Blind Navigation

Adwait Sanjeev
Department of Computer Engineering
St. John College of Engineering and Management
Palghar, India

Mansi Suhas Raut
Department of Computer Engineering
St. John College of Engineering and Management
Palghar, India

Arindam Alok Samanta
Department of Computer Engineering
St. John College of Engineering and Management
Palghar, India

Angelin Florence A
Department of Computer Engineering
St. John College of Engineering and Management
Palghar, India

Abstract: This paper presents a system for those people of our society who are suffering from visually challenging situations. The system is able to understand obstacles around the subject in the range 2 cm - 400 cm using ultrasonic sensors. Sensor are placed on the stick. It calculates distance of the detected obstacle from the user and gives feedback in the form of voice output. The proposed system uses Arduino Uno based system to process real time data collected using ultrasonic sensor network. Based on the detected signal from the obstacle, appropriate pre-recorded voice output is given to the user via Bluetooth module to their smart phone. The feedback is given to the user via earphones.

Keywords: Arduino, Blind people, Bluetooth Module, Ultrasonic Sensors, Earphones.

1. INTRODUCTION

According to a survey approximately vision impairment is found in 1.3 billion people [1]. Due to ageing population and many changes in lifestyle increased number of people are suffering from blinding conditions such as diabetic retinopathy is projected to rise. Without effective, major intervention, the number of blind people worldwide has been projected to increase to 76 million by 2020 if current trends continue [2]. In present time many traditional navigations systems are used. Usage of all these travel aids for detecting obstacles for smooth navigation requires a good training. Presently several electronic travel aids (ETA) are available for visually impaired and blind people. These aids are designed using recent technological developments in automation.

Although many advanced electronic systems for the visually challenged people are present in the market, only few of them are useful. Therefore, user acceptability assessment of such systems is very important. The important parameters which should be considered in this are size, portability, reliability, useful functionalities, simple user interface, training time, system robustness and affordability in terms of cost. To overcome all these limitations, a system considering all the needs of the user has been proposed in this paper.

1.1 Motivation

We often see a blind person having difficult time walking down a busy street. Blind people always needed someone to guide them. They have to be dependent on someone or the other. People are very busy with their own life and they are hardly bothered about anyone else. This makes the life of such blind people very difficult. To help them in such a way that they won’t be a burden to anyone again is the need of the hour. So, in the proposed system depicts the idea of smart stick for the blinds which will help them find the way on their own without the help of anyone.

1.2 Problem Statement

Helping the blind in navigation outdoors as well as indoors is an important issue. Being self-dependent is the most important trait in an individual in the modern world. The existing systems help the visually impaired people but they are not effective enough. These systems could not detect the obstacles they would encounter while moving forward. They are mostly for the obstacles just lying around. The proposed system will thus aim to solve all these issues and help to make their lives easy and simple.

1.3 Objectives

- To design a system to detect obstacles the user would encounter.
- To make the visually impaired people self-dependent.
- To make the life of visually impaired people simple and easy.
- To implement the system as cost efficient

2. REVIEW OF LITERATURE

Literature Review acts as the basis of research and study of the various concepts required for a particular domain. It describes the theories and other methodologies that can be adopted in order to implement modules of the proposed system.

2.1 3D Ultrasonic Stick for Blind

Today technology is improving daily in different aspects in order to provide flexible and safe movement for the people. In this technology driven world, where people strive to live independently, this system propose a low-cost 3D ultrasonic stick for blind people to gain personal independence, so that they can move from one place to another easily and safety. A portable stick is design and developed that detects the obstacles in the path of the blind using ultrasonic sensors. It consists of these sensors to scan three different directions, a microcontroller, buzzer and DC vibration motor. The buzzer and vibration motor are activated when any obstacle is detected. In addition, the stick is equipped with GPS and SMS message system. GPS system provide the information regarding the location of the blind person using the stick to his family members. SMS system is used by the blind to send SMS message to the saved numbers in the microcontroller in case of emergency. The programming of GPS modem, GSM modem, buzzer and vibration motor has been successfully done for this system. Computer simulation is done to essence the performance of the system using Proteous software and Easy pic kit.

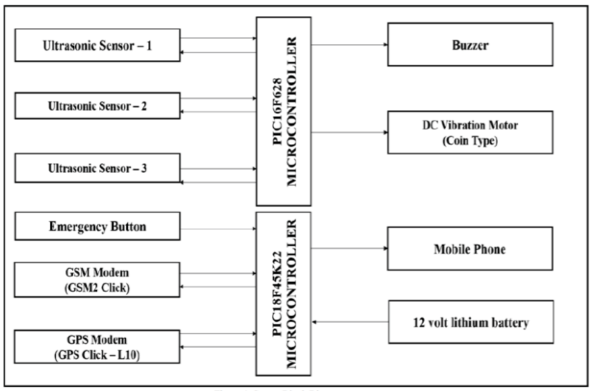

Figure 2.1: Block Diagram for 3D Ultrasonic Stick for Blind

2.2 Ultrasonic Spectacles and Waist-belt for Visually Impaired and Blind Person

This system presents an electronic navigation system for visually impaired and blind people (subject). This system understands obstacles around the subject up to 500 cm in front, left and right direction using a network of ultrasonic sensors. It effectively calculates distance of the detected object from the subject and prepares navigation path accordingly avoiding obstacles. It uses speech feedback to aware the subject about the detected obstacle and its distance. This proposed system uses AT89S52 microcontroller based embedded system to process real time data collected using ultrasonic sensor network. Based on direction and distance of detected obstacle, relevant pre-recorded speech message stored.

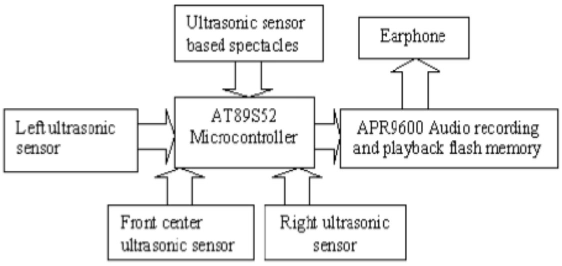

Figure 2.2: Ultrasonic Spectacles and Waist-belt for Visually Impaired and Blind Person

2.3 Distance Sensing with Ultrasonic Sensor and Arduino

A sensor is a device that converts one type of energy to another. Arduino is a small microcontroller board with a USB plug to connect to the computer. The Arduino board senses the environment by receiving input from a variety of sensors and can affect its surroundings by controlling LCDs, speakers, motors and GS module. Ultrasonic Sensor measure the distance of target objects or materials through the air using “non-contact” technology. They measure distance without damage and are easy to use. The output Signals received by the sensor are in the analog form, and output is digitally formatted and processed by microcontroller. In present work, it is used to detecting an obstacle, along with its exact distance. The internal analog to digital converter is used is calibrated to get almost accurate distance measurement. The measured distance is also displayed on an LCD screen.

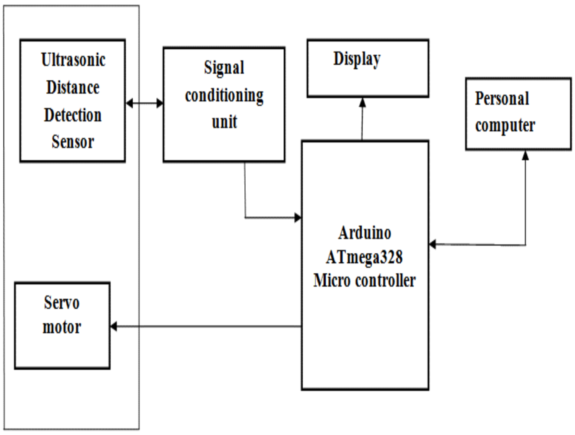

Figure 2.3: Block diagram of Ultrasonic Distance Detection with Arduino

3. METHODOLGY

The proposed system concentrates on helping the visually impaired people in navigation in their day to day life and to make their life easy and relatively simple. The proposed system aims to detect objects in the path of the visually impaired people and notify them via voice output. This method of object sensing is carried out using ultrasonic sensors. The system will use Ultrasonic sensors interfaced with Arduino Uno R3 [3]. Using Arduino, the detected ultrasonic signals will be converted to numeric value in the form of distance to the detected object. According to the processed signals from the Arduino, the voice messages will be retrieved and voice output through the user's smartphone will be provided to the user via ear phones. The system will thus help them to navigate around surroundings with ease without depending on any other people for help.

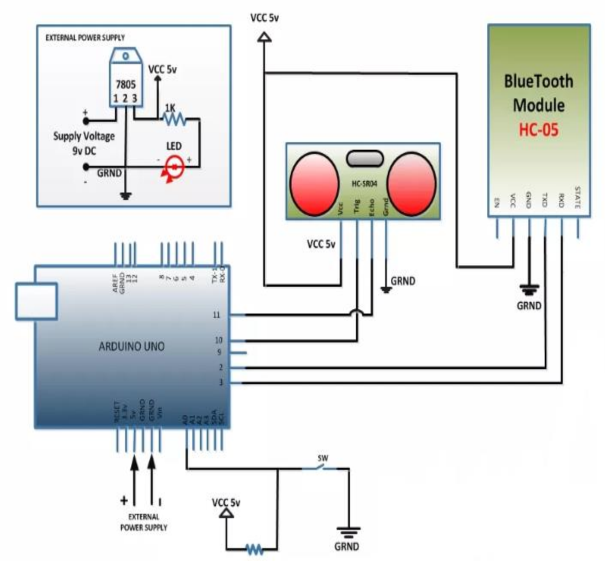

Fig: 3.1 Architecture Diagram

The architecture of the proposed system is as shown in Fig 3.1. The Arduino Uno is the main processing unit of the system. It receives signals from the HC SR-04 sensors. The voice output is transferred to the user's smartphone through the Bluetooth module. The voice output to the user is given through the earphones.

Fig .3.2: HC-SR04 Ultrasonic Sensors

The HC-SR04 ultrasonic sensor uses sonar to determine distance to an object like bats do. It offers excellent non-contact range detection with high accuracy and stable readings in an easy-to-use package.

From 2cm to 400 cm or 1" to 13 feet. Its operation is not affected by sunlight or black material like sharp rangefinders are (although acoustically soft materials like cloth can be difficult to detect). It comes complete with ultrasonic transmitter and receiver module. The ultrasonic sensors are as shown in Fig 3.2.

Fig 3.3: Arduino Uno

The Arduino UNO is an open-source microcontroller board based on the Microchip ATmega328Pmicrocontroller and developed by Arduino.cc. The board is equipped with sets of digital and analog input/output (I/O) pins that may be interfaced to various expansion boards (shields) and other circuits. The circuit of Arduino Uno is as shown in Fig: 3.3.

4. OBSTACLE DETECTION AND COMPONENTS USED

To help detect the objects in front of the user ultrasonic sensors are used. Ultrasonic sensors work in pairs, one of which is used to transmit ultrasonic signals while the other is used to receive the signals. The working of these sensors is similar to the SONAR system used in ships. Once detected the signals are transmitted to the Arduino Uno. Two ultrasonic sensors are used in this system

4.1 Software Unit

4.1.1 Arduino IDE

The coding of the entire process is done in this software. It helps the Arduino to carry out the tasks as per the given instructions in the code. It also converts the ultrasonic signals to numeric values in terms of distance from the detected object. Once the code is written it is uploaded in the Arduino IC.

4.2 Hardware Unit

4.2.1 Ultrasonic Sensors (HC SR-04):

These sensors work in the range of 2cm - 400cm. It consists of two parts one transceiver and one receiver. The transceiver transmits the ultrasonic signals while the receiver receives them. The signals are then given to the Arduino for further processing.

4.2.2 Arduino UNO

It will be connected to computer with a USB cable. Thus, the detected signal will be transferred to the Arduino Uno. It also interfaced the APR33A3 voice module. The Arduino converts the signals into numeric values in the form of distance from the detected object.

4.2.3 Bluetooth Module

The text string containing the distance of the user from the object is transferred to the Bluetooth module from the Arduino Uno which is then transferred to the user's smartphone and voice output is given to the user.

4.2.4 Earphones

Earphones are used to transmit the voice message from the Voice Module to the user.

5. WORKING OF THE SYSTEM

5.1 Setting Up the System

Arduino is interfaced with Bluetooth module along with the ultrasonic sensors. The code is uploaded into the Arduino before starting the system. Text messages are transferred to the user's smartphone which are then played as voice output.

5.2 Working of The System

Switch on the ultrasonic sensors to start sensing the objects. The ultrasonic sensors will sense the objects in the user's proximity and send the necessary signals to the Arduino. The Arduino processes these signals and converts it to numeric value in the form of distance from the detected object. The distance in the form of text strings are then transferred to the user's smartphone via the Bluetooth module. This message is then played as voice output to the user via earphones.

6. CONCLUSION

Using the above methodology, distance of the objects was calculated using Ultrasonic sensor (HC SR-04). The readings were noted based on the distance calculated by the sensors.

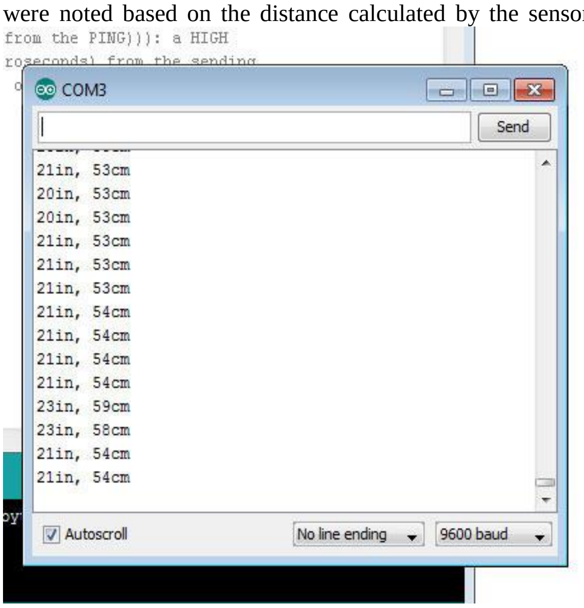

Figure 6.1: Readings as shown on Arduino IDE

Readings were shown in Arduino IDE based on the distance of the object from the sensors. The readings are as shown in Fig 6.1.

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International Journal of Computer Applications Technology and Research
Volume 8–Issue 06, 221-223, 2019, ISSN:-2319–8656

Expert System for Problem Solution in Quality Assurance System

Adesh Vikram Singh
DY Patil Institute of Engineering and Technology
Pune, Maharashtra
India

Ashish Kaul
DY Patil Institute of Engineering and Technology
Pune, Maharashtra
India

Ankit Kumar Thakur
DY Patil Institute of Engineering and Technology
Pune, Maharashtra
India

Abstract: To find a particular solution for a given problem or to answer any question we need to find a solution from the given set of solution by pair wise comparisons. A historical set of data help us to find different answers for the same question asked multiple times. In our proposed system there are two models one is "offline model" and another one is "online model". In offline learning component we establish training samples with the help of data driven observations. In online search component a pool of candidate answer is collected for a given question by finding similar types of questions. With the help of offline trained model candidate answer are sorted in preference order. A comparative demonstration of the experiments on the real-world community-based question answering is shown.

Keywords: pair-wise**;** offline mode; online model; training samples; comparative.

1. INTRODUCTION

As our project purely based on data mining, the data mining is the computing process of discovering patterns in large data sets involving methods at the intersection of machine learning, statistics, and database system. It is an interdisciplinary subfield of computer science. The overall goal of the data mining process is to extract information from a data set and transform it into an understandable structure for further use. Aside from the raw analysis step, it involves database and data management aspects, data preprocessing, model and management aspects, data pre-processing and interface considerations, interestingness metrics, complexity considerations, post-processing of discovered structures, visualization, and online updating. Data mining is the analysis step of the "knowledge discovery in databases" process, or KDD. Community Question Answering (CQA) is gaining popularity online. They are seldom moderated, rather open, and thus they have few restrictions, if any, on who can post and who can answer a question. On the positive side, this means that one can freely ask any question and expect some good, honest answers. On the negative side, it takes effort to go through all possible answers and to make sense of them.
For, example, it is not unusual for a question to have hundreds of answers, which makes it very time consuming to the user to inspect and to winnow. The challenge we propose may help automate the process of finding good answers to new questions in community created forum.

2. LITERATURE REVIEW

1) "Data-Driven Answer Selection in Community QA Systems", Liqiang Nie, Xiaochi Wei, Dongxiang Zhang, Xiang Wang, Zhipeng Gao, and Yi Yang, we present a novel scheme to rank answer candidates via pairwise comparisons. In particular, it consists of one offline learning component and one online search component. In the offline learning component, we first automatically establish the positive, negative, and neutral training samples in terms of preference pairs guided by our data-driven observations. We then present a novel model to jointly incorporate these three types of training samples. The closed-form solution of this model is derived. In the online search component, we first collect a pool of answer candidates for the given question via finding its similar questions.

2) "Disease inference from health-related questions via sparse deep learning" L. Nie, M. Wang, L. Zhang, S. Yan,B. Zhang, and T. S. Chua, [2] Proposed a paper aims to build a disease inference scheme that is able to automatically infer the possible Diseases of the given questions in community-based health services. In this paper, we first report a user study on the information needs of health seekers in terms of questions and then select those that ask for possible diseases of their manifested symptoms for further analytic. We next propose a novel deep learning scheme to infer the possible diseases given the questions of health seekers. The proposed scheme comprises of two key components.

3) "Multi-VC Rank with applications to image retrieval", X. Li, Y. Ye, and M. K. Ng, propose and develop a multi-visual concept ranking (Multi-VC-Rank) scheme for image retrieval. The key idea is that an image can be represented by several visual concepts, and a hypergraph is built based on visual concepts as hyperedges, where each edge contains images as vertices to share a specific visual concept.

4) "Beyond text QA: Multimedia answer generation by harvesting Web information", L. Nie, M. Wang, Y. Gao, Z. Zha, and T. Chua, in this paper, we propose a scheme that is able to enrich textual answers in cQA with appropriate media data. Our scheme consists of three components: answer medium selection, query generation for multimedia search, and multimedia data selection and presentation. This approach automatically determines which type of media information should be added for a textual answer. It then automatically collects data from the web to enrich the answer.

5) "A ranking approach on large-scale graph with multidimensional heterogeneous information," IEEE Trans. W. Wei, B. Gao, T. Liu, T. Wang, G. Li, and H. Li, address the large-scale graph-based ranking problem and focus on how to effectively exploit rich heterogeneous information of the graph to improve the ranking performance. Specifically, we propose an innovative and effective semi-supervised Page Rank (SSP) approach to parameterize the derived information within a unified semi-supervised learning framework (SSLF-GR), and then simultaneously optimize the parameters and the ranking scores of graph nodes.

3. EXISTING SYSTEM

To make question respondent system time effective and to cut back user's efforts to search out actual answers for his question by suggesting him antecedent answered same form of queries with its ranking. to beat this downside, we have a tendency to use sentence level bunch, this system provides multiple answers which is able to be the precise match for that question. However, the actual queries have multiple answers. So, it's tough to outline a selected declare single question.

4. PROPOSED SYSTEM

Offline Learning: -
In the offline learning component, instead of long and labour-intensive annotation, we tend to tend to automatically construct the positive, neutral, and negative coaching job samples inside the kinds of preference pairs guided by our data-driven observations.

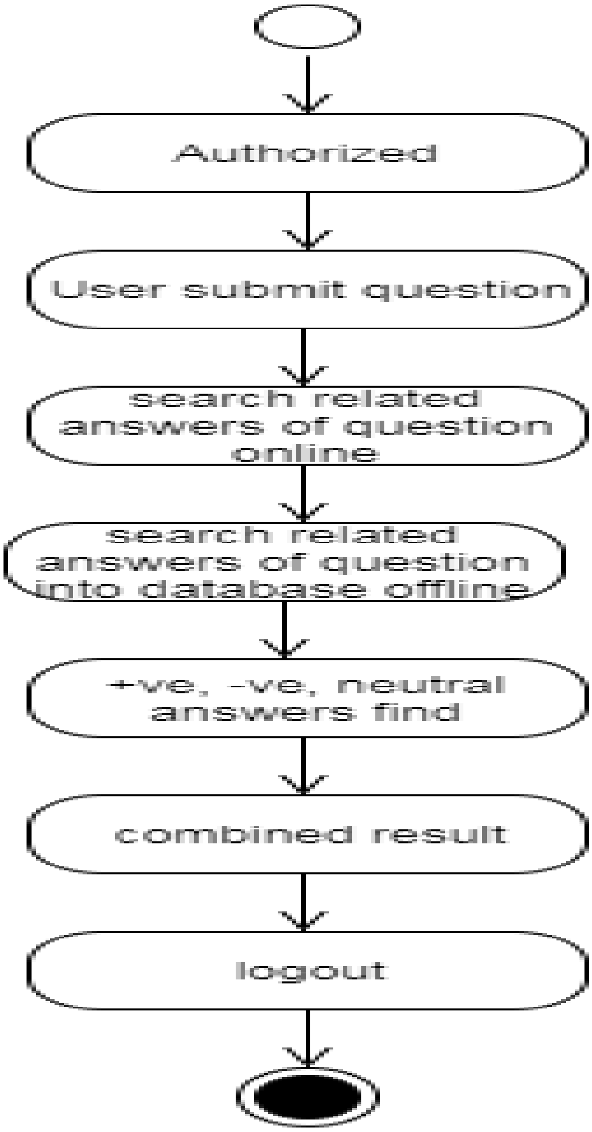
Online search: -
We initial collect a pool of answer candidates via finding its similar queries.

Database: -
A tremendous vary of historical QA pairs, as time goes on, area unit archived inside the cQA databases. information seekers thus have large prospects to directly get the answers by trying from the repositories, rather than the long waiting.

Sentence level clustering:
A question that has multiple forms of answers, however providing best suited answer of that question.

Expert Recommendation system:
Same sort of question that is answered by consultants those consultants are recommending to user for more queries.

5. FLOW DIAGRAM



6. SYSTEM ARCHITECTURE

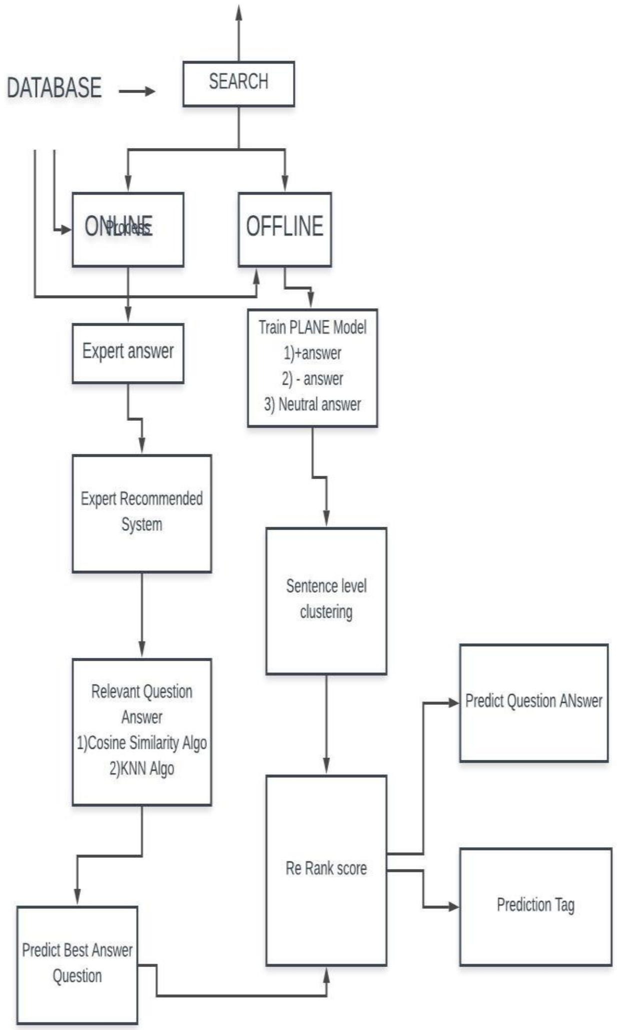


Fig. System Architecture

7. FUTURE SCOPE AND CONCLUSION

Attribute-based encoding has been wide employed in cloud computing wherever information suppliers source their encrypted information to the cloud and might share the info with users possessing mere credentials. On the opposite hand de-duplication is a vital technique to avoid wasting the space for storing and network information measure, that eliminates duplicate copies of identical information.

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International Journal of Computer Applications Technology and Research
Volume 8–Issue 06, 224-228, 2019, ISSN:-2319–8656

Integrated Automatic Control of Water, Fertilizer and Pesticide Based on Weather Change in Intelligent Agriculture

Xiping Wen
College of Communication Engineering
Chengdu University of Information Technology
Chengdu, China

Bin Wen
College of Communication Engineering
Chengdu University of Information Technology
Chengdu, China

Abstract: In the process of planting crops, it is greatly affected by the growing environment. The effects of weather, watering, fertilization, and pesticide s are important for the growth of crops and the final harvest. In order to cope with the bad weather, agricultural greenhouses have emerged. In order to make watering, fertilization and pesticide s more convenient and effective, water and fertilizer integrated control equipment has emerged. But so far, there have been no equipment facilities that can combine several, so that it is impossible to fundamentally solve the impact of weather and water and fertilizer on crops. In order to further promote the development of modern agriculture and fundamentally solve the problem of crop growth, this paper puts forward the automatic control equipment of dynamic water, fertilizer and pesticide, which adjusts the dynamic water, fertilizer and pesticide according to the different dynamic changes of weather, soil properties and crop varieties.
Keywords: Intelligent agriculture, integration of water, fertilizer and pesticide, weather, automation and dynamic change

1. INTRODUCTION

The integrated technology of water, fertilizer and pesticide is a new agricultural technology that integrates irrigation, fertilization and pesticides. It has “three festivals” (water saving, fertilizer saving, pesticide saving), “three provinces” (work saving, labor saving, worry saving) and the good effect of “three increases” (increasing production, increasing income, and increasing efficiency) is the “No. 1 Technology” for developing modern agriculture and accelerating the transformation of agricultural development methods[1].

At present, the water, fertilizer and pesticide integrated control unit on the market adopts three fixed working modes: fixed parameter setting, starting timing and fixed number of times. The method is adopted by storing the water consumption, the amount of fertilizer and the dosage of different root lengths of different crops during the growth period in the storage module. The digitizer and the timer are connected to the controller to realize the timing and the number of times of starting the pump and the fertilizer pump. Once the number of times and timing are configured, it cannot be adjusted in real time according to the weather changes. Even if there is obvious precipitation process tomorrow, the whole process must be completed according to the set method[2]. Due to the different planting objects and different planting areas, the three-level mode has a large amount of control unit configuration information and it is inconvenient to modify the control parameters on site. Moreover, it is also necessary to face the problem of reconfiguring parameters when the user replaces the product. In short, this mode is a mode in which all the workflows set by the operator are automatically completed after the operator starts the control flow and the control scheme. Regardless of the changing weather conditions, regardless of the actual situation of crop growth, the mode of working according to the pre-set process, after years of practice, is increasingly unsuitable for the needs of modern agricultural development.

To this end, we design a control method that dynamically adjusts water spray, fertilization, and pesticide spray according to different actual conditions such as planting objects, soil properties, and weather changes[3]. Fully invoke the role of meteorological big data in all key aspects of crop growth, and dynamically influence or change the operational process of water and fertilizer integration.

2. PROPOSAL OF A NEW METHOD

This method of dynamically adjusting the integration process of water, fertilizer and pesticide according to the actual situation of planting objects, soil properties, weather changes, etc. is realized in three stages, without additional memory, timers and counters. Only one STM32 core micro-control chip is needed to realize the design difficulty of the controller, and the amount of data scheduled by the controller is also greatly reduced, the use is simple, convenient, and the cost is greatly reduced. The first stage is called the water diversion stage (or water diversion time). Depending on the crop object, the crop root system is different from the fertilizer absorption method, and the length of time is determined. At this stage, only water is not fed, making a certain water content around the root of the crop, so that the fertility quickly penetrates into the place where the root of the crop needs the most fertility. The length of time is determined by water pressure, pipe network size, crop objects, and the like[4]. The second stage, called the topdressing stage (or topdressing time), determines the amount of fertilizer used depending on the crop growth period and the nature of the soil. Since the input pipe network is fixed, the water pressure is fixed, the fertility conveying rate is constant, and the time of topdressing is calculated according to the amount of fertilizer. The third stage is the hydration stage (or replenishment time). The purpose is to transfer all the fertilizer on the pipeline to the field and fertilize it to the ground as needed. The length of time is still determined according to the needs of the crop.

In the actual production process of agriculture, the operation process of water, fertilizer and pesticide integration should be dynamic, and the time adjustment of the three stages is not only based on the three different situations above. More importantly, it is necessary to dynamically change the three times according to the weather conditions, as well as the workflow of the water, fertilizer and pesticide controller. The method is to determine the total amount of water theoretically required for each growth stage, and calculate the water diversion time, top dressing time, and water replenishment time from the ratio of water to fertilizer and water to pesticide[5]. The process of introducing meteorological elements into the integrated water, fertilizer and pesticide process is based on the temperature and humidity of the air in the first three days and the water content of the soil and the forecast of key climatic factors in the region over the next three days to change the work flow and farming arrangements of the water, fertilizer and pesticide.

To this end, the water, fertilizer and pesticide integrated control device not only needs to achieve three stages of control functions, but also complete the collection of key climatic factors (such as air temperature, humidity, soil moisture, etc.). At the same time, it can remotely receive relevant parameters and weather forecast information of the cloud data center, and integrate it into the whole control process of water and fertilizer integration to accurately realize modern fertilization and fight drugs. Fully achieve the purpose of “three festivals”, “three provinces” and “three increases” to minimize the impact of chemical raw materials on the environment[6].

3. THE REALIZATION PRINCIPLE OF THE INTEGRATED CONTROL SCHEME OF DYNAMIC WATER, FERTILIZER AND PESTICIDE

3.1 Meteorological information acquisition

(1) The automatic control device collects relevant climatic elements every 10 minutes and stores them in the local memory. At the same time, the NBIO IoT communication module obtains temperature, precipitation and other related forecast information from the weather network.

(2) Use the SQLIT database in the device memory to store the latest 10 days of climate data collected by itself and weather forecast information within 3 days.

3.2 Meteorological Information Processing

3.2.1 Data preprocessing

Meteorological information is processed in units of time in the integrated control of water, fertilizer and pesticide. First, data quality control is performed to extract or correct useful meteorological information data; the average value of each climatic element, the maximum value and the minimum value of each day are calculated again, and stored in the data table.

3.2.2 Advanced processing of core meteorological elements

In this algorithm, deep meteorological processing of temperature, water, light and other core meteorological elements is required. For example, data such as accumulated temperature, daily difference, illumination duration, and precipitation frequency satisfying certain conditions are calculated and stored in the data table. The table is stored in the latest 10 days of data.

3.3 Design of Integrated Control Algorithm for Water, Fertilizer and Pesticide

In the design of the integrated control algorithm of water, fertilizer and pesticide, the weather condition should be pre-judgized, according to the different period of crop growth, the changing weather conditions, and the weather forecasting situation of the water and fertilizer integration process. Through the new control algorithm to change the current water, fertilizer and pesticide integration process can not be changed according to the actual situation, only according to the set, timing, quantitative, fixed process three fixed operational procedures[7]. Through the integration process of water, fertilizer and pesticide integration into the changing weather process, the refined water and fertilizer integration process is completed, and the pesticide spraying process is more refined and intelligent to reduce pesticide residues and dosage.

3.3.1 Conditional calculation of core meteorological indicators

Activity accumulated temperature: $Aa = \sum_{i=1}^{n} T_i$ ($T_i > B$; When $T_i \le B$, $T_i = 0$), T_i is temperature data after quality control; B is a certain minimum temperature required for planting objects; N is 30, and the equipment stores real-time data for 30 days.

Effective accumulated temperature: $Ae = \sum_{i=1}^{n} (T_i\text{-}B)$ ($T_i > B$; When $T_i \le B$, $T_i = 0$).

Frequency counting: $Na = \prod_{i=1}^{n} X_i$ ($X_i > B$), Na plus 1, when $X_i \le B$, Na is unchanged. X_i is a meteorological element (such as temperature, temperature, etc.).

Diurnal range: $Ba = T_i - T_j$; The difference between the average daily temperature of T_i from 08 am to 20 pm and the average daily temperature from 20 pm to 08 am).

Sunshine duration: $Sn = X_i - X_j$; X_i is the daily sunshine time data from the sensor at 8:00 am; X_j is the number of hours of sunshine read from the sensor at 20 pm every day.

3.3.2 Farming activity weather grade discrimination rules

Watering, fertilizing, and spraying pesticide are all agricultural activities in agricultural production. It is necessary to first determine whether this farming activity is appropriate. The rules for determining meteorological conditions are as follows:

If all the conditions for a certain agricultural activity are appropriate, the meteorological level of the agricultural activity is appropriate;

If the arbitrary discriminant condition of a certain agricultural activity is unsuitable, the meteorological level of the agricultural activity is not suitable;

In other cases, the meteorological level of the agricultural activity is more appropriate.

According to the degree of satisfaction of weather conditions, the score is 2 when satisfied, 0 when not satisfied, and 1 in other cases. According to formula (1), the product of each discriminant condition score value is obtained. If A is 0, the meteorological activity meteorological grade is unsuitable. If A is not 0, the judgment is continued, and each discriminant condition is obtained according to formula (2). For the total value of the score value, if the value of B is $2n$, the

International Journal of Computer Applications Technology and Research
Volume 8–Issue 06, 224-228, 2019, ISSN:-2319–8656

meteorological level of the agricultural activity is appropriate, otherwise the weather level of the agricultural activity is more suitable, and the rule conditions are shown in Table 1.

$$A = \prod_{i=1}^{n} X_i \qquad (1)$$

$$B = \sum_{i=1}^{n} X_i \qquad (2)$$

In the formula:

A is the product of the score values for each discriminating condition.

X_i is the i-th discrimination condition score value.

n is The total number of different conditions for a farming activity.

B is the total value of each of the discrimination condition score values.

Table 1. Examples of rules for the rules of agricultural production of agricultural products

Agricultural activities	Project	Suitable conditions	Favorable condition	Unsuitable condition
Fertilizing	Pre-day precipitation	No precipitation or paroxysmal precipitation, light rain, moderate rain, light snow		Heavy rain, heavy snow, frozen snow
	Yesterday's precipitation	No precipitation or paroxysmal precipitation	Light rain, moderate rain, light snow	
	Daytime precipitation during the day	No precipitation		Precipitation (rain, snow)
	Average daily temperature	< 28℃		≥ 28℃
	Daytime wind speed	≤Level 3		> Level 3
Spraying pesticide	Daytime precipitation during the day	No precipitation		Precipitation (rain, snow)
	Average daily temperature	< 5℃	3~5℃	≤ 3℃
	Daytime wind speed	≤ Level 3		> Level 3
Watering	Pre-day precipitation	No precipitation or paroxysmal precipitation, light rain, moderate rain, light snow		Heavy rain, heavy snow, frozen snow
	Yesterday's precipitation	No precipitation or paroxysmal precipitation	Light rain, moderate rain, light snow	
	Daytime precipitation during the day	No precipitation or paroxysmal precipitation, light rain		
	Maximum temperature of the day	> 4℃		

3.3.3 Water, fertilizer and pesticide integrated process flow algorithm combined with meteorological information

According to the growth stage of the crop, the water content of the soil, the temperature of the air in the past 3 days, the air temperature and temperature forecast in the last 3 days, and the forecast of precipitation, the integrated process of water, fertilizer and pesticide is adjusted, and the process change response is first, the water, fertilizer and pesticide integrated controller is the length of the output control time. Second, the control of the opening and closing angle of the valve changes the pressure of the water delivery pipe[8]. The algorithm stipulates that when the agricultural activities are appropriate, the basic control ratio of water, fertilizer and pesticide integration is 100%, and the basic control ratio is increased or decreased according to multiple impact factors. The algorithm implementation steps are as follows:

Step 1: according to the conditions of Table 1 and the rules, combined with the meteorological data of the previous 3 days and 3 days later, determine whether the agricultural activities are appropriate. If it is not suitable for the controller to feedback to the user, do not carry out this farming activity, and withdraw from the integrated operation process of water, fertilizer and pesticide; if it is suitable to transfer to the second step. The first step solves the problem of controlling the control of water, fertilizer and pesticide by meteorological conditions.

Step 2: after judging the suitable operation of water, fertilizer and pesticide integration, according to the different farming activities such as fertilization, spraying, irrigation, etc., combined with the most critical climatic factors affecting the agricultural activities, dynamically assigning water diversion, topdressing and hydration the relationship between time[9]. The weighting value of the meteorological information related to this agricultural activity is assigned, and the weight distribution example table is shown in Table 2. And go to the third step to calculate the time of this farming operation.

Step 3: matching the crop growth stage according to the system time, extracting the influence weight and the hydration time ratio of the meteorological elements required for the growth stage, and transferring to the fourth step.

Step 4: When the water, fertilizer and pesticide integrated system is installed, the controller sets a default water diversion time, top dressing time and replenishment time for the planting object. Due to changes in weather conditions, the influence weights and time ratios of meteorological elements are obtained from Table 2, Table 3, and Table 4, and the time of water diversion and replenishment time is changed, thereby completing the change of the integrated process of water, fertilizer and pesticide. After calculating the time in each step, move to the fifth step.

Step 5: The controller issues control commands to the control port according to the length of each phase and the time-to-front relationship, respectively controlling the opening and closing of the water spray valve, the fertilizer valve, and the spray valve until each stage is set. Time is up and an operation completion message is sent to the user.

Table 2. Example of the influence weight of meteorological factors on fertilization activities of a planting object

Agricultural activities	Fertilizing	Figures
Effective accumulated temperature	Positive weight	10
	Negative weight	10
Sunshine duration	Positive weight	10
	Negative weight	10
Soil moisture	Positive weight	20
	Negative weight	20
Water diversion time ratio		1:3

Table 3. Example of the influence weight of meteorological factors on pesticide spray activities of a planting object

Agricultural activities	Spraying pesticide	Figures
Effective accumulated temperature	Positive weight	10
	Negative weight	10
Sunshine duration	Positive weight	10
	Negative weight	10
Soil moisture	Positive weight	20
	Negative weight	20
Water diversion time ratio		1:1

Table 4. Example of the influence weight of meteorological factors on water spray activities of a planting object

Agricultural activities	Spraying water	Figures
Effective accumulated temperature	Positive weight	0
	Negative weight	0
Sunshine duration	Positive weight	0
	Negative weight	0
Soil moisture	Positive weight	20
	Negative weight	20
Water diversion time ratio		No rehydration time

4. CONTROL PRINCIPLE OF WATER, FERTILIZER AND PESTICIDE INTEGRATED CONTROL DEVICE

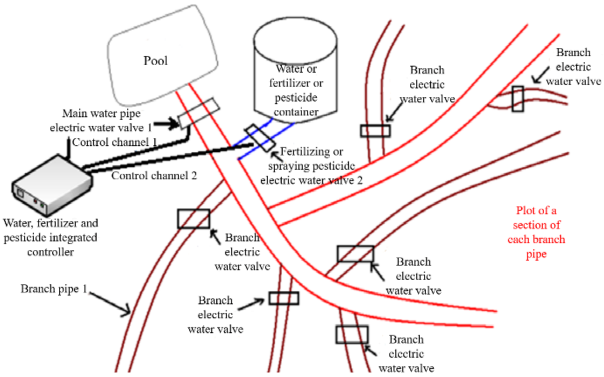

Figure. 1 Schematic diagram of water, fertilizer and pesticide integration

Description:

(1) Each branch is fitted with an electric water and fertilizer, and each electric water valve is equipped with a separate controller. Each controller can communicate independently with the cloud management center. The watering area of each branch pipe determines the area to be watered according to the geographical environment of the mountain area or the actual conditions of water pressure.

(2) The main water pipe electric valve and the fertilization and pesticide spray electric valve are controlled by the same controller, and the controller communicates with the cloud management center independently.
The water, fertilizer and pesticide integration function is completed by the front and rear logic and switch control time of the main water pipe and the fertilization electric valve.
(3) Each controller adopts low-power design and is powered by solar + battery to reduce the construction difficulty on site. The principle of connection between the power supply and the electric water valve is shown in Figure 2.

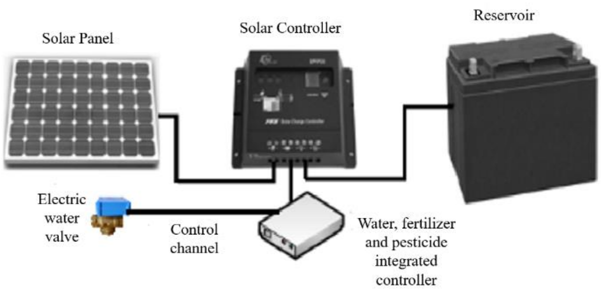

Figure. 2 Water, fertilizer and pesticide integrated controller solar power supply and electric water valve connection schematic

5. CONCLUSION

In summary, based on the different dynamics of planting objects, soil properties, weather changes and other actual conditions, the corresponding control methods of water spray, fertilization and pesticide spray can not only achieve “three sections” (water saving, fertilizer saving, pesticide saving), "three provinces" (work-saving, labor-saving, worry-free) and "three increase" (increasing production, increasing income, increasing efficiency), and can fully invoke meteorological big data to participate in all key aspects of crop growth, at the largest To the extent that the crops are combined with the actual environment in which they are grown, it is possible to adapt to local conditions, avoid pollution and damage to the soil by chemical substances, and ensure healthy foods that are green and environmentally friendly at the production site. The degree of focus then dynamically influences or changes. The water, fertilizer and pesticide integrated automatic control equipment of this project is an important response to the background of the rapid development of modern agriculture and environmental sustainable development, and is of great significance “Technology No.1”.

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International Journal of Computer Applications Technology and Research
Volume 8–Issue 06, 229-268, 2019, ISSN:-2319–8656

Application of Artificial Neural Network in Crop Production: Modeling and Simulation of Plantain Growth Prediction

Dr. Oye N. D.
Department of Computer Science
Mautech, Yola Nigeria

Adesanya A. A.
Department of Computer Science
Mautech, Yola Nigeria

Abstract:

Artificial neural networks (ANN) have become very significant tools in many areas including agricultural system. ANN was used in this research for modeling and simulation of plantain growth prediction. Plantain production is concentrated in the rain-forest belt of West and Central Africa where it constitutes an important staple food of the local population. Using ANN to stimulate the growth of plantain will make plantain farmers to plan their planting. They would already know the outcome of the production and can forecast the financial expenses before and after planting. If they know the height of the plant sucker, (NEL); Leaf width, (LW(cm)); and the Leaf length, (LL(cm)) to predict into future the values of Ht , G50, NEL, LW, LL, BW in kg (Bunch weight), NHB (Number of hands in the bunch) and NFB (Number of fingers in the bunch) of plantain plant based on the planting conditions for dataset used for training in this research. Elman time series neural network, a back-propagation algorithm, with 1 input neuron and 1 output neuron with varying number of neuron in the hidden layer was employed to train the parameters. The network result of Ht, G50, NEL, LW and LL, are used to train the network of BW, NHB, and NFB. Their corresponding coefficient of determination (R^2) and the Root Mean Squared Error (RMSE) were recorded to determine the acceptance of each network architecture. After all these parameters have been trained, the network predicted into future the value of plantain height, the girth at 50 cm above the soil level, number of emitted leaves, leaf width, leaf length, bunch weight of plantain, number of hands in the plantain bunch and number of fingers in the plantain bunch given the known value (from the plantain sucker, an experimental value) of Ht, G50, NEL, LW, and LL to the network. It was evidenced that the neural network was able to predict future values of plantain plant and yield at harvest.

Key Words: Artificial Neural Network; Modeling; Plantain Growth; Prediction; Simulation.

1. INTRODUCTION

Background of the study

As a productive part of the economy of a country, Agriculture plays a significant role in the national production and Artificial Neural Networks has been used in Agriculture for predicting farm products. Studies have shown that several models and algorithms have been developed to predict yield of agricultural productions and many authors have found linear correlation of yield with soil properties and environmental conditions (Khakural, Robert and Huggins, 1999; Gemtos, Markinos and Nassiou, 2005). However, using nonlinear methods mainly artificial neural networks (ANNs) for yield prediction have become more common (Kominakis, Abas, Maltaris and Rogdakis, 2002; Kaul, Hill and Walthall, 2005; Sharma, Sharma and Kasana, 2007; Papageorgiou, Markinos and Gemtos, 2011; Papageorgiou, Aggelopoulou, Gemtos and Nanos, 2013). Artificial neural network is a simulation of system of human brain. An interconnected group of artificial neurons that uses mathematical model or computational model for information processing based on the connectionist approach to computation. The interconnection of artificial neurons which may share some properties of biological neural networks, an information processing paradigm that is inspired by biological system and compose of interconnection of processing elements (neurons) working together to solve a specific task.

In 1943, a neurophysiologist, Warren McCulloch and a young mathematician, Walter Pitts introduced models of neurological networks, recreated threshold switches based on neurons which showed that even simple types of neural networks could, in principle, calculate any arithmetic or logical function (McCulloch and Pitts, 1943).Hebb (1949) wrote a book entitled "The Organization of Behaviour" which brings the idea that formulated the classical Hebbian rule which represents in its more generalized form the basis of nearly all neural learning procedures. This rule implies that the connection between two neurons is strengthened when both neurons are active at the same time. This change in strength is proportional to the product of the two activities.

Many researchers (Rosenblatt, 1961; Minsky and Papert, 1969) worked on perceptron. The neural networks can be proved to adjust to the correct weight that will solve the task. Minsky and Papert showed that perceptron could not learn those functions which are not linearly separable and opined that neural network research should be discredit and divert neural network research funding to the field of "Artificial Intelligence" and so put an end to overestimation, popularity and research funds. After Minsky and Papert's demonstration of the limitations of perceptrons, research on neural network still continued but there were neither conferences nor other events and therefore only few publications. Among those that published in the 1970s include Malsburg (1973), Werbos (1974), Grossberg (1976), Hopfield (1982) and Fukushima, Miyake, and Ito (1983). These people among other researchers were the people who put the field of neural network on a strong expectations and prepared the lead for the renaissance of the field.

Through the work of John Hopfield, with his lectures, encouraged hundreds of highly qualified scientists, mathematicians, and technologists to join the emerging field of neural networks and the wide publication of backpropagation by Rumelhart, Hinton and Williams (1986). The field exploded and nonlinearly separable problems could be solved by multilayer perceptrons, and this disproved Marvin Minsky's negative evaluations. After this time, the development of neural network has almost been explosive. The economic significance of plantain cannot be over emphasized, its health uses, and it forms significant part of the diets of people living in the rain-forest belt. In this research, Artificial Neural Network was used for modeling and simulation of plantain growth development, the morphology growth of plantain and yield with some certain criteria as identified parameters.

Plantain production is concentrated in the rain-forest belt of west and central Africa where it constitutes an important staple food of the local population. Plantains (Musa paradisiaca) are potent sources of micronutrients especially vitamins A and C, potassium and fibre. A firm ripe plantain have high carbohydrate content, a good sources of vitamins and minerals in addition to being low in fat (Yusufu, Mosiko and Ojuko, 2014). Musa species are useful as food to be consumed by human either as flour to be used in confectionaries or as jams and jellies; in chips etc. Its peel can be used as animal feed. All parts of the plantain plant have medicinal applications: the flower in bronchitis and dysentery and on ulcers, cooked flowers are given to diabetics etc. Its leaves are also useful for lining cooking pots and for wrapping. Improved processes have also made it possible to utilize banana fibre for ropes, table mats and handbag (Chandler, 1995).

Ngo-Samnick, E.L. (2011) discussed the agronomic requirements for planting a plantain as:

Temperature: The optimal temperature for growing plantain is 28°C. From 28ºC to 20°C, growth will gradually slow down, and will become negligible around 16ºC-18°C.

Light: Shade accelerates height growth, and it is advisable to determine the density depending on the cultivar selected, in order to provide the best light conditions for the plantation.

Water: Plantain needs a lot of water. It should get around 200 mm per month throughout its life cycle.

Wind: Plantain is very sensitive to strong wind, which can cause physical damage to the plant (torn leaves, toppling). Soil: Plantain grows best in deep soil that is well drained and rich in organic matter. Fallow land can also be used, but the yield will depend on what was previously grown and the duration of the fallow.

Statement of the Problem

Plantain farmers experience low production due to lack of proper planning, sometimes fail to put good measure in place that will increase their farm productivities. Poor preparation before the start of production will bring low yield of crop which also will lead to waste of resources in material and man effort. Using Artificial neural network to stimulate the growth of plantain development will make plantain farmers to plan their planting, they would already know the outcome of the production and can forecast the financial expenses before and after planting which will reduce the waste of resources and increase the agricultural economy of the country. With this scientific approach, the plantain farmers can predict the growth and yield of the plant if they know the Pseudostem height of the plant sucker, Ht (cm); Pseudostem girth at 50cm above soil level, G50 (cm); Number of emitted leaves on the sucker, NEL; Leaf width, LW (cm); and the Leaf length, LL (cm) to predict into future the values of Pseudostem height, Ht (cm); Pseudostem girth at 50cm above soil level, G50 (cm); Number of emitted leaves, NEL; Leaf width, LW (cm); Leaf length, LL (cm); Bunch weight, BW (Kg); Number of hands in the bunch, NHB and Number of fingers in the bunch, NFB of plantain plant based on the planting conditions for dataset used for training for this research.

Aim and Objectives of the Study

This research modeled and simulated the growth of plantain development using artificial neural network and the identified objectives are:

i. Developed a three-layer network Architecture using Error correction learning algorithm.
ii. developed a time series Elman neural network code and simulate the sample data collected for the model using MATLAB software.
iii. calculated the output of the network and compare to the corresponding target vector.
iv. measured at every stage of iteration, the difference between the target value and the experimental value was maintained in other to keep control until target value was reached.
v. the weights of the neurons are adjusted according to the algorithm, back-propagation which tends to minimize the error, to produce the desired output.
vi. Calculated RMSE to verify how concentrated the data around the line of best fit.

Justification and Significance of the Study

This study is significant in that it:

1. Allowed the farmers to have better conditions for planning, maximizing the efficiency of the business process without loses because it will provide reliable estimates for the optimal time of a harvest that will lead to increased shelf life.

2. Plan financing aspects of production before and after planting and this encourage the continuation of studies to verify which variables most influence on the final production. This will improve the agricultural economy of Nigeria if practice and however also reduce waste of resources available.

2. LITERATURE REVIEW

2.1. Application Areas of Artificial Neural Networks in Agriculture

Artificial neural networks have become very significant tools in many areas including agricultural system. Agricultural system is a complex system since it deals with a number of factors with a large data situation. Different techniques and approaches have been adopted to show any interactions between factors that is affecting yields with plant growth. Many researchers have shown the application of artificial neural networks (ANNs) in agriculture (Diamantopoulou, 2005; Movagharnejad and Nikzad, 2007; Zhang, Bai and Liu, 2007). Most of these studies were dedicated to the predictions of yield. (Jiang, Jiang, Yang, Clinton and Wang, 2004) showed in their work using ANNs model with the back-propagation training algorithm to forecast the yield in wheat winter crops by using remote sensing information. (Uno, Prasher, Lacroix, Goel, Karimi, Viau and Patel, 2005) developed models for the prediction of yield in maize, by using statistical methods and ANNs with various indexes of vegetation; the greater accuracy in the prediction was obtained with the ANNs model, which was superior to any of the three conventional empirical models.

2.2 ANN for Modeling in Agriculture

Zee and Bubenheim (1997) developed a plant growth (physiology) model using artificial neural networks. In their approach, they identified four crop processes to crop-base life support systems operation which were identified as Assimilation, Allocation, Nutrient Uptake and Transpiration. Taken together these four processes result in a complete life support system package, can be highly reliable and controllable. They presented the modeling of a single plant process of transpiration (water production) with varying inputs of air temperature, canopy temperature, relative humidity, and plant type. In their report, they discussed four different mathematical models for transpiration during crop growth which are: flow model using Ohm's law, transport flow model, radiation balance, and mass flux. In their conclusion, they identified the major challenge for implementing artificial neural network model as large amounts of training data required over a range of environmental conditions and plant growth experiments usually require several weeks to several months, and usually very few data are recorded.

Bala, Ashraf, Uddin and Janjai, (2005) presented experimental performance and artificial neural network modeling of drying of litchi flesh in a parabolic greenhouse solar dryer. The dryer consists of a parabolic roof structure covered with polycarbonate sheets on a concrete floor. An artificial neural network (ANN) approach was used to model the performance of the dryer for the drying of litchi flesh. Using solar drying data of litchi flesh, the ANN model was trained using the back-propagation algorithm with seven sets of data used for training and three sets were used for testing the ANN model. Ten tests of the dryer for the drying of litchi flesh were performed during three harvest seasons of litchi, namely 2008, 2009 and 2015. They showed the comparison of air temperatures at three different locations inside the dryer, namely front, middle and back, for a typical experiment of solar drying litchi flesh. Temperatures at different positions in these three locations varied within a narrow band. The airflow rate increases sharply in the early part of the day, then becomes fairly constant and then drops sharply in the afternoon. They concluded that solar radiation followed similar patterns for all days during drying. Moisture content of the litchi flesh was reduced from an initial value of 84% (wb) to the final value of 13% (wb) within 3 days. The dryer can be used to dry up to 100 kg of litchi flesh.

Liu, He, Song, and Yang (2010) developed a prototype system to verify the feasibility and effectiveness of structure and function of plant growth model. For different characteristics of plant growth, and supply convenience for the appearance of the whole plant such as texture, light and color and so on, changing properties of relevant organs and physiological function parameters, the process of simulated results can be obtained. The unilateral light of long-term effects is caused by trend-reaction, resulting in plant morphology of bending to the bright side, reflected in the uniform of light intensity to the role of the top growth characteristics. The plant shows malformation growth under strong winds, leading to change of plant structure. The simulation of plant growth process shows that the physiological characteristics of plants will respond accordingly and lead to the change of plant morphology and topology according to the rules when light, temperature, moisture and nutrients that affect plant growth and other conditions change during the process between the beginning and maturation.

2.3. ANN for Prediction in Agriculture

Qiao, Shi, Pang, Qi, and Plauborg (2010) estimated the water uptake by plant roots with artificial neural network. Seven factors were used as input parameters which were soil moisture, potential evapotranspiration, atmospheric humidity, electrical conductivity of soil solution, air temperature, plant shoot height and diameter while root water uptake rates at different depth in the soil profiles were taken as the outputs. Root capability to extract water from soil depends on both soil and plant properties. Determination of volume, conformation and distribution of the roots in soil poses a lot of difficulties to scientists, since non-invasive methods for explicit description of the whole plant root system have not yet been elaborated. They used a feed-forward three layers neural network model and this model effectively came out with a small relative error, which was less than 17%.

Soares, Pasqual, Lacerda, Silva, and Donato (2013) proposed a methodology for predicting the bunch's weight in banana plants. The implemented ANN produced an efficient prediction of the production. The networks were trained with experimental data representing the characteristics of the growth and development of the plant in order to obtain the production, which can achieve greater ability to generalize since more data is supplied to the network for training. The data from the first cycle were used to build the prediction model and data from the second cycle were reserved to test the predictive capability of the model. Safa, Samarasinghe, and Nejat (2015) showed in their study the first time an ANN model was designed to predict agricultural production using direct factors as well as indirect factors, and it showed the potential of using indirect factors to predict agricultural production (wheat production of farm inputs using indirect parameters). The final neural network model, using a carefully selected set of six inputs from more than 140 different factors, can predict wheat production based on wheat area, irrigation frequency, machinery condition (tractor hp ha^{-1} and number of passes of sprayer), and farm inputs (N and fungicides consumption) in Canterbury arable farms with an error margin of ±9% (± 0.89 t ha^{-1}). The results of their study showed the ability of ANN models to predict wheat production using heterogeneous data better than using a multiple regression model (as a common model used in agricultural studies).

3. METHODOLOGY

3.1 Neural Networks Overview and Heuristics

Basic Concepts of Neural Networks

The "Neural Network" as employed in this research is obviously not a biological concept, it is artificial. In the field of neural networks, "Neural Networks" and "Artificial Neural Networks" are interchangeable. Neural networks are inspired by the functioning of the biological network of neurons in human brain. A human brain contains approximately 10^{11} computing elements called neurons. Those neurons are fully connected and communicate with each other. The inputs are received by the sensory receptors and sent to the neurons in the network. The neurons process the inputs and send information to the next neurons (Zurada, 1992).

A neuron is nothing more than a switch with information input and output. The switch will be activated if there are enough stimuli of other neurons hitting the information input. Then, at the information output, a pulse is sent to other neurons. Incoming signals from other neurons or cells are transferred to a neuron by special connections, the synapses. Such connections can usually be found at the dendrites of a neuron, sometimes also directly at the soma (cell body).

3.2 Computational Model of Human Neuron

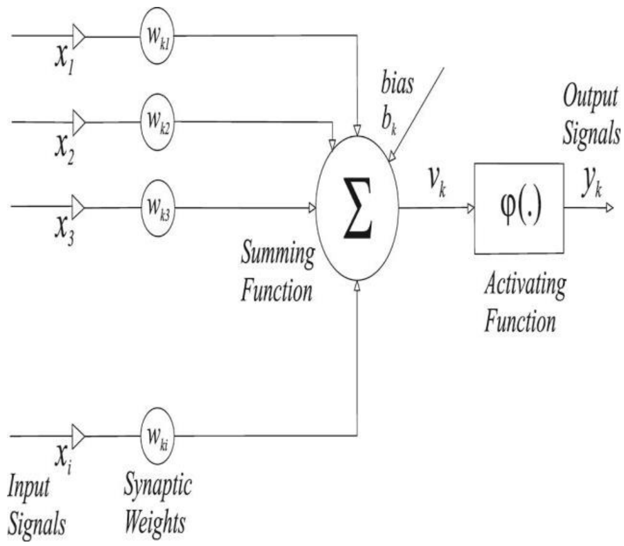


Figure 3.1: Design of a simple Artificial Neural Network with i input variables and k neurons in its output layer (modified after Aji et al. 2013)

Figure 3 . 1 shows the artificial neuron model. The sets $x_1, x_2, \ldots x_i$ represent input signals (for example in agriculture; leaf water content, nutrients, soil quality and other agricultural factors), the w_{ki} are synaptic weights (The strength of the neuron) which indicate the connection weight from neuron j to neuron k, b_k is a bias (which can increase the adaptability of neurons and neural networks.) from neuron k, v_k is an activation potential of the neuron k, $\varphi(.)$ is an activation function, y_k is the output signal of the neuron k and u_k is the net input, which is the sum of all inputs multiplied by all synaptic.

The output is of the form

$$u_k = \sum_{j=1}^{i} w_{kj} x_j \quad \ldots \quad 1$$

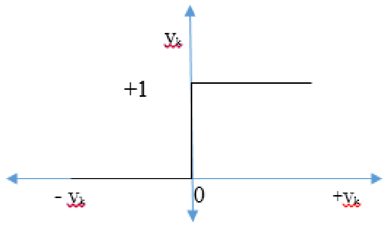
and the combined output, $v_k = u_k + b_k$

where $y_k = \varphi(u_k + b_k)$ … 2

The Threshold Function

If $v_k \geq 0$, $y_k = 1$ otherwise, $y_k = 0$

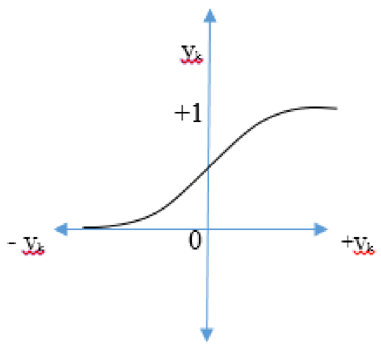
The response graph is:



Applying the activation function $\varphi(.)$ So that equation turns to non-leaner function, sigmoid function is applied.

$$\varphi(v_k) = \frac{1}{1+\ell^{v_k}}$$

The response graph is



3.3. Architecture of the Neural Network

The architectural structure is a three-layered Elman time series neural network as depicted in the figure 3.2. The input layer of Neurons are the inputs to the network. Elman network is a feedback neural network that has the weights of the first layer coming from the input and each subsequent layer has a weight coming from the previous layer. All layers except the last one have a recursive weight and the last layer is the network output.

Elman network use a memory called content unit (q) to store the values of the hidden layer outputs and feedback these values to the network for retraining.

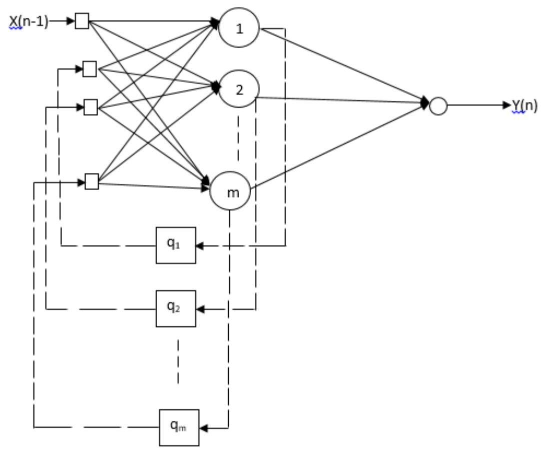


Figure 3.2: A Time series Elman neural network with one input, 1 hidden layer of m neurons and one output.

3.4. Data Collection and Analysis

The dataset used for this work was the 'Plantain-Optim' dataset, from the 'Plantain-Optim' experiment conducted from 2009 to 2011 at CARBAP experimental station in Cameroom (Sylvain, Frédéric, Médard, Désirée, David, Jean-Pierre, Bernard and Thierry, 2018). The column of data considered from this dataset are Days after planting, DAP; Pseudostem height, Ht (cm); Pseudostem girth at 50cm above soil level, G50 (cm); Number of emitted leaves, NEL; Leaf width, LW (cm); Leaf length, LL (cm); Bunch weight, BW (Kg); Number of hands in the bunch, NHB and Number of fingers in the bunch, NFB which are the identified parameters considered for the neural network used for this work.

From the 'Plantain-Optim' experiment, each leaves emitted on individual plant were numbered and measured. The leaf width and leaf length were taken into account for each emitted leaf. However for this work, the leaf width and leaf length assumes the value of the emitted number of leaves at every instance of time interval of 15-day accuracy of record for the 'Plantain-Optim' dataset. For instance, if the emitted number of leave is 7 at a particular time in days, the value of leave width and leave length was the leave width and leave length of the 7th leave of the plant. The dataset were recorded every 15 days interval and the first observation of data recorded was at 35 days from the first day of planting.

From the 'Plantain-Optim' dataset, it was observed that some plants do not have values at the harvest period which make those plants not usable or considered to be used for the neural network prediction. It was also noticed that there are off set in harvest period. Some plants matured in 10 months, some are in 11 months, 12 months, 13 months and 14 months. The dataset are categorised based on this harvest periods and 11 months plants were selected to limit the error variation of values predicted by the neural network result because plants that fall in this category are much and the more the dataset, the better the neural network's result. However, due to time factor to format the dataset in the specific arrangement that the network can access it properly, only 51 dataset are used, containing of 5 varieties of plantain plant data.

The dataset was prepared for a time-series multi-step prediction network. The number of days of sampling of the data was interpolated to decrease sampling period from 15 days to 1 day as opposed every 15 days in the 'Plantain-Optim' dataset. The MATLAB code is given below:

```
DAPx = DAP;
        clear Y
        % interpolate to decrease
sampling period from 15 days to 1
day
        x = min(DAPx):max(DAPx);
        Y = interp1(DAPx,Datat,x);
% interpolate G50 so instead of
two weeks, it is sampled each day

        % X
        XX = Y(1:end-1); % inputs

        % Y
        YY = Y(2:end); % targets

        % Standardize the data
        mux = (mux*(count-
1)+mean(XX))/count; sux = ((count-
1)*sux+std(XX))/count;
        % update mean and standard
deviation of X for current excel
file

        muy = (muy*(count-
1)+mean(YY))/count; suy = ((count-
1)*suy+std(YY))/count;
        % update mean and standard
deviation of Y for current excel
file

        clear Yp Ya
        Ya = YY;
        YY = (YY-muy)/suy; %
standardize Y using mean ans std
of Y
        XX = (XX-mux)/sux; %
standardize X using mean ans std
of X
```

3.5. Plantain Variety

There are many varieties of plantain in existence by nature, nine varieties were experimented at CARBAP experimental station in Cameroom, which are Batard, Big Ebanga, CRBP39[a] (Hybrid plant), D248[a] (Hybrid plant), D535[a] (Hybrid plant), Essong, French Clair, FHIA21[b] (Hybrid plant) and Mbouroukou n^{0}3. Forty-five numbered elementary experimental plots were used and each experimental plot included nine plants of one variety. Each variety was represented by 45 plants.

3.6. Planting Conditions

This work adopted all the planting conditions that were put in place (including climate conditions, water percentage and soil texture) for the 'Plantain-Optim' dataset for the result of the neural network to be accepted.

3.7. Input and Output

In this case, a time series neural network with an input layer, a hidden layer of m neurons (this is different for each network parameter) and an output layer is used for Pseudostem height, Ht (cm);

Pseudostem girth at 50cm above soil level, G50 (cm); Number of emitted leaves, NEL; Leaf width, LW (cm) and Leaf length, LL (cm).

For number of neurons in hidden layers, there is no hard and fast rule to compute that for optimal architecture of the network (Khazaei, Tavakoli, Ghassemian, Khoshtaghazaa, Banakar, 2013), either most of the time, one just go with what works best to have a good result from the network prediction by cross validation. The number of neurons in input layer always equals the number of features considered. One (1) input neuron in the case for Ht, G50, NEL, LW and LL since we are treating each parameter as time series, so the current value is predicted by past values while the neurons in the hidden layer differ for each identified parameter and the neuron in the output layer is 1 but for Bunch weight, BW (Kg); Number of hands in the bunch, NHB and Number of fingers in the bunch, NFB their number of inputs are 5 (based on the output generated for the values from Ht, G50, NEL, LW and LL), a hidden layer with m neurons and 1 output neuron in the output layer since we only need one output.

BW, NHB and NFB has no much dataset for training neural network as lots of dataset is required by artificial neural network to predict very accurately, for that reason, the networks were trained over and again for 30 times to have better result and their hidden neurons were changed (see Table 4.7, Table 4.8 and Table 4.9) to verify the best architecture for each network. Table 4.7 shows the architectures and statistical parameters for artificial neural networks tested for bunch weight, Table 4.8 shows the architectures and statistical parameters for artificial neural networks tested for number of hand in the bunch and Table 4.9 shows the architectures and statistical parameters for artificial neural networks tested for number of fingers in the bunch.

3.8. Training Algorithm

For the Ht, G50, NEL, LW and LL, the networks were trained with Gradient decent with momentum and adaptive LR (trangdx) training algorithm with data division as random (dividerand), using the default ratio, 70% of dataset for training, 15% of dataset for validation and 15% of dataset for test. Mean square error (MSE) was used as performance measure.

For the BW, NHB and NFB, the artificial neural networks use an Input-Output Fitting Neural Network and the networks were trained with trainlm algorithm. Trainlm is a network training function that updates weight and bias values according to Levenberg-Marquardt optimization. It is often the fastest backpropagation algorithm in the Matlab toolbox, and is highly recommended as a first-choice supervised algorithm, although it does require more memory than other algorithms.

RMSE (Root Mean Squared error) was used to verify how concentrated the data is around the line of best fit. It shows how much the predicted values deviate from the experimental values in the data set on average. The metric unit is the same unit as its variable.

The network was trained on normalized values, so once the predictions is done, the output is also normalized but the actual values (the experimental values) which are subtracted from the predicted values to get RMSE are not normalized, therefore, the output was de-normalize as well.

So in this case: Yp = cell2mat(net(X,Xi,Ai)); and Yp = Yp*suy +muy;

Yp = cell2mat(net(X,Xi,Ai)); gives the normalized (or standardized) output

Yp = Yp*suy +muy; scales the output to the original values where suy is the standard deviation of output data used for standardization of actual (experimental) output and muy is the mean of output data.

After the first training was done, the network was trained further for nine times to reduce the amount of error generated by employing Monte Carlo simulation to repeat the same experiment again and again and then taking average.

3.9 Algorithm for Training Network

The basic algorithm loop structure of Back-propagation algorithm

Initialize the weights

Repeat

For each training pattern

"Train on that pattern"

End

Until the error is acceptably low.

The learning method is a supervised learning, there is a set of training samples and neural network adjusts its connection weights according to the difference between predicted outputs and experimental outputs.

The learning algorithm: Error correction learning law

$$e_i(t) = Yp_i(t) - Ya_i(t)$$

Where $Yp_i(t)$ is the predicted output of ith neuron at time t; $Ya_i(t)$ is the actual output of ith neuron at time t and $e_i(t)$ is the output error of ith neuron at time t. The goal is to minimize some function of $e_i(t)$.

3.10. System Requirement

The MATLAB software version used was MATLAB R2015a and the system configuration used to carry out this is HP 250 with Windows 8.1 running on it as operating system.

System processor: Intel(R) Pentium(R) CPU B960 @ 2.20GHz

System installed memory (RAM): 4.00GB 3.89GB (usable)

System type: 64-bit Operating system, X64-based processor

Hard drive: 500GB

3.11. Time delay Neural Network, an option to Elman Neural network

Time delay networks are similar to feedforward networks, except that the input weight has a tap delay line associated with it. This allows the network to have a finite dynamic response to time series input data with the availability of full dynamic derivative calculations (fpderiv - Forward propagation derivative function and bttderiv - Backpropagation through time derivative function). Elman networks are feedforward networks (feedforwardnet) with the addition of layer recurrent connections with tap delays. Elman networks with one or more hidden layers can learn any dynamic input-output relationship arbitrarily well, given enough neurons in the hidden layers. However, Elman networks use simplified derivative calculations (using staticderiv - Static derivative function, which ignores delayed connections) at the expense of less reliable learning (Mathworks, 2018).

4. RESULTS PRESENTATION AND ANALYSIS

4.1 Training Analysis

Fig. 3.2 shows the architecture of the neural networks developed by using the 'back-propagation' algorithm for the prediction of the plantain plant growth. The networks were trained with experimental data obtained from the 'Plantain-Optim' dataset, from the 'Plantain-Optim' experiment conducted from 2009 to 2011 at CARBAP experimental station in Cameroom, representing the characteristics of the growth and development of plantain plant. The dataset used are 11 months harvest period of different varieties of plants as discussed in the methodology. The results of this process are described below. Since this is a time series neural network, each parameters identified as plant growth parameters were trained separately. Each of the training sections was carried out with different initial weights and hidden layer neuron from 1 to 10 to know the best architecture for each network, each network were trained over and again for 10 times and put under observation so that the data will not over fit until the lowest average error was obtained. The network with the lowest RMSE (root mean squared error) was selected.

Table 4.1, explains the architectures and statistical parameters for ANNs tested for Ht (cm) and the best neural network architecture for Ht (cm) prediction model was made up of a network with architecture of 1:3:1. Table 4.2 explains the architectures and statistical parameters for ANNs tested G50 (cm) and the best neural network architecture for G50 (cm) prediction model is 1:2:1. Table 4.3 explains the architectures and statistical parameters for ANNs tested for NEL and the best neural network architecture for NEL prediction model is 1:3:1. Table 4.4 explains the architectures and statistical parameters for ANNs tested for LW (cm) and the best neural network architecture for LW (cm) prediction model is 1:2:1 and while Table 4.5 explains the architectures and statistical parameters for ANNs tested for LL (cm), and the best neural network architecture for NEL prediction model is 1:9:1.

Table 4.1, Table 4.2, Table 4.3, Table 4.4 and Table 4.5 summaries the characteristics and the parameters of the tested artificial neural networks for each variable parameter, which are: Network Architecture, Min. Performance gradient, Max. Number of epoch trained, Learning rate (ɳ), Performance goal, R^2 and RMSE. The predicted values by the ANNs against the experimental data were used to calculate the coefficients of determination (R^2) and the Root Mean Squared Error (RMSE). It was observed from all the architectures and statistical parameters for ANNs tested tables that when the RMSE reduces, the R^2 will increase and where the RMSE increases, the values of the R^2 were also affected and reduces accordingly. The architecture with smallest RMSE and high R^2 were selected as the best architecture.

Table 4.1: Architectures and statistical parameters for ANNs tested for Ht (cm)

	ANNs for sampling data							
Network Architecture	1:1:1	1:2:1	1:3:1	1:4:1	1:5:1	1:6:1	1:7:1	1:8:1
Min. Performance gradient	0.00001	0.00001	0.00001	0.00001	0.00001	0.00001	0.00001	0.0000
Max. Number of epoch trained	1000	1000	1000	1000	1000	1000	1000	1000
Learning rate (η)	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
Performance goal	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
R^2	0.9997	0.9988	**0.9999**	0.9996	0.9938	0.9996	0.9997	0.9957
RMSE	2.3477	4.645	**1.5320**	2.8564	10.2897	3.1259	2.7422	8.2836

Table 4.2: Architectures and statistical parameters for ANNs tested for G50 (cm)

	ANNs for sampling data							
Network Architecture	1:1:1	1:2:1	1:3:1	1:4:1	1:5:1	1:6:1	1:7:1	1:8:1
Min. Performance gradient	0.00001	0.00001	0.00001	0.00001	0.00001	0.00001	0.00001	0.0000
Max. Number of epoch trained	1000	1000	1000	1000	1000	1000	1000	1000
Learning rate (η)	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
Performance goal	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
R^2	0.9995	**0.9999**	0.9991	0.9995	0.9996	0.9992	0.9997	0.9993
RMSE	0.5469	**0.2229**	0.7997	0.6530	0.5525	0.6357	0.4178	0.6977

Table 4.3: Architectures and statistical parameters for ANNs tested for NEL

	ANNs for sampling data							
Network Architecture	1:1:1	1:2:1	1:3:1	1:4:1	1:5:1	1:6:1	1:7:1	1:8:1
Min. Performance gradient	0.00001	0.00001	0.00001	0.00001	0.00001	0.00001	0.00001	0.0000
Max. Number of epoch trained	1000	1000	1000	1000	1000	1000	1000	1000
Learning rate (ƞ)	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
Performance goal	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
R^2	0.9993	0.9967	**0.9997**	0.9989	0.99895	0.99892	0.9991	0.9994
RMSE	0.2857	0.6889	**0.2202**	0.3885	0.4051	0.4293	0.3561	0.2908

Table 4.4: Architectures and statistical parameters for ANNs tested for LW (cm)

	ANNs for sampling data							
Network Architecture	1:1:1	1:2:1	1:3:1	1:4:1	1:5:1	1:6:1	1:7:1	1:8:1
Min. Performance gradient	0.00001	0.00001	0.00001	0.00001	0.00001	0.00001	0.00001	0.0000
Max. Number of epoch trained	1000	1000	1000	1000	1000	1000	1000	1000
Learning rate (ƞ)	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
Performance goal	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
R^2	0.99888	**0.9995**	0.99917	0.99866	0.99784	0.99915	0.99889	0.9984
RMSE	0.61538	**0.3656**	0.56195	0.62776	0.81974	0.54533	0.57367	0.7548

Table 4.5: Architectures and statistical parameters for ANNs tested for LL (cm)

	ANNs for sampling data							
Network Architecture	1:1:1	1:2:1	1:3:1	1:4:1	1:5:1	1:6:1	1:7:1	1:8:1
Min. Performance gradient	0.00001	0.00001	0.00001	0.00001	0.00001	0.00001	0.00001	0.0000
Max. Number of epoch trained	1000	1000	1000	1000	1000	1000	1000	1000
Learning rate (η)	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
Performance goal	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
R^2	0.9986	0.9996	0.9998	0.9988	0.9998	0.9997	0.9997	0.9993
RMSE	2.1858	1.2897	1.1942	2.0256	1.36	1.2456	1.1886	1.5789

4.2. Acceptance of Architecture

After the network was fully trained (the network was trained over and again for 10 times) for the Ht, G50, NEL, LW and LL, the figure 4.1 shows the regression plot graph for Ht and it was observed that the data were very close to the line of best fit. The dataset were divided to three, 70% of dataset for the training, 15% for validation and 15% for test. From figure 4.1, the correlation coefficient of determination (R^2) for the overall is 0.9999 which (PFP) to the harvest time. At this point is when the plantain plant starts to bring out the NFB (number of fingers in the bunch) and NHB (number of hands in the bunch). The planting to flowering period is around 230 days for the dataset used for this network training. However, due to slight variation in data, there is a close range of values of data before the PFP to the PFP in the dataset (see Table 4.6 for the experimental dataset of a plant), which looks like the PFP starts before 200 days from the time series response graph but looking very closely in a magnified view, the PFP actually starts after 200

is a strong correlation value for R^2. The correspon of determination (R^2) plot graph for G50, NEL, figure 4.8, figure 4.9 and figure 4.10 respectively.

Figure 4.2 shows the time series response graph plants was increasing and becomes constant at pla days. At 176 days (DAP: Days After Planting observed that the range of values were very close t become constant for all the parameters identifi parameters in this research.

Comparing the time response graph of Ht, G50, NEL, LW and LL it was concluded that there is correlation from the time series response graph of these parameters. The values were constant at the same period. See Figure 4.3, Figure 4.4, Figure 4.5 and Figure 4.6 for the time series response graph for G50, NEL, LW and LL respectively.

Table 4.6: dataset of a plant used for training.

DAP	Ht	G50	NEL	LW	LL	BW	NHB	NFB
35	28	6.5	2	18	35	0	0	0
49	38	9.5	4.8	24.5	47	0	0	0
63	50	12	7.2	31	55.8	0	0	0
77	77.2	18	10.2	39.2	77	0	0	0
92	107	27.9	13.4	49	93.5	0	0	0
105	141	29.3	16	55.5	120.2	0	0	0
121	172	38.5	19	61.2	149.7	0	0	0
133	196	47	21	72	166	0	0	0
148	218	49.8	23.2	71.5	184	0	0	0
162	257	58.8	25.4	78	201	0	0	0
176	285	67	27.4	74	214	0	0	0
190	295	70	31.8	74.6	217	0	0	0
203	322	73	31.2	74.6	217	0	0	0
217	339	68	32	74.6	217	0	0	0
232	325	70	32	74.6	217	0	7	99
246	325	70	32	74.6	217	0	7	99
260	325	70	32	74.6	217	0	7	99
273	325	70	32	74.6	217	0	7	99
288	325	70	32	74.6	217	0	7	99
302	325	70	32	74.6	217	0	7	99
317	325	70	32	74.6	217	0	7	99
321	325	70	32	74.6	217	20	7	99

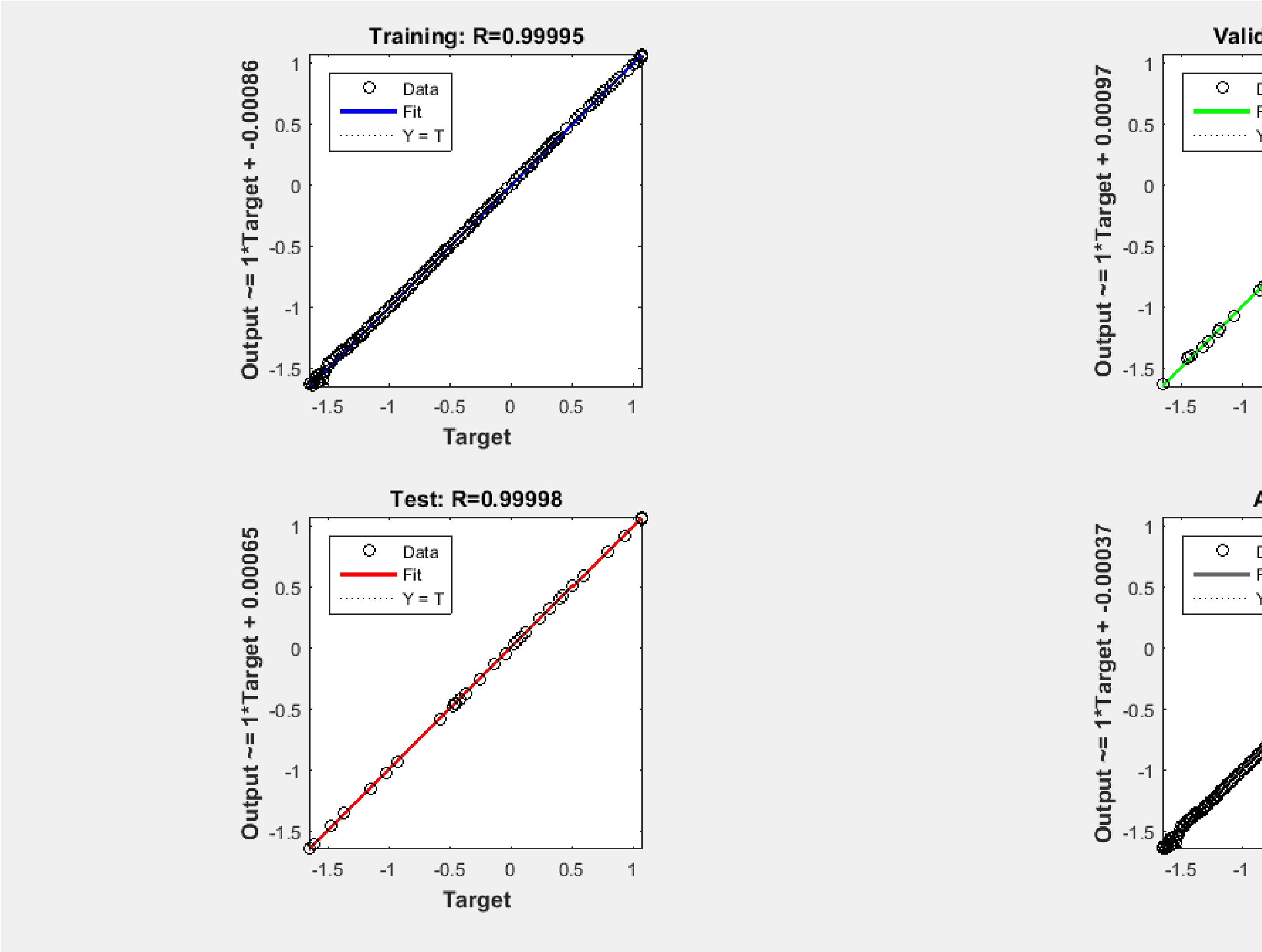


Figure 4.1: The regression plot for Ht

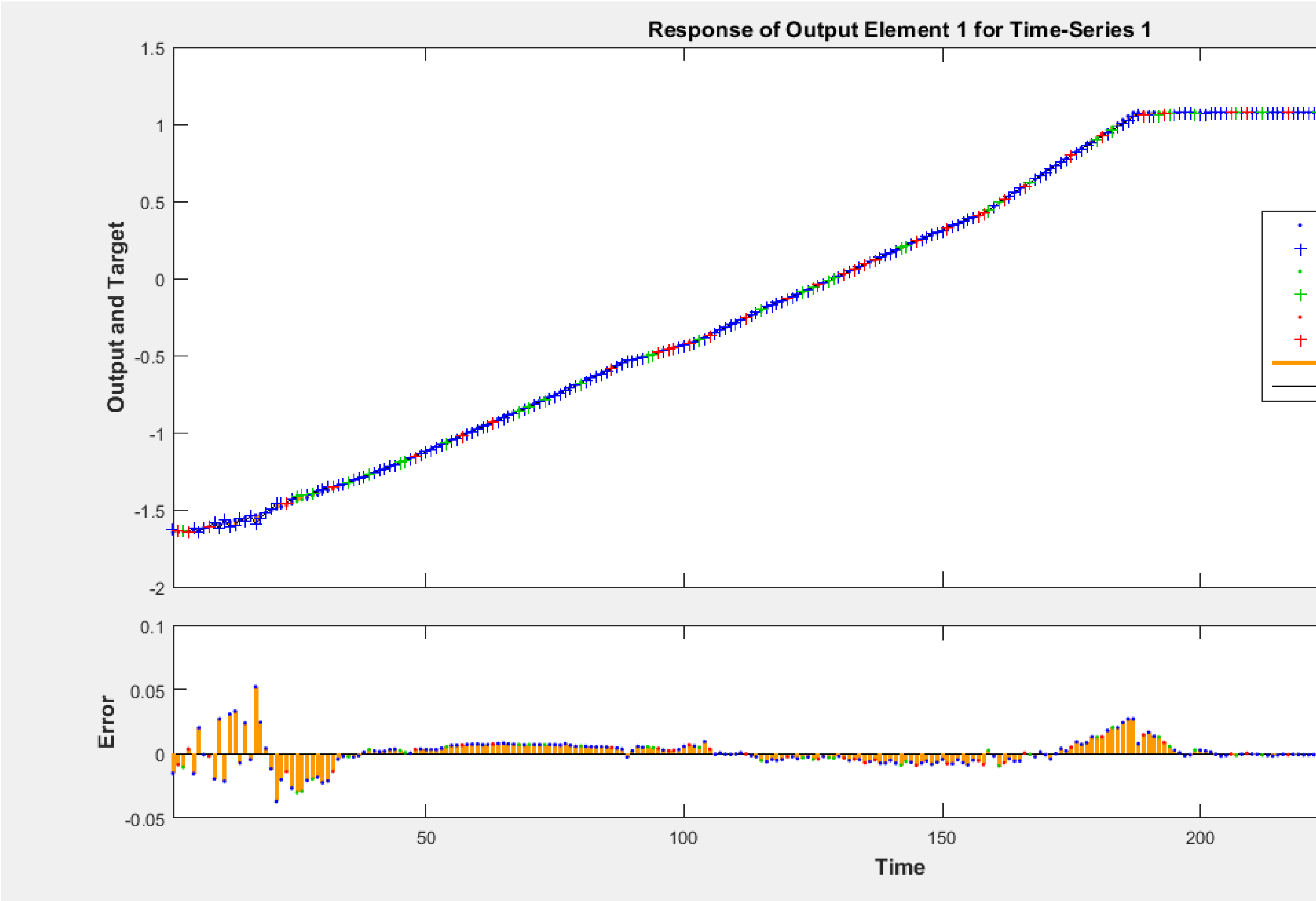


Figure 4.2: time series response graph for Ht

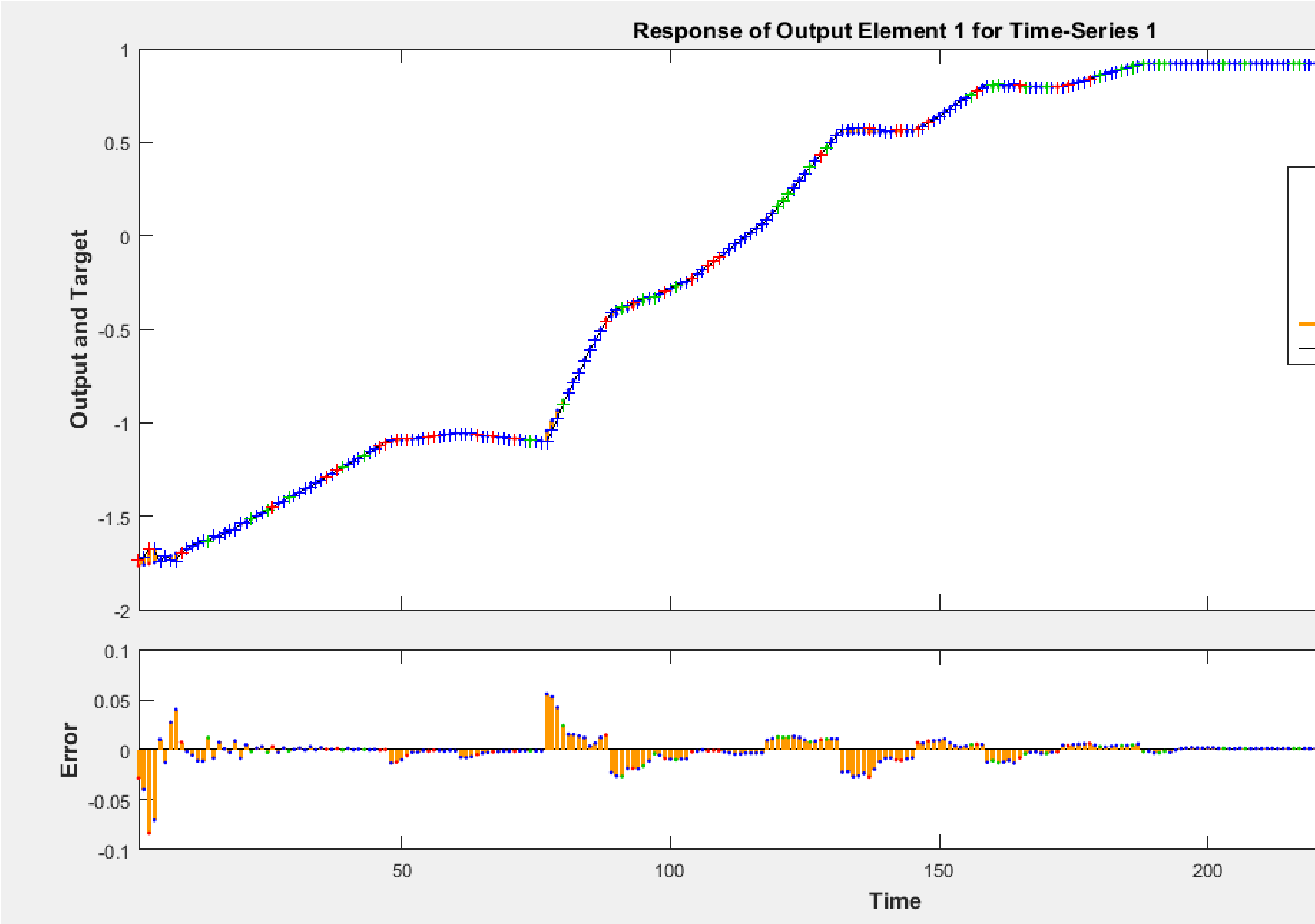


Figure 4.3: time series response graph for G50

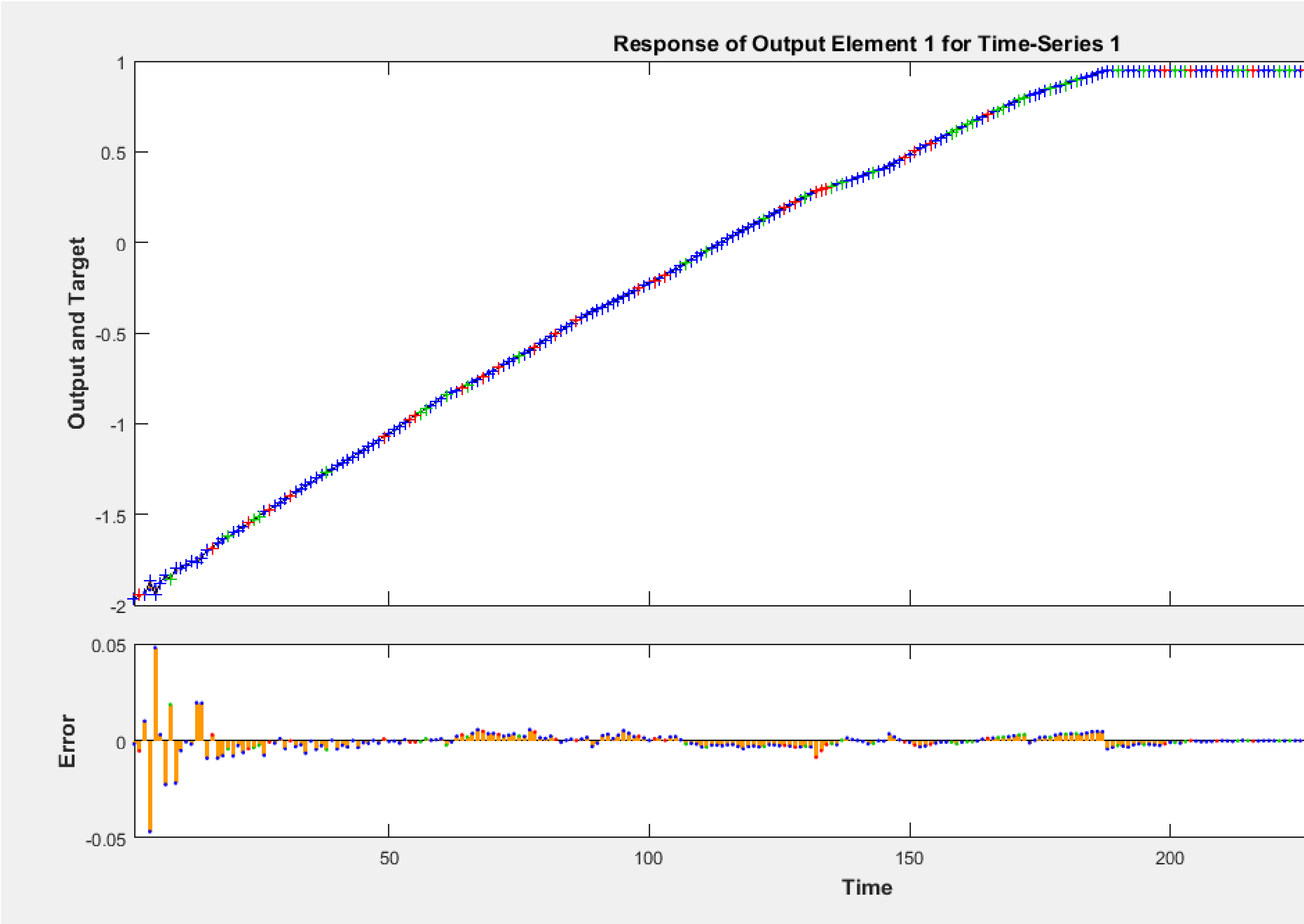


Figure 4.4: time series response graph for NEL

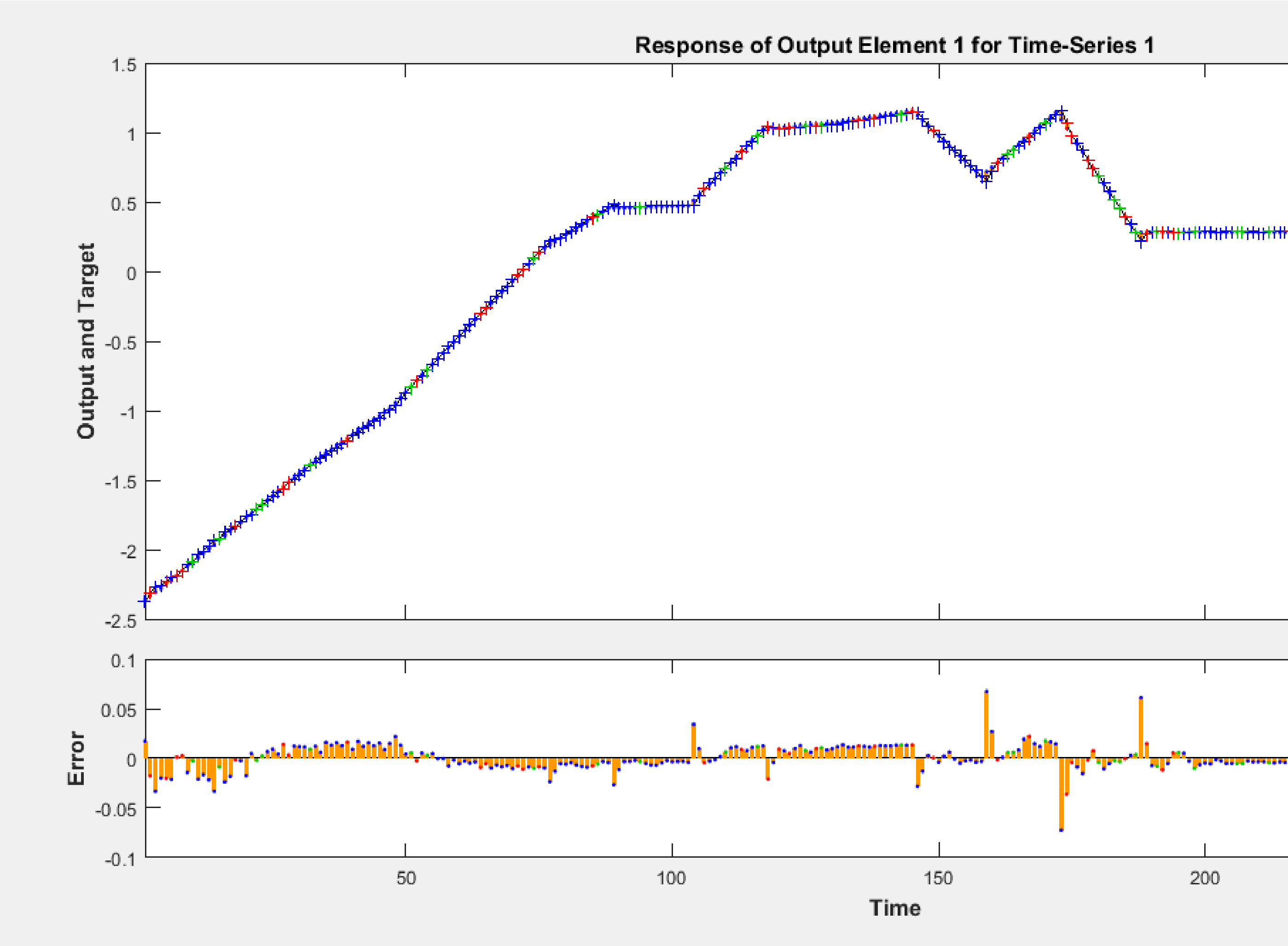


Figure 4.5: time series response graph for LW

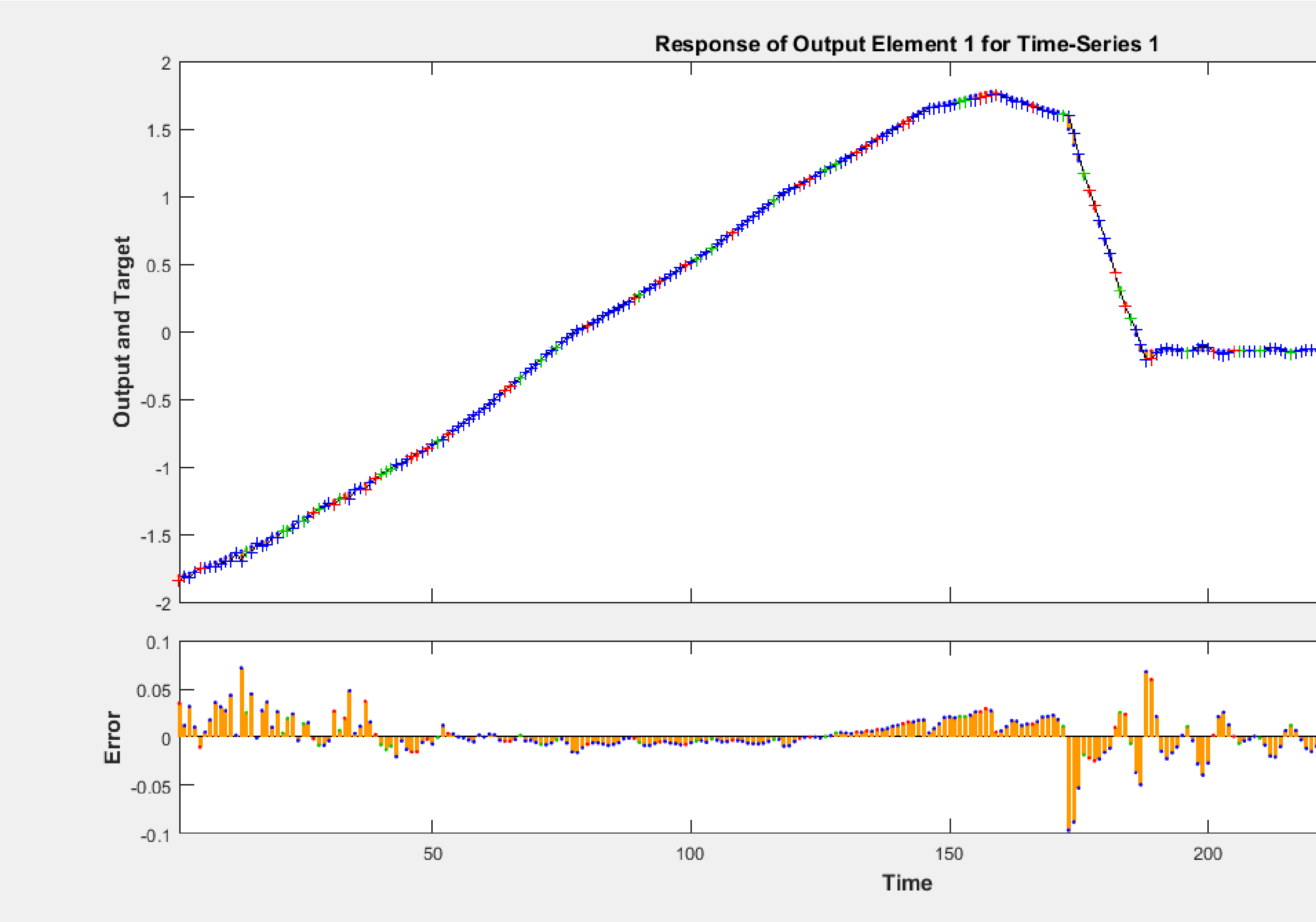


Figure 4.6: time series response graph for LL

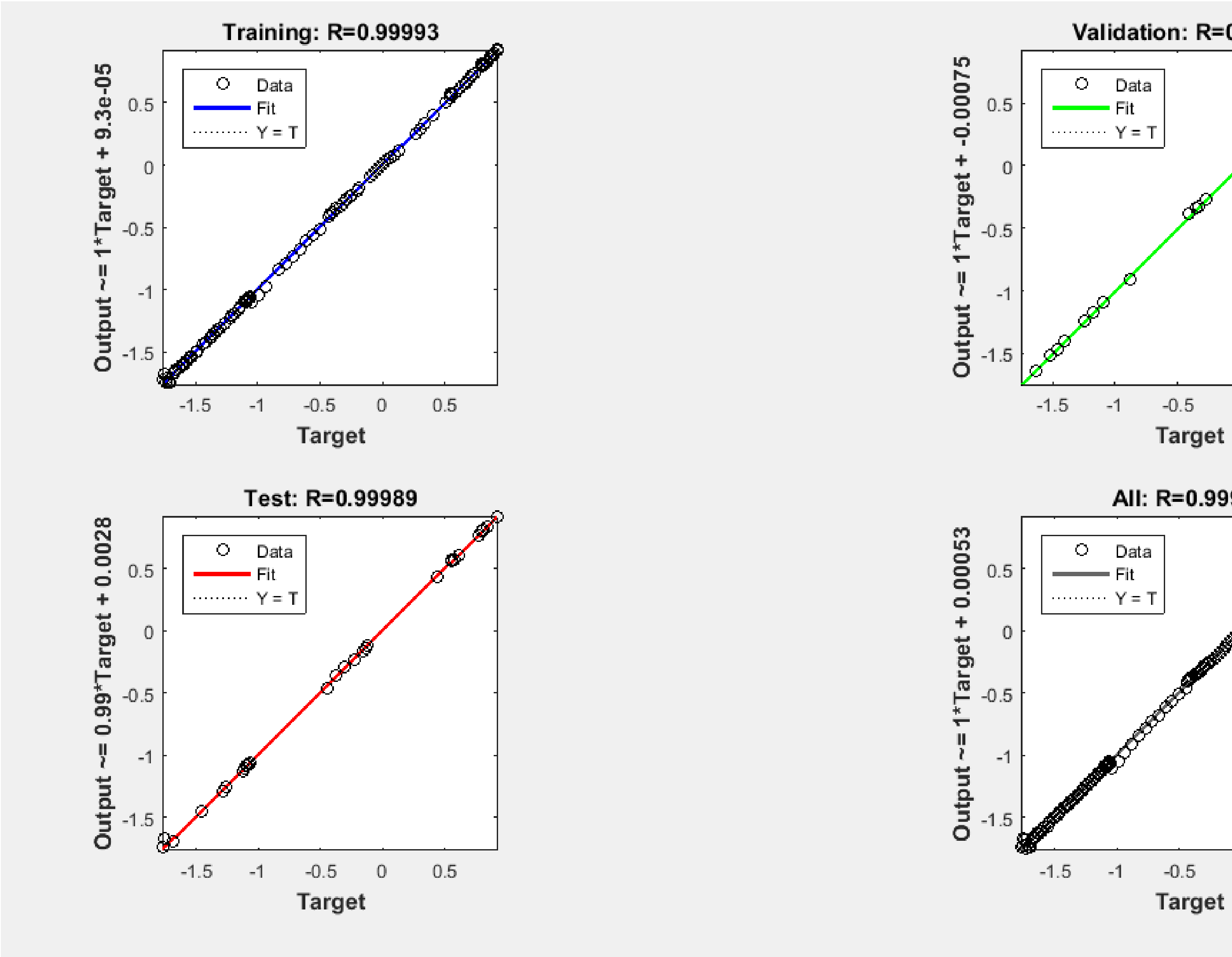


Figure 4.7: The regression plot for G50

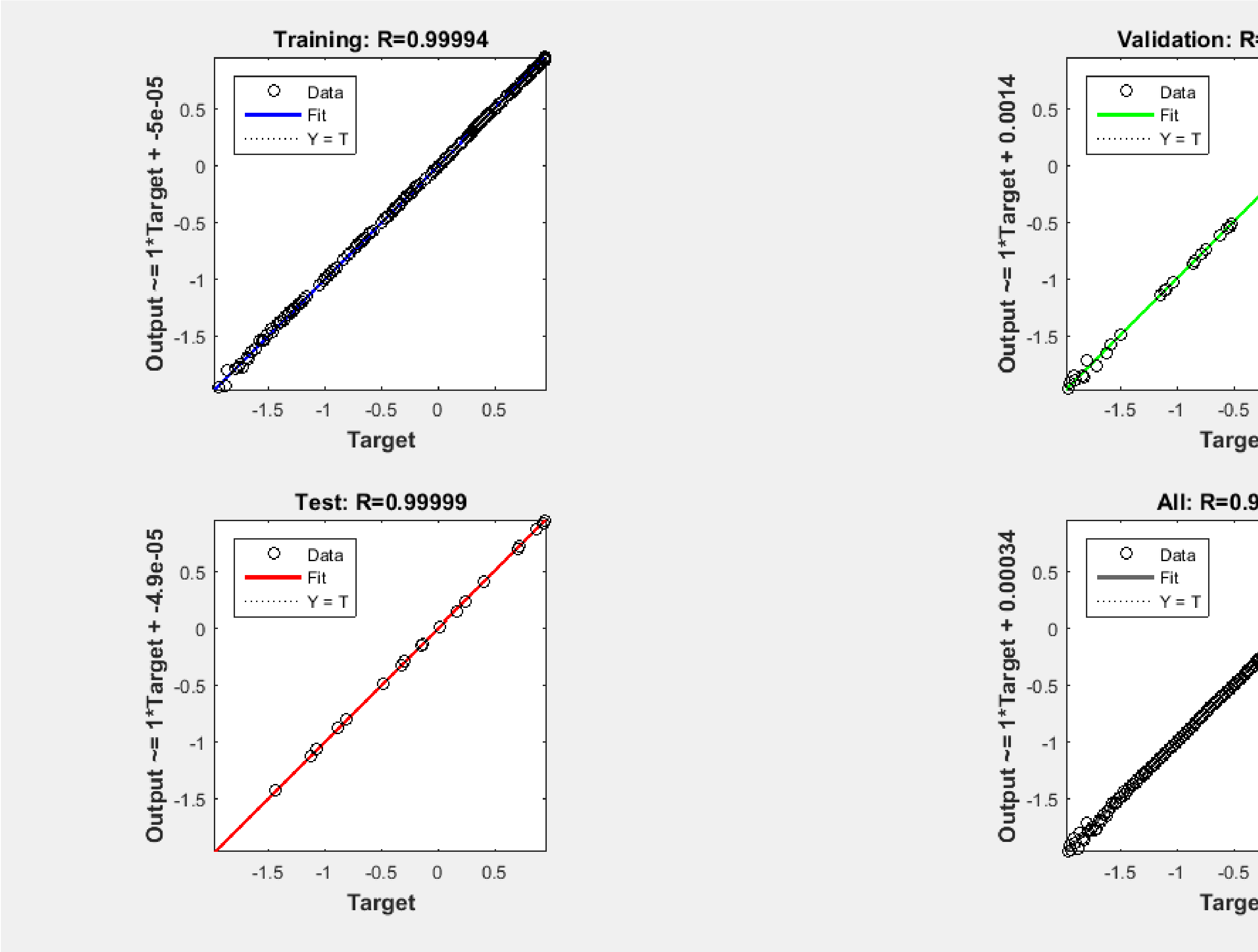


Figure 4.8: The regression plot for NEL

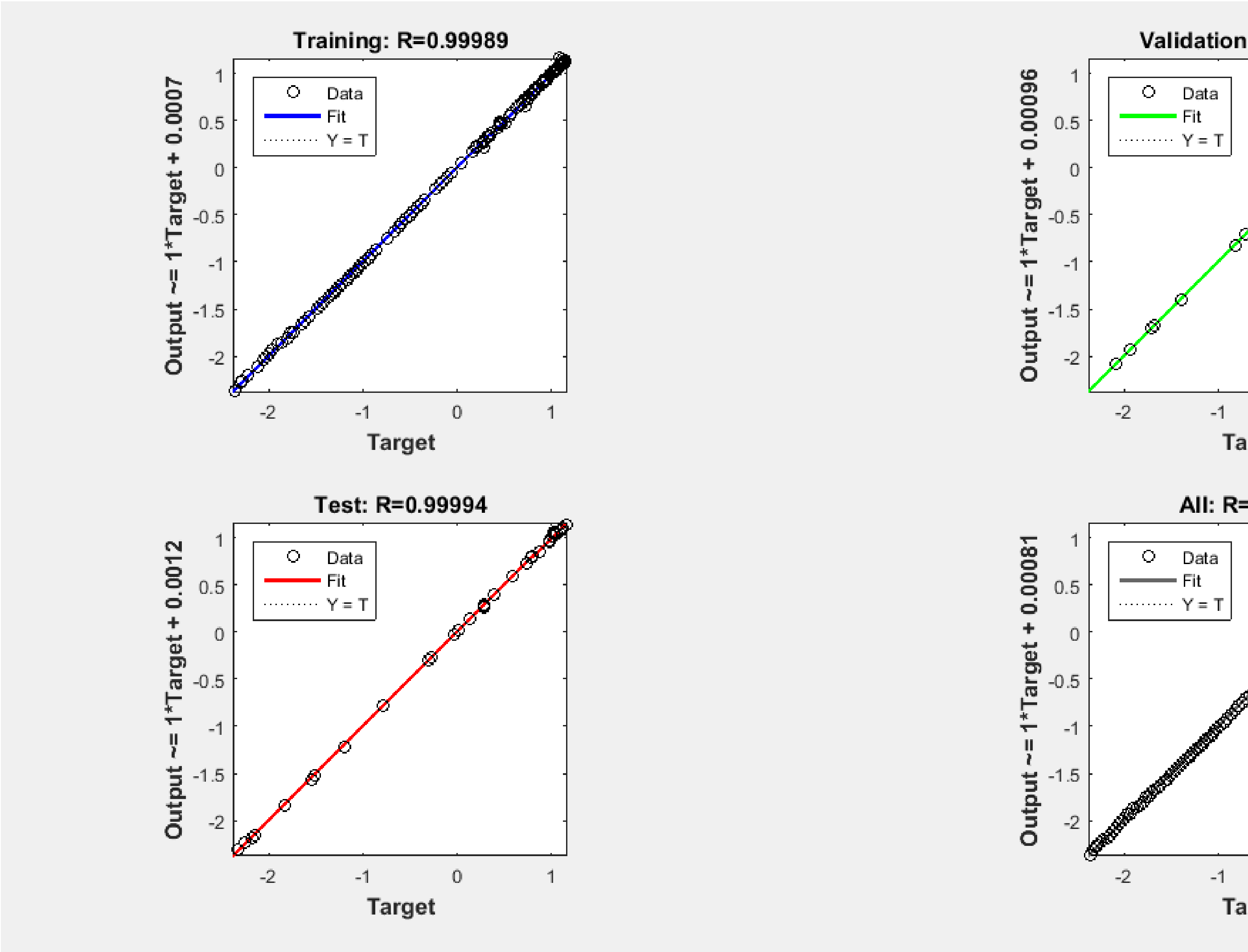


Figure 4.9: The regression plot for LW

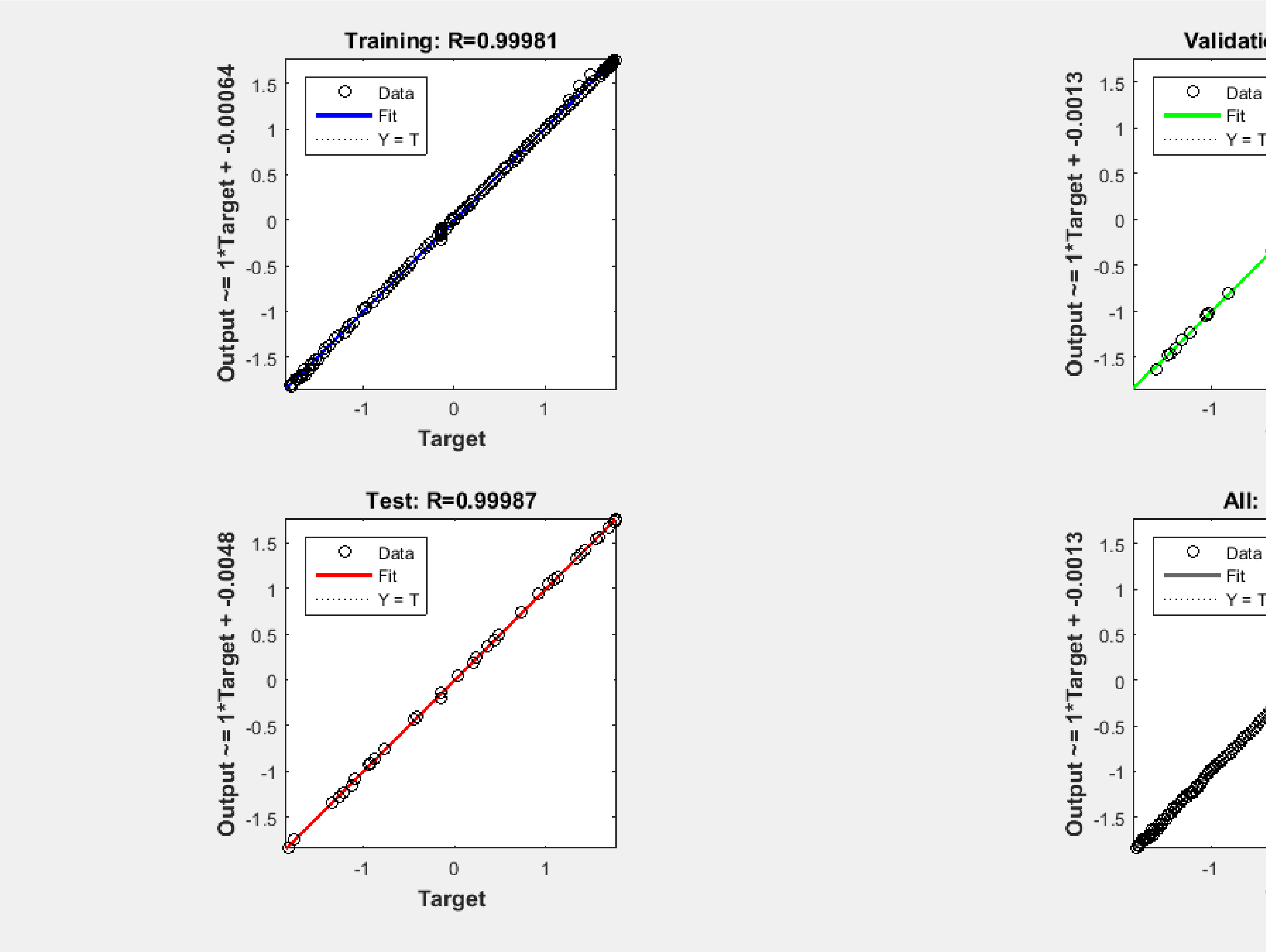


Figure 4.10: The regression plot for LL

4.3 Predicting Values

The network results of Ht, G50, NEL, LW and LL, are used to train the networks of BW, NHB and NFB. Their corresponding coefficients of determination (R^2) and the Root Mean Squared Error (RMSE) were recorded to determine the acceptance of each network architecture. See Table 4.7, Table 4.8 and Table 4.9 for the architectures and statistical parameters for ANNs tested for BW, NHB and NFB respectively and the coefficients of determination (R^2) plot graph for each of these networks, see figure 4.11, figure 4.12 and figure 4.13 respectively. There are no enough data for the neural network to train each of BW, NHB and NFB networks. However, their training results can still be accepted base on the R^2 values and the RMSE values. The architecture for BW network is 1:15:1 network is 1:25:1 and the architecture for NFB ne

After all these parameters have been trained, the ne the values of plantain height, the girth at 50 cm al of emitted leaves, leaf width, leaf length, bunch w of hands in the plantain bunch and number of fin given the known values (from the plantain sucker Ht, G50, NEL, LW and LL to the network. Data (se from the dataset of a plant ('Plantain-Optim' datas to the network, the result of the network was give

Table 4.7: Architectures and statistical parameters for ANNs tested for BW (Kg)

Network Architecture	1:5:1	1:10:1	1:15:1	1:20:1
Min. Performance gradient	0.0000001	0.0000001	0.0000001	0.0000001
Max. Number of epoch trained	1000	1000	1000	1000
Learning rate (η)	0.01	0.01	0.01	0.01
Performance goal	0.00	0.00	0.00	0.00
R^2	0.71907	0.8274	**0.8294**	0.66319
RMSE	2.422	1.9424	**1.9391**	2.6717

Table 4.8: Architectures and statistical parameters for ANNs tested for NHB

Network Architecture	1:5:1	1:10:1	1:15:1	1:20:1
Min. Performance gradient	0.0000001	0.0000001	0.0000001	0.0000001
Max. Number of epoch trained	1000	1000	1000	1000
Learning rate (ɳ)	0.01	0.01	0.01	0.01
Performance goal	0.00	0.00	0.00	0.00
R^2	0.77781	0.9224	0.89317	0.83905
RMSE	0.3730	0.2496	0.2902	0.3330

Table 4.9: Architectures and statistical parameters for ANNs tested for NFB

Network Architecture	1:5:1	1:10:1	1:15:1	1:20:1
Min. Performance gradient	0.0000001	0.0000001	0.0000001	0.0000001
Max. Number of epoch trained	1000	1000	1000	1000
Learning rate (ɳ)	0.01	0.01	0.01	0.01
Performance goal	0.00	0.00	0.00	0.00
R^2	0.88915	**0.92419**	0.91731	0.93217
RMSE	13.4241	**11.2626**	12.8368	10.7898

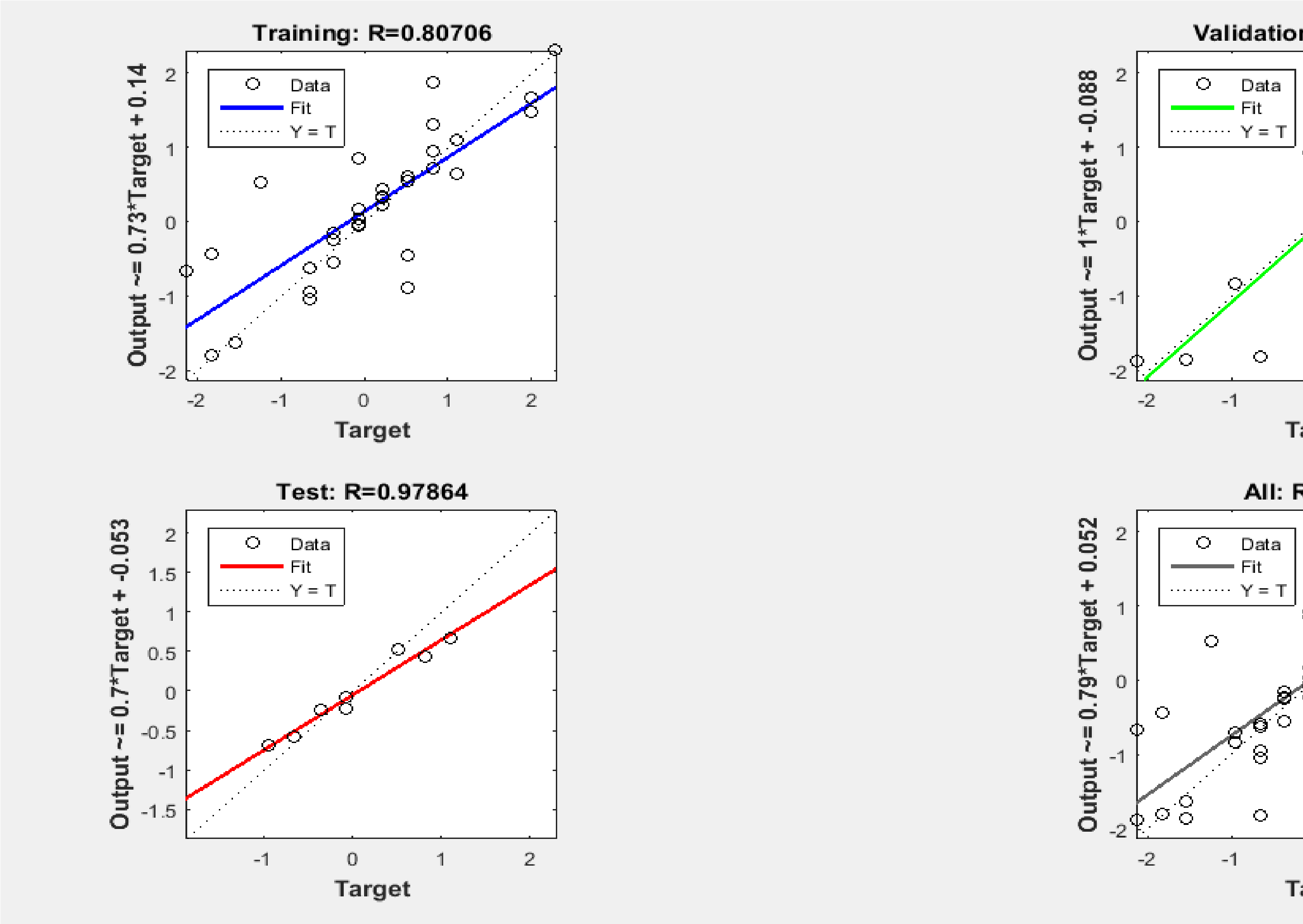


Figure 4.11: The regression plot for BW (Kg)

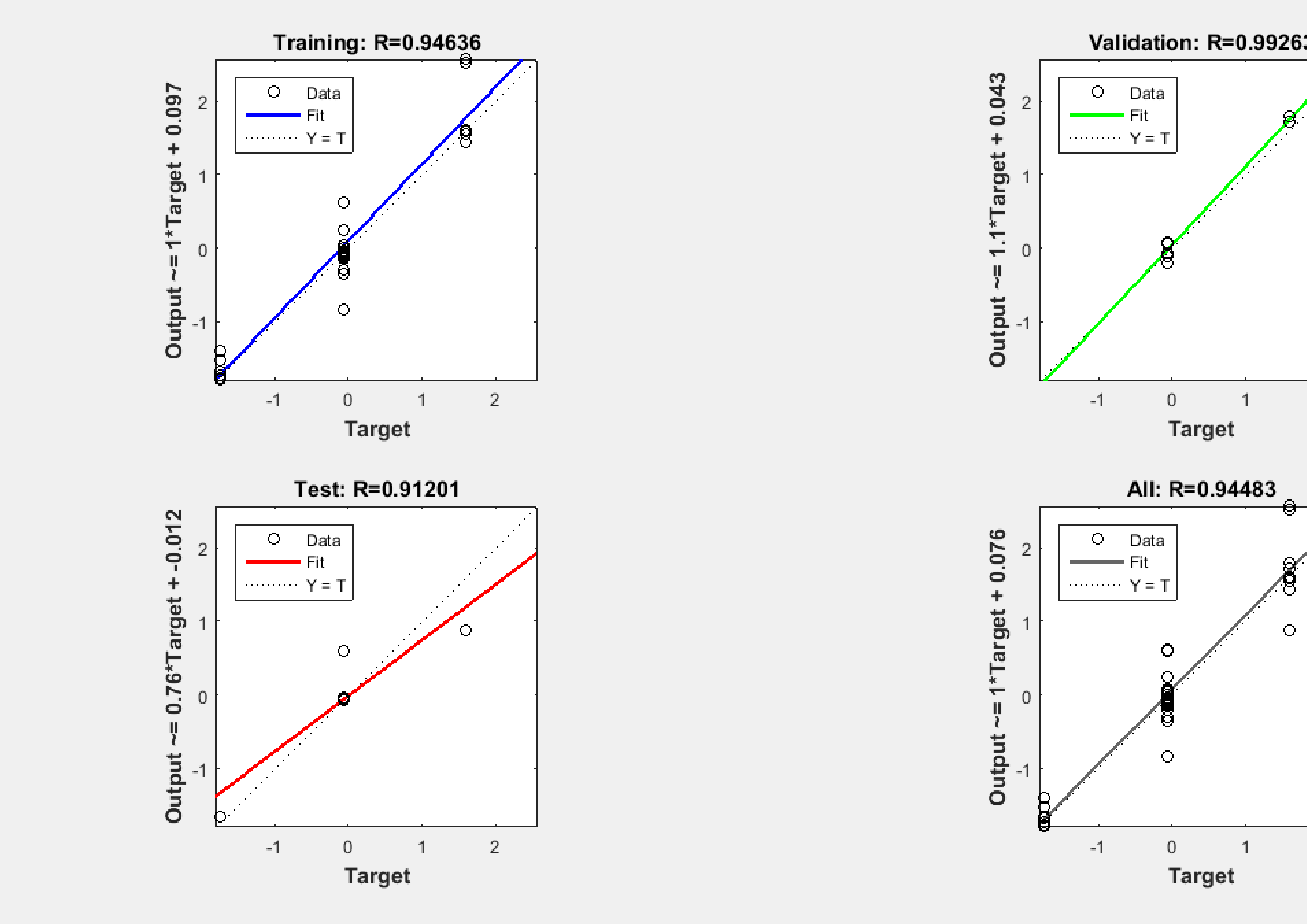


Figure 4.12: The regression plot for NHB

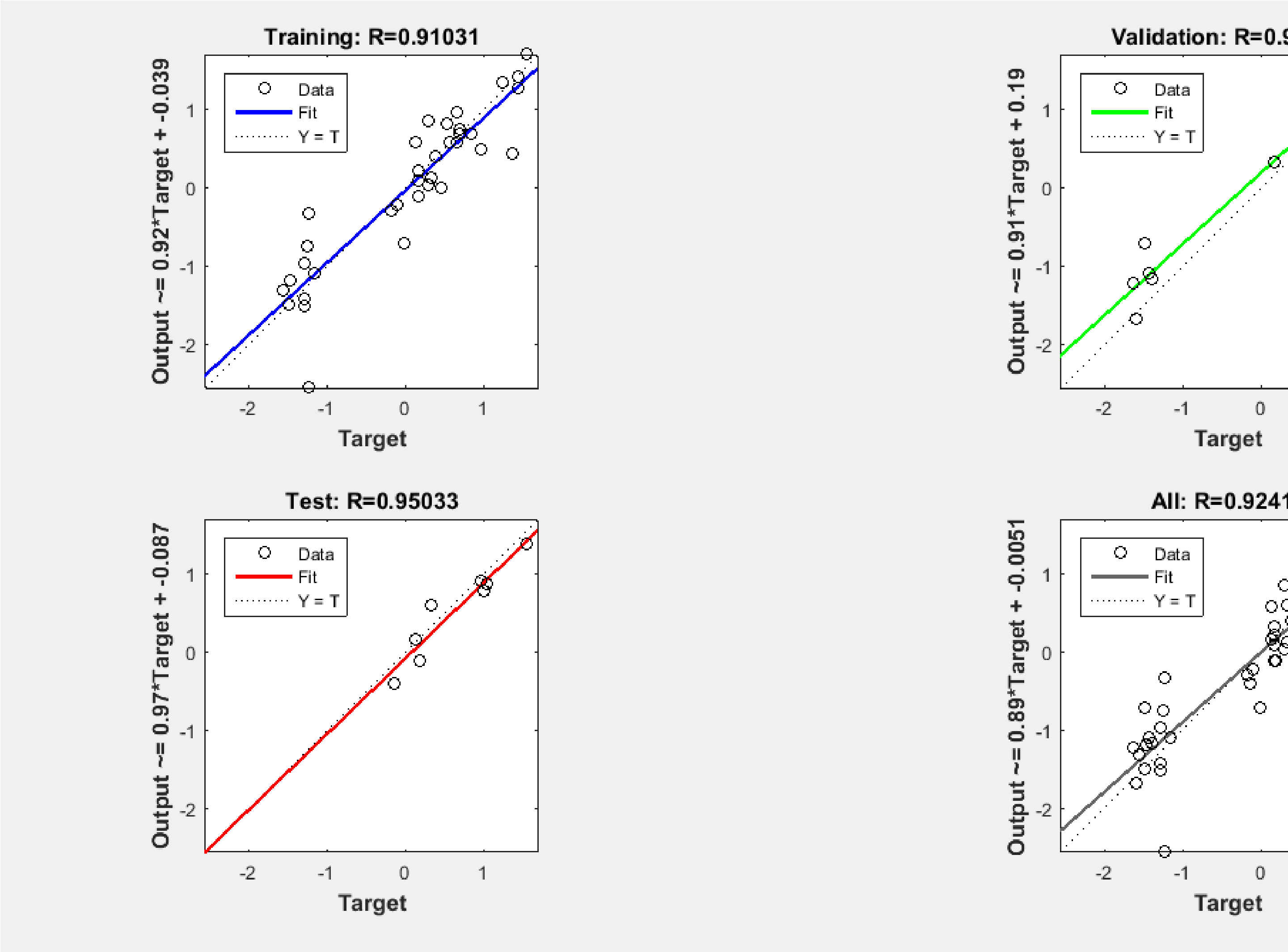


Figure 4.13: The regression plot for NFB

Table 4.10: Dataset of a plant not shown to the network during training

DAP	Ht	G50	NEL	LW	LL	BW	NHB	NFB
35	22	8	2	25	37	0	0	0
49	35	10	5	28.6	50.2	0	0	0
63	52	14	8	32	63	0	0	0
77	76.4	20.8	11	42.4	81	0	0	0
92	108	28	14.6	56	106	0	0	0
105	134	29.2	17.2	50.5	117	0	0	0
121	162	37.4	20	70	146	0	0	0
133	195	43.6	22.6	73	168	0	0	0
148	220	53	25	77.3	189	0	0	0
162	254	60.4	27.4	82	199	0	0	0
176	277	67.3	30	89	225	0	0	0
190	303	71	32	88	227.7	0	0	0
203	341	77	34.2	91	270	0	0	0
217	390	73	36.4	81	234	0	0	0
232	400	74	37	81	234	0	0	0
246	400	74	37	81	234	0	7	80
260	400	74	37	81	234	0	7	80
273	400	74	37	81	234	0	7	80
288	400	74	37	81	234	0	7	80
302	400	74	37	81	234	0	7	80
317	400	74	37	81	234	0	7	80
318	400	74	37	81	234	26	7	80

Table 4.11: Elman Network Results when DAP was 121 at current and 318 for future values

Known values to network	
Enter the number of days to future	318
Current number of days	121
Enter current value of Ht	162
Enter current value of G50	37.4
Enter current value of NEL	20
Enter current value of LW	70
Enter current value of LL	146
The network outputs for 318 days	
Predicted value of Ht to future	476.0604
Predicted value of G50 to future	31.2002
Predicted value of NEL to future	5.4523
Predicted value of LW to future	129.863
Predicted value of LL to future	296.9355
Predicted value of BW to future	49.7751
Predicted value of NHB to future	7.0331
Predicted value of NFB to future	123.4779

4.4. Evaluation of Predicted Values

The known values supplied to the network for prediction at current values was at 121 days (DAP) and the number of days to future was the harvest period at 318 (see Table 4.10). The variation in the predicted values and the experimented are summarized in Table 4.12. These variations can be explained from the table of architectures and statistical parameters for ANNs tested for each of the parameters and secondly, the sample data size used for the training is too small for training neural networ can be very more accurate with enough dataset a train. Also the dataset used has five varieties and e different variations under the same planting condi For Ht, the RMSE is 1.532, though this value is hi since the metric unit is in cm and the variation tha value is still in a margin of acceptance since we are predicting the growth of plant and all plants cannot have the same height under the same planting condition.

For G50, the RMSE is 0.2229, the result of the network can still be accepted for this parameter since the margin difference in cm is not much for a plant. However, for NEL, the margin error is too much. If network could be trained with more dataset, it would be more acceptable. accurate if network has enough data for trainin because the difference is not eligible. BW, NHB a the values obtained from Ht, G50, NEL, LW an divergence in the values of these 5 parameters outputs of BW, NHB and NFB.

Table 4.12: The variation in the predicted values and the experimented when DAP was 121 at current and 318 at future values (Elman N

Parameters	Experimented values	Predicted values	Difference
Ht (cm)	400	476.0604	76.0604
G50 (cm)	74	31.2002	42.7998
NEL (unit)	37	5.4523	31
LW (cm)	81	129.863	48.863
LL (cm)	234	296.9355	62.9355
BW (Kg)	26	49.7751	23.7751
NHB (unit)	7	7.0331	0.0331
NFB (unit)	80	123.4779	43.4779

4.5. Time-delay Neural Network compared to Elman Networks

Further research to prove the acceptance of result of the Elman neural network developed, it was observed that Elman network output saturates after specific number of steps. When it was tested on another input, when the known values supplied to the network for prediction at current values was at 63 days (DAP) and the number of days to future was at 148 days, a future day that is not the harvest period from Table 4.10. The result of the network was not really differ, no significant change between the results generated by Elman network with Table 4.11. Table 4.13 is the result outputted by the Elman network when current values of parameters were at 63 days and the expected future values were at 148 days. The values of BW, NHB, and NFB are NIL because 148 days was not the harvest period. These values only appear in real life when the harvest period is flowering period. The flowering period can be ob response graphs where the values become constan

Elman neural networks use simplified (using staticderiv - Static derivative functio connections) at the expense of less reliable learnin derivatives using the chain rule from the networ back to its inputs. For time series data and dyna ignores the delay connections resulting in an app good or not) of the actual derivative which is not recommended for dynamic networks

Further to this approach, Time-delay neural network was introduced as an option to Elman neural network and it was observed that the network result was more better than the results of Elman neural r result outputted by the Time-delay neural netwo parameters were at 63 days and the expected futur

Table 4.13: Elman Network Results when DAP was 63 at current and 148 at future values

Known values to network	
Enter the number of days to future	148
Current number of days	63
Enter current value of Ht	52
Enter current value of G50	14
Enter current value of NEL	8
Enter current value of LW	32
Enter current value of LL	63
The network outputs for 148 days	
Predicted value of Ht to future	476.0604
Predicted value of G50 to future	31.2002
Predicted value of NEL to future	5.4523
Predicted value of LW to future	129.863
Predicted value of LL to future	37.4404
Predicted value of BW to future	NIL
Predicted value of NHB to future	NIL
Predicted value of NFB to future	NIL

Table 4.14: Time-delay neural network Results when DAP was 63 at current and 148 at future values

Known values to network	
Enter the number of days to future	148
Current number of days	63
Enter current value of Ht	52

Enter current value of G50	14
Enter current value of NEL	8
Enter current value of LW	32
Enter current value of LL	63
The network outputs for 148 days	
Predicted value of Ht to future	182.1825
Predicted value of G50 to future	45.2846
Predicted value of NEL to future	25.0498
Predicted value of LW to future	69.0828
Predicted value of LL to future	124.3288
Predicted value of BW to future	NIL
Predicted value of NHB to future	NIL
Predicted value of NFB to future	NIL

4.6. Analysis of Time-delay Neural Network results

The architecture of the time delay neural network used for the variable Ht, G50, NEL, LW and LL were 1:2:1 and were only trained repeatedly 2 times except for G50 that was trained repeatedly for 3 times. The RMSE and the R^2 values selected for all the variables were recorded in Table 4.15.

Table 4.16 shows the Time delay Network Results when DAP was 121 at current and 318 at future values. The result generated and the error values were more reasonable compared to what Elman network outputted. The variation in the predicted values and the experimented, when DAP was 121 at current or present day and 318 at future values Elman network can be explained from the Table 4 Comparing the RMSE for each variable param network, it was observed that the variation in the experimental values can be tolerated for each of t delay network, however the error difference from could be expected from the architecture selected predicted more accurately the future values of pa plantain plant growth and yield.

Table 4.15: The RMSE and the R^2 values for Time delay network architecture selected

Variable Parameters	Ht	G50	NEL	LW	LL	BW	NHI
Architecture	1:2:1	1:2:1	1:2:1	1:2:1	1:2:1	5:3:1	5:8:1
Repeated training times	2	3	2	2	2	10	10
R^2	1.000	0.9999	1.000	0.9995	0.9993	0.2715	0.33
RMSE	0.6005	0.1756	0.0475	0.3524	1.1660	3.2806	0.50

Table 4.16: Time delay Network Results when DAP was 121 at current and 318 at future values

Known values to network	
Enter the number of days to future	318
Current number of days	121
Enter current value of Ht	162
Enter current value of G50	37.4
Enter current value of NEL	20
Enter current value of LW	70
Enter current value of LL	146
The network outputs for 318 days	
Predicted value of Ht to future	405.0015
Predicted value of G50 to future	74.3601
Predicted value of NEL to future	38.3278
Predicted value of LW to future	76.698
Predicted value of LL to future	155.4723
Predicted value of BW to future	21.8758
Predicted value of NHB to future	10.3096
Predicted value of NFB to future	142.0251

Table 4.17: The variation in the predicted values and the experimented when DAP was 121 at current and 318 at future values of Time delay network and Elman Network

Variable Parameters	Experimented values	Predicted values	Difference	Predicted values	Difference
		Elman Network		Time delay Network	
Ht (cm)	400	476.0604	76.0604	405.0015	5.0015
G50 (cm)	74	31.2002	42.7998	74.3601	0.3601
NEL (unit)	37	5.4523	31	38.3278	1.3278
LW (cm)	81	129.863	48.863	76.698	4.302
LL (cm)	234	296.9355	62.9355	155.4723	78.5277
BW (Kg)	26	49.7751	23.7751	21.8758	4.1242
NHB (unit)	7	7.0331	0.0331	10.3096	3.3096
NFB (unit)	80	123.4779	43.4779	142.0251	62.0251

5. SUMMARY

This research developed a scientific method using artificial neural network to predict the development growth and yield of plantain plant. Elman time series neural network, a back-propagation algorithm, with 1 input neuron and 1 output neuron with varying number of neurons in the hidden layer was employed in this research to train the parameters identified for plantain growth development. Each of these parameters, the Ht, G50, NEL, LW and LL, were tested on different architecture by varying the number of neurons in the hidden layer to know the best architecture to use. The results of these networks were used to train the BW, NHB and NFB networks. Some predicted results generated by the neural network can still be accepted as the variation in the predicted value and the experimented value are not too much. RMSE was used to know how much the predicted values deviate from the experimental values in the data set on average. The metric unit is the same unit as its variable and the predicted values by the ANNs against the experimental data were used to calculate the coefficients of determination (R^2).

Another network, Time delay neural network was employed and the result of this network was more accurate than the result of the Elman neural network even with having the dataset of different varieties of plantain plants together for training.

6. CONCLUSION

With this scientific approach for predicting the growth and yield of plantain plant, famers or plantain producers can have better conditions for planning, maximizing the efficiency of the business process without loses because it will help to plan their planting if they know the Pseudostem height of the plant sucker, Ht (cm); Pseudostem girth at 50cm above soil level, G50 (cm); Number of emitted leaves on the sucker, NEL; Leaf width, LW (cm); and the Leaf length, LL (cm) to predict into future, the values of Pseudostem height, Ht (cm); Pseudostem girth at 50cm above soil level, G50 (cm); Number of emitted leaves, NEL; Leaf width, LW (cm); Leaf length, LL (cm); Bunch weight, BW (Kg); Number of hands in the bunch, NHB and Number of fingers in the bunch, NFB of plantain plant based on the planting conditions for dataset used for training for this research. They would already know the outcome of the production and can forecast the financial expenses plan before and after which will reduce the waste of resources and increase the agricultural economy of the country if implemented. It was evidence that the neural network was able to predict future values of plantain plant growth and the yield which can help the plantain farmers to know their expected farm output before they even go into the farming. If there are enough dataset to train the network for each variety of plantain plant, there could be more accuracy in the result than having all the varieties together.

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International Journal of Computer Applications Technology and Research
Volume 8–Issue 06, 269-271, 2019, ISSN:-2319–8656

Research on 5G Miniaturized Quasi-Yagi Antenna

Meng Li
School of Communication Engineering,
Chengdu University of Information Technology
Chengdu, China

QiuQiang Luo
School of Communication Engineering,
Chengdu University of Information Technology
Chengdu, China

Hao Zou
School of Communication Engineering,
Chengdu University of Information Technology
Chengdu, China

Jiaming Xia
School of Communication Engineering,
Chengdu University of Information Technology
Chengdu, China

Abstract: This paper proposes an improved miniaturized quasi-Yagi antenna that works in the 5G millimeter wave band. Compared with the traditional quasi-Yagi antenna, reasonable use of the layout can reduce the longitudinal space of the antenna, greatly reducing the size of the antenna to a size of 15 mm ×26mm×1mm.,This antenna achieves a measured 43.8%(23.7-37GHz) frequency bandwidth for voltage standing-wave ratio 2 has a wider bandwidth. The maximum measured gain of the antenna is 7.41dBi at 29GHz and yhe minimum is 4.44dBi at 32GHz .Meet the efficiency requirements of 5G millimeter wave mobile communication systems
Keywords: millimeter wave; Miniaturized; Microstrip; quasi-Yagi antenna; Broadband.

1. INTRODUCTION

The position of the antenna in the entire radio communication system is very important, quality is directly affecting the distance and communication effect of the transmission and reception distance. It can be said that there is no radio communication without the antenna. As a kind of antenna with simple structure and good orientation, Yagi antenna has been studied by many experts and scholars at home and abroad, and is also widely used in various communication systems[1-2]. However, the traditional Yagi antenna is bulky and costly. Microstrip antennas are widely used due to their small size, light weight, simple manufacturing, and easy conformality. With the development of microstrip antenna technology, the design principle of Yagi antenna is combined with microstrip technology, which is called "quasi-yagi antenna"[3]. Y. Qian et al. first applied microstrip technology to Yagi antenna design [3]. Therefore, the miniaturization of Yagi antenna has become a hot topic in today's society. The bow-tie antenna is considered to be the starting point for the development of a miniaturized model with similar characteristics [4-5]. Mr tang of Huaqiao University and others have made the substrate size of the antenna only only 1/3 of the free wavelength of the center frequency through reasonable layout and glory loading technology, and relative bandwidth is 42.6%, but the gain is only 4dBi. Based on this research, this paper designs a miniaturized quasi-Yagi antenna that works in the 5G high frequency band to achieve extremely wide bandwidth (48% for VSWR 2 measurement).

2. QUAI-YAGI DESIGN

Figure 1 shows the general shape of a ternary quasi-yagi antenna. The antenna consists of a port, a 50 Ω feed line, an impedance transformer, a balun transformer, a director, and a reflector.

As can be seen from the figure 1, the space under the unused portion of the conventional quasi-Yagi antenna is too large. Therefore, we improve the antenna according to the rational layout and capacitive loading technique in [6]. Design the shape of the director to resemble a bow shape, slightly modifying the shape of the balun transformer。The designed antenna is shown in figure 2.

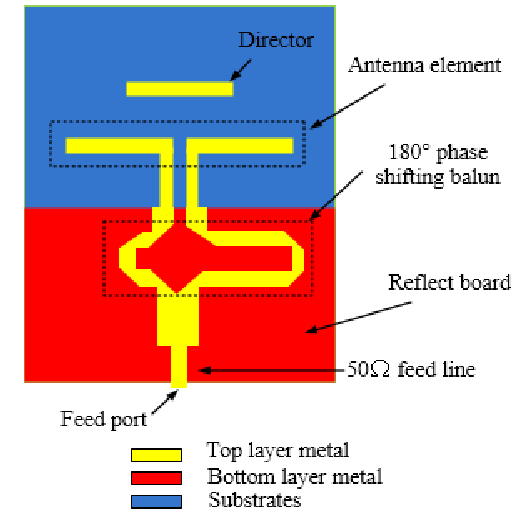

Figure. 1. traditional of the quasi-Yagi antenna

Figure 2 shows the layout of the designed quasi-yagi antenna. The antenna is fabricated on a substrate of material FR4 (substrate thickness h is 1 mm). The bottom consists of a "U"-shaped copper plate. The top-level quasi-yagi antenna passes through a reasonable layout, and the distribution is more concentrated than the traditional quasi-yagi antenna in Figure 1. The backside conductor of the substrate designed to be "U" shaped serves as both the ground for the microstrip line circuits (ports, feeders, impedance transformers and baluns) and also acts as a reflector to the antenna. There is a big breakthrough in the traditional rectangular bottom plate.

The design of the antenna in figure 2 maintains the use of a truncated ground plane as the reflector element. The driven printed dipole is used to generate TE_0 surface waves with very small undesired TM_0 content [6]. In this optimized quasi-Yagi design, the antenna director components are

variable	length	variable	length	variable	length
W	7.125	fl1	6.2	fs1	2.7
L	14.25	fl2	9.4	fs2	4
fw1	1.8	fl3	2.4	fs3	4.425
fw2	2.7	fl4	3.2	rl1	6.1
fw3	1.8	bl1	11.2	rl2	6.1
fw4	3.2	bl2	3.6	bw	1.8
fw5	3	fd	2.2	rw	1.8

Table 1. Antenna parameter table (unit:mm)

shorter than conventional quasi-Yagi antenna designs, contributing to a wide range of antenna band characteristics.

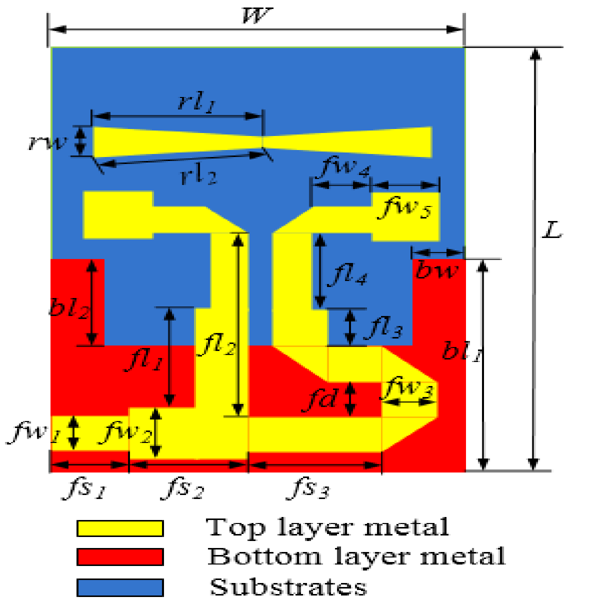

Figure.2.Schematic of the quasi-Yagi antenna.

3. SIMULATIONS

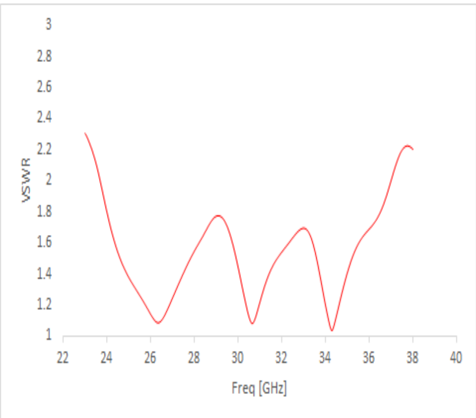

Figure.3. Voltage standing wave ratio

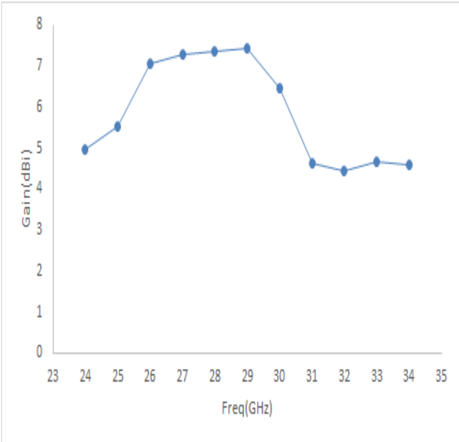

Figure.4. Gain of Antenna

It can be seen from the figure 3 and figure 4 that we have achieved extremely broad bandwidth (measured 48% for VSWR 2) in23.7-37-34 GHz in the 5G FR2 band, which meets the requirements in the millimeter wave band. The maximum measured gain of the antenna is 7.41dBi, which is 3.5dBi higher than the gain in general literature, and the size is only 15mm×26mm×1mm, which realizes the miniaturization of the quasi-Yagi antenna.

4. CONCLUSION

This paper proposes a miniaturized quasi-Yagi antenna, which saves space by changing the layout of the antenna and the change of the shape of director and the balun transformer. The size of the antenna is 15mm×26mm×1mm. The director is designed as a bow shape, which expands the bandwidth of the antenna. This antenna achieves a measured 43.8% (23.7-37GHz) frequency bandwidth for voltage standing-wave ratio 2, and have a wider bandwidth. In the same kind of literatures, the antenna size is smaller and the gain is higher, and can be used in 5G mobile communication systems and other wireless communication systems in the frequency band, and has high engineering practical value.

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