of the output. In the study, 5,000 real-time data for the parameters were collected over weeks and two hidden layers were created. With each hidden layer having 10 neurons or nodes. To provide the appropriate outputs the controlled parameters were trained over 10, 000 epochs in the cloud tensor flow, and Python was the library and language used for training the data. From the study, 88% accuracy was achieved in predicting the best output action. Nugroho [41] also used the DNN algorithm, using water level, water temperature, humidity, and light intensity as the input parameters (with 4000 collected data sets) to predict the actuator actions for the system. The study resulted in 81% accuracy.

[42] The authors of this study used the K-Nearest Neighbor (KNN) algorithm to predict nutrient control in a NFT system. About 5750 sensor data points were col-

lected from the prototyped system and were used to model the KNN algorithm. The collected parameters in the study included pH, TDS, air temperature & humidity, water temperature, and water level. The KNN algorithm created nutrient condition classification and provided actuator actions for each classification. The system achieved an accuracy of 93.3%

Other authors who employed the machine learning approach to predict variables include [43] designing a system that could predict the crop growth rate of a tomato in a hydroponics system. They utilized dry matter weight of the tomato plant, nutrient solution consumption, uptake of inorganic cations such as sodium(Na), Potassium(K), and nitrogen content for several parts of the plant. While [44] used KNN and Lasso regression algorithms to monitor the nutrients in the plant and send instructions to relevant actuators.

Alipio, M.I, et al. (2017) [45] gathered data from the sensors on the hydroponics parameters and used a Bayesian inference network (BN) to obtain an optimum value for each parameter. They developed a system with three components sensors, data analytics, and the web interface. Sensors measured the hydroponics parameters such as light intensity, electrical conductivity, water temperature, and relative humidity. The second component data analytics comprises the BN with a cloud server required for storage and predictive analysis. The final component includes a web interface that enables the farmer to monitor and control the farm remotely. Using lettuce as its case study they compared manual farming and automatic farming (BN), the study recorded a 66.7% gain difference in no of yielded crops, a 27.25% in weight of crops, 20.47% in height, and 40.00% in the number of leaves.

M Kazheunikau, et al.(2004) [46] conducted prediction comparisons between two models: the dynamic Takagi-Sugeno algorithm, and B-spline neural networks in the prediction of the growth of tomato plants. The experiment aimed to forecast the growth in a greenhouse using input parameters such as temperature, solar radiation, and relative humidity. The study compared the two algorithms based on their generalization capabilities and model complexity. This resulted in the B-spline model showing the best generalization model and being less complex. The Maximal Prediction Error (MPE) of the B-spline model was 0.0087.

2.1.4 Hybrid algorithms

For hybrid control, several studies explored their integration. Qi Chen, et al.(2017) [47] employed the PID-FLC algorithm to control or regulate environmental parameters in a plant cabinet system, (a small structure built like a greenhouse). Within the study, ANN and Kalman Filtering Fusion were also utilized to predict plant maturity. The standalone ANN achieved 94% and after fusing with Kalman filtering the accuracy increased to 97.5%. Vito Vincentdo and Nico Surantha [48] applied the ANFIS control algorithm to adjust the environmental parameters specifically pH and TDS. The study compared it with the standard sugeno FLC algorithm and concluded that it was 67% more accurate. Jorge A Hernández-Salazar et al.(2019) [49] designed the ANFIS controller to estimate the evapotranspiration of a tomato plant in a traditional farming setup, achieving RMSE of 16.2464g.

Further literature explored the implementation of computer vision for predicting and estimating nutrient deficiencies. [50] developed an algorithm to predict macronutrient deficiencies in chili plants using imagery data collected from a hydroponics setup. The study used data on leaf color, texture, and shape captured by a camera to identify and estimate macronutrient deficiencies. [51] utilized multispectral imagery to predict nitrogen deficiency in sandalwood leaves with the help of the SVR machine learning method.

2.2 Use of hybrid algorithms in other applications

In other applications, hybrid algorithms are gaining popularity as engineers seek to enhance individual algorithms by combining them to compensate for each other's weaknesses. For instance, [52] implemented the PID-FLC algorithm to control the speed of a DC motor leveraging the PID's simplicity and clear functionality with the fuzzy logic capabilities for performing better in complex nonlinear systems. [53] applied PID-FLC to control the pitch angle of an aircraft demonstrating better responses to the standard PID controller, in terms of delay time, rising time, settling time, and steady-state error. [54] used the PID-FLC to control the automatic generation control of a multisource interconnected power system, concluding that it had better performance than the recently used techniques in the field by comparing its peaks and settling time.

LSTM based ANN controller is used by Yerragolla Hazarathaiah and B. Venkata Rami Reddy [55] to manage the power supply balance in a hybrid photovoltaic and wind system. The study concluded that there is substantial improvement in system performance, highlighting the controller's effectiveness in optimizing power distribution. The table below, Table 2.1 provides an overview of the performance of research works from literature that inspired this study, with some serving as benchmarks for comparison with the developed control algorithms in the research study.

Ref.	Category	Description	Performance
Dervin	On-off	The study monitors and controls water temperature and water in a hydroponic tank using NodeMCU esp8266 microcontroller, standard C++ code.	Settling time: 6.48 minutes for water level control. Temperature control: 2 minutes settling time from 29°C to 28°C
Indra Aeustian	FLC	Mamdani fuzzy logic controller was developed using Arduino Mega 25600 to reduce active times for pH and nutrient pumps to control the pH level. Two cases were studied within the study being pH down and pH up.	Settling times: pH up–150s, pH down–150s. Max error in pH active duration–91.86ms, RMSE–225ms
Chen Hung Chen	FLC	Developed fuzzy logic controller to adjust the working times of the solutions pumped to the hydroponics tank using Raspberry Pi 3. Tests were done with lettuce, strawberry, and broccoli.	Lettuce: EC–1200s, pH–1000s; Strawberry: EC–400s, pH–250s; Broccoli: EC–430s, pH–300s
Nugroho	DNN	Used a DNN algorithm with water level, temperature, humidity, and light intensity as inputs.	81% accuracy

Table 2.1: Overview of inspiring literature and their control performance in hydroponic systems

2.3 Conclusion

A great amount of work has been done in implementing intelligent controllers in the hydroponics system, fuzzy logic control showing its effectiveness in maintaining suitable environmental conditions, ANN or machine learning algorithms showing their capabilities in predicting growth rate and/ nutrient deficiencies, With such this study focuses on comparing the intelligent controllers using transient performance parameters(settling time, rise time, steady state error, and overshoot) on simulation and a small prototype to improve resource efficiency.

3 Methodology

3.1 Introduction

The chapter describes actions that are done to complete the research project which is design implementation and performance evaluation of intelligent control algorithms for a farming system. Figure 3.1 shows the sequential process, that is taken to carry out the project, the key steps being literature review, system modeling, software design (designing the control algorithms), electronics design and finally prototyping.

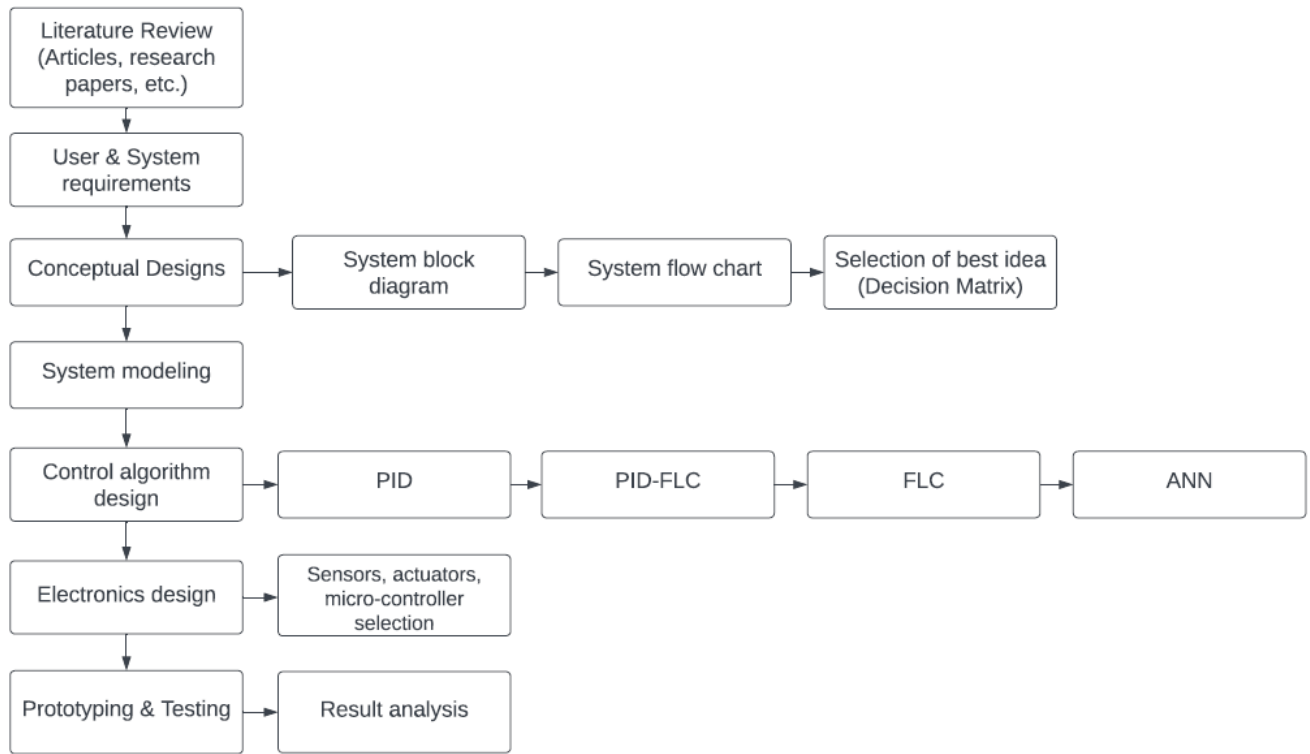


Figure 3.1: Methodology

3.2 Plant and System requirements

Hydroponics is a farming process capable of cultivating different types of plants, mainly leafy plants. However, outstanding cultivation of the plants depends on understanding environmental condition requirements, water solution demands, and ambient conditions. In this study, a lettuce type called Lola rosa is chosen as the study plant. The focus is on the exact control and management of water/nutrient solution requirements,

such as pH, water level, and temperature, as these are the main factors in the success of the plant's growth.

For the control system, the controller's performance is analyzed using transient parameters, overshoot, rise time, settling time, and steady-state error. Each of these factors has its error margins based on its importance in promoting optimal plant development in the hydroponic environment. The regulation of pH levels is a critical aspect of hydroponics control requiring an extremely low margin of error. The controller should be able to make significant changes/highly sensitive to every change in pH error. Similarly, water temperature and water level are also important factors in hydroponics regulation. Certain growth processes can be accelerated by higher temperatures, whereas lower temperatures might have the reverse effect or vice versa. Furthermore, accurate management of water level is critical, since fluctuations in these parameters can have a considerable influence on plant health and output. To enable efficient hydroponic crop production, the control system must be precise in handling these important factors.

3.3 Hydroponics system selection

There are various types of hydroponics systems, for example, ebb and flow, deep water culture, and nutrient film technique each with its own set of qualities, benefits, and downsides. The study is focused on selecting the best technique which further enhances the performance of the controller consequently improving the overall system performance. The decision matrix tool is used to facilitate the selection process. Within the decision matrix specific decision criteria are developed to guide choosing the best system. To assist the review process, the choice criteria, which are thoroughly specified below, are allocated weights in Table 3.1. The weights are assigned higher ratings to characteristics that showed greater influence on parameter control, such as the system's performance in maintaining pH and EC levels. Additionally, it takes into consideration the overall impact on plant growth, including improvements in growth speed. These weighted criteria are then applied to each hydroponic system to generate a performance score. Finally, the system with the greatest score appears as the best option for our investigation. From the literature deep water culture and nutrient film techniques are chosen and evaluated through this process to select the best system.

Deep water culture is a system whereby the plant roots are submerged within the main nutrient solution container [56]. The changes and adjustments by the controller are done within the same section whereas for NFT method there is a subsection of the main nutrient solution and the nutrient solution is pumped to the plant roots section [57], the controller makes adjustments at the nutrient section Figure 3.2 and 3.3 shows the process flow of the DWC and NFT system respectively.

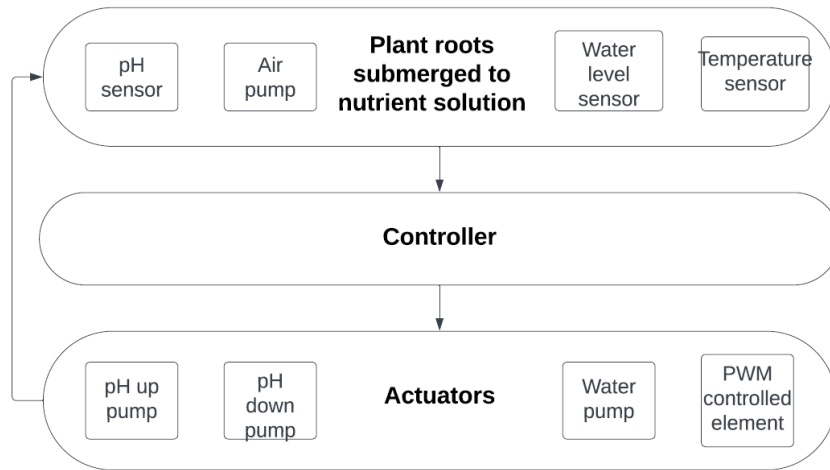


Figure 3.2: Deep water culture block diagram

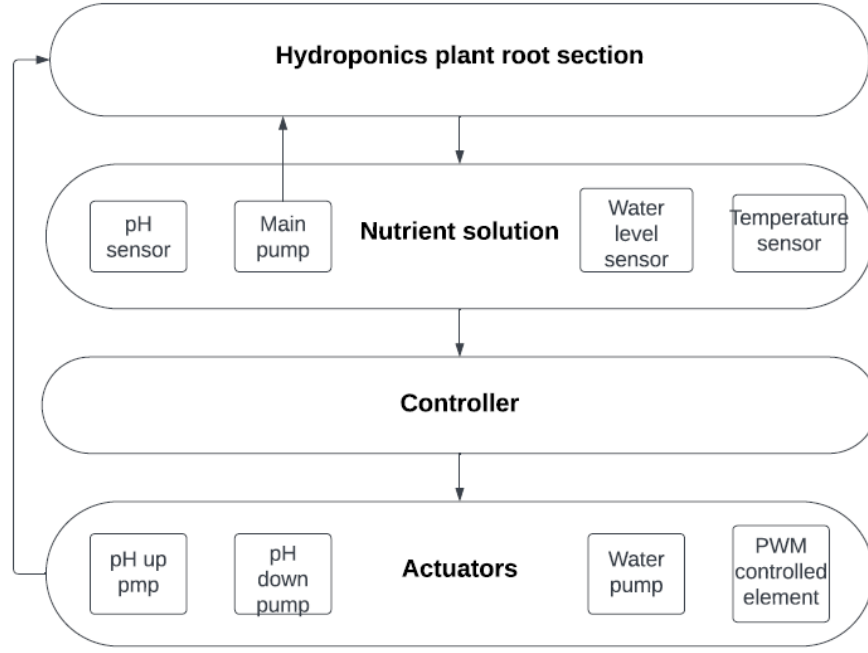


Figure 3.3: Nutrient film technique block diagram

3.3.1 Definition of decision criteria

To establish the decision criteria a few studies are evaluated elaborating on the importance of the different types of hydroponics systems [58], [59], [60], the following points are highlighted across the different studies to develop the criteria.

1. Maintenance of pH and EC- the criteria evaluates how the system can keep constant pH and EC values for a long period of time. The higher the performance the more it can increase the controller's efficiency,
2. Oxygen reach- evaluates how easily the system can distribute oxygen to the plant roots,
3. Energy efficiency- which system can save up more energy in terms of power usage,
4. Nutrient accumulation- can the nutrients be easily distributed throughout the system without causing overconcentration in a single pipe,
5. Maintenance of system- does the system require regular cleaning, and how dependent is it on the user,

6. Cost- which system can provide a more cost-effective option,
7. Assembly- how easily can the system be set up?

3.3.2 Assignments of weights

Criteria	Weight	Merit factor	Total
Maintenance of pH and ec	30	10	300
Oxygen reach	30	10	300
Energy efficiency	15	10	150
Nutrient accumulation	10	10	100
Maintenance of system	5	10	50
Cost	5	10	50
Assembly	5	10	50
Total	100		1000

Table 3.1: Assignment of weights to decision criteria parameters

3.4 System modeling

To simplify the hydroponics environment, it is divided into 3 different simulation environments pH, water level, and temperature level control. These simulation environments are then modeled into MATLAB Simulink with each control algorithm tested against each transient parameter(overshoot, settling time, steady state error, rise time). From the study, first-order differential equations are derived to depict the different types of environments for a hydroponics model. The simulation process follows the basic closed-loop control process block diagram in Figure 3.4.

Where the set point (control system requirements) is the input to the summing junction and the difference between the reference input and feedback from the sensor is input to the algorithm and system mathematical model or plant.

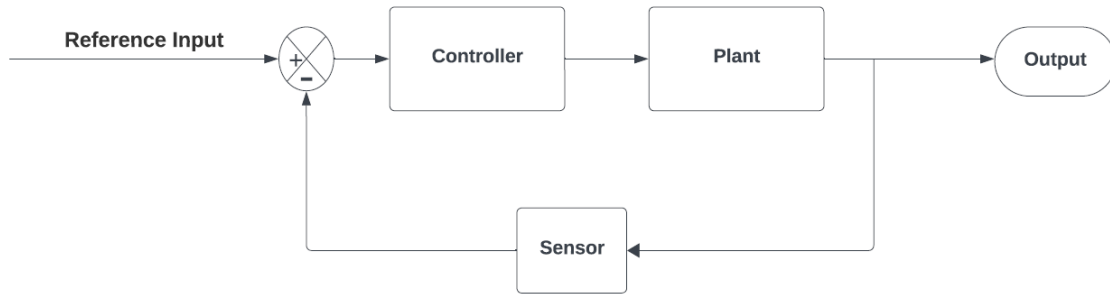


Figure 3.4: Basic control system block diagram

3.4.1 Water level control

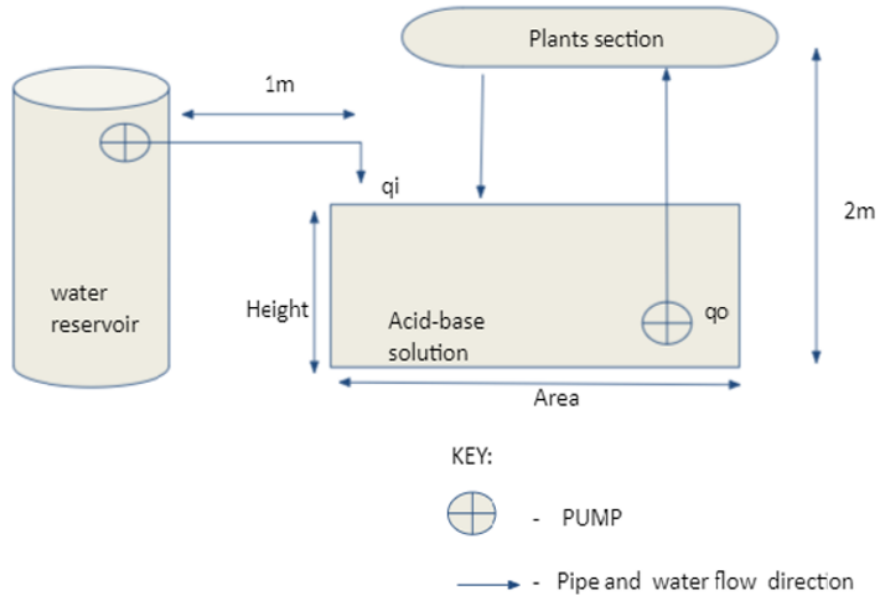


Figure 3.5: Water system block diagram

The above Figure 3.5 depicts how every component relates to each subsector. Water is pumped from the water reservoir by pump q_i to the acid-base solution and pumped to the plant section by pump q_o . The water from the plant section then flows back to the acid-base solution container. Water varies because of evaporation and absorption of water into the plant cells. According to a study by [61] the rate of Lettuce evapotranspiration is 1.8L/day in $1m^2$ surface area therefore it will be used as one of our assumptions in our model. The system is described or modeled on mass balance principles which states that the amount of water in should be equal to the amount of water

out. With a first-order differential equation obtained from [62], the water environment above is modeled having the input as the water flow and output as the height of water. The final transfer function Equation 3.4 is deduced using the initial parameter in Table 3.2. The equation is then modeled in MATLAB Simulink as shown in Figure 3.6. Figure 3.6 shows the model without a controller with Figures A.1,A.2,A.3 showing the process equation simulated with PID and FLC , and PID-FLC respectively.

$$A \frac{dh}{dt} = q_i - ET - (1 - q_o) \quad (3.1)$$

$$\frac{dh}{dt} = \frac{q_i - ET - (1 - q_o)}{A} \quad (3.2)$$

$$\frac{H(s)}{Q(s)} = \frac{1}{A(s + \frac{ET + (1 - \alpha)q_o}{A})} \quad (3.3)$$

$$G(s) = \frac{H(s)}{Q(s)} = \frac{2}{1.295s + 1} \quad (3.4)$$

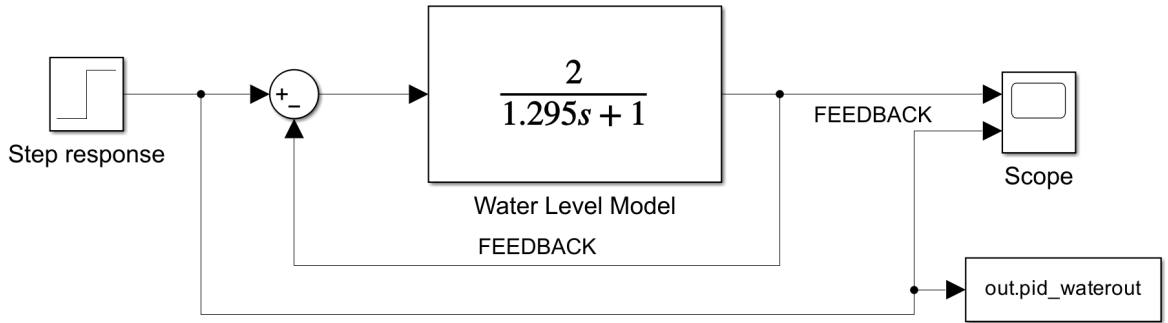


Figure 3.6: Simulink water level model without controller

3.4.2 Temperature level control

Equation 3.5 describes the energy balance of a system showing that temperature change is controlled by mass flows in and out or by an external source [63]. From using laplace transform Equation 3.8 is obtained. The input of the transfer function $G(s)$ is the power of the heating element or fan and output is the temperature of the liquid. The equation considers the heat capacity and density of water, together with the input and output flow of the water in the system. Table 3.2 shows the initial conditions of the hydroponics system by substituting these conditions it results in Equation 3.8, which is then simulated in MATLAB Simulink to evaluate the different control

algorithms. Figure 3.7 shows the Matlab Simulink model when without a controller whereas Figures A.4, A.5, and A.6 show the system implemented the PID, FLC and PID-FLC controller respectively.

$$d(mC_p \cdot T) = \rho C_p F_i T_i - \rho C_p F_o T + K_h P_h \quad (3.5)$$

$$m = \frac{pAh}{1} \quad (3.6)$$

$$F_i = F_o \quad (3.7)$$

$$G(s) = \frac{T(s)}{P_h(s)} = \frac{\frac{K_h}{\rho C_p F_o}}{\frac{Ah}{F_o}s + 1} \quad (3.8)$$

Variable	Value	Units
Water flow in (q_i/F_i)	360	[L/h]
Water flow out (q_o/F_o)	1400	[L/h]
Water heat capacity (C_p)	4.18	[J]
Water density (ρ)	1	[kg/m ³]
Water height(h)	100	[%]
Area (A)	0.5	[m ²]
Evapotranspiration rate(ET)	1.86	[L/h]
Percentage of water retained (α)	0.71	[%]
Gain of power to heating element (K_h)	624	[J/(min%)]

Table 3.2: Initial parameters for water and temperature model

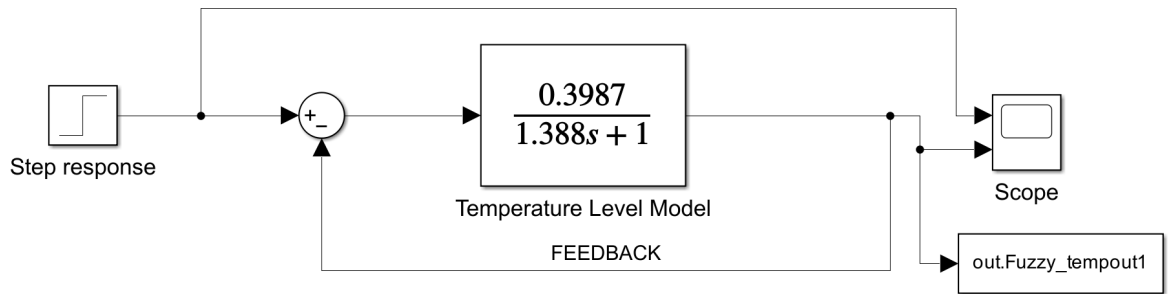


Figure 3.7: Simulink temperature level model without controller

3.4.3 pH level control

pH control is one of the crucial factors in a hydroponics system, from literature various models have been implemented to describe the pH variation process. For easy implementation, the pH neutralization is used to represent the model. This is obtained from [64] where they used an experimental setup to obtain the mathematical model. Equation 3.9 is the obtained pH neutralization process. The equation is modeled on the basis that there is an influent stream and the effluent stream [65]. The effluent and the influent stream are adjusted to keep adjusting the level of pH in the acid-base solution. From the setup, the acid-base solution is the input control variable. Figure 3.8 shows the equation modeled in Simulink, with various control algorithms implemented as shown in Figures A.7, A.8, and A.9.

$$G(s) = \frac{2.453e^{-8.802s}}{0.6374s + 1} \quad (3.9)$$

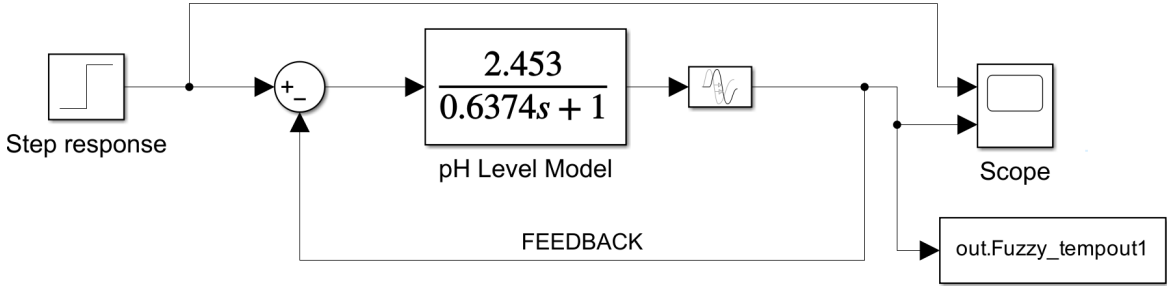


Figure 3.8: Simulink model for pH level without controller

3.5 Control algorithm design

The selection of control algorithms is done to compare the common PID controller with the new emerging algorithms. The chosen algorithms are fuzzy logic, hybrid PID-FLC, and ANN controller. The study aims to select the best intelligent controller that could provide the best results in terms of transient performance analysis.

3.5.1 Controller performance requirements

To analyze how well different controllers perform, the desired conditions for the hydroponics environment are first defined [66]. The plant requirements are thoroughly considered, with a strong emphasis on the impact of each parameter on plant health, as well as the efficient use of resources [6], [67]. The transient performance targets are set by studying existing research projects and the engineers desired control targets. Every control algorithm must strive to meet these requirements as closely as possible, with minimal deviations for acceptable operation. Table 3.3 below shows all the set transient targets for each transient parameter. The best algorithm is selected by analyzing the overall controller's performance across the transient parameters and by using a decision matrix in Table 3.4.

Parameter	Target		
	Water level	pH level	Temperature level
Overshoot [%]	5	2	5
Settling time [s]	350	300	5
Steady-state error	0.5	1	1
Rise time [s]	300	100	4

Table 3.3: Transient performance parameter targets

Criterion	Weight	Controller Merit Factor
Rise Time (Tr)	20	10
Settling Time (Ts)	30	10
Overshoot (Mp)	20	10
Steady-State Error (Ess)	30	10
Total	-	-

Table 3.4: Decision Matrix for best algorithm selection

3.5.2 PID

PID controller comprises 3 subcontrollers combined namely the Proportional, Integral, and Derivative controller. These are in the form of gains serving different purposes in optimizing a system. The controller is governed by Equation 3.10 [68] below, comprising of the proportional gain, integral gain, and derivative gain.

$$u(t) = K_p e(t) + K_i \int_0^t e(\tau) d\tau + K_d \frac{d}{dt} e(t) \quad (3.10)$$

The proportional gain $u(t) = K e(t) + u_b$ offers a control measure that is generally proportionate to the difference between the error signal and the desired signal. Varying the proportional gain affects the transient response parameters differently, which is shown in Table 3.5 [69].

Integral gain $u_o = K_i \int_0^t e(\tau) d\tau$ ensures that the process output matches the desired value by reducing the steady-state errors. While the derivative gain $u(t) = K \left(e(t) + T_d \frac{de(t)}{dt} \right)$ enhances the transient response. There are various ways of obtaining the gains of the algorithms, trial, and error, Ziegler Nichols, Cohen and Coon, and Chien, Hrones, and Reswick method. The trial-and-error method together with the MATLAB PID Auto tuner toolbox is used. These methods are chosen as they are easier and faster to implement. The 2 methods are altered until the systems produce transient responses that meet the user's system requirements.

Gain	Overshoot	Settling time	Steady state error	Rise time
Proportional gain	decrease	slight increase	reduced	reduced
Integral gain	slight decrease	increased	high reduction	slightly reduced
Derivative gain	slight decrease	decreased	no significant change	slightly reduced

Table 3.5: Changes in performance due to parameter changes

3.5.3 Fuzzy Logic Control

FLC control works on the concept of deciding the output of a system by mimicking how humans perform decision-making. FLC helps computers or machines process vague data that are part of human decision-making or real-world data. It uses linguistic

language as its brain box to process the system's data from input to output [70]. FLC primarily consists of 3 main steps fuzzification, rule inference stage, and defuzzification stage. Fuzzification is the first step, involving the conversion of crisp data to fuzzy sets that can be easily interpreted by the algorithm. Crisp data is sent as the input to the fuzzy algorithm which is then converted to fuzzy value(linguistic variables) by using what is referred to as membership functions. The membership function is designed to weigh the input to a specific value within the Universe of Discourse of the system (UOD). This is done through the rule base or inference stage which composes a set of linguistic rules that are generated through the use of human experts or knowledge of a particular system/environment [71]. The fuzzy set rules use the IF-Then statement to determine the control output. The output from the rule base is then input to the defuzzification process where the linguistic values are converted back to the crisp data which are interpreted by the control system or actuators. It uses various techniques for the defuzzification process namely, center of gravity(COG), mean of maximum(MOM), and center of average methods. In this paper centroid/COG was used to determine the output crisp data. It uses the center of gravity of a fuzzy set to determine the actual value of the output [72].

Fuzzification and membership functions

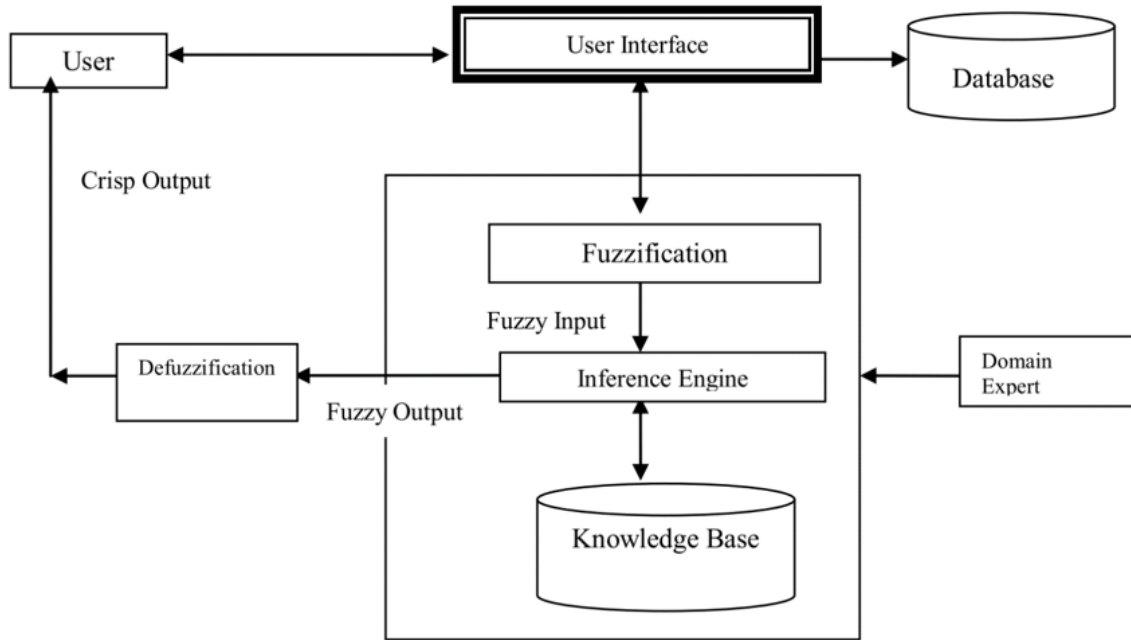


Figure 3.9: Basic fuzzy logic block diagram

Input and output variables definition

Fuzzification control imitates human thinking it is capable of controlling a system without its mathematical model with only knowledge of how the system works, that is it can use qualitative for its process. Figure 3.9 adapted from [73] is an image that depicts the basic template of a fuzzy logic process. Showing the key processes of a fuzzy logic algorithm. The first step in fuzzification is the definition of input and output variables. For every parameter i.e. pH, water level, and temperature various input and output variables are defined depending on the system's needs. pH level control algorithm requires the amount of error and change in error present at a particular point in time, this then determines the amount of acid or base required to make the control change. Water level also uses the system concept above using error and change in error to determine the amount of water needed to compensate for the errors that have occurred. For temperature control, direct reading from the sensor is used to determine the state of the system. With the output transmitted to the relevant actuator. Table 3.6 shows a summary of the input and output variables for the system parameters.

System parameters	Input variables	Output variables
Water level control	Error	Acid or Base
	Change in error	
pH level control	Error	Water flow
	Change in error	
Temperature control	Temperature sensor	power

Table 3.6: Defined input and output variables for fuzzification

Membership function selection

Triangular membership functions are used in this study, due to the easy implementation of membership functions, that is calculations can be done easily, and they are easy to define and represent. It also has better performance in steady-state situations [70]. The membership function also has good adaptability when it comes to systems with high fluctuations in a short period [74]. The figures below Figure 3.10 and 3.11 show the implemented membership functions.

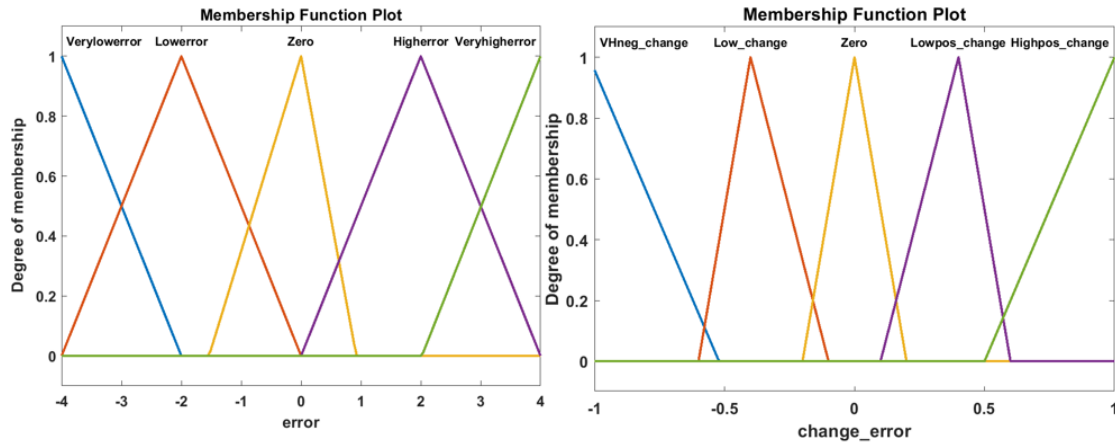


Figure 3.10: pH and water level membership functions

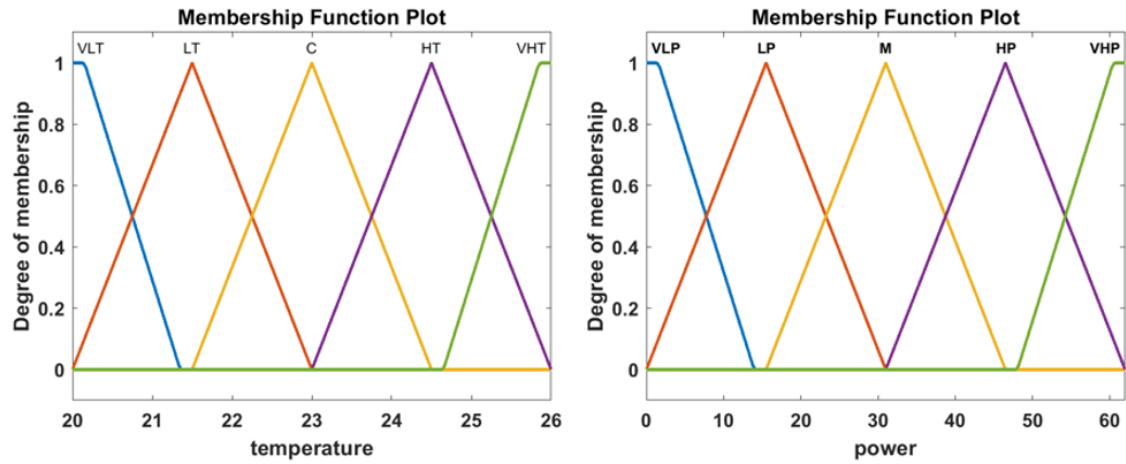


Figure 3.11: Temperature level membership functions input(temperature), output(power)

Inference Engine

The rules are depicted through a lookout table which summarizes all rules. Below are the lookout tables for pH, water, and temperature control.

Change in error	Target				
	Very low error	Low error	Zero	High error	Very high error
Very high negative change	Very low flow	N/A	N/A	N/A	N/A
Low negative	N/A	Low flow	N/A	N/A	N/A
Zero change	N/A	N/A	Normal/No	N/A	N/A
Low positive	N/A	N/A	N/A	Midflow	N/A
High positive	N/A	N/A	N/A	N/A	Highflow

Table 3.7: Lookout table for pH and water level control

	Temperature				
	VLT	LT	C	HT	VHT
Output	VHP	HP	M/No	LP	VLP

Table 3.8: Lookout table for temperature level control

From defining membership functions and the inference rules, the fuzzy inference system (FIS) algorithm is demonstrated by the control surface shown in Figure 3.12 and Figure 3.13, respectively, for pH and water level control and temperature level control. These graphics clarify the controller's basic control logic and provide a comprehensive framework for understanding and optimizing the system's performance.

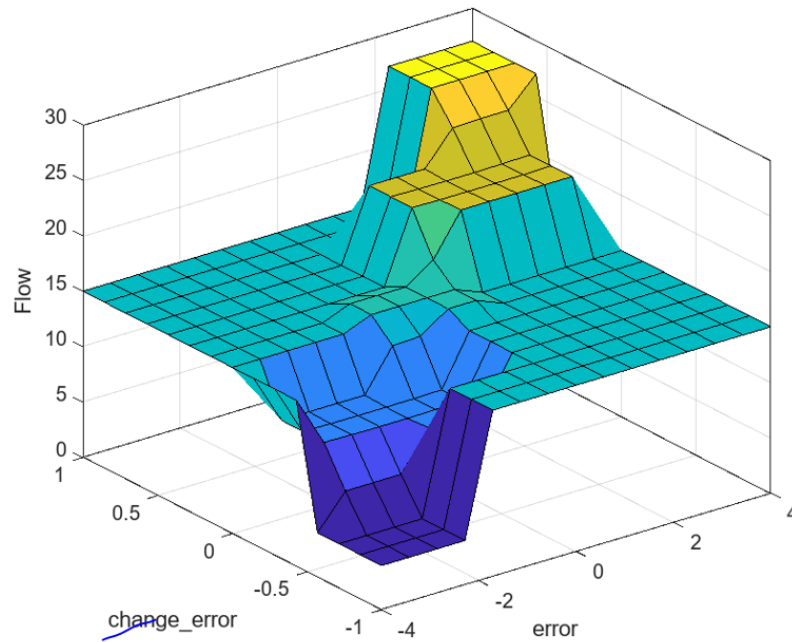


Figure 3.12: Control surface for pH and water level control

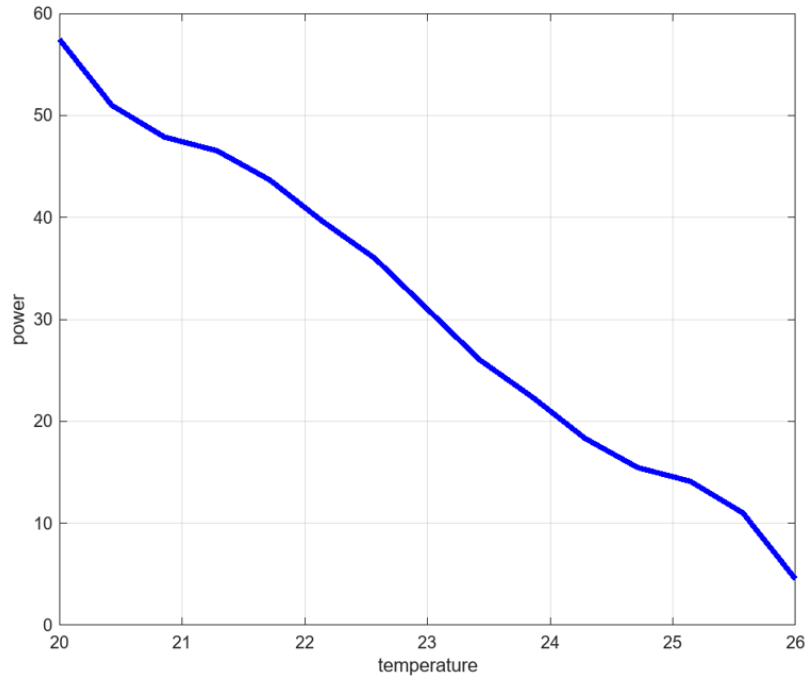


Figure 3.13: Control surface for temperature level control

3.5.4 PID-Fuzzy Logic Control

This is a combination of the conventional PID controller and the intelligent algorithm fuzzy logic. Hybridization is important to compensate for the weakness of each algorithm. As stated above PID needs to be tuned to the parameter gains that is (proportional gain, integral gain, and derivative gain) Intelligent controllers have become some of the tuning tools. There are many benefits to integrating the fuzzy logic controller. FLC is a highly non-linear controller it can handle non-linearities with ease [54]. Fuzzy logic enables control engineers to work without using mathematical models of the system [75]. Only the experience of the user or engineer is required as it uses heuristic rules and logic of the real system [76].

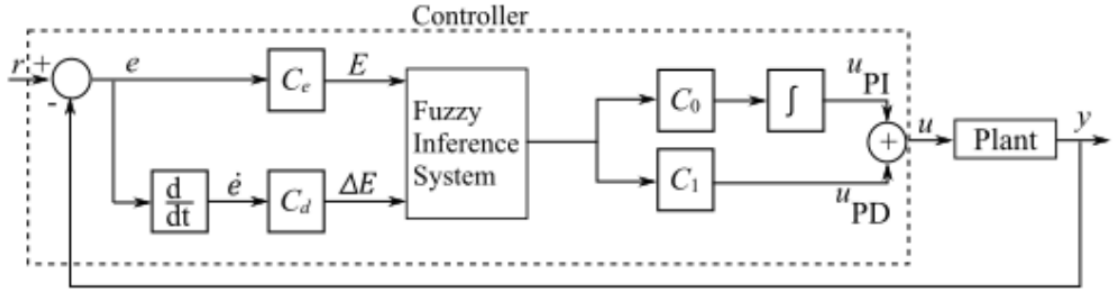


Figure 3.14: PID-FLC controller architecture

With various PID-FLC techniques [77] uses the PID-FLC architecture above Figure 3.14, the input to the fuzzy logic controller is error and change in error. The membership functions are described in Figure 3.15 below. These have scaling factors C_e and C_d which are used to scale the error and change in error. The output from the FLC is multiplied with gains C_o and C_1 which form the PI and PD branches respectively then transmitted to the plant for control. Triangular membership functions have been used with a UOD (-1:1) in both inputs.

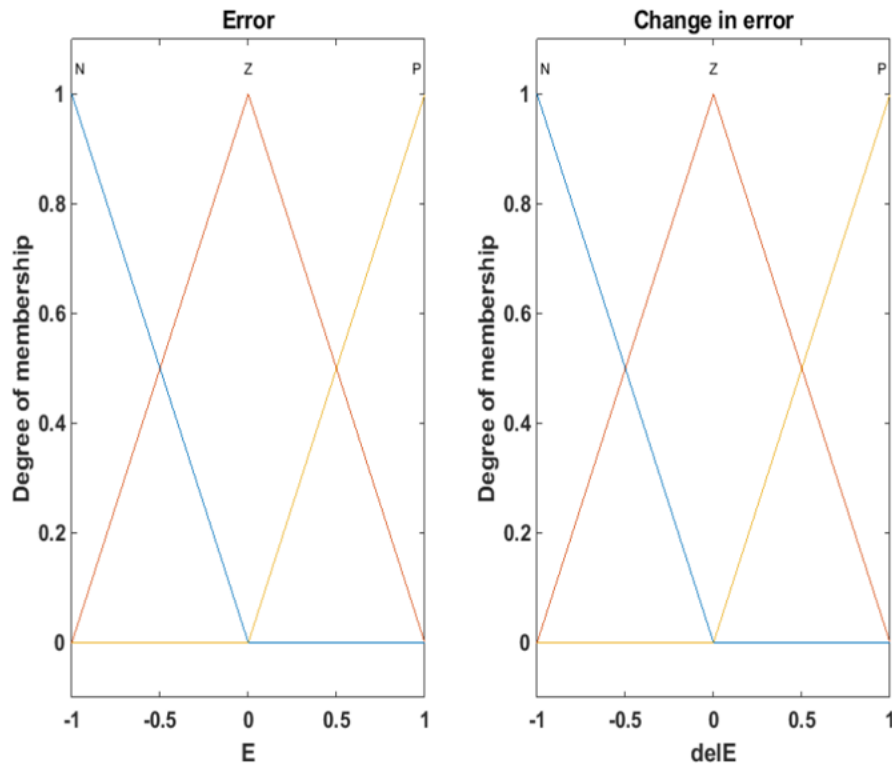


Figure 3.15: PID-FLC controller membership functions

The scaling factors and gain factors improve the systems response therefore proper

tuning is required [78]. There are various tuning methods, in the study to calculate the scaling factors and gains the transfer function is described as in Equation 3.11 C is the gain, L is the time delay and T is the times constant. Using Equations from 3.12-3.15 the gains are obtained.

$$G(s) = \frac{Ce^{-Ls}}{Ts + 1} \quad (3.11)$$

$$C_d = \min(T, \frac{L}{2}) * C_e \quad (3.12)$$

$$C_o = \frac{1}{C * C_e(\tau + \frac{L}{2})} \quad (3.13)$$

$$C_1 = \max(T, \frac{L}{2}) * C_o \quad (3.14)$$

$$C_e = \frac{1}{r(t_r) - y(t_r)} \quad (3.15)$$

3.5.5 ANN

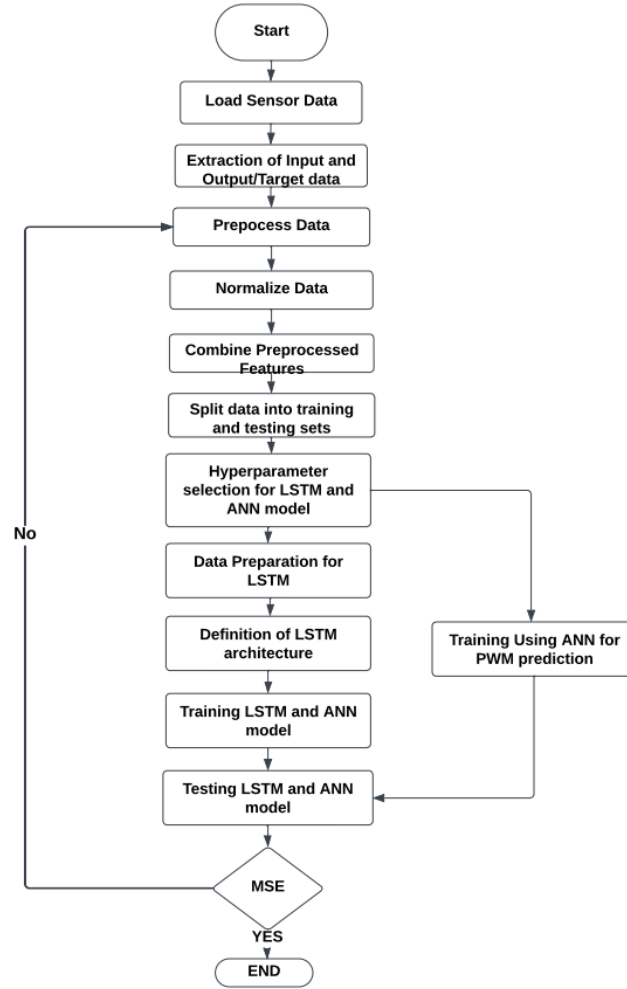


Figure 3.16: LSTM ANN design flowchart

ANN is an algorithm that imitates the structure of the human brain, applying the concept of artificial neurons structured in layers. Layers are connected through weights which are used in the learning process. In the study LSTM-ANN model is used, to design the ANN model several steps have to be taken to develop the algorithm. Figure 3.16 above shows the steps taken in the study. The hybrid predicts environmental parameter's future values through the LSTM model and controls the system through the ANN model, which is trained to predict actuator values. Due to lack of online datasets, the collection of data is carried out from the 24-plant system prototype. Sequential data is collected from the system therefore Recurrent Neural Network(RNN) is better suited for prediction can learn relations from past data to current data as

it has a memory function [79], [80]. The sequential data is used for both LSTM and ANN training. In the case of ANN, the sequential data is trained to map out generated PWM values as outputs. Enabling the ANN to learn the relationship between sensor values and control signals, allowing it to predict actuator values. The RNN method used in the study is the Long Short Term Memory(LSTM), it learns past events to predict future values or events. The LSTM method assesses learning sequences, stores important features/sequences for long durations in the memory cell internal state, and modifies the trained sequences when new important features are introduced into the model in the input and forget gate [81] Figure 3.17.

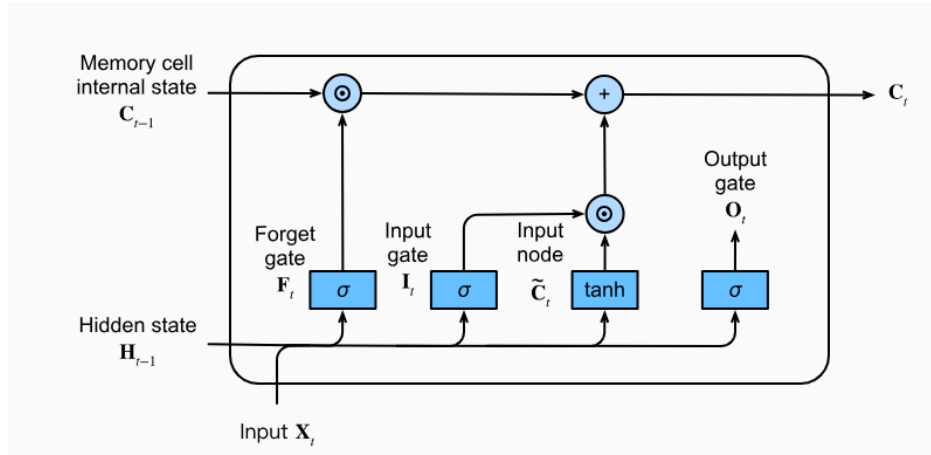


Figure 3.17: LSTM model(https://d2l.ai/chapter_recurrent-modern/lstm.html)

Matlab is used in the study to design the hybrid algorithm. The data is loaded into the workspace and preprocessed to remove outliers, negative values, and missing values. Then finally normalization is done to remove the dominance of one feature towards others or to remove the difference in magnitude between features [82]. For LSTM preprocessed data is split into 80% training and 20% testing and validation. In the network architecture, four input layers are used, for the four features recorded from the plant. The hidden layers(LSTM layers) used are 125 neurons, with the third layer having four neurons to connect to the output layer and finally, the regression layer which the network uses to train and predict future values. The activation function in the hidden layer is the tanh activation function, and the output layer is the linear activation function. These help the network in learning complex non-linear patterns and relationships in the data [34]. For ANN the data is split into 75% training and 25% testing and validation. The network architecture is a feedforward net with 10 hidden

layers using the tanh activation function. Finally, the performance of the algorithm is evaluated using Mean Squared error(MSE) and Root Mean Squared Error (RMSE). The process is iterated to obtain target performances. The trained models are then combined with the LSTM model predicting future sensor values which are then fed to the ANN model and final results are used to predict control actions for the actuators Figure 3.18 adapted from [83] shows the sample of the LSTM ANN architecture.

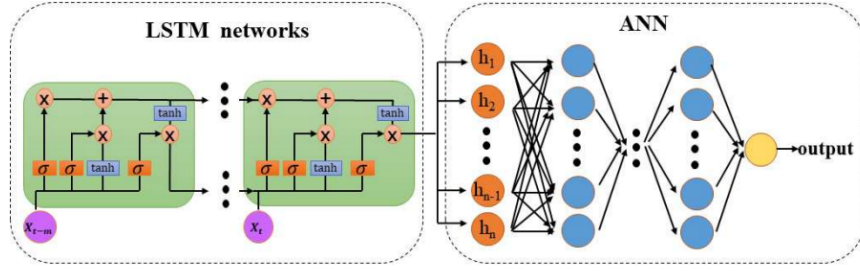


Figure 3.18: LSTM ANN model

3.6 Experimental setup

From designing and testing out different algorithms from simulation the best algorithm was chosen and then implemented in the hydroponics plant shown in Figure 4.23. Firstly, the experimental setup is done without a controller, this is to collect data for the manual control setup, evaluate the data then compare it with results where an intelligent controller has been implemented. This approach improves the controller performance analysis by collecting primary data which facilitates the optimization of the controller to the specific hydroponic system. The collected data is used to design the ANN algorithm as stated above then the intelligent controller from the simulation is evaluated against it.

3.6.1 User and system requirements

The specific needs of the plant cultivated determine the system's requirements. The plant grown in the study is lettuce(Lola rosa) with

1. pH requirements of 5.5-6.0
2. EC = 1.2us/cm

3. Water temperature = 24 - 26°C

The controllers to be designed should maintain the given conditions throughout the cultivation stage.

3.6.2 Hydroponics system used



Figure 3.19: NFT prototype system

In the study, a 24-plant NFT system is the proposed system for implementation for both automatic control (use of intelligent controllers) and manual control for testing and analysis Figure 3.19. It comprised a nutrient solution tank, plant root section, and the main pump responsible for circulating the nutrient solution up to the root section. At the root section stream, there is an overflow of the nutrient solution back to the main tank maintaining a continuous recirculation of the nutrient solution. For

automatic control, the system is augmented with a microcontroller Arduino Atmega as it has many I/O ports and greater memory, [84], [85] compared to the Arduino uno [86]. The sensors and actuators respond to the instructions from the control algorithm implemented in the microcontroller.

3.6.3 System flow chart

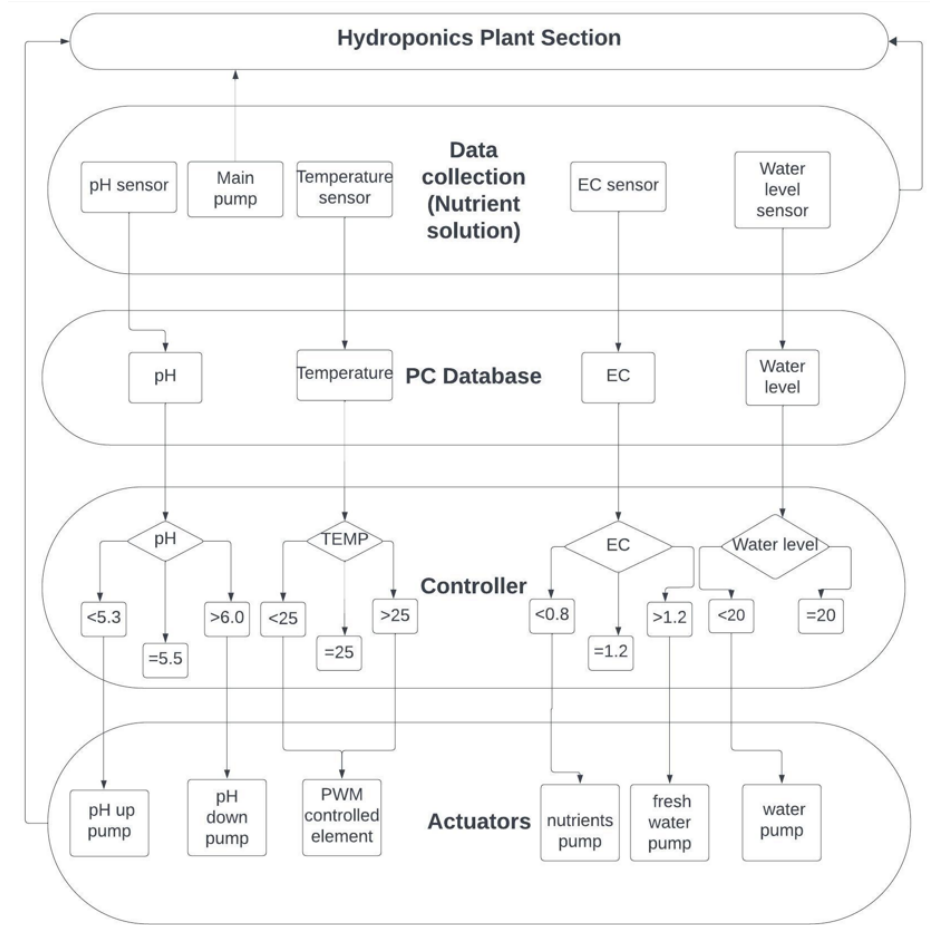


Figure 3.20: NFT flowchart

The figure above shows the control process of the control system showing data flow and how parameters are interpreted within the system. The system flow chart is also a pseudo for our control algorithms. Sensory data is collected from the nutrient solution section (pH, temperature, and water level), and then the data is sent to the pc/microcontroller. Control decisions are being carried out at the microcontroller relative to each parameter, using a control algorithm. In the study, the best option selected from the analysis is implemented into the microcontroller. The microcontroller

transmits information to respective actuators to execute the necessary changes. Using pre-defined set points as given above for the Lola rosa lettuce control algorithm will analyse the data received and adjust accordingly. For the pH algorithm when the pH reading is below 5.0 a signal will be sent to activate a lime or base solution pump which increases the pH level. When the pH reading is higher than 6.0 signal will be sent to activate the acid pump which decreases the pH level. This is followed across all the different hydroponics parameters, as shown in the system flow chart.

3.6.4 Sensors and actuators

The sensors and actuators used in the study are as follows, they have been divided into the manual control section and the automatic control system.

Manual control

Part	Uses	Description
Ec, temperature, pH tester	Measures the EC, pH, and temperature with different modes	
30 cm rule	Manually measures the water level in the water tank	

Table 3.9: Manual sensors

During the manual control testing and analysis stage, the combined EC, temperature, and pH tester are utilized to monitor the dynamic changes in the system see Figure 3.21. For water level readings a 30cm rule is employed, taking the bottom of the tank as the reference point see Figure 3.22. The readings are taken two times a day at 0815 and 1545 over a month. Whenever the system is out of bounds of the set parameters changes made to the system are made manually by adding the necessary solutions. For example, if the system's pH is either higher or lower than the given setpoint, the farmer or operator manually adds the pH up or pH down solution to revert the conditions of the solution to the required values.



Figure 3.21: pH, temperature, and ec level manual sensor



Figure 3.22: Water level manual reading

Automatic control

To collect data and monitor the plant the sensors shown in Table 3.10 are used giving their uses and specification descriptions.

Part	Uses	Description
pH sensor Sen0161	Placed in the nutrient solution tank to monitor the pH value within the tank	range: 0 ~ 14, temperature: 0~60°C, response time: $\leq 1ms$
Water temperature sensor DS 18B20	Measures the water temperature of the nutrient solution	input voltage: 0 ~ 5.5V, temperature range: -55~+125°C, accuracy: ± 0.5 from -10 to +85°C
Water level sensor HC-SR04	used to measure the water level sensor of the tank by using the ultrasonic principle, this enables us to be able to convert the distance to digital readings which the microcontroller can read.	input voltage: 5V, operating frequency: 4MHZ, detection range 2cm ~ 400cm, measuring angle: 30°, resolution: 3mm, operating current: <15mA
EC sensor RS485	Placed in the nutrient solution tank to measure the amount of nutrients or soluble solids in the tank,	range: 0 ~ 200ms/cm, temperature: 0~120°C pressure: 0~1.0 MPa

Table 3.10: Automatic control sensors

The actuators used in the study are shown in Table 3.11;

Part	Uses	Description
Pump Peristaltic dosing pump K335BT	Used to transfer liquids from one container to the other,i.e water, nutrient solution, acid, and base	Max head: 8m, Max flow:2000ml/min, pressure:0.17Mpa, power: 48W, voltage: 12V
Water heater	Maintaining a constant temperature for the nutrient section at the roots.	Power: 450W
Motor control driver(L293D)	control peristaltic pumps with PWM	supply voltage: 4v to 36V,output current: peak 1.2A, power: 5W,

Table 3.11: Automatic control actuators

Sensor Calibration

Calibration is carried out weekly during data collection to ensure the reliability and accuracy of sensor readings. For the manual pH meter and the Sen0161 pH sensor, known buffer solutions are used to calibrate the devices. Three standard solutions are applied to set the sensor to known pH values: 1.2 (acidic), 7.0 (neutral), and 9.0 (alkali). To prevent contamination of the sensor probes, distilled water is used to rinse them before and after each calibration and usage. The ultrasonic sensor is validated manually using a steel ruler to compare the sensor's measured distance with the actual distance, ensuring the readings are within acceptable error margins. The DS18B20 temperature sensor is calibrated by comparing its readings with those of a laboratory-grade thermometer in a controlled water bath. Readings are verified across different temperature ranges such as ice water, room temperature, and warm water to confirm accuracy and consistency. Any discrepancies observed are accounted for during data processing.

3.6.5 Electrical circuit for automatic control

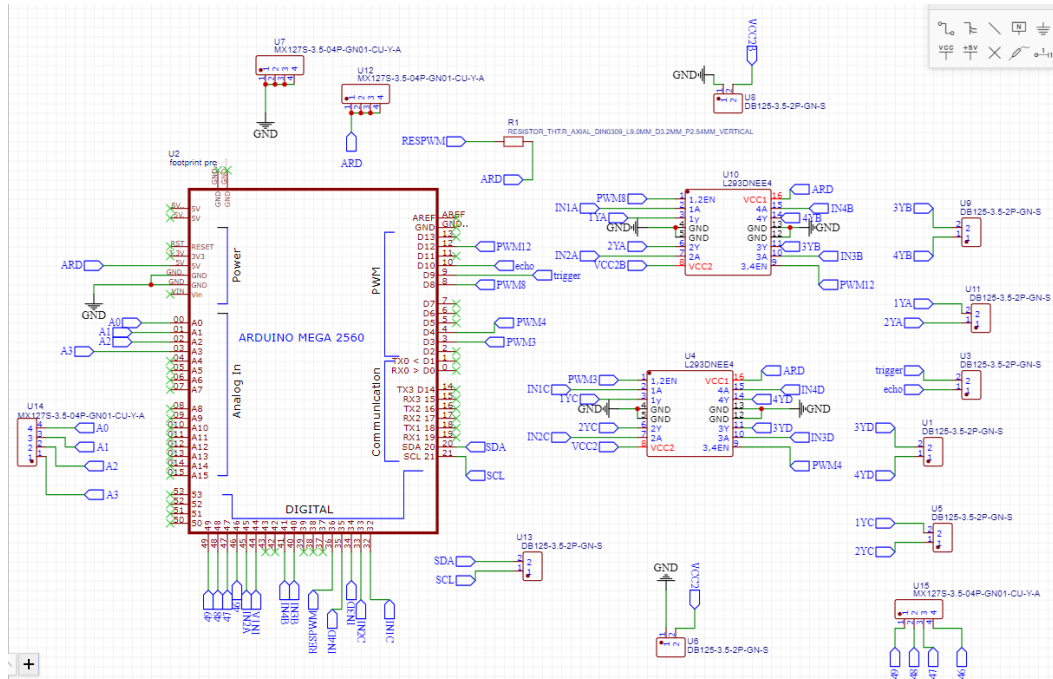


Figure 3.23: PCB schematic diagram

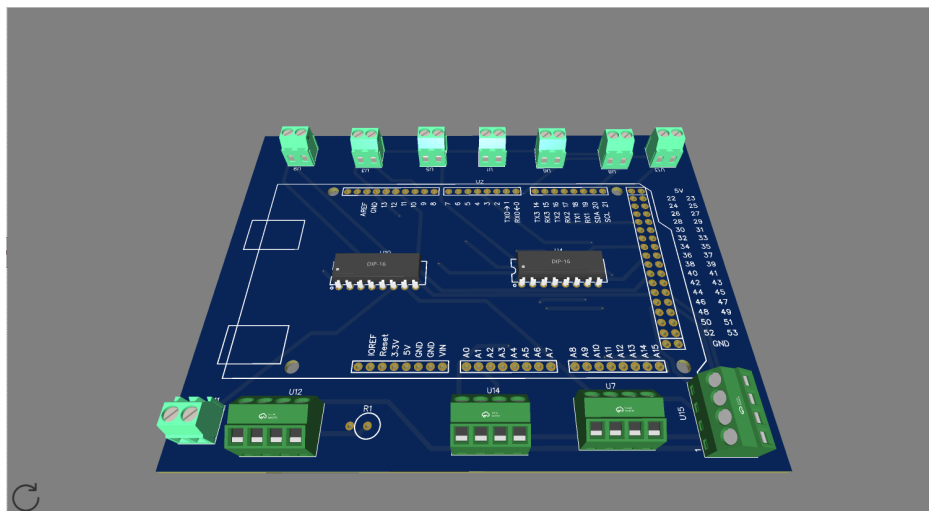


Figure 3.24: PCB 3D model

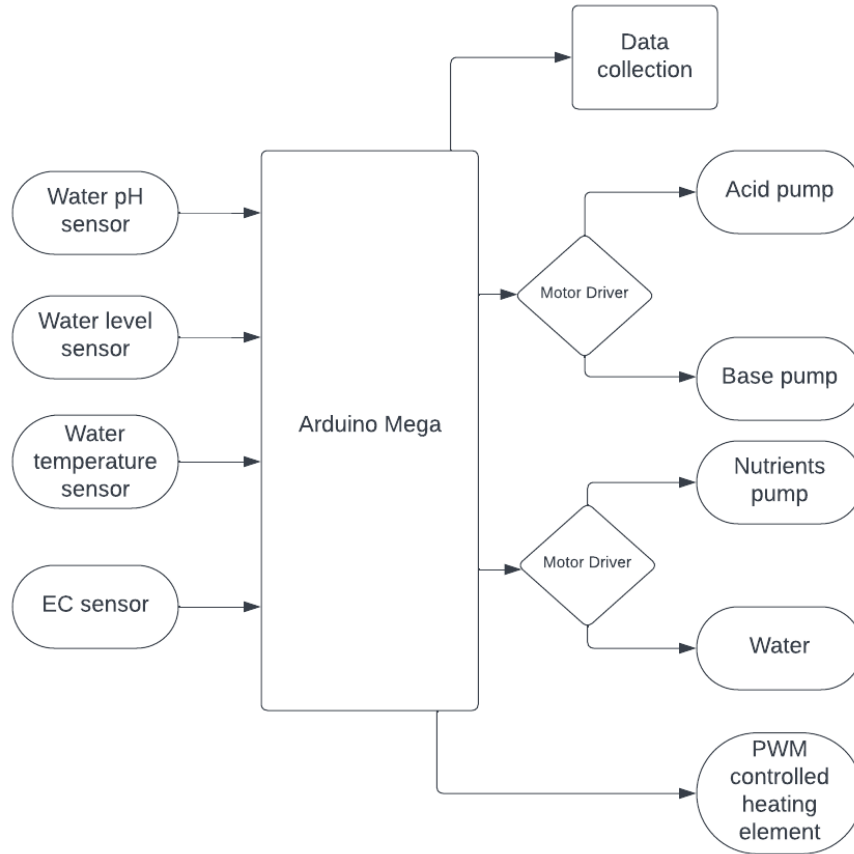


Figure 3.25: Arduino Interfacing

As stated above sensor data is collected from the nutrient solution and sent to Arduino Mega. The Arduino processes the data collected and sends it to the relevant actuator. It processes this by using the uploaded control algorithm. In the study control algorithm uploaded is the PID-FLC algorithm and the data-driven algorithms ANN algorithm. The study aims at making a comparison between the 2 control algorithms hence the significance of uploading the 2. The Arduino mega is interfaced with the pumps(actuators) through the use of an L293DE module controller. The module enables us to connect 2 motors in a single module, and be able to control the speed and direction of the motors. Figure 3.25 shows how the actuators and pumps are interfaced to the Arduino. Figures 3.23 and 3.24 show the designed PCB electronic circuit in 2D format and 3D format respectively which is to be used to develop the physical prototype.

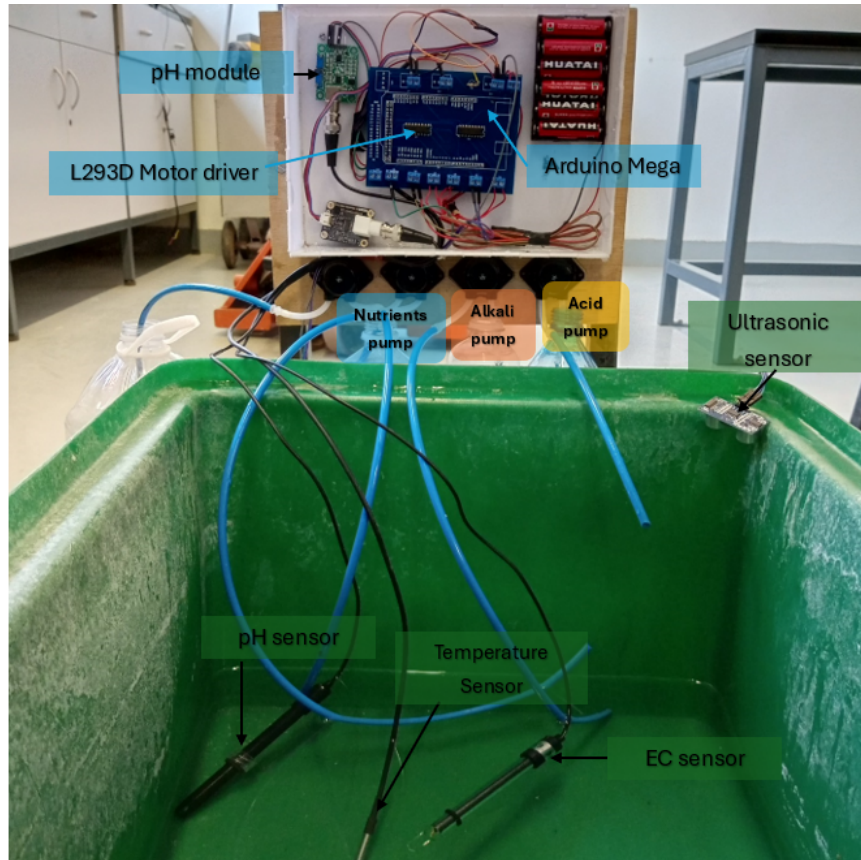


Figure 3.26: Arduino physical implementation

Figure 3.26 depicts the physical implementation of the system. It shows the peristaltic pumps, the motor driver L293DE, and the Arduino mega together with the sensors. Each pump is associated with a container from which it draws the relevant solution. For example, the acid pump draws its contents from the acid container and dispenses them to the main nutrient solution tank.

3.7 Economic Analysis

In this part, the study analyses the benefits of the controller compared to a local farmer using the manual setup. It studies the economic viability of the project and returns of investments. It assesses the startup cost, operational costs, energy savings, profitability of the project, and potential payback periods.

$$\text{Total Cost} = \text{Setup cost} + \text{Operating Cost per day} \quad (3.16)$$

$$\begin{aligned} \text{Labour Cost savings} &= \text{Manual Labour Cost per day} \\ &\quad - \text{Controller Labour Cost per day} \end{aligned} \quad (3.17)$$

$$\begin{aligned} \text{Water Cost savings} &= \text{Manual Water Usage Cost per Day} \\ &\quad - \text{Controller Water Usage Cost per day} \end{aligned} \quad (3.18)$$

$$\begin{aligned} \text{Total Cost Savings per Day} &= \text{Water Usage Cost Savings per Day} \\ &\quad + \text{Labour Cost Savings per Day} \end{aligned} \quad (3.19)$$

$$\text{Net Present Value} = \sum_{t=1}^n \left(\frac{B_t}{(1+r)^t} \right) - C_0 \quad (3.20)$$

Where:

- B_t = Net benefit (or cash inflow) at time t
- r = Discount rate per period
- t = Time period
- n = Total number of time periods
- C_0 = Initial investment or cost

$$\text{Payback Period} = \frac{\text{Initial Investment}}{\text{Annual Net Benefits}} \quad (3.21)$$

4 Results and Analysis

4.1 Introduction

This chapter represents results derived from our methodology beginning from simulation to the physical implementation of the hydroponics system. As stated above in methodology, each parameter is modeled in MATLAB and controlled using the various control algorithms. A comparison of the algorithms in each parameter is done and analyzed with the best algorithm selected for physical implementation. A data-driven control algorithm is developed using the data collected from the physical system which is also evaluated with the chosen control algorithm from simulation. Implementation is done using DIY components on a small-scale hydroponics NFT plant system. Transient parameters are recorded and used for comparison purposes. The chapter is structured as follows; Section 4.2 which shows the process of deciding on the best hydroponics farming method that can increase the effectiveness of the control algorithms, Section 4.3 shows performance results for all simulations which are modeled in the MATLAB Simulink software, Section 4.4 this section focuses on the physical implementation of the study, showing how the selected algorithm from simulation and the developed data-driven algorithm performed in the physical setup. These are then compared with existing ideas from literature.

4.2 Selection of hydroponics system

As discussed earlier the best technique ought to be chosen to best complement the control system. Therefore, a decision matrix is used to select the best technique from the many hydroponics systems. In our study, the techniques are drawn down to 2 options NFT system and the deep-water culture system. Below, Table 4.1 and 4.2 show the weighted systems and their performance comparisons. The NFT system demonstrated slightly better performance with a score of 810, compared to the DWC system's score of 750. NFT has slightly better performance as it has higher capabilities for maintaining the nutrient solution parameters due to its recirculation of nutrient solution in the plant streams.

Concept 1 NFT system				
	Weight	Characteristics	Merit factor	Total
Maintenance of pH, Ec	30	Regular feeding provides uniformity	10	300
Oxygen reach	30	Upper roots are dry and have access to oxygen	10	300
Energy efficiency	15	Has an extra pump	5	75
Nutrient accumulation	10	A constant flow of nutrients	8	80
Maintenance of system	5	Regular checking for root clogging	3	15
Cost	5	P60/m	3	15
Assembly	5	Easy	5	25
Total	100			810

Table 4.1: Decision matrix for NFT system

Concept 2 DWC system				
	Weight	Characteristics	Merit factor	Total
Maintenance of pH, Ec	30		8	240
Oxygen reach	30	roots submerged under water	7	210
Energy efficiency	15	no extra pump required	10	150
Nutrient accumulation	10	possibility of nutrient accumulation	8	80
Maintenance of system	5	less maintenance required	5	25
Cost	5	P50/m	4	20
Assembly	5	Easy	5	25
Total	100			750

Table 4.2: Decision matrix for DWC system

4.3 Simulation results

Water Level Control

These are the results obtained from the Matlab simulation platform, analysing the performance of water pH, temperature, and water level. The water model showed that without any control algorithm, the system response has highly significant errors, with a steady state error of 6.79 showing the need for the use of control algorithms. This is shown in Figure 4.1 which graphically shows the response of the system with various control algorithms and without a control algorithm. Figure 4.1 also shows the ability of the controllers to track the setpoint, which is set to 7.5. As seen in the Figure, there are significant differences in the transient performance analysis. The water model showed that the PID-FLC controller performed better for the overshoot and settling time criteria registering 0%, and 2.56s, respectively. The FLC controller proved to be more responsive than other controllers as it registered 0.50s but with a very high settling time of 2.57%. PID controller was the highest with an overshoot of 6.85s but is the second best in settling time at 4.99s. Table 4.3 summarises the results of the algorithms with different hydroponic parameter models.

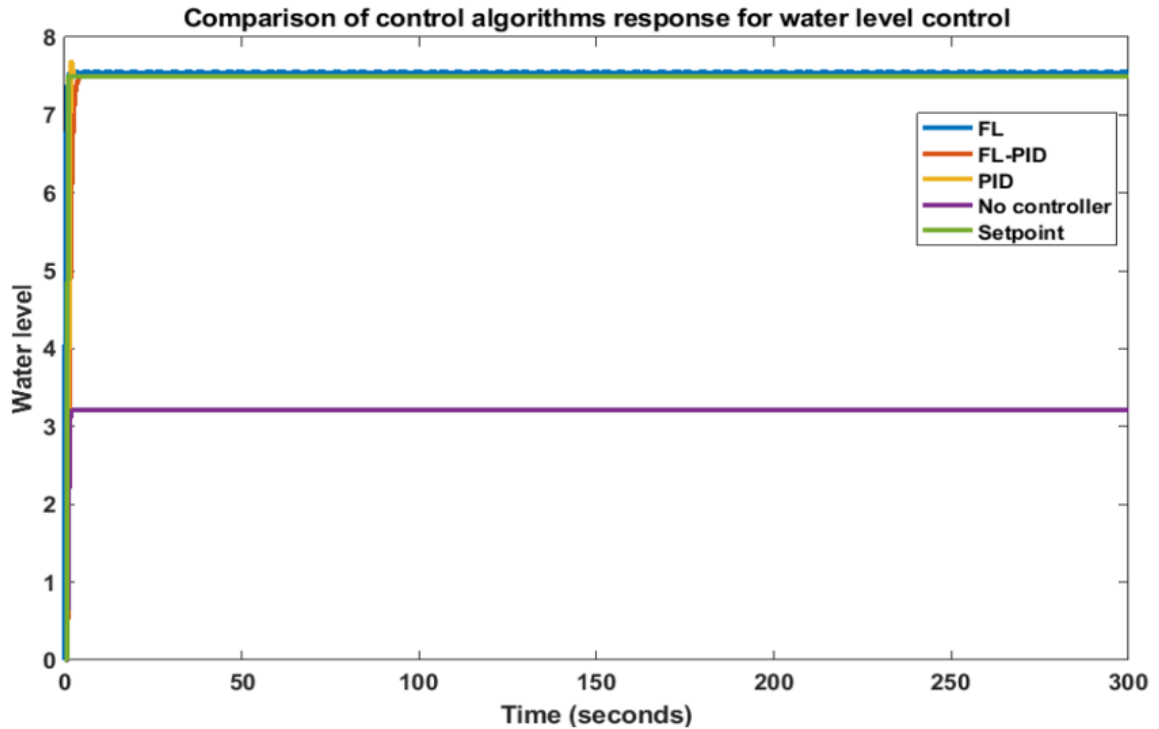


Figure 4.1: Water level comparison graphs

Water Temperature Control

In Figure 4.2 it can be seen graphically that the temperature model without a controller has a high steady-state error of 4.88. The implementation of all the controllers has eliminated the steady-state error to approximately 0. The PID controller has the highest over-shoot at 2.68%, followed by the FLC and PID-FLC controller at 0%. PID-FLC performed better on settling time at 3.20s and showed to be more responsive compared to other controllers which recorded 1.24s.

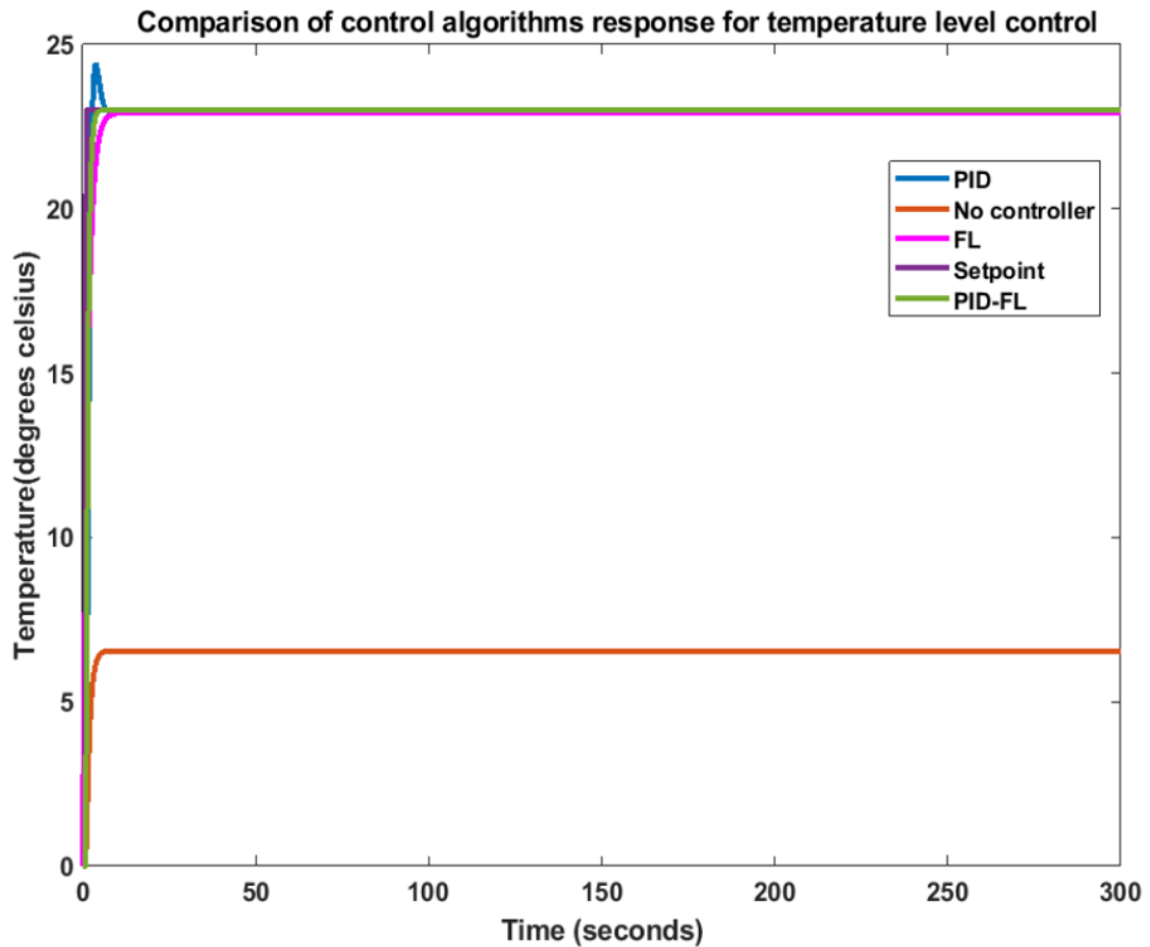


Figure 4.2: Temperature level comparison graphs

pH Level Control

For pH control, the PID-FLC controller performed better in terms of responsiveness. It registered 7.25s but is the second best in settling time at 50.84s. The highest overshoot and rise time, 3.73% and 90.11 seconds respectively, are recorded by the PID controller. All algorithms in the various parameters registered a steady-state

error of approximately 0.0 which is within the given setpoints, showing that all control algorithms can be used in the hydroponic setup, with PID-FLC having the edge. Figure 4.3 shows the graphical representation of the responses, showing the turbulent nature of pH control as it is highly non-linear.

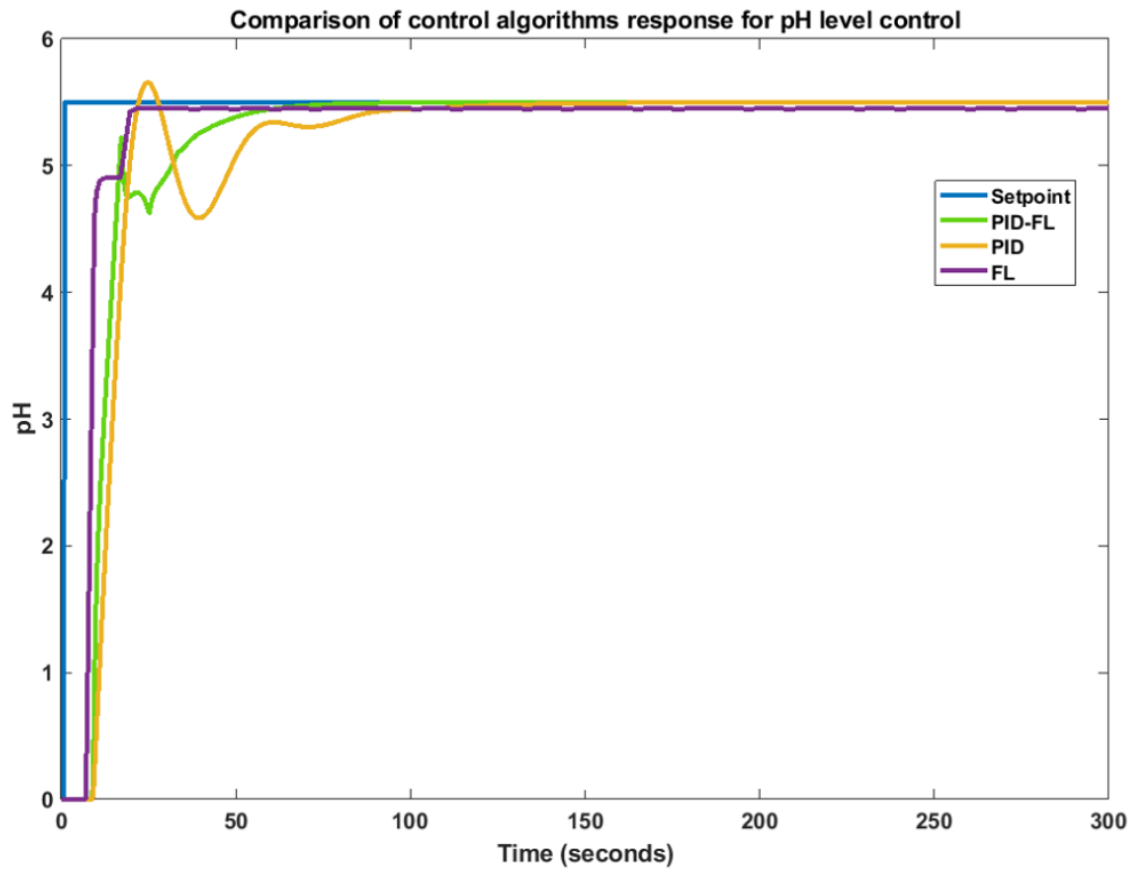


Figure 4.3: pH level comparison graphs

4.3.1 Comparison performance analysis

Water level control						Temperature level control					pH level control				
	SP	NC	PID	FLC	PID- FLC	SP	NC	PID	FLC	PID- FLC	SP	NC	PID	FLC	PID- FLC
Overshoot [%]	5	0.00	6.85	0.06	0.00	5	0.00	2.68	0.00	0.00	2	0.00	3.73	0.02	0.0
Settling time [s]	350	1.61	4.99	7.55	2.56	5	4.88	5.68	5.42	3.20	300	299.53	90.00	19.22	50.84
Steady-state error	0.5	6.79	0.73	0.10	0.4	1	16.44	0.01	0.082	0.00	1	3.70	0.00	0.05	0.00
Rise time [s]	300	0.34	1.13	0.50	0.88	4	2.18	1.69	3.04	1.24	100	18.91	90.11	7.27	7.25

Table 4.3: Performance Comparison of Simulation Results

Criterion	Weight	PID	FLC	PID-FLC
Rise Time (T_r)	2	7	8	7
Settling Time (T_s)	3	4	5	7
Overshoot (M_p)	2	7	10	10
Steady-State Error (E_{ss})	3	10	10	10
Total	10.00	70	81	85

Table 4.4: Decision Matrix to select the best algorithm

It is important to note that each controller can perform better than others in various aspects of the transient performance criterion, as can be seen in Table 4.3, from analysis it is shown that PID-FLC has lower rise times in 2 of the models registering 1.24s, and 7.25s, in temperature and pH, respectively. This makes the hybrid controller more responsive than the others. The low settling time of 2.56s and 3.2s in water level and temperature, respectively, also shows that it reacts better to abrupt changes. The high response rates are probably due to the simplified design of the rules and the fast reaction of the PID part of the hybrid. In terms of over-shoot, FLC and PID-FLC performed the same, showing how intelligent controllers outperform the conventional PID controller with high overshoots. Both FLC and PID-FLC can handle non-linearities better than the conventional PID controller alone. Table 4.4 is used in the study to objectively select the best controller that is best suited for our application. The PID-FLC controller, which has lower rise times and settling times, gives the controller the ability to make rapid changes within the system caused by external disturbances and can therefore always maintain the required environmental conditions.

4.4 Experimental Results

Prototyping is carried out using the NFT plant system in Figure 4.4. The experiment is carried out to test out the selected algorithm from the simulations to test out its performance in a physical system. As the PID-FLC algorithm is seen as the better algorithm it is analyzed in the experimental setup.

No Controller



Figure 4.4: NFT system prototype

To enhance our controller performance analysis, the hydroponic system is studied in a manual control state. In this state, the farmer makes adjustments manually, reacting to the readings from sensors, and adapting the system accordingly. The farmer either increases or decreases the pH level by adding pH up and pH down solutions shown in Figure 4.5. Notably, Figure 4.4 indicates a lack of measuring equipment, hence varying changes occurred making it difficult to make consistent system adjustments. EC changes are also made by increasing water using 5L bottles which decreased the EC level and increasing the EC level by adding hydroponics nutrients shown in Figure 4.5. All readings/measurements taken throughout the month are recorded as shown in the snippet in Table 4.5 with the rest in Table B.1. Table 4.5 represents the readings that are recorded during the cultivation period. These represent the different environmental parameter recordings and the changes that the farmer carried whenever there is an error in the parameters against the setpoint.



Figure 4.5: NFT system solutions

Date	Time	EC(μ scm)	pH	Temperature	Water Level(mm)	Changes made
12 th	0815	1150	6.40	23	10	
	1545	1160	6.42	23.3		
13 th	0815	1398	6.46	18.1		
	1545	1395	6.45	21.1	9.5	
14 th	0815	1387	6.45	18.2		Added 5L water
	1545	1300	6.54	22.3	8	
15 th	0815	1396	6.66	20.0		
	1545	1397	6.54	24.6		
16 th	0815	1386	6.56	18.3	9	Added 10L of water
	1545	1236	6.7	22.0		

Table 4.5: A snippet of the data collected from June 12th 2023 – July 14th 2023

PID-FLC Control for pH level

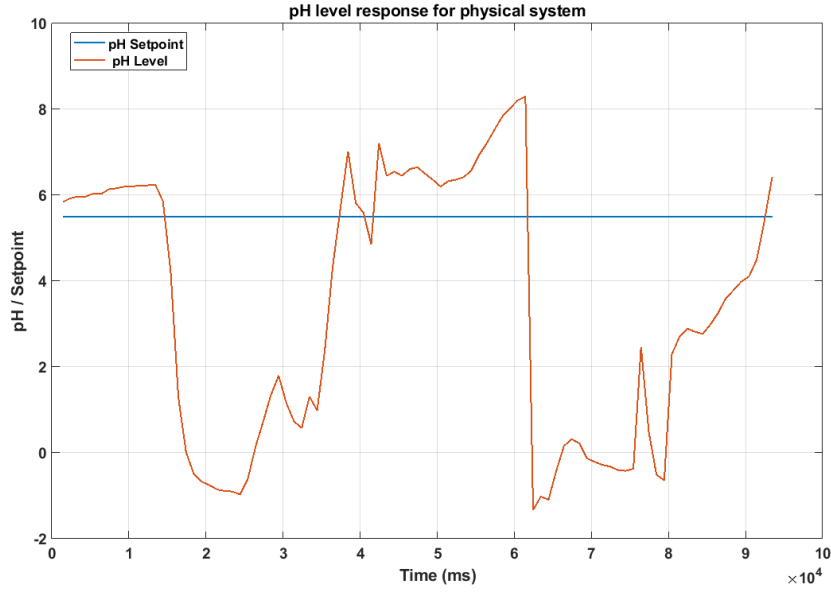


Figure 4.6: pH dynamic response for under low performing control

From the physical system of a hydroponics system, pH control is highly dynamic. The distribution of either the acid or the base can significantly change the pH level as seen in Figure 4.6. Adding acid/base can highly increase or decrease the pH level. With a low-performing controller, the pH has high overshoots, fails to track the setpoint and the system response does not become stable. This is in contrast with the performance of an improved performance in Figure 4.7 showing better setpoint tracking. With an overshoot of 1.80%, and a steady-state error of 0.4. In the study, evaluation is done under 2 scenarios one for pH up and one for pH down. This is to test the controller under different conditions that it might encounter. Under both scenarios, the control algorithm has low rise times as compared to the target showing the aggressive nature of the controller as seen at the simulation stage. The rise times are 60s in Figure 5.7 for pH up and 70s in Figure 4.8 for pH down. As stated earlier controlling pH is very non-linear each drop of acid or base does not produce a consistent change in pH. For instance, one drop of acid might increase the pH by 1, while another drop could cause an increase by 2. This variability explains the numerous fluctuations observed between 3 ms and 12 ms 10^4 and high settling times for the pH down scenario shown in Figure 4.7. Several reasons could cause high settling times, that is the position of the pH sensor from the actuation point. The high ripple nature of the environment

causing inconsistencies in the readings, and the types of acid and base solutions in the experiment some not being highly concentrated causing small changes to the system. The sensor also requires regular calibration hence affecting the accuracy of the system over time.

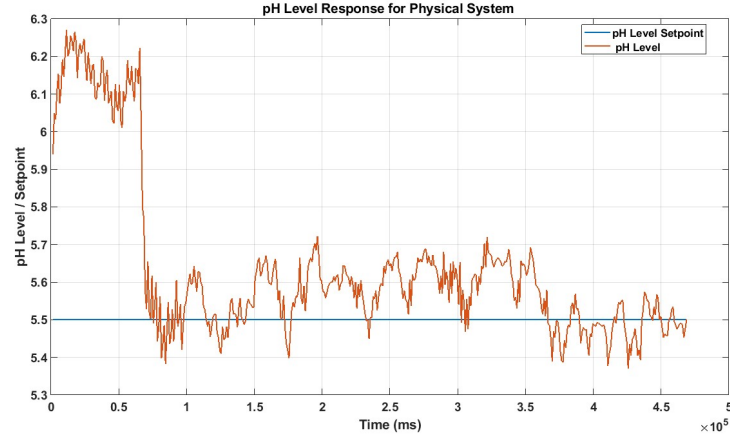


Figure 4.7: pH down response for PID-FLC

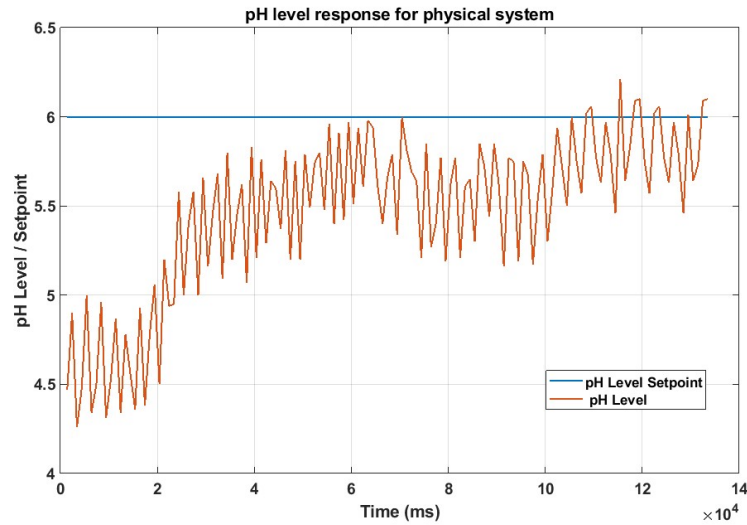


Figure 4.8: pH up response for PID-FLC

PID-FLC Control for Water level

Due to limitations in the acquisition of the ideal water pump with the flow rate modeled under simulation, the water level control is carried out using a small-scale prototype. The intended pump is 360L/h on an area of $0.5m^2$ rather in the study a 90ml/min to a $150cm^2$ is used. Figure 4.9 below shows the control response of the control al-

gorithm for water level control, showing an overshoot of 1.25%, rise time of 1.25%, and a steady state of 0%, this shows good performance as the above-stated transient parameters meet the transient parameter targets. It can be observed that the system has a high settling time of 504.96s which is very high from the set 300s. High settling times are caused by the peristaltic pumps having a lower maximum flow rate to compensate for the large volume of water in the nutrient solution container. The pumps also had mechanical faults, preventing them from receiving the lowest PWM, thus the algorithm couldn't set the preferred PWM, directly affecting the flow rate. The graph shows many fluctuations until the settling point, caused by the ripple effect during water pouring. The ultrasonic sensor received varying values due to reflections from the water waves. The more the water is disturbed, the more fluctuations occur. Therefore inconsistencies in the recorded readings. Table 4.6 represent a summary of the performances for both pH and water level control.

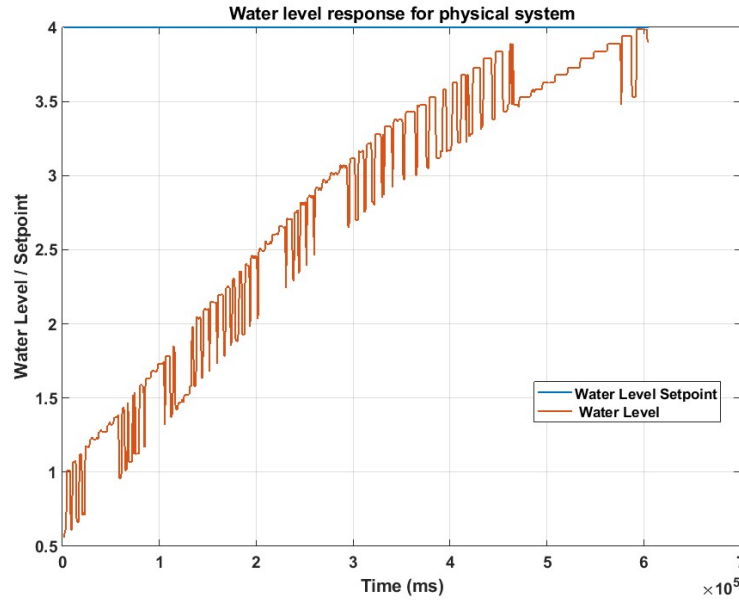


Figure 4.9: Water response for PID-FLC

Table 4.6: Performance Evaluation for PID-FLC in Physical System

Parameters	Water		pH		
	Target	Observed	Target	pH up	pH down
Overshoot [%]	5	2.31	2	1.80	-1.81
Settling time [s]	350	504.96	300	119.48	370.78
Steady state error	0.5	-0.10	1	-0.4	-0.07
Rise time [s]	300	590.0	100	60.0	70.0

ANN Control for pH and Water level in Physical System

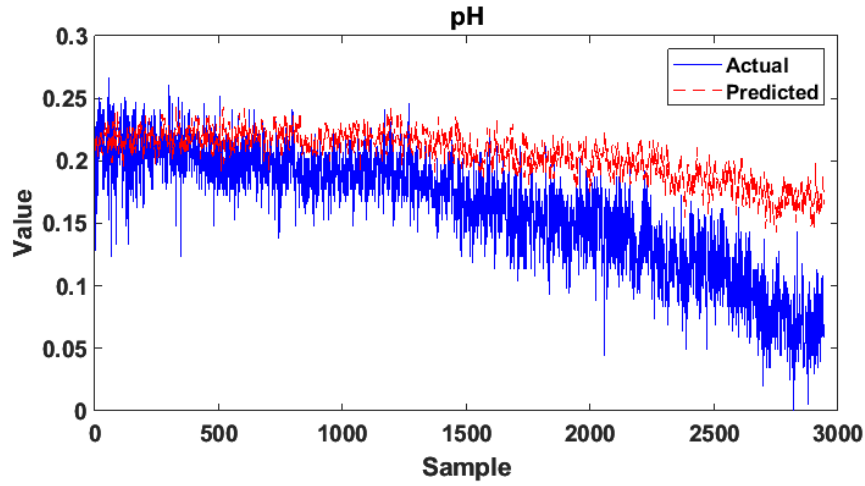


Figure 4.10: pH prediction

In ANN control, an LSTM-ANN hybrid is used in the study using the effective time series prediction of LSTM models to complement the ANN algorithm. The time series data of about 11000 data sets is collected at a sampling rate of 3.5s. It is then trained on the LSTM model for the prediction of future sensor values. Figures 4.10, 4.11 and 4.12 show how the model performs in the prediction of actual pH, temperature, and water level respectively. The RMSE errors are 0.0472 for pH, temperature RMSE is 0.0355, and RMSE for water level prediction is 0.033. ANN is initially trained to learn the relationship between the hydroponics environment and actuator control actions. In combining the LSTM and ANN, the LSTM predicts future values then ANN uses the predicted values to map out the control actions. Figure 4.13 shows the predicted PWM values when training for all the 3 parameters evaluated in the study.

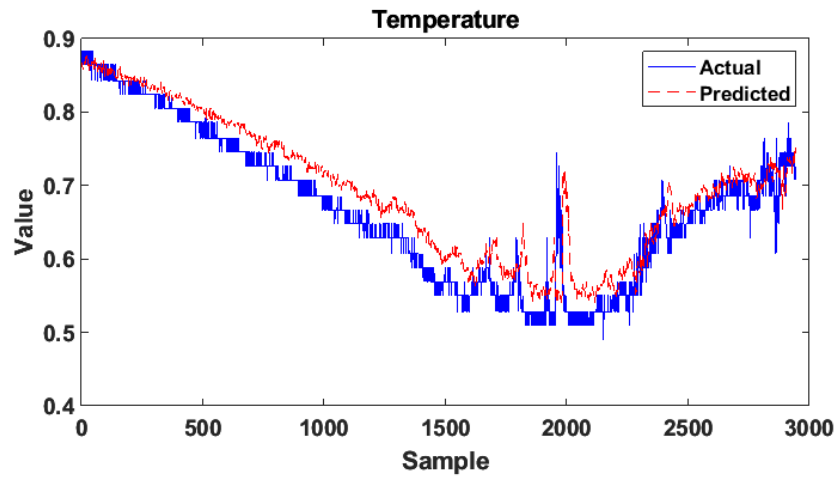


Figure 4.11: Temperature prediction

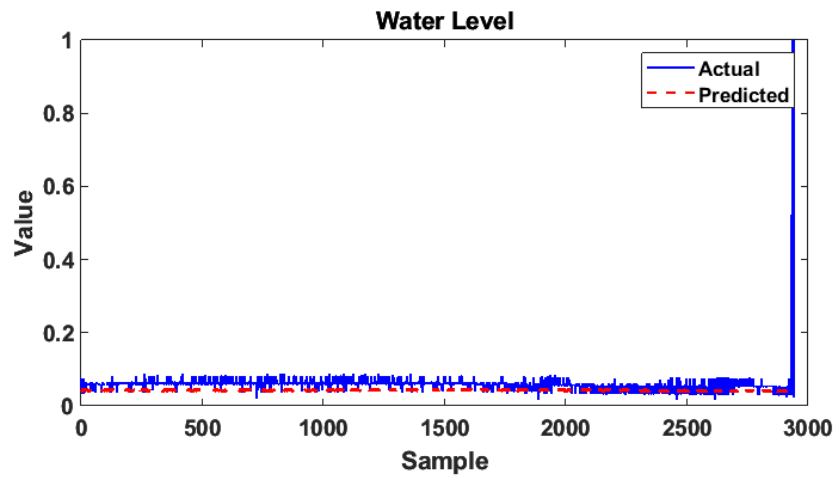


Figure 4.12: Water Level prediction

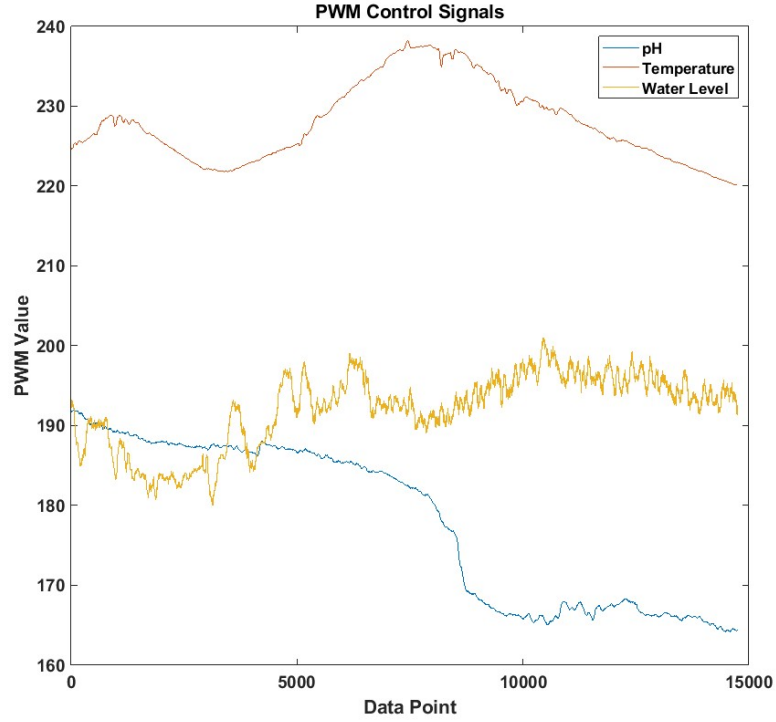


Figure 4.13: Predicted Control Signals

Figure 4.14 and Figure 4.15 present the performance of the ANN controller during pH up and pH down scenarios. In both scenarios, the controller is effective in reaching the desired steady-state value and reducing system overshoot showing its capabilities in ensuring system stability and accuracy in pH regulation. The algorithm has high settling times exceeding the set target with 400s for pH up and 320s for pH down. Furthermore, the rise time of the controller does not meet expectations, with values of 230 seconds for the pH increase and 120 seconds for the pH decrease, indicating a slower response than anticipated.

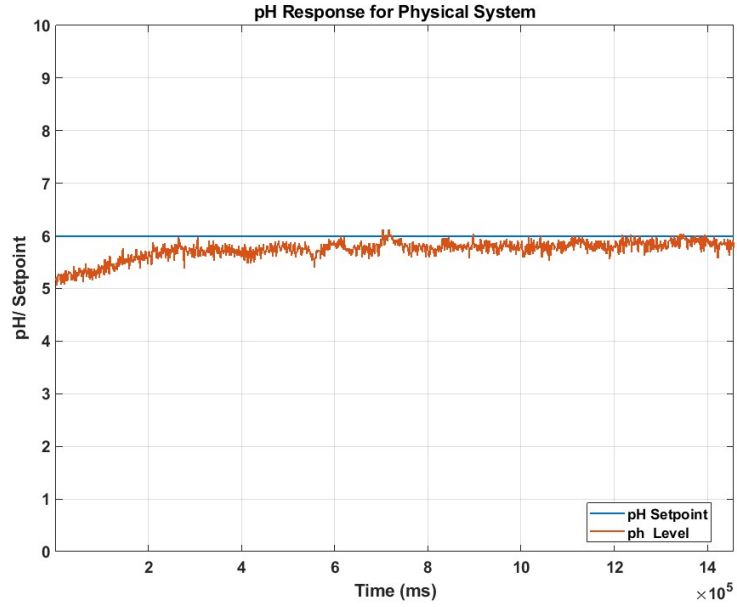


Figure 4.14: ANN pH up scenario

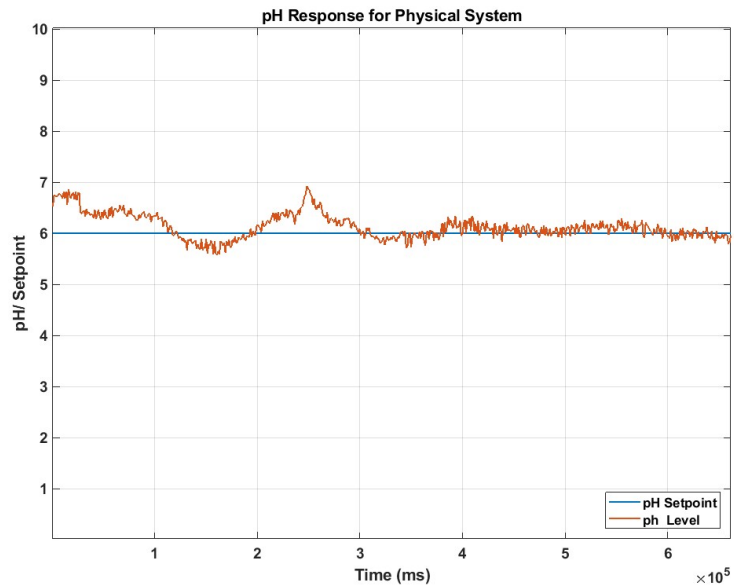


Figure 4.15: ANN pH down scenario

As for water level control shown in Figure 4.16, it has a very high settling time and rise time of 790s and 660s respectively. This could be caused by inaccurate actuator predictions when encountering large errors, predicting small PWM/flow rates when the system needs to be aggressive to change. This further shows there is still room for improvement and optimization. Despite having poor performance on other transients

it shows it can maintain stability in a system by having very low steady-state errors and overshoots with 0.04 and overshoot of 1.25% respectively. A summary of the transient performance is shown in Table 4.7 for both water and pH level control.

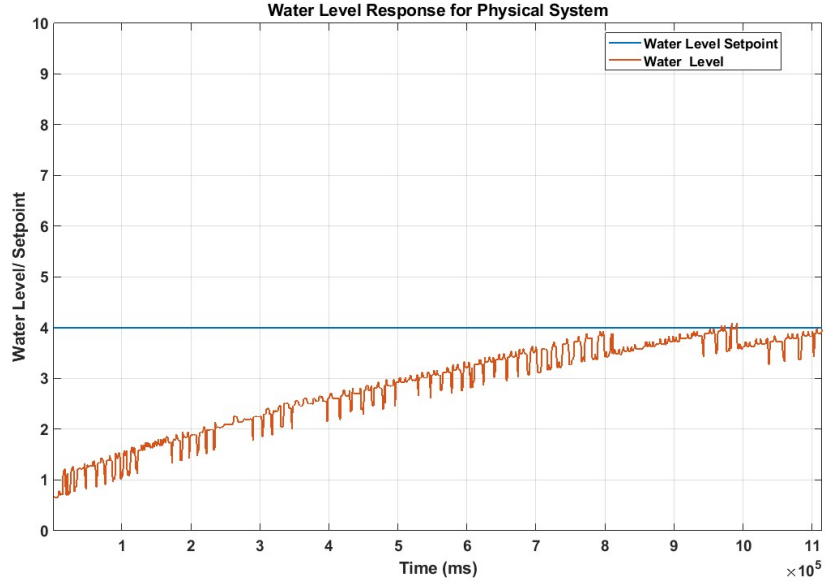


Figure 4.16: ANN water level

Table 4.7: Performance Evaluation for ANN in Physical System

Parameters	Water		pH		
	Target	Observed	Target	pH up	pH down
Overshoot [%]	5	1.25	2	1.66	-4.99
Settling time [s]	350	790.0	300	400.00	320.0
Steady state error	0.5	-0.04	1	-0.10	0.03
Rise time [s]	300	660.0	100	230.0	120.0

4.4.1 Comparison of Control algorithms in physical system

Water level control				
	Target	PID-FLC	ANN	Existing Idea [87]
Overshoot[%]	5	2.31	1.25	-
Settling time[s]	350	504.96	790.0	388.0
Steady-state error	0.5	-0.10	-0.04	-
Rise time[s]	300	390.0	660.0	-

Table 4.8: Water level control performance comparison

pH level control							
Parameters	Target	PID-FLC		ANN		Existing [17], [18], [88]	
		pH up	pH down	pH up	pH down	pH up	pH down
Overshoot[%]	5	1.80	-1.81	1.66	-4.99	-	-
Settling time[s]	300	119.48	370.78	400.0	320.0	340.0	420.0
Steady-state error	1	-0.40	-0.07	-0.10	0.03	-	-
Rise time[s]	100	60.0	70.0	230.0	120.0	-	-

Table 4.9: Comparison of pH level control for PID-FLC, ANN, and Existing projects

Tables 4.8 and 4.9 show comparison results for the control algorithms tested in the physical system, and evaluated against existing prototypes found in literature. For existing prototypes, the most recent work is used and that closely resembles this research study's work. Just like in simulation different control algorithms perform better than others in different transient parameters. For water level control [87] recorded a lower settling time of 388s from an empty state to the setpoint whereas in the study PID-FLC registered 504.96s. ANN recorded 790s, the author did not explicitly state the pump flow rates. The lower settling times could be because of high flow rates suggesting a holistic approach in the selection of control algorithms and actuators.

When it comes to comparing the PID-FLC to ANN, PID-FLC has shown high responsive rates throughout the study hence the low rise times compared to the ANN algorithm. Though the ANN algorithm is not responsive it has shown more effectiveness in achieving stability. ANN sacrifices speed for greater accuracy and reduced overshoots, recording lower overshoots of 1.25% and steady-state error of 0.04.

Furthermore, in pH level control FLC is mostly used in the projects found in literature with [88] recording 340s and 420s in terms of settling times for pH up and down scenarios in 50L container. Whereas other studies [17] also recorded 150s for settling times and 120s for rise times in a 20L container, while [18] recorded 1000s in settling times for pH control. The algorithms in the study show comparable performance, with PID-FLC performing better in most aspects recording lower settling times of 119.48s and 370.78s in pH up and pH down respectively in 50L volume of nutrient solution. It also shows higher responsiveness with shorter rise times of 60s and 70s as compared to ANN control with 230s and 120s recorded. A similar pattern of stability management is also observed as seen in water level control in terms of ANN registering lower overshoot compared to the PID-FLC.

4.5 Economic Analysis

This section assesses the financial viability of the project by initially estimating the initial cost of the system, followed by the calculation of its operational costs. It then evaluates the system's efficiency which is subsequently used to calculate the system benefits in terms of cost savings. Finally, the study calculates the Net Present Value (NPV) and payback period of the system. Table 4.10 shows the estimated cost of the system based on quotations from international markets for example Alibaba or Aliexpress. It then shows the estimated price for the designed controller in the study.

Table 4.10: Costs of Setup (Nutrient Delivery System)

Item	Units	Peak Power Rating(w)	Cost per Unit (P)	Total Cost (P)
PID-FLC Irrigation Controller	1	15	3000.00	3000.00
Actuator Pumps	4	48	625.00	2500.00
pH sensor	1	-	500.00	500.00
Water temperature sensor	1	-	520.00	520.00
Water level sensor	1	-	510.00	510.00
Water Tank (per cubic metre)	2	-	800.00	1600.00
Thermal Water Heater	1	450	100.00	100.00
Consumables Spares & Tools	-	-	-	1500.00
Installation Labour	6 hours	-	300.00	1800.00
Total Costs				12030.00

The controller mostly consumes the following resources water, electrical power from the heating element, and actuator pumps, these are then used to calculate the cost of operations for the system in a day as shown in the table below.

Table 4.11: Cost of Operating (Nutrient Delivery System)

Item	Total Peak Power(w)	Hours of Use/Day(hrs)	Power Use/Day (kWh)	Total Power Cost/Day (P)
PID-FLC Irriga- tion Controller	15	24	0.36	0.54
Thermal Water Heater	450	18	8.1	12.15
Actuator Pumps	192	18	3.4	5.00
Total Cost			11.86	17.69

BPC Business electricity tariff: P1.506 per kWh

The total cost per day for the system is P12050.76 obtained from summing the operational cost to the initial startup cost. The yearly cost which is P19605.40 is obtained from accumulating the daily operational costs over one year and then adding to the setup cost. This number gives a clear picture of the total amount of money needed to operate and maintain the system for a year, considering both the initial investment and recurring costs.

$$\text{Total Cost per year} = \text{Setup cost} + (\text{Operational cost per day} \times 365) \quad (4.1)$$

$$\text{Total Cost per day} = 12047.69 \text{ per day}$$

$$\text{Total Cost per year} = 18480.40 \text{ per year}$$

Tables 4.12 and 4.13 illustrate the cost savings achieved by using the intelligent controller compared to a farmer who manually operates their farm with two regular check-ups. The data shows a significant reduction in water costs due to the controlled system. Additionally, since the controlled system does not require supervision, there are no labor costs incurred. It is important to note that the controlled system consumes more power than the manual system. However, this increased power consumption is offset by the long-term benefits of the system, as demonstrated by the NPV calculations

and total benefits. Table 4.14 shows that it saves us P14.74/day to operate the system giving us a relatively short payback period of 2.23 years as seen in Table 4.15. The system also shows a positive NPV of P4,891.00 in the first year, growing to P21,028.39 over 10 years. This indicates the long-term viability of the system, even within the small-scale scenario used in the study. Additionally, the short payback period further supports the financial attractiveness of the system, as it indicates that the initial investment can be recovered relatively quickly. These results highlight the system's potential for sustainable economic benefits over time.

Table 4.12: Water Savings per Square Metre Growing Lettuce

Growing Area Scenario (m ²)	Manual control Water usage per Day (L)	PID-FLC Water Usage per Day (L)	PID-FLC Water Cost per Day (P)	PID-FLC Water Cost Savings per Day (P)
1	12.3	8.9	0.16	0.06

Water Utilities Business Water Tariff: P0.0185 per Litre

Table 4.13: Labour Savings per Square Metre Growing Lettuce

Growing Area Scenario (m ²)	Manual control labour per day(hrs)	Regular labour cost per Day (L)	PID-FLC labour cost per Day (P)	PID-FLC labour cost savings per day (P)
1	2	14.68	0.00	14.68

Botswana minimum labour rate: P7.34 per hour

Table 4.14: Total Benefits (PID-FLC Cost Savings)

Growing Area Scenario (m ²)	PID-FLC Water Usage Cost Sav- ings per Day (P)	PID-FLC Labour Cost Savings per Day (P)	Total PID-FLC Cost Savings per Day (P)
1	0.06	14.68	14.74

Table 4.15: Payback Period

Growing Area Scenario (m ²)	Initial Cost Setup	Annual Net Ben- efits (P)	Payback Period
1	12030.00	5380.1	2.23

$$NPV = \sum_{t=1}^{10} \left(\frac{5380.10}{(1 + 0.10)^t} \right) - 12030.00$$

Where:

B_t = Annual Net Benefits (P5,380.10)

r = Discount Rate (10% or 0.10)

t = Year (from 1 to 10)

n = Project Duration (10 years)

C_0 = Initial Investment (P12,030.00)

Net Present Value for a year = P4891.00

Net Present Value for a 10 years = P21028.39

4.6 Conclusion

In this section, performance evaluation is carried out in two aspects simulation and a NFT hydroponics system. A best-performing controller is first selected from simulation

which in the study PID-FLC is chosen and tested against a developed data-driven ANN controller in the prototype system. Only the pH and water level parameters were evaluated in the physical system and compared to the simulation results. The control algorithms demonstrated their capability to manage and maintain the required levels, achieving the set targets for most transient parameters. Additionally, they outperformed existing research projects in terms of response times. However, the control algorithms exhibited significantly lower response times in the physical system compared to the simulations, likely due to limitations in the simulations, such as the inability to model certain aspects or account for noise present in the physical system. The use of an intelligent controller is then analysed economically to study its viability and benefits.

5 Conclusions

The main aim of the research project was to develop an intelligent controller that could be used in hydroponics farming to improve farming yields, addressing the poor hydroponics farming management situation in Botswana. An intensive literature review was conducted on automating the system, specifically focusing on monitoring and controlling the nutrient solution for pH, water level, and temperature. The study discovered extensive work done in hydroponics farming systems and focused on evaluating commonly used conventional algorithms such as the PID controller, as well as artificial intelligence controllers like the fuzzy logic controller (FLC), along with emerging hybrid controllers such as the PID-FLC and artificial neural network (ANN) controllers. The performance of these controllers was analyzed to recommend the best one. Several objectives were pursued to carry out this analysis.

The first objective was to model the hydroponics system. A suitable hydroponics farming system needed to be selected to develop the model. Given the variety of farming systems available, a decision matrix was employed to select the system that would best complement the control algorithms and enhance their effectiveness. The nutrient film technique (NFT) was selected because it offered superior capabilities in maintaining the nutrient solution parameters. First-order differential equations were used to develop transfer functions to model the farming system in MATLAB Simulink. Each environmental parameter had its own transfer function, which was then used to evaluate the different control algorithms.

The second objective focused on the development of different control algorithms. PID, PID-FLC, and FLC control algorithms were implemented in simulations, testing each against the transfer functions for each nutrient solution parameter. The algorithms were evaluated based on transient performance parameters, namely: overshoot, settling time, steady-state error, and rise time. The study showed that no single algorithm exhibited absolute dominance, with each performing better in different aspects. Overall, the PID-FLC controller demonstrated high responsiveness, registering a shorter rise time in temperature and pH level control at 1.24s and 7.25s, respectively, compared to PID at 1.69s and 90s, and FLC at 3.04s and 7.27s. It also performed better in terms of settling time for temperature and water level control, recording 2.56s and 3.2s, respectively, compared to its counterparts.

When it came to steady-state error, all control algorithms proved capable of maintaining the desired requirements, with results ranging between 0 and 1. However, in terms of overshoot, the PID controller exhibited higher tendencies, recording 6.85%, 2.68%, and 3.73% in water level, temperature, and pH level control, respectively. Both PID-FLC and FLC showed close results in the overshoot criterion, registering less than 0.05%, proving the effectiveness of intelligent algorithms over the conventional PID controller. A decision matrix was then used to select the best algorithm for further evaluation in a prototype setup.

The final objective involved the development of an LSTM-ANN using the prototype setup to collect primary data from the system. This model was implemented alongside the PID-FLC algorithm, and the two were compared to existing projects in the literature. Both algorithms demonstrated their capability to maintain nutrient solution parameters effectively as they were able to meet the steady state error targets. However with huge room for improvement. In pH level control PID-FLC performed better overall in terms of responsiveness recording low rise times and settling times compared to the ANN and existing projects. The rise times for pH up were the 60s, and 70s for pH down whereas ANN were 230s and 120s respectively. With existing projects registering 120s for both pH up and down. As for settling time, PID-FLC had 119.48s pH up settling time however ANN had a lower settling time of 320.0s in pH down compared to PID-FLC's 370s. The control algorithms did not perform well in terms of responsiveness in water level control recording high settling times as compared to existing projects. However, they were able to maintain low overshoots and steady-state errors of less than 2.5%. Furthermore, the system demonstrates potential economic benefits due to its short payback period, indicating that the initial investment can be recouped quickly. These findings highlight the system's potential for long-term, stable economic returns.

5.1 Future Work

This work can be further improved to enhance results in the following ways:

- Implementation into a large-scale farm and the use of industry-grade sensors and actuators.

- Implementation under a greenhouse setup to integrate more environmental parameters like humidity and light intensity.
- Analysis of the rate of growth of plants in relation to the performance of the control algorithms.
- Expand the data collection period to capture more details across growing periods and stages to improve the LSTM-ANN model.

A Appendix

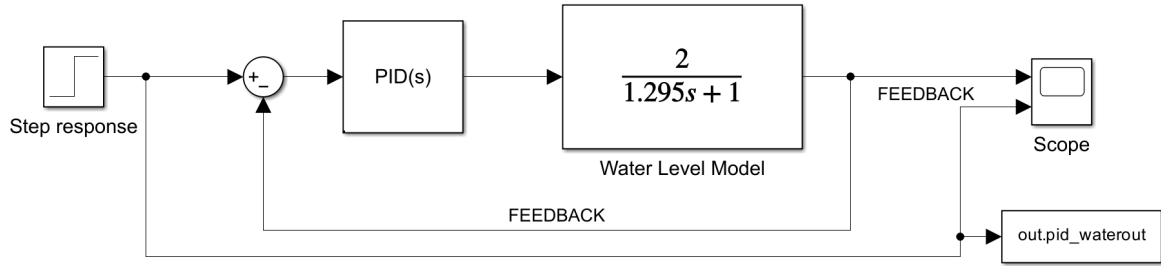


Figure A.1: Matlab Simulink water level model for PID control

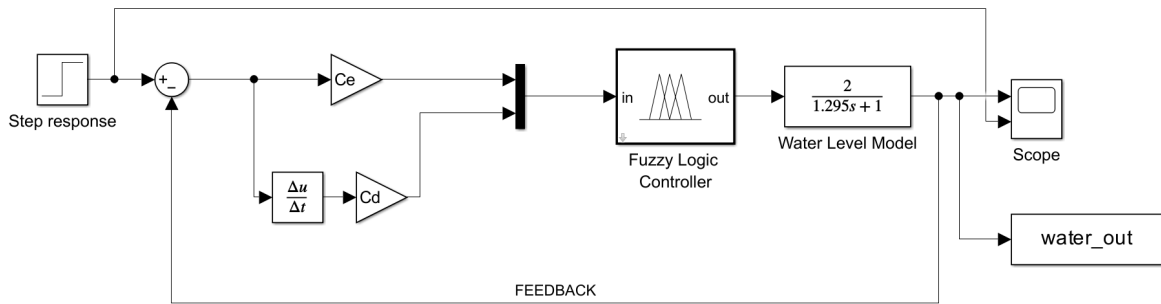


Figure A.2: Matlab Simulink water level model for FLC

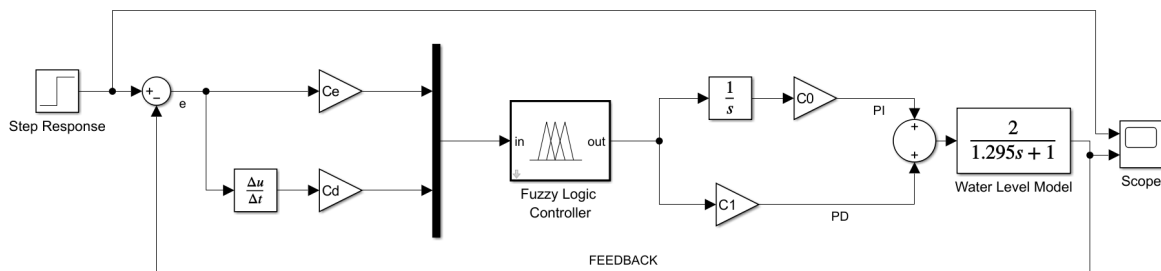


Figure A.3: Matlab Simulink water level model for PID-FLC

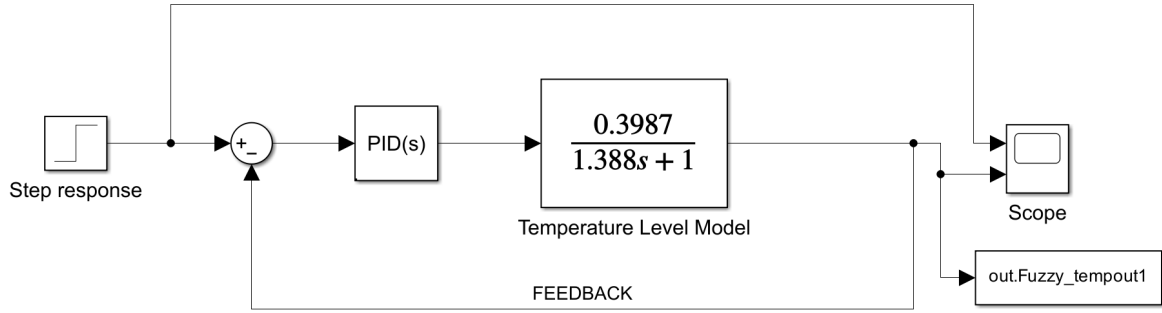


Figure A.4: Matlab simulink temp level model for PID control

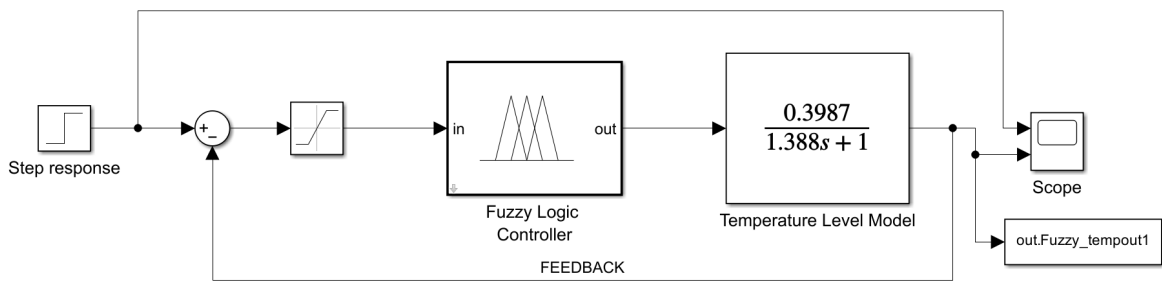


Figure A.5: Matlab simulink temp level model for FLC

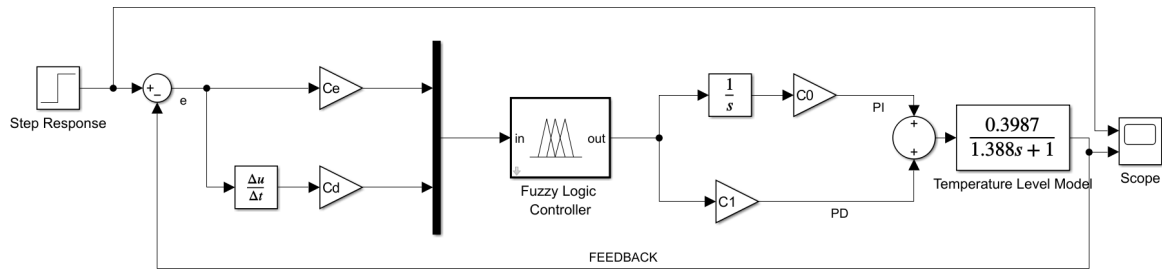


Figure A.6: Matlab simulink temp level model for PID-FLC

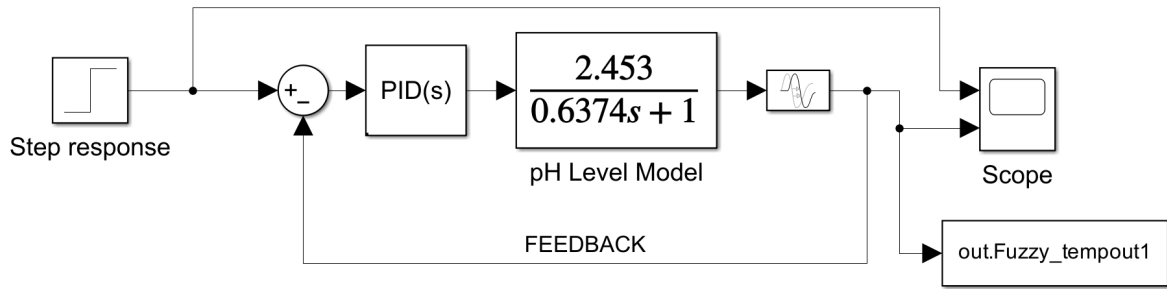


Figure A.7: Matlab simulink pH level model for PID control

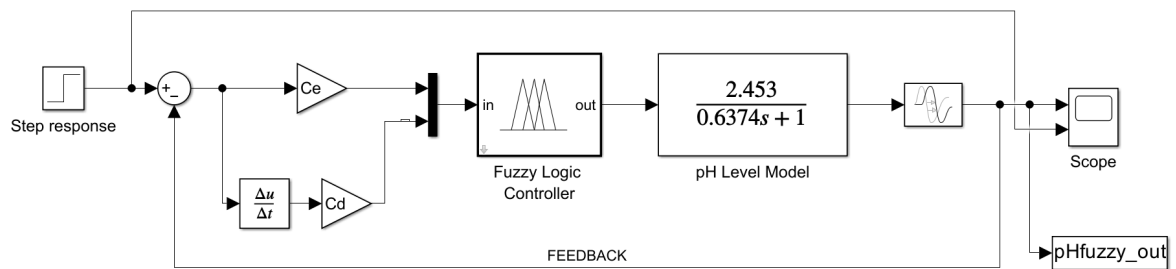


Figure A.8: Matlab simulink pH level model for FLC

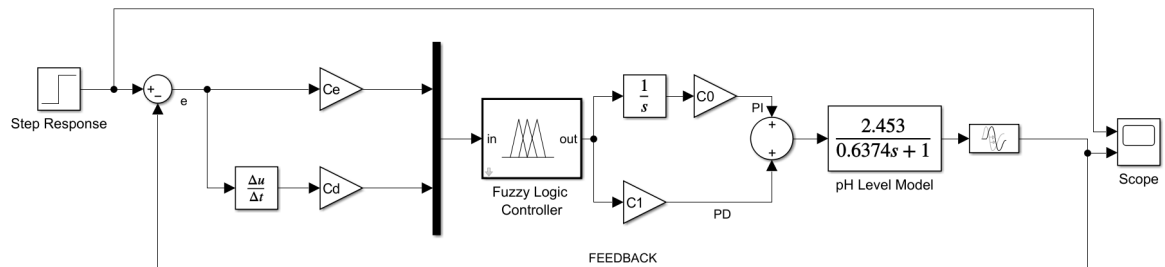


Figure A.9: Matlab simulink pH level model for PID-FLC

B Appendix

Date	Time	EC (uS/cm)	pH	Temperature (°C)	Water level (mm)	Changes made
12	0815	1150	6.40	23.0	8.0	
	1545	1160	6.42	23.3	7.9	
13	0815	1398	6.46	18.1		
	1545	1385	6.48	19.5		
14	0815	1387	6.44	18.3		Added 5L water
	1545	1300	6.54	22.3		
15	0815	1196	6.60	20.9		Added 10L of water
	1545	1397	6.64	24.6		
16	0815	1386	6.55	18.3		
	1545	1125	6.72	22.0		
17	0815	1214	6.78	17.9		
	1545	1237	6.79	20.5		
18	0815	1257	6.41	17.5		
	1545	1275	6.35	19.8		
19	0815	1200	6.33	18.3		
	1545	1248	6.32	22.3	5.7	Added 5L of water
20	0815	1387	6.26	15.6	8	
	1545	1286	6.36	20.0	10.2	Added 5L of water
21	0815	1267	6.56	14.1	10	
	1545	1207	6.48	20.1	9	
22	0815	1220	6.51	17.1	8.33	
23	0815	1264	6.49	18.4	8	Added 4L of water
	1545	1184	6.56	20.1	7.9	
24	0815	1230	6.45	17.5	8.8	
	1545	1245	6.48	21.1	8.3	
25	0815	1240	6.56	18.1	8.3	
	1545	1258	6.51	20.1	8.0	

Table B.1: Uncontrolled plant growth and observation data (June/July 2023)

Date	Time	EC (uS/cm)	pH	Temperature (°C)	Water level (mm)	Changes made
30	0815	1244	5.7	23.0	6.55	Added 2L water
	1545	1244	5.7	23.0	6.55	
1	0815	1212	6.45	19.0	7.5	
	1545	1212	6.45	19.0	7.5	
3	0815	1245	5.84	21.7	6.0	
4	1256	5.60	22.3	6.0		
5	0815	1240	5.84	18.0	7.0	Added 5L water, Added pH up
	1545	1244	6.10	21.0	7.0	Added 5L water, Added pH up
6	0815	1186	6.46	18.4	9.0	Added 5L of water, Added pH up
	1545	1161	6.36	21.2	8.5	
7	0815	1195	6.38	19.0	8.0	
	1545	1161	6.36	22.7	6.36	
10	0815	1286	6.15	14.9	6.0	
	1545	1256	6.36	21.1	8.0	Added 10L of water
11	0815	1194	6.57	16.3	7.3	
	1545	1168	6.49	22.5	7.3	
12	0815	1211	6.52	17.4	6.8	Added 5L of water
	1545	1168	6.52	24.3	8.0	
13	0815	1166	6.60	17.4	7.5	
	1545	1136	6.60	22.7	7.4	
14	0815	1276	6.70	17.1	7.0	Added pH down

References

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