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Research article

Smart irrigation system for environmental sustainability in Africa: An Internet of Everything (IoE) approach

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Abstract: Water and food are two of the most important commodities in the world, which makes agriculture crucial to mankind as it utilizes water (irrigation) to provide us with food. Climate change and a rapid increase in population have put a lot of pressure on agriculture which has a snowball effect on the earth's water resource, which has been proven to be crucial for sustainable development. The need to do away with fossil fuel in powering irrigation systems cannot be over emphasized due to climate change. Smart Irrigation systems powered by renewable energy sources (RES) have been proven to substantially improve crop yield and the profitability of agriculture. Here we show how the control and monitoring of a solar powered smart irrigation system can be achieved using sensors and environmental data from an Internet of Everything (IoE). The collected data is used to predict environment conditions using the Radial Basis Function Network (RBFN). The predicted values of water level, weather forecast, humidity, temperature and irrigation data are used to control the irrigation system. A web platform was developed for monitoring and controlling the system remotely.

Keywords: smart irrigation; smart agriculture; Internet of Everything; Internet-of-Things; neural networks; decision support

1. Introduction

Agriculture is key to sustainable development and poverty alleviation in many third world countries. Fantu et al. in [1] showed the evidence of this using Ethiopia has a case study. Modernization and development cannot take place in a country until the issue of sustainable development in agriculture has been addressed [2], whereas irrigation is crucial to the realization of this sustainable development. Irrigation demands a stable source of electricity, but the absence of stable grid-connected power source in many remote areas means that most of these systems rely on diesel engines for power. Agriculture is one of the major contributors to climate change [3] although not all of that is as a result of the use of fossil fuel in irrigation systems. Moreover, climate change is expected to impact negatively on agriculture and pose a major threat to food security [4]. To address this issue, Renewable Energy Sources (RES) such as solar energy [5] can be employed to power irrigation systems. Another crucial factor in irrigation systems is the need for efficient water management to avoid wastage. Mismanagement of water resource can have adverse effect on the world as whole therefore there is a need for smart monitoring and control in irrigation systems.

Common Agricultural Policy (CAP) 2014/2020 adopted by the European Commission suggested the “Greening” policy [6], which, among others, aims to obtain energy efficiency in agriculture production. This goal can be achieved by applying new technologies in farms. The implementation of RES powered irrigation systems can be seen as one of the many aspects of green computing, which aims at decreasing carbon emissions and creating effective methods to utilize our computing technological advancements without having an adverse effect on the environment [7]. Green computing has many aspects, Murugesan [8] identified four aspects which are green use, green disposal, green design, and green manufacturing [9,10]. Sustainability is all about ensuring to present and future generations the capability for self-sufficiency [11]. Computing accounts for about 10 percent of world CO2 emissions [11] therefore RES in an IoE environment as an aspect of green computing can have a major role to play in environmental sustainability in developing countries [12].

Today, agriculture uses nearly 85% of worldwide freshwater resources while still using traditional irrigation methods and the demand for water is expected to soar in the coming years. RES integrated with irrigation and irrigation scheduling control has become a major research topic, which includes irrigation scheduling in a solar powered irrigation system [4], solar-powered water pumping systems [13], off-grid solar irrigation [14], wind powered pumping systems for irrigation [15,16], water consumption prediction models [17], smart water management [18], wireless sensor networks for data collection and monitoring [19]. For large agricultural areas, a Wireless Sensor Network (WSN) can be employed in which multiple sensor nodes can be distributed over the large area [20–22]. The effectiveness of smart agriculture can be improved by predicting the ideal time for manuring, applying fertilizer and pesticides as was demonstrated in [23] using Long Short Term Memory (LSTM) networks for predicting soil humidity, soil temperature and air temperature. The IoT-based smart system proposed in [24] uses a smart algorithm, which uses sensed data and predicted weather parameters (humidity, precipitation, air temperature and UV level).

In summary, the majority of previously developed irrigation systems do not consider the predicted weather conditions while making irrigation decisions. Several authors did focus on the prediction of weather, environment and soil conditions [25–27], but not in the context of developing smart agriculture systems. As a result, large amounts of water and energy are wasted, leading to crop failures (due to excess water) when watering of the crop coincides or is immediately followed by precipitation.

To avoid such problems, the intelligent IoT based solutions must be developed to ensure decision support for irrigation by using local weather prediction. The novelty of this paper is the adoption, modelling and implementation of a solar powered irrigation system using the Internet of Everything (IoE) [28] approach.

2. Materials and method

2.1. State-of-the-art

Automation of drip irrigation was the focus of research presented in [29]. The authors employed the smartphone to captures the soil image, while the hardware microcontroller calculates the wetness of the soil. The system tested in Tamilnadu allowed to save 41.5% and 13% of water when compared to the conventional irrigation methods of flood and drip. Chang and Lin [30] combines computer vision to perform variable rate irrigation within a cultivated field. Fuzzy logic controller is used to evaluate the data on the wet distribution area of surface soil in order to perform variable rate irrigation and to achieve water savings. The proposed system performs watering while maintaining the deep soil wetness at 80 ± 10%. Corbari et al. [31] advocated the use of weather forecasting to support precision smart irrigation use in the South of Italy. The system provides the reliable forecast of soil moisture for three days in advance. Diffalah et al. [32] implemented smart irrigation strategy using wireless sensor networks of WSN and IoT. The sensor nodes are cheap, self-organized and event-driven, providing a low-cost and energy-efficient solution to the problem. Geetha and Sathya Priva [33] employed Wireless Sensor Networks (WSNs), GSM and Android phone supporting android applications and an expert irrigation scheduling using fuzzy logic in order to optimize water usage for smart agriculture irrigation. Goap et al. [34] used Support Vector Regression (SVR) and k-means clustering for predicting change in soil moisture due to local weather conditions. Hema & Kant [35] specifically acknowledged the need to acquire real-time data in order to calculate soil conditions for smart agriculture. Kamienski et al. [36] described the implementation of IoT platform for precision irrigation that provides management of thousands of sensors for large-scale soil monitoring. Katvara et al. [37] used WSNs as remote terminal units (RTUs) and local control for supervisory control and data acquisition, allowing to save large amount of waters in Pakistan. Abayomi-Alli et al. [38] used wireless moisture sensors with independent solar power supply, and communication with central control unit using Near Radio Frequency (NRF) for smart irrigation system. Keswani et al. [21] presented the WSN framework consisting of soil moisture, temperature, environmental temperature, environmental humidity, CO2 sensor, daylight intensity sensors to acquire real-time information, while neural network-based prediction of soil moisture was used to control water valves. Similarly, Mohapatra et al. [39] used a radial basis function type of neural network to predict hourly soil moisture content in India. On the other hand, Munir et al. [40] used fuzzy logic rules to decide on the amount of water needed based on the current moisture in soil, humidity, and time of the day. Summarizing, the need for optimization of water usage is recognized by all state-of-the-art irrigation systems, and the authors employ a variety of solutions based on sensor networks, microcontrollers and machine learning (or fuzzy logic) to evaluate and predict water needs for irrigation in order to ensure efficient use of water.

2.2. Architecture

The smart irrigation systems has the following components: solar power station, networking infrastructure and water management and control stations, which includes water storage, irrigation sprinklers, water pumps, sensors and micro-controller unit (MCU).

Figure 1 shows by use of a block diagram the entire system. The solar power station is independent of the other subsystems rather the other subsystems depend on input from the solar power plant. Other systems are co-dependent on each other as input from the networking subsystem affects the IoE environment, which in turn affects the water management and control subsystem. The integration of the solar power subsystem, the networking architecture and water management and control subsystem in an IoE environment makes up the complete functional system.

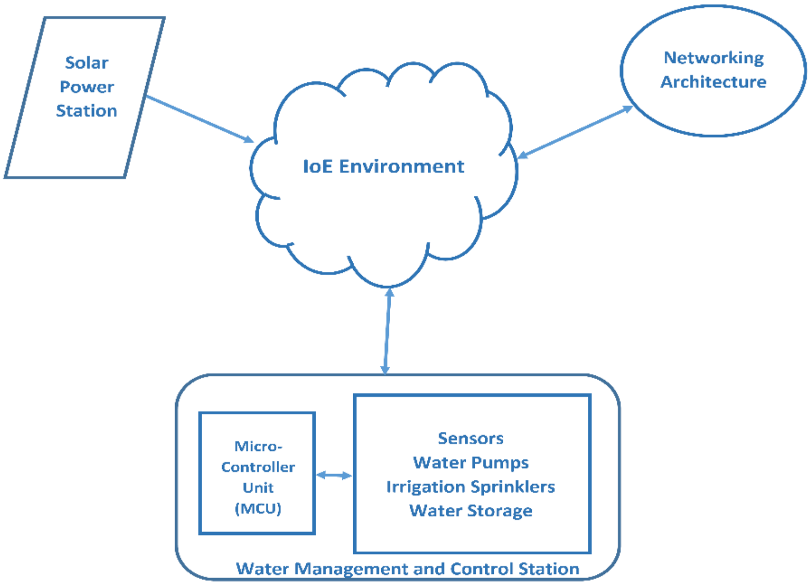

Figure 1. Block diagram showing the interconnection of the subsystems.

Figure 2 shows the overall logic and operation of the developed smart irrigation system. The sensors read data from the environment. This data is stored in the web server and is used for automating the irrigation process. Only user inputs from authorized personnel can be used to alter the irrigation process parameters. A web-based interface of the entire system can be accessed by authorized personnel through the web server. Water in the storage tank is maintained above 70% capacity at all times to ensure availability in case of days with low solar irradiance due to adverse weather conditions.

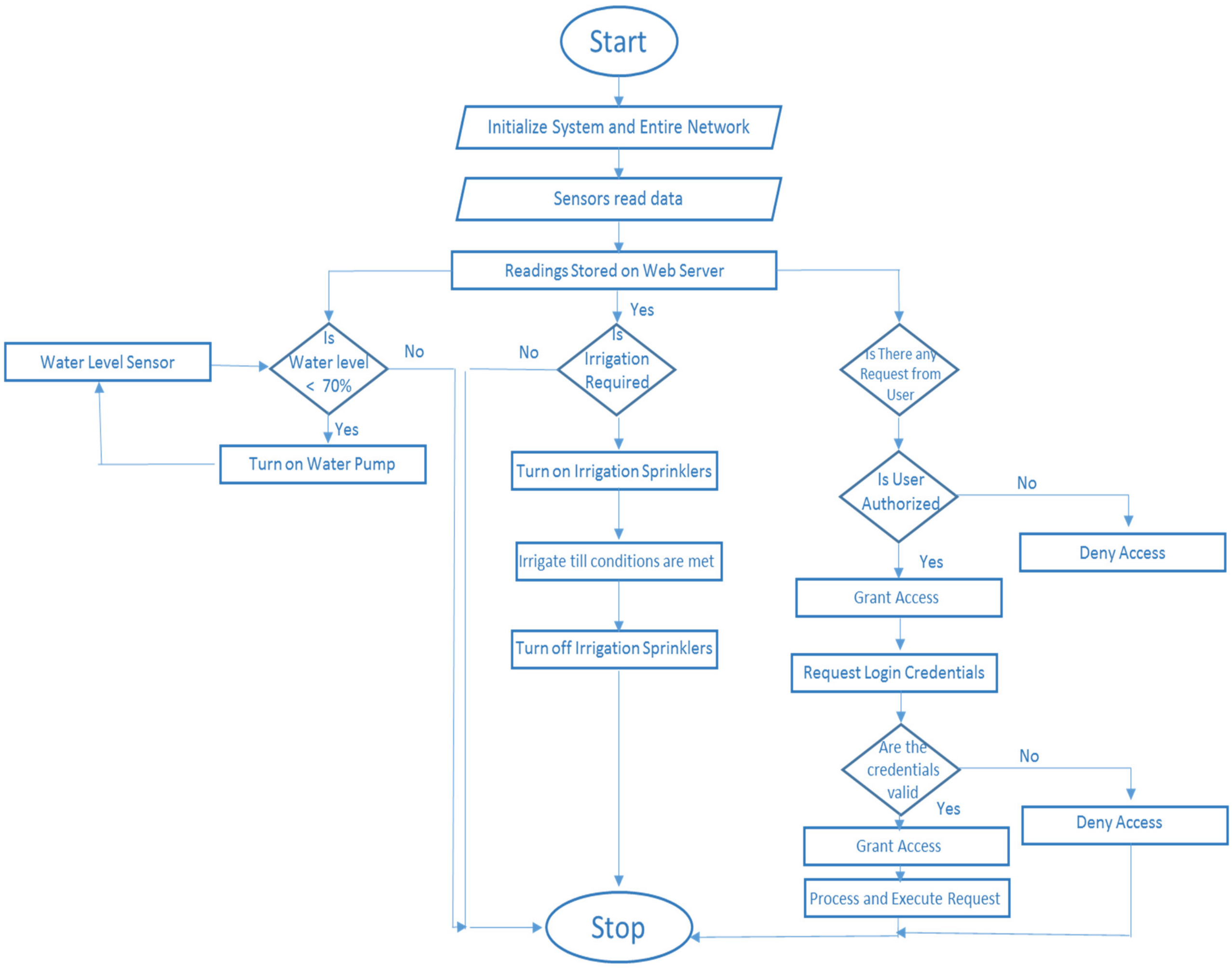

Figure 2. Process flow diagram of the system.

2.3. Solar power station

The smart irrigation system is powered solely using the photovoltaic (PV) cells of the solar panel. The power thus generated is stored in a battery pack and is used to power the pumps in the water management and control station. At day time the solar panels keep the battery charged so that during the night time in the absence of solar irradiance the battery pack has sufficient power to keep the pumps going when necessary.

The solar power station is implemented as follows. If a Direct Current (DC) pump is to be used the battery supplies the pump directly, if an Alternating Current (AC) pump is to be used an inverter system is put in place to convert the generated DC power to AC.

2.4. Water management and control station

The water management and control station consist of water pumps, sensors, irrigation sprinklers water storage and a micro-controller unit (MCU) (see Figure 3). The MCU controls the operation of the station. Water pumps connected to the power station are used to pump water, which is then stored in tanks in case of a power outage this reservoir ensures irrigation can be carried out when needed.

Temperature, humidity, soil moisture and atmospheric pressure sensors in conjunction with the MCU are used to control the irrigation process hereby improving the water management efficiency all this are interconnected and linked to a web server from which data can be pulled and devices can be controlled by an authorized personnel using web access from a remote location. Irrigation sprinklers are used to deliver water to the crops when necessary. The temperature, humidity and soil moisture sensors measure environmental parameters like soil temperature, humidity, moisture level which are crucial to irrigation, are processed by the and are also stored in the web server.

The sensors are placed at the crop rooting depth (typically, 15–30 cm). Moisture sensor triggers irrigation when 20% of available soil water is depleted. Temperature sensors measure temperature in the range of 0–40 °C, while the optimum range in our system is set to 20–30 °C.

The atmospheric pressure sensor is used to aid weather forecasting the pressure change over a period of time can be used to predict upcoming weather events which is very useful in utilizing water judiciously. The temperature sensor, humidity sensor and soil moisture sensor are integrated into one humiture (humidity-temperature) sensor, which makes the simulation easier to carry out.

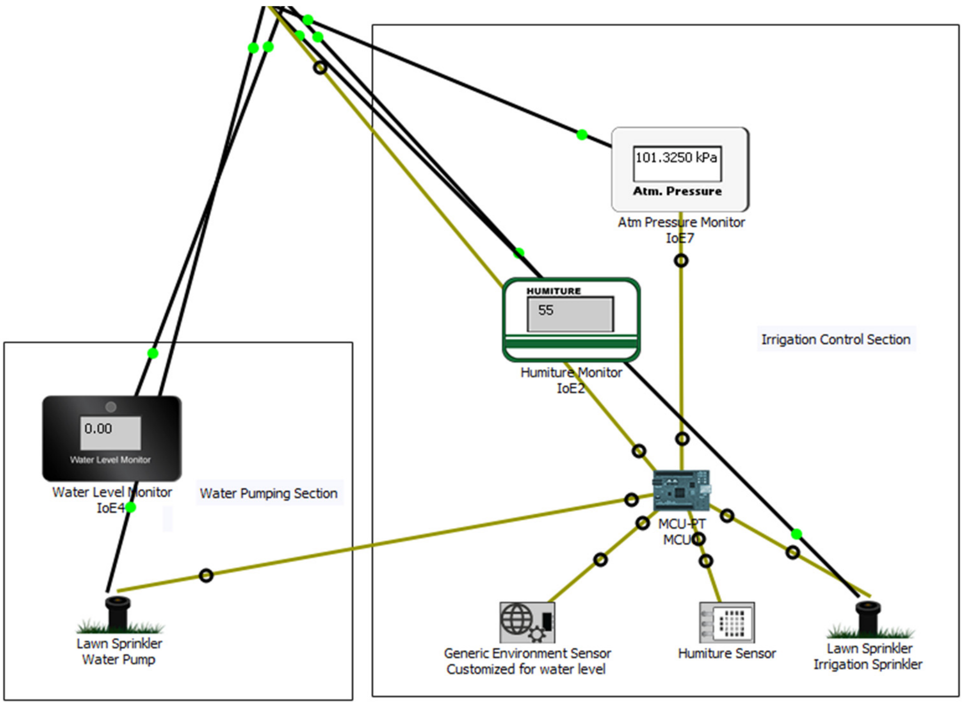

Figure 3. Water management and control station.

2.5. Network architecture

Figure 4 shows the interconnection of the various stations and sub systems in cluster form as simulated in the packet tracer tool each cluster has its own interconnection of devices within the solar power station and the water management and control station have been discussed in earlier sections the office and home networks are connected together via a generic cloud this enables the home network have access to the server that holds the web app in the office network.

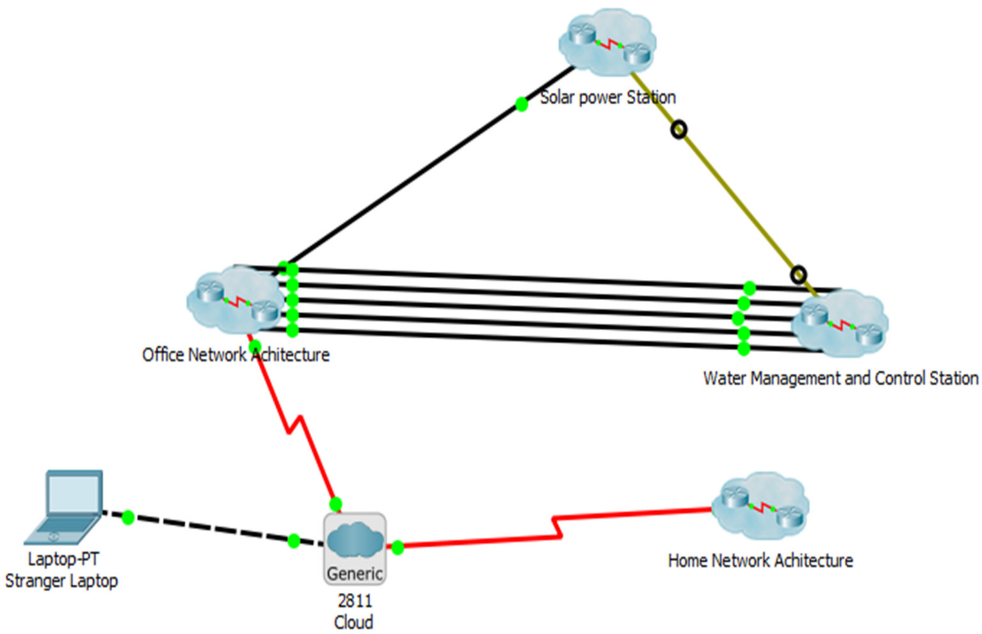

Figure 4. Overview of proposed network architecture.

The office network consists of several end devices (laptops and PCs) these are connected to a switch, the IoE devices from solar power station and water management station are also connected to the switch. An office router which to which the smart irrigation server is connected is configured to interact with eternal networks that would be authorized to have access to the irrigation server. The irrigation server is a remote IoE server to which IoE devices can connect to via the router–switch connection. From the server authorized users can have access to sensor information and can manually trigger the irrigation devices if the need be. The home network is similar to the office network as it has a router and a switch that form the backbone of the network the end devices are connected to the switch, an access point is also connected to the network to enable wireless access to the network via smart phones. The switch is connected to the router, which is in turn connected to the office network via the internet cloud.

To ensure low energy consumption we have adopted the approach described in [41] and an energy efficient communication protocol proposed in [42]. The network nodes are split into active and inactive nodes to eliminate sleeping nodes and reduce data redundancy. The energy efficient IoT protocol provides for maximum bandwidth and security while keeping energy consumption low. An optimized obtaining strategy [43] for acquiring sensor data in WSN uses a hierarchical clustering algorithm for obtaining a better clustering structure and decreasing network communication overhead, thus reducing power requirements, and increasing network lifetime.

2.6. Prediction of environment conditions using neural network

To predict the environmental conditions most important for the region of application. i.e., the precipitation, we employ Radial Basis Function Network (RBFN) [44]. The inputs of the network are local daily historical data of precipitation, while the output is the predicted event of precipitation the next day. RBFN is a single hidden layer feed-forward neural network (see Figure 5). The first layer connections are not weighted. The transfer functions in the hidden nodes are defined by the multivariate Gaussian density function as follows:

$$\varphi_j(x) = e^{\left(-\frac{\|x-\mu_j\|^2}{2\sigma_j^2}\right)} \tag{1}$$

here x is the input vector, μ_j and ρ_j are the mean and the deviation of the Gaussian variables. Each RBF unit is activated over a region determined by μ_j and ρ_j. The connections in the second layer are weighted. The output nodes perform linear summation. The value of the *k*-th output node y_k is defined by

$$y_k(x) = \sum_{j=1}^{h} w_{kj}\varphi_j(x) + w_{k0} \tag{2}$$

where w_{kj} is the weight of the connection between the *k*-th output node and *j*-th hidden node, and w_{k0} is the bias term.

RBF networks have three layers: input layer, hidden layer and output layer. Input layer has one neuron for each predictor variable. In our case, we used precipitation values of 7 preceding days as well as mean historic precipitation of current month, as well as atmospheric pressure, high and low temperatures in each day, air humidity, wind direction and wind velocity in 7 preceding days and resulting in 50 neurons in input layer. The output layer in our case has only one neuron, since we predict only precipitation event. The hidden layer can have a variable number of neurons. We followed the following rule of thumb: the number of hidden neurons should be 2/3 of the input layer size, plus the size of the output layer [45]. Therefore, we have 35 neurons in the hidden layer.

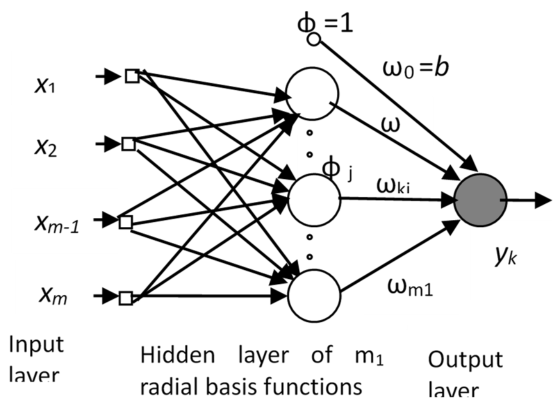

Figure 5. Schematic Diagram of RBF neural network.

The RBFN training is performed in three steps as follows. The learning stage applies the batch mode K-means clustering algorithm to find the unit centers μ_j. Starting from a set of initial random seed values, the unit centers are adapted by applying the learning rule

$$\mu_j = \frac{1}{|C_j|} \sum_{x_k \in C_j} x_k \tag{3}$$

The optimization of error is realized by utilizing the learning rule

$$\Delta\mu_{j^*} = \frac{1}{N_{j^*} + 1} \left(x_k - \mu_{j^*}\right) \tag{4}$$

here N_{j^*} is the count of wins of unit j^* in the competition.

The process is repeated until cluster centers do not change their position during the subsequent iteration. Next, a heuristic approach is used to determine unit widths and ρ_j as maximum Euclidean distance between the cluster centers. Finally, we use linear regression with a least-squares objective function to find the weights of the second layer.

To prevent network overfitting, we perform network regularization using the dropout method [46]. Every unit of the network is assigned the probability (dropout rate) of being temporarily ignored in calculations. The dropout rate is set to 0.5. Then, in each iteration, we randomly select the neurons that are dropped according to their dropout rate.

2.7. Evaluation

The dataset was collected in Ota, Nigeria, from March 1st to November 30th, 2018, resulting in 275 instances of data. We used 80% of data for network training, and withheld 20% of data for testing.

For the evaluation of the weather event prediction results were verified by the following evaluation indices as suggested in [25]:

$$HR = \frac{A + D}{A + B + C + D} \tag{5}$$

$$CR = \frac{A}{A + B} \tag{6}$$

$$Sen = \frac{A}{A + C} \tag{7}$$

$$Spec = \frac{D}{B + D} \tag{8}$$

here *HR* is hit rate (accuracy), *CR* is caching rate, *Sen* is sensitivity, *Spec* is specificity, *A* is a number of events where the predicted event matched the observed fact, *B* is the number of events where the predicted event failed the observed fact, *C* is the number of events where the predicted event failed non-event (when the result of observed fact was weather event), and *D* is the number of events where the predicted event matched non-event (when the result of observed fact was a non-event).

3. Results and discussion

Figure 6 shows the interface of the desktop internet application, all remote field sensors can be accessed from here and there is an option to turn on the irrigation sprinkler or water pump if need be as there might be certain conditions that might call for the system to be operated outside the standard automatic thresholds. The IoE devices are programmed to do specific things in relation to the other IoE devices using JavaScript or python, there is also a condition tab in the web app where rules are set that trigger the water pump and irrigation sprinkler when the readings from the water level monitor and humiture monitor get to certain thresholds this keeps the whole process automated.

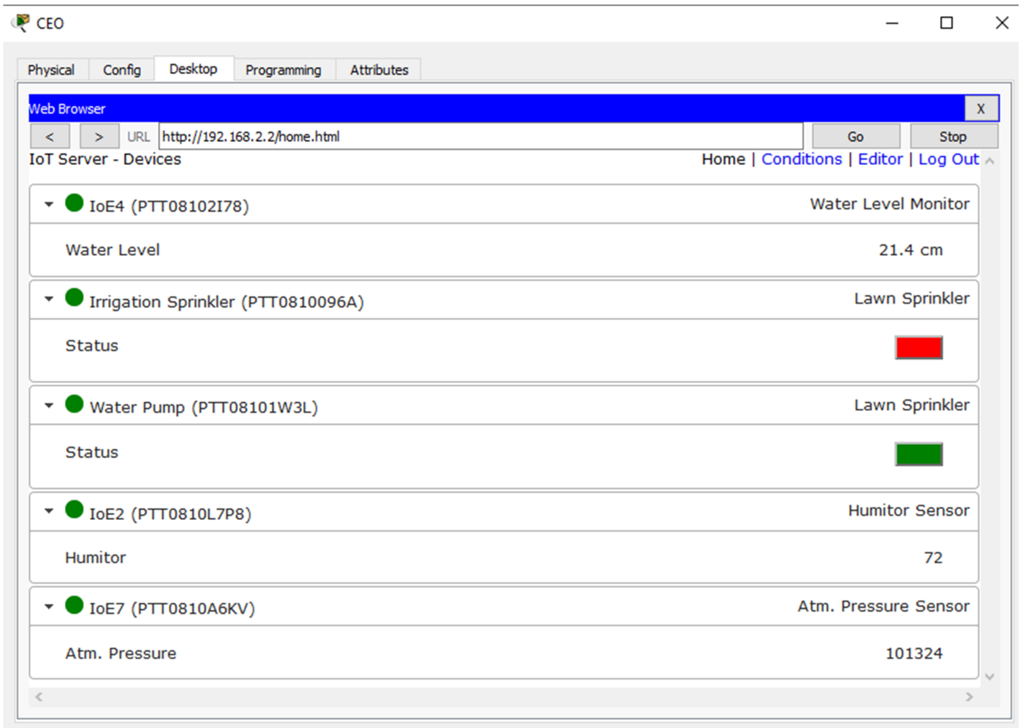

Figure 6. IoE devices as shown in the web access platform.

To create RBF network, we chose to use R, a statistical programming tool that allows for creation of neural networks. We selected the *neuralnet* package to implement a neural network for precipitation event predictions. As compared to existing models the proposed model makes use of IoE to give remote control and security to an automatic irrigation system. This model makes use of all required sensors in a sensor based irrigation scheduling system, gives the user a field status report and the ability to monitor the weather using atmospheric pressure sensor. In addition to this the remote web access is restricted to only authorized personnel. This implies that a stringent water management system is put in place. Using RES means it would cut down the carbon emissions leading to improved environmental sustainability.

The prediction results for precipitation in Ota, Nigeria, March-November, 2018 using RBFN are summarized in Table 1. The collected data was used to implemented prediction of precipitation events using RBFN and achieving the hit rate of 0.85, and the caching rate of 0.77, sensitivity of 0.77 and specificity of 0.90.

To compare the results with other machine learning approaches, we have implemented precipitation prediction using Probabilistic Neural Network (PNN), Learning Vector Quantization (LVQ) Neural Network, Extreme Learning Machine (ELM) and Support Vector Machine (SVM). The results presented in Table 2 show superiority of the proposed RBFN architecture (best results are shown in bold).

The scalability of the developed system is very important for the approach to be developed elsewhere. Our approach uses local environmental data derived from soil temperature, moisture, humidity as well as local precipitation data to predict the precipitation events. Therefore, we belief that the system could be transferred and used in other geographical localities, too.

Table 1. Precipitation prediction results for Ota, Nigeria, March–November, 2018.

Month	Metric				Daily event			
	HR	CR	Sensitivity	Specificity	A	B	C	D
March	0.9032	0.7000	1.0000	0.8750	7	3	0	21
April	0.8667	0.7500	0.5000	0.9583	3	1	3	23
May	0.7419	0.9000	0.5625	0.9333	9	1	7	14
June	0.9667	0.8750	1.0000	0.9565	7	1	0	22
July	0.8065	0.6923	0.8182	0.8000	9	4	2	16
August	0.7419	0.7143	0.4545	0.9000	5	2	6	18
September	0.9000	0.6667	1.0000	0.8750	6	3	0	21
October	0.9355	0.8000	1.0000	0.9130	8	2	0	21
November	0.8333	0.8571	0.6000	0.9500	6	1	4	19
Mean	**0.8551**	**0.7728**	**0.7706**	**0.9068**				

Table 2. Comparison of precipitation prediction results for Ota, Nigeria, March–November, 2018.

Classification method	Hit rate	Caching rate	Accuracy	Sensitivity
PNN	0.8223	0.7517	0.6909	0.8925
LVQ	0.8042	0.7271	0.6435	0.8918
ELM	0.7210	0.5376	0.6087	0.7790
SVM	0.7729	0.6465	0.6384	0.8411
RBFN	**0.8551**	**0.7728**	**0.7706**	**0.9068**

4. Conclusion

We have implemented the solar powered smart irrigation system was implemented using the Internet of Everything (IoE) environment. Sensors and environmental data were used to control the irrigation process from an IoE perspective automatically. A web platform was implemented to allows remote manual control in case of an oversight or sudden unexpected event that requires a prompt response. Access to the web platform was restricted to only authorized personnel. The control and monitoring of a solar powered smart irrigation system is achieved using sensors and local environmental data.

The developed system demonstrated the viability of the IoE-based approach for solar powered smart irrigation system, while the use of the artificial intelligence (Radial Basis Function Network, RBFN) allows to save on precious natural resources such as water by avoiding unnecessary irrigation when a precipitation event is predicted to happen. The predicted values of water level, weather forecast, humidity, temperature and irrigation data are used to control the irrigation system.

Future work will include the extension of the system with other types of renewable energy sources and hybrid energy grid to unsure grid independence and sustainability of the system and setting the conditions for the use of the system in remote rural regions of sub-Saharan Africa.

Conflict of interest

The authors declare no conflict of interest.

References

1. B. N. Fantu, B. Guush, M. Bart, et al., Agricultural Transformation in Africa? Assessing the Evidence in Ethopia, *World Dev.*, **105** (2018), 286–298.
2. S. Trilles, J. Torres-Sospedra, Ó. Belmonte, et al., Development of an open sensorized platform in a smart agriculture context: A vineyard support system for monitoring mildew disease, *Sustain. Comput. Infor.*, (2019), in press.
3. Intergovernmental Panel on Climate Change, Climate Change 2014: Synthesis Report. Contribution of Working Groups I, II and III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change [Core Writing Team, R.K. Pachauri and L.A. Meyer (eds.)]. IPCC (2014), Geneva, Switzerland, 151 pp., [online] Available from: https://www.ipcc.ch/site/assets/uploads/2018/02/SYR_AR5_FINAL_full.pdf.
4. A. M. García, I. F. García, E. C. Poyato, et al., Coupling irrigation scheduling with solar energy production in a smart irrigation management system, *J. Clean. Prod.*, **175** (2018), 670–682.
5. M. Kala, U. Sadrul and B. Steven, Solar photovoltaic water pumping—opportunities and challenges, *Renew. Sust. Energ. Rev.*, **4** (2008), 1162–1175.
6. European Commission, Overview of CAP Reform 2014–2020, December 2013, [online] Available from: http://ec.europa.eu/agriculture/policy-perspectives/policy-briefs/05_en.pdf.
7. S. Biswajit, Green Computing, *Int. J. Comput. Trends Technol.*, **14** (2014), 46–50.
8. S. Murugesan, Harnessing green IT: Principles and practices, *IT Prof.*, **10** (2008), 24–33.
9. E. Okewu, S. Misra, R. Maskeliunas, et al., Optimizing green computing awareness for environmental sustainability and economic security as a stochastic optimization problem, *Sustainability*, **9** (2017), 1857.
10. E. Okewu, S. Misra, L. Fernandez-Sanz, et al., An e-environment system for socio-economic sustainability and national security, *Probl. Ekorozw.*, **13** (2018), 121–132.
11. A. C. Orgerie, Green Computing and Sustainability, *Journées scientifiques*, **15,** (2016), 23–27.
12. A. Al-Zamil and A. K. J. Saudagar, Drivers and challenges of applying green computing for sustainable agriculture: A case study, *Sustain. Comput. Infor.*, (2018), in press.
13. A. Mansur, H. Ghassan, S. A. Syed, et al., A review of solar-powered water pumping systems, *Renew. Sust. Energ. Rev.*, **87** (2018), 61–76.

14. N. Mehdi, M. Peyman, N. Mohammad, et al., Techno-economic feasibility of off-grid solar irrigation for a rice paddy in Guilan province in Iran: A case study, *Sol. Energy*, **150** (2017), 546–557.
15. P. E. Campana, H. L. Li and J. Y. Yan, Techno-economic feasibility of the irrigation system for the grassland and farmland conservation in China: Photovoltaic vs. wind power water pumping, *Energ. Convers. Manage.*, **103** (2015), 311–320.
16. P. E. Campana, H. L. Li and J. Y. Yan, Dynamic modelling of a PV pumping system with special consideration on water demand, *Appl. Energy*, **112** (2013), 635–645.
17. Z. Gu, Z. Qi, L. Ma, et al., Development of an irrigation scheduling software based on model predicted crop water stress, *Comput. Electron. Agric.*, **143** (2017), 208–221.
18. R. López-Luque, J. Reca and J. Martínez, Optimal design of a standalone direct pumping photovoltaic system for deficit irrigation of olive orchards, *Appl. Energy*, **149** (2015), 13–23.
19. G. Vellidis, M. Tucker, C. Perry, et al., A real-time wireless smart sensor array for scheduling irrigation, *Comput. Electron. Agric.*, **61** (2008), 44–50.
20. T. Ojha, S. Misra and N.S. Raghuwanshi, Wireless sensor networks for agriculture: the state-of-the-art in practice and future challenges, *Comput. Electron. Agric.*, **118** (2015), 66–84.
21. B. Keswani, A. G. Mohapatra, A. Mohanty, et al., Adapting weather conditions based IoT enabled smart irrigation technique in precision agriculture mechanisms, *Neural Comput. Appl.*, **31**(S1) (2018), 277–292.
22. S. T. Oliver, A. González-Pérez and J. H. Guijarro, An IoT proposal for monitoring vineyards called SEnviro for agriculture, *Proceedings of 8th International Conference on the Internet of Things*, (2018), 20. ACM.
23. S. A. M. Varman, A. R. Baskaran, S. Aravindh, et al., Deep learning and IoT for smart agriculture using WSN, *IEEE International Conference on Computational Intelligence and Computing Research, ICCIC 2017*, (2018).
24. A. Goap, D. Sharma, A. K. Shukla, et al., An IoT based smart irrigation management system using machine learning and open source technologies, *Comput. Electron. Agric.*, **155** (2018), 41–49.
25. T. Kashiwao, K. Nakayama, S. Ando, et al., A neural network-based local rainfall prediction system using meteorological data on the Internet: A case study using data from the Japan Meteorological Agency, *Appl. Soft Comput.*, **56** (2017), 317–330.
26. O. Adeyemi, I. Grove, S. Peets, et al., Dynamic neural network modelling of soil moisture content for predictive irrigation scheduling, *Sensors*, **18** (2018), 3408.
27. L. Huang, L. Chen, Q. Wang, et al., Regional short-term micro-climate air temperature prediction with CBPNN, *E3S Web of Conferences*, **53** (2018).
28. L. T. Yang, B. Di Martino and Q. Zhang, Internet of Everything, *Mob. Inf. Syst.*, (2017).
29. S. R. Barkunan, V. Bhanumathi and J. Sethuram, Smart sensor for automatic drip irrigation system for paddy cultivation, *Comput. Electr. Eng.*, **73** (2019), 180–193.
30. C. Chang and K. Lin, Smart agricultural machine with a computer vision-based weeding and variable-rate irrigation scheme, *Robotics*, **7** (2018), 38.
31. C. Corbari, R. Salerno, A. Ceppi, et al., Smart irrigation forecast using satellite LANDSAT data and meteo-hydrological modeling, *Agric. Water Manag.*, **212** (2019), 283–294.
32. W. Difallah, K. Benahmed, B. Draoui, et al., Implementing wireless sensor networks for smart irrigation, *Taiwan Water Conservancy*, **65** (2017), 44–54.

33. S. Geetha and R. Sathya Priya, Smart agriculture irrigation control using wireless sensor networks, GSM and android phone, *Asian J. Inf. Technol.*, **15** (2016), 3780–3786.
34. A. Goap, D. Sharma, A. K. Shukla, et al., An IoT based smart irrigation management system using machine learning and open source technologies, *Comput. Electron. Agr.*, **155** (2018), 41–49.
35. N. Hema and K. Kant, Cost-effective smart irrigation controller using automatic weather stations, *Int. J. Hydrol. Sci. Technol.*, **9** (2019), 1–27.
36. C. Kamienski, J. Soininen, M. Taumberger, et al., Smart water management platform: IoT-based precision irrigation for agriculture, *Sensors*, **19** (2019), 276.
37. S. Katyara, M. A. Shah, S. Zardari, et al., WSN based smart control and remote field monitoring of Pakistan's irrigation system using SCADA applications, *Wireless Pers. Commun.*, **95** (2017), 491–504.
38. O. Abayomi-Alli, M. Odusami, D. Ojinaka, et al., Smart-Solar Irrigation System (SMIS) for Sustainable Agriculture, *International Conference on Applied Informatics, ICAI 2018*, (2018), 198–212.
39. A. G. Mohapatra, S. K. Lenka and B. Keswani, Neural network and fuzzy logic based smart DSS model for irrigation notification and control in precision agriculture, *P. Natl. A. Sci. India A*, **89** (2019), 67–76.
40. M. S. Munir, I. S. Bajwa, M. A. Naeem, et al., Design and implementation of an IoT system for smart energy consumption and smart irrigation in tunnel farming, *Energies*, **11** (2018), 3427.
41. X. Fan, W. Wei, M. Wozniak, et al., Low energy consumption and data redundancy approach of wireless sensor networks with bigdata, *Inf. Technol. Control*, **47** (2018), 406–418.
42. A. Venčkauskas, N. Jusas, E. Kazanavičius, et al., An energy efficient protocol for the internet of things, *J. Electr. Eng.*, **66** (2015), 47–52.
43. W. Wei, Z. Sun, H. Song, et al., Energy balance-based steerable arguments coverage method in WSNs, *IEEE Access*, **6** (2018), 33766–33773.
44. C.M Bishop, *Neural networks for pattern recognition*, Oxford University Press, 1995.
45. Z. Boger and H. Guterman, Knowledge extraction from artificial neural network models, *IEEE Systems, Man, and Cybernetics Conference*, **4** (1997), 3030–3035.
46. N. Srivastava, G. Hinton, A. Krizhevsky, et al., Dropout: a simple way to prevent neural networks from overfitting, *J. Mach. Learn. Res.*, **15** (2014), 1929–1958.