



# Research Journal of Pharmaceutical, Biological and Chemical Sciences

## Enhancing Agricultural Productivity Using Zigbee Based Low-Cost Field Sensor Embedded Device and Prediction Models

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### ABSTRACT

For enhancing agricultural productivity, a zigbee based field sensor embedded device (FSED) that senses parameters like humidity, soil moisture and temperature has been proposed. The soil moisture conditions in the near future are predicted using prediction models based on Auto Regressive Moving Average (ARMA) technique and neural networks (NN). The predicted conditions aid the farmers in planning for the type of crop to be cultivated, amount of water and power supply required well ahead of time. The proposed FSED was tested in two different agricultural fields in Tamil Nadu, India.

**Keywords:** Field sensor embedded device, microcontroller, neural networks, prediction model, soil moisture, zigbee

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## INTRODUCTION

India is a country where in agriculture is the main livelihood of a huge majority. A major cross-section of the people who are into agriculture is illiterate and lives below the poverty line. They depend mostly on the benefits from Government policies and other Non-Governmental Organizations (NGOs). Availability of user-friendly low-cost technology for farming will be helpful for them in improving their agricultural productivity.

In the present scenario, the water requirement of a particular field depends on the type of crop grown. The farmer will generally have an inherited knowledge about it. Unfortunately, the lives of these farmers have been made miserable by the uncertain weather conditions, depleting water table and long power shutdowns. This paper attempts to provide solutions to these trouble-stricken farmers by providing a low cost FSED. This helps them in regulating the water supplied to the agricultural field, maintaining the required soil moisture, increasing productivity and also conserving electricity.

A brief survey on the previous research works carried out in this area has been presented here. The applications of wireless sensor networks (WSN) are widespread [1]. There have been a considerable number of WSN- based applications, specially for agricultural needs in the recent years. Oliver et al. designed and evaluated the effectiveness of a reactive soil moisture wireless sensor network [2]. A detailed review on apparent soil conductivity measurements in agriculture has been presented by Corwin and Lesch [3]. Kim et al. proposed a new WSN architecture with autonomous robots based on beacon mode for real time monitoring of agricultural system [4]. A comprehensive review on the recent developments and future prospects of wireless sensors in agriculture and food industry has been presented by Wang et al [5]. Garcia-Sanchez et al. developed wireless node prototypes for providing agricultural data monitoring, motion detection, camera sensor and long distance data transmission [6]. An artificial neural network based approach to estimate the stem water potential has been presented by Marti [7]. Temperature, relative humidity, solar radiation and soil moisture at 50 cm were used as input variables for the regression equation. Precision agriculture aims at addressing the within-field variability and optimizes the inputs within the fields. A low-cost microcontroller-based system to measure and record canopy-, soil- and air temperature and soil moisture in cropped fields has been proposed by Fischer and Kebede [8]. Sudduth et al. investigated the accuracy issues in electromagnetic induction sensing of soil electrical conductivity for precision agriculture [9].

Vijayakumar and Rosario have proposed the use of motes for sensing external parameters like soil moisture, soil pH and atmospheric pressure to regulate the watering of fields and selecting the right quantity of fertilizers [10]. Since the use of motes is a very costly affair, the proposed new design based on FSED is a very cost effective and attractive alternative. The methodology proposed here has an inbuilt prediction system whose time horizons can be changed as per requirement. The microcontroller, which is the heart of the device, holds the responsibility of turning on and off the water pump depending on the input from soil moisture sensor. The block diagram of the entire work can be seen in Fig.1.

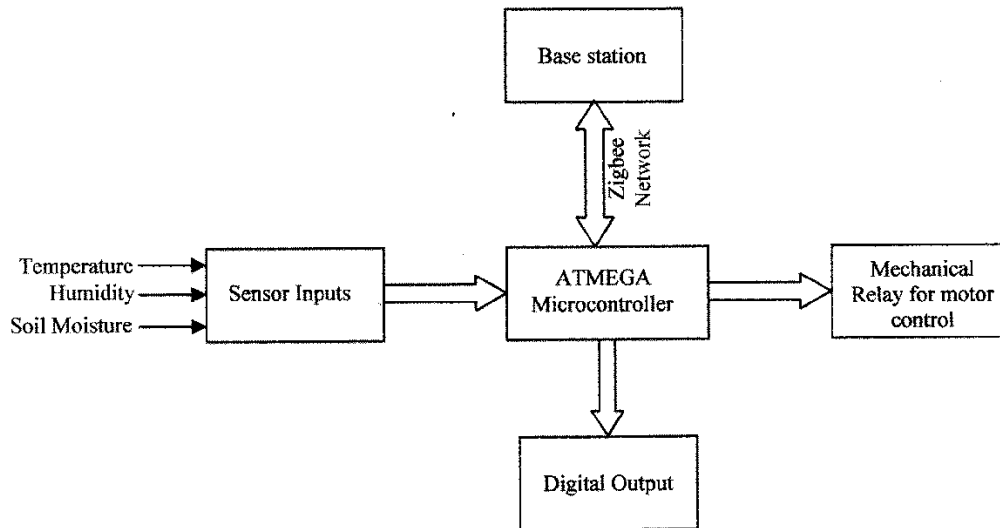


Figure 1: Block diagram

### PREDICTION OF ENVIRONMENTAL PARAMETERS

Forecasting plays a significant role in planning and controlling every area of life. The need for forecasting holds great importance especially in the area of agriculture as it is highly dependent on several random atmospheric parameters and power supply. Prediction models built using appropriate techniques can be stored in the base station. The prediction horizon, data, methodology and accuracy suited for this application has been discussed in detail in this section.

#### Prediction horizon

Prediction horizon of a particular parameter of interest is defined as the time period in future for which it will be forecasted [11]. A very short term prediction horizon may span from few minutes up to an hour. Short term horizon spans over 1 to 12 hours, medium term may span over days and long term can span over months for this particular application. A prediction algorithm with a very short prediction horizon will give the value of soil moisture for the next 30 minutes or so, to alert the farmer regarding the amount of water and power supply required. A prediction algorithm with long term horizon will aid the farmer in planning for the type of crop he can grow, fertilizers, finance, power supply etc. required.

#### Prediction data

Time-series analysis of any data helps in description, modeling, forecasting and control. In this paper, the time-series data of soil moisture is used to predict its future values. Soil moisture refers to the water contained in the soil pores. Soil solution, which is made up of dissolved salts, is an important medium for supply of nutrients to growing plants. Soil water regulates soil temperature and determines the crop yield. It also helps in the chemical and biological activities of the soil and is a principal constituent of the growing

plant [12]. Hence it can be concluded that a significant increase in crop yield can be obtained by maintaining optimum level of soil moisture.

In this paper, a cost effective circuit called FSED has been proposed for measuring the soil moisture and other related parameters like temperature and humidity of a particular field. The predicted values enable the farmers to think in advance about the power requirement and plan accordingly. As the soil moisture content depends on atmospheric temperature, humidity and other environmental parameters, the long-term prediction model has also been built based on this.

### Choice of Land

Soil moisture and pH basically differs with the kind of crop grown in a particular field. Hence the data collected in different fields may vary from each other. Two different sets of time-series soil moisture data have been collected from two types of agricultural lands.

#### Case 1: Land yet to be tilled

An open field, which was being prepared for growing crops, was chosen and the soil moisture was noted down using soil moisture sensor.

#### Case 2: Land with sugarcane plant

A field with sugarcane plant was chosen and the readings of soil moisture were observed using moisture sensor.

Case 3: This is a special case chosen for two reasons: To study the impact of long term predictions for which the time horizons may range in months and secondly to study the impact of external variables like temperature and humidity on soil moisture. To illustrate this, four months data obtained from Tamil Nadu Agricultural University, Coimbatore, India was used (Fig. 2). The data of atmospheric temperature and humidity have been used as predictors for soil moisture.

### Prediction Methodology

Two different prediction methodologies have been used in this paper, the linear ARMA method and neural networks.

#### ARMA method

Time series data can be used to estimate parametric autoregressive (AR), autoregressive and moving average (ARMA) and state-space time-series models. In this paper, ARMA models have been used to model the soil moisture data. The ARMA model for the single-output time-series is given by the following equation:

$$A(q)y(t) = C(q)e(t) \quad (1)$$

where  $y(t)$  is the output signal at time  $t$ ,  $e(t)$  is the white noise at time  $t$  and  $q$  is the backshift operator.  $A(q)y(t)$  is the autoregressive (AR) part and  $A(q) = 1 + a_1q^{-1} + a_2q^{-2} + \dots + a_{n_a}q^{-n_a}$ , where  $a_1, \dots, a_{n_a}$  are the parameters of AR part and  $n_a$  is the AR order.  $C(q)e(t)$  is the moving average (MA) part and  $C(q) = 1 + c_1q^{-1} + \dots + c_{n_c}q^{-n_c}$  where  $c_1, \dots, c_{n_c}$  are the parameters of MA part and  $n_c$  is the MA order [13].

The time series data of soil moisture is used to build ARMA models, which are tested for very short term horizon.

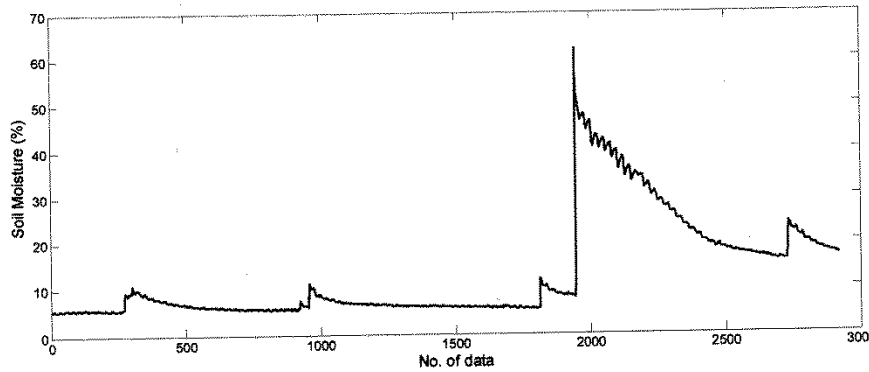


Figure 2: Hourly data of soil moisture from June 2010 –September 2010

### Neural Networks

Artificial Neural Networks (ANN) refers to a network of highly interconnected and functionally related artificial neurons. They can be used for prediction, association and classification upon proper training. Input vectors along with target vectors are used to train the network and the performance of the network will be tested by simulating its performance using test data comprising of only input vectors. The accuracy is calculated based on the difference between the actual target of the test data and the predicted value.

### Prediction Accuracy

The performance of the models was evaluated using Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) as performance metrics.

$$MAE = \frac{1}{N} \sum_{i=1}^N |M_e(i) - M_a(i)| \tag{2}$$

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^N (M_e(i) - M_a(i))^2} \tag{3}$$

where  $M_e$  is the estimated soil moisture,  $M_a$  is the actual soil moisture and  $N$  is the total number of data.

## CIRCUIT DIAGRAM AND DESCRIPTION

The low cost FSED consists of an Atmega microcontroller with arduino bootloader, 7805 voltage regulator, capacitors, humidity DHT11 sensor, temperature sensor, soil moisture sensor, 20 MHz crystal oscillator, 9V battery (or) 5 volt DC adapter, 6V relay for water pumping motor control (Fig. 3).

The FSED is designed to be a monitoring system which caters to the requirements of small and marginal farmers. It is a portable, reliable, easily affordable device that can be manufactured locally. It determines significant thresholds in soil moisture, and monitors the air temperature, humidity, etc. Through FSED the water usage efficiency can be improved up to 60 to 80 percent, compared to the traditional surface irrigation techniques. It also helps in improving the farming strategies in the face of highly variable conditions, particularly for the risk management strategies (choice of crop varieties, sowing and harvesting periods, prevention of pests and diseases, efficient use of irrigation water etc).

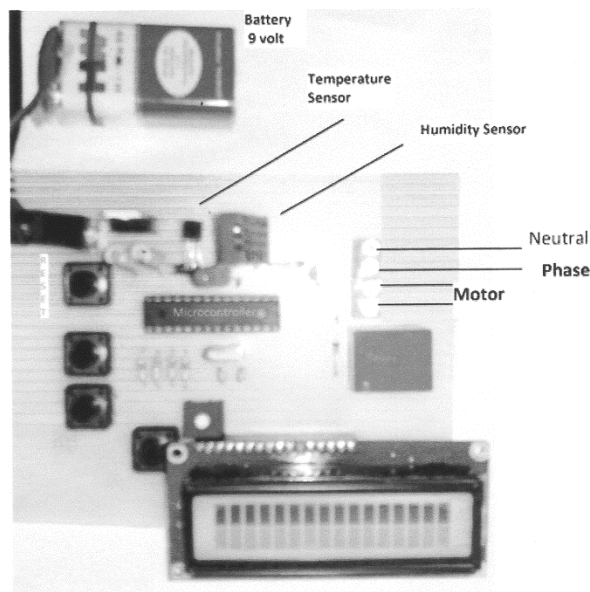


Figure 3: Components of FSED

### Working of FSED

The ATMEGA microcontroller is a high-performance, low-power Atmel 8-bit AVR RISC-based microcontroller with 32kB of programmable flash memory, 2kB of static random access memory and 8-channel 10-bit analog to digital converter. The microcontroller is programmed using a Arduino bootloader. The XBee PRO S2B module (Fig. 4) has been used for implementing the zigbee network. It has improved power output and data protocol of the Pro Series 2. Series 2 modules facilitate the creation of complex mesh networks. It has a range of 90m indoors or 3200m outdoors. It can be directly connected to the serial port of the microcontroller or can be interfaced to 5V Transistor-Transistor Logic (TTL) devices having serial interface. The application discussed in this paper requires a minimum of three sensors – temperature, humidity and soil moisture. Fig. 5 shows the DHT11 temperature

and humidity sensor that has been used for this purpose. It is relatively inexpensive and performs well.

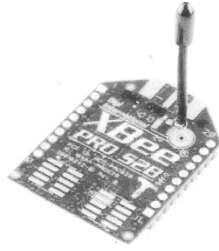


Figure 4: Xbee PRO S2B wireless zigbee communication module

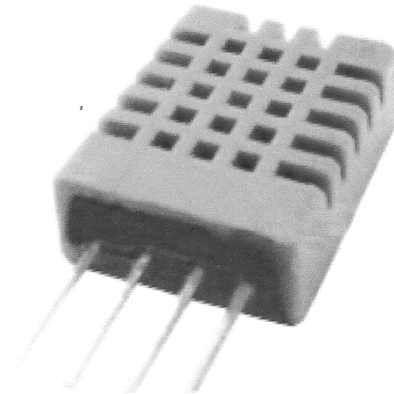


Figure 5: DHT11 temperature and humidity sensor

A soil moisture sensor (Fig. 6) reads the amount of moisture content in the soil. This sensor uses two probes to pass current through the soil and then it reads the resistance to get the moisture level. When the moisture content of the soil is more, a large current flows, implying lesser resistance. A dry soil allows a very little current, implying high value of resistance.

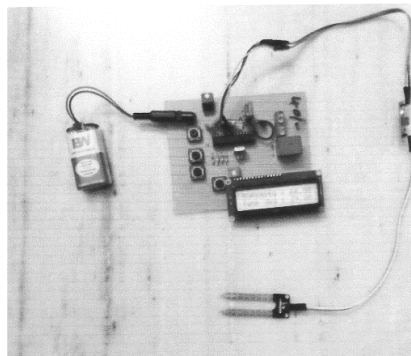


Figure 6: Soil Moisture sensor

### Water pumping motor control

The water pumping motor control is programmed based on the soil moisture content. Fig. 7 shows the logic of this module. The current moisture content value ( $M_c$ ) is obtained from the sensor and it is compared with the threshold moisture content ( $M_{th}$ ). The value of  $M_{th}$  basically depends on the crop that is being grown and can be set accordingly.

$M_c$  is compared with  $M_{th}$  and if it is lesser, the water pump is turned on. The switching off of the water pumping motor is carried out by continually monitoring the moisture content.

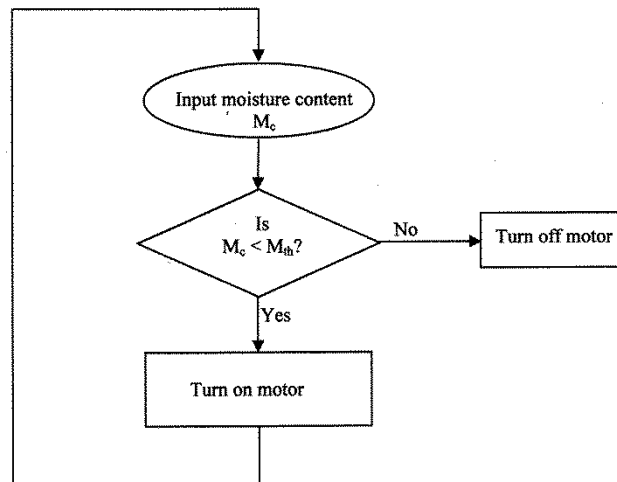


Figure 7: Water pumping motor control

Such a control for water pumping motor definitely will ensure minimal water wastage, improves sanitation and does not require human intervention. It is also easy to operate by farmers.

### RESULT ANALYSIS

The description of data used, readings observed from the FSED, performance of the prediction algorithms and the cost estimation of the entire work is discussed in this section.

#### Data description

The total number of data used for case 1 is 80, out of which 50 data was used to build the model and the remaining 30 were used to validate the model. The number of data used for case 2 is 245. The ARMA model was built with 150 data and the remaining data were used to validate the model. The data for Case 3 was obtained from Tamil Nadu Agricultural University, Coimbatore. The Government of Tamil Nadu has funded the establishment of Tamil Nadu Agricultural Weather Network (TAWN), by installing 385 Automatic Weather Stations (AWS) under the National Agricultural Development Project (NADP) [14]. The Agro Climate Research Centre (ACRC), Directorate of Soil and Crop Management Studies (DSCMS), Tamil Nadu Agricultural University (TNAU), Coimbatore in collaboration with Department of Agriculture, Tamil Nadu established the TAWN. Ten different parameters are collected at an hourly interval from all the 224 AWS. They are Air Temperature ( $^{\circ}\text{C}$ ), Relative Humidity (%), Wind Speed (kmph), Wind Direction (degree), Soil Moisture (%), Soil Temperature ( $^{\circ}\text{C}$ ), Rainfall (mm), Solar Radiation ( $\text{cal}/\text{cm}^2$ ), Atmospheric Pressure (hPa) and Leaf Wetness (hr). The collected weather parameters and the medium range weather forecast developed using these parameters are hosted in their website. Such dense network of weather monitoring stations is the first of its kind in India, and is intended to help in monitoring global warming, climate change impact and also to develop weather based agro advisories at block level for farmers. The data obtained for this research pertains to the weather data of Sulur Station, located near Coimbatore in Tamil Nadu, India.



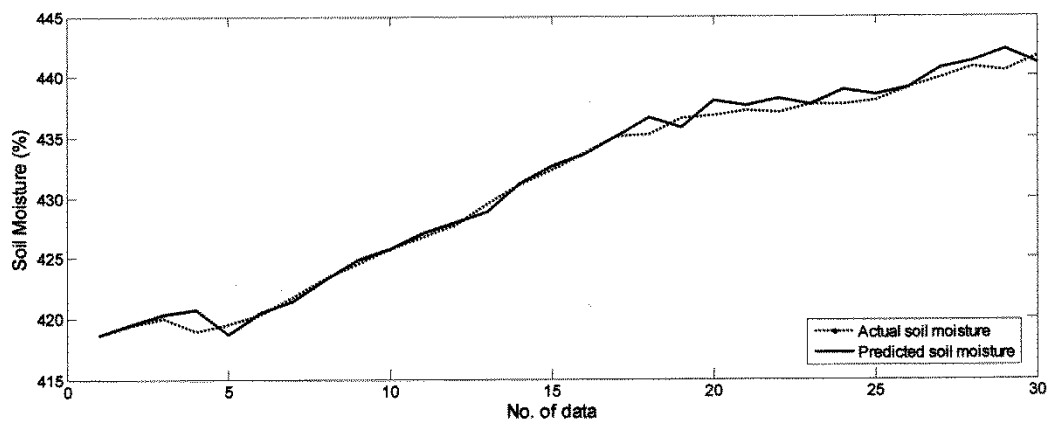
### Performance of prediction models

The general identification process of the linear ARMA model as defined in Eq. 1 consists of order determination, parameter estimation and diagnostic check. The model order is defined using the Akaike’s Final Prediction Error criterion. The model orders identified and their parameters for case 1 and case 2 are presented in Table 1.

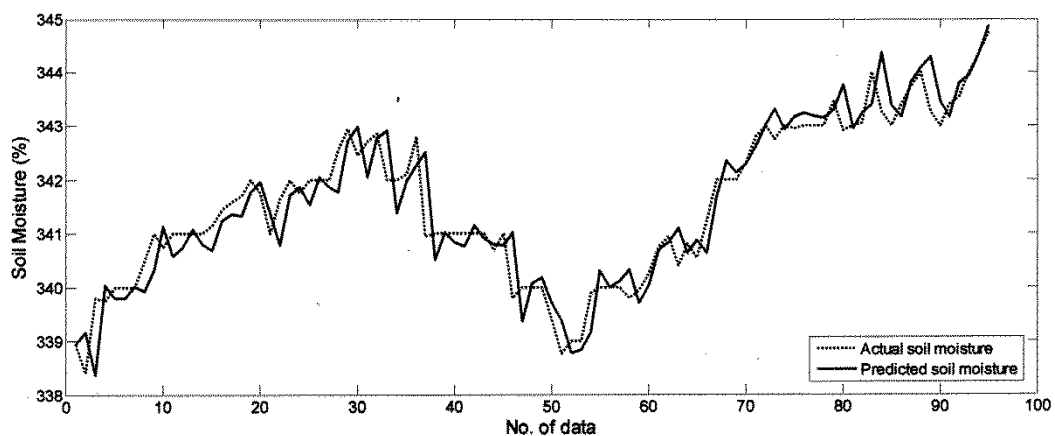
**Table 1: ARMA model orders and parameters**

	Model order	Parameters
Case 1	ARMA(3,2)	$a_1 = -1.4520; a_2 = 0.4538; a_3 = 0.0318;$ $c_1 = 0.1811; c_2 = 0.0248$
Case 2	ARMA(5,4)	$a_1 = -1.8457; a_2 = 0.9940; a_3 = -1.0416; a_4 = 1.5141; a_5 = -0.6202;$ $c_1 = -0.5794; c_2 = 0.0693; c_3 = -1.0239; c_4 = 0.5340$

Fig. 8 and Fig. 9 shows the performance of ARMA (3,2) and ARMA (5,4) models for case1 and case 2 respectively.



**Figure 8: Performance of the ARMA(3,2) – Case 1**



**Figure 9: Performance of the ARMA(5,4) – Case 2**

The architecture of the neural network that was used as a prediction model for case 3 is shown in Table 2. The performance metrics of the prediction methodologies have been

defined in Eq. 2 and Eq. 3. The MAE and RMSE values for all the three cases are shown in Table 3.

**Table 2: NN architecture used for prediction – Case 3**

Architecture	Feed-Forward Backpropagation
Training Set	50% data of temperature, humidity & soil moisture
Testing Set	50% data of temperature, humidity & soil moisture
Hidden neurons	5
Data preprocessing	'mapminmax'
Transfer Function	'tansig' for hidden layers and 'purelin' for output layer
Network Training Function	Levenberg-Marquardt backpropagation
Weight/bias Learning Function	Gradient descent with momentum weight and bias learning function

**Table 3: Performance Metrics**

	Model	RMSE	MAE
Case 1	ARMA(3,2)	0.5323	0.7460
Case 2	ARMA(5,4)	0.3477	0.4675
Case 3	NN	1.0720	0.7807

The error values of NN model is comparatively higher because the number of data used is very high compared to the other two cases. The performance of linear ARMA models can be improved by using non-linear ARMA models, solved by neural networks or data mining algorithms. This may be required when the datasets involved are large.

**Cost estimation**

The cost of the proposed device is definitely very cheap and suits the farmers' cause. The cost details of the product have been presented in Table 4.

**Table 4: Cost details of FSED**

Sl. No.	Component	Cost (in Rs.)
1	XBee PRO S2B wireless zigbee communication module	2650
2	Atmega microcontroller with Arduino bootloader	250
3	DHT11 humidity sensor	250
4	Soil moisture sensor	200
5	9 V battery (or) 5 V DC adapter	100
6	PCB board and etching kit	80
7	7805 voltage regulator	10
8	5 capacitors	25
9	Temperature sensor	30
10	20 MHz crystal	200
10	6 V relay	30
11	Solder, wires etc.	30
	Total	3855



## CONCLUSION

A low cost, labour-saving, easily deployable and programmable device for farming applications with inbuilt prediction models has been assembled and tested. The time horizon of the prediction model can be chosen as per the requirement of the farmer. Two different prediction models were built based on ARMA and NN techniques. The use of FSED combined with the benefits of the prediction models will definitely be a great boon to farmers as it enables them to multiply the agricultural productivity, conserve water, enhance sanitation and equips them to plan well ahead for future.

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