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A Framework for a Real-Time Cloud-Based Weather Forecasting System for Mauritius

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Abstract

With the advent of global warming and other climatic imbalances, several countries are experiencing drastic weather conditions such as flash-floods which lead to major collateral damage and life loss. Predicting such weather conditions with conventional forecasting systems is not possible because these systems provide predictions for large regions over hours. However, there are several weather forecasting systems based on localised sensors connected to cloud computing facilities that can provide real-time forecasts for small regions. These forecasting systems make use of techniques such as neural networks, Fuzzy logic, time series and regression analysis. Recently, Mauritius has also faced major problems due to drastic flash floods which could not be predicted with the conventional weather forecasting system in place in the country. The main aim of this research is to first give an overview of the climatic profile in Mauritius, the existing weather forecasting systems as well as the recent issues that Mauritius has faced due to dramatic climatic conditions that could not be predicted on time. A detailed analysis of the techniques used in real-time cloud based weather forecasting systems will then be made and eventually a framework for a real-time cloud based weather forecasting system that could be set up in Mauritius will be proposed.

Keywords: *Weather Forecasting, Cloud-Computing, Real-time, Mauritius.*

1. Introduction

The erratic behaviour of the weather associated to effect of climate change is presently becoming an increasingly important subject of concern. A typical description of climate change is in terms of average changes in precipitation or temperature. However, it is the shifts in severity and frequency of disastrous events which result in most economic and social costs (Karl, et al., 2008). With 2005 globally marked as the warmest year since 1880 (National Climatic Data Center, 2011), the former fact is well illustrated by the several costly weather disasters in 2010. These two years were marked in history due the exceptional damaging weather events, such as the Hurricane named Katrina in 2005 and the deadly Russian heat wave in 2010. Some of the remarkable events of 2010 include: the biggest flood of Pakistan, the driest year of South-West Australia, and the warmest year in Canada. A similar trend

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continued in 2011. The U.S. experienced its second hottest summer throughout history, Australia went through flooding on a large scale, Texas, Arizona, and New Mexico went through shattering wildfires and drought, together with notable floods in Lower Mississippi, North Dakota and the North East (BBC News, 2011), (Huber & Gulledge, 2011). Without any doubt, weather forecasting is crafting a very important and critical role to play with these unavoidable modifications in the climate of the world which are leading to catastrophic events.

The aim of weather forecasting is to determine in what way the weather will vary over a given interval and what will be the status of the weather over the forecast period. To achieve this, several parameters have to be measured in the atmosphere for e.g. atmospheric pressure, wind direction and speed, temperature, precipitation, cloud cover and so on. There are also computational models which can give weather forecasts based on temporal atmospheric changes caused by several factors such as warming differences across the earth's surface from solar radiation, cooling at night, atmospheric warming as a result of latent heat release during condensation, etc. Once weather data has been collected, there are several conventional techniques that are used to process these data and give a weather prediction. An overview is given next [5].

(i) Persistence forecasting is a prediction based on the assumption that the future weather condition will be an extrapolation of the present one i.e. the weather conditions will remain constant [5].

(ii) Steady-state or Trend Forecasting is a method where the forecaster observes the changes happening in the weather systems. These could be the air masses, high and low pressure systems and fronts. The forecast is based on the hypothesis that these changes will persist at the same rate they have been occurring [5].

(iii) Analogue method or pattern recognition – It uses the assumption that available weather patterns on weather charts resembling previous weather patterns on previous charts must lead to similar weather elements, or phenomena, produced by the previous patterns. It is also referred as Synoptic weather prediction. It concerns the observation of different weather elements within a given observation time. A forecasting station generates a sequence of synoptic charts every day, which are the very basis of weather prediction [6]. It consists of a large collection and analysis of weather data captured by thousands of weather stations. The images provide data for various types of atmospheric changes and expected change in climate due to current atmospheric conditions of a particular area.

(iv) Climatological Forecast - This method uses statistical records such as the mean value of weather parameters elements of an area, the highest or lowest frequency of occurrence of some weather phenomena, the maximum and minimum values of weather parameters, etc. to predict the value of those weather parameters for a given future interval [5].

(v) Numerical Weather Prediction – It uses mathematical models of the atmospheric processes that create changes to weather elements; such as, pressure, wind speed, temperature, wind direction, moisture content, etc., which have an effect on the atmospheric [5]. Numerical weather prediction (NWP) models are appropriate for large-scale medium-range weather forecasting. Typically, this "state of the atmosphere," or "picture" is defined by weather values at several disparate locations, called grid points, at ground or sea level as well as vertically in the atmosphere. Essentially it is the troposphere and lower stratosphere that are concerned. After obtaining the weather observations and the values of the measured weather elements have been input entered into the program, the equations of the model can be solved to determine new values of the weather elements for a given time interval in the future [7], [8], [9], [10].

However, conventional weather forecasting systems provide predictions over extended periods of time for large regions which could span several Kilometres. Weather stations, generate forecasts based on a set of observations and computer models obtained from stations that could be very far from the region whose weather is being forecast. Given the large coverage area of these forecast models, a 40% probability of rain implies there is a 40% probability of rain at any given point across the whole area. In other words, the forecast is being made for a large number of individuals separated by large distances. Hence it’s realistically unfeasible to obtain a correct forecast for everyone in a given TV or

radio market. Realistically therefore, an 80% chance of sunshine means that there is even a possibility of rain somewhere [11]. Another limitation is that drastic changes in climatic conditions such as flash floods and cloudbursts are difficult or too costly to predict in real-time. For example Cloud Burst forecasting is predicted by the prediction of rainfall and formation of clouds. The satellite based systems are expensive and require full system support. Another technique for cloud burst prediction is Data Mining techniques for weather prediction. Data mining is a technique for extracting meaningful patterns from large amount of data. Data mining is also defined as the process of extracting implicit, previously unknown and meaningful information and knowledge from large amounts of incomplete, noisy, random and ambiguous data for practical application. Laser beam atmospheric extinction measurements from manned and unmanned aerospace vehicles are also a method to predict cloud burst. The technique consists of making measurements of the laser energy incident on target surfaces of known geometric and reflective properties, using infrared detectors or infrared cameras calibrated for radiance. It is too costly and requires full government support for deployment [12].

Given the limitations associated with conventional weather forecasting systems, several systems based on wireless sensor networks connected to micro-controllers that can even be relayed to a cloud computing facility have been used. These systems can incorporate several forecasting algorithms based on artificial neural networks, fuzzy logic, time series analysis and regression. The emergence of the Internet of Things (IoT) has also provided new avenues to address the weather forecasting problem. Essentially, these systems are able to provide localised, real-time weather forecasts. An overview of such systems is given next.

In [13] the authors proposed an application called CloudCast that provides short-term location dependent weather forecasts. Given the low probability of severe weather, CloudCast uses a pay-as-you go cloud platform so as not to use a dedicated computing infrastructure.The two main components of CloudCast are firstly an architecture that connects weather radars to cloud facilities, and secondly an algorithm for producing precise short-term weather predictions known as Nowcasting. Using data obtained from an on campus weather radar, real-time experiments were performed with the CloudCast architecture. The results showed a very high accuracy in forecasting. The delay between generation of data at the radar and the sending of a 15-minute Nowcast image to a mobile client was on average below 2 minutes. The feasibility of commercial and research cloud services to execute the real-time CloudCast application was thus demonstrated. Hence the proposed system allowed precise, short-term weather forecasts to be sent to mobile users.

An Arduino based cloudburst predetermination system with real time calculation of rainfall intensity was proposed in [12]. The proposed system was based on Arduino connected to a rain gauge in order to calculate real time rainfall intensity. A Float Switch is connected to the rain gauge that monitors the water level in the rain gauge. Additionally a submersible pump is also attached to the rain gauge. The rain gauge calculates real time rainfall intensity with the help of arduino and arduino records the data. A Servo mounted on the arduino board provides the capability of controlling the board from anywhere in the world. The board is programmed with 3 stages of alarms which are raised according to the real time intensity. Cloud burst generally occurs at rainfall intensity greater than or equal to 100 mm per hour. Alarm stages are associated with 3 threshold values. The data recorded by Arduino board is monitored at base station or is sent to the configured device directly. Whenever alarm rises, alert messages are broadcasted to the cellular phones of the people of nearby areas. The extreme condition of alarm is Alarm 3 at which people are transported to a safe place. Message broadcasting to the cellular phones of the nearby people is done with the help of an extra module mounted on the board. This extra module is plugged in the Arduino board and is called Arduino GSM Shield [12].

In [14] a wireless sensor network employing the Zigbee/IEEE802.15.4 standard was used to develop a weather station network that could transmit weather forecasts and generate alerts in the event of a disaster. In order to determine the conditions for generating an alert, decision tree techniques were used to analyse the weather data. The wireless sensor networks used by the system are capable of long distance transmission via a mesh topology and also decreases the power consumed. Hence, the system can be deployed in remote locations with limited accessibility, where hardwiring would be

impossible and even electricity is unavailable. The proposed system meets three main objectives which are showing weather information, generating alerts when required and storing weather statistics.

Another related work in [15] proposed a Flash Flood Warning System Using SMS with advanced warning information. The system employed a prediction algorithm which had as its inputs rising water speed and water level. The main triggers of a flash flood were assumed to be the water speed and water level. Hence these two parameters were the main inputs of the regression based prediction algorithm. The regression equation was formulated using training data recorded for seven days. Moreover, real time data were input to the regression model. The system computed the risks of current and forthcoming floods using the model and this information was sent via SMS to the users.

Finally in [16] an Internet of Things (IoT) based approach was proposed to record rainfalls, river discharge and the temporal correlation between them to trigger early alarms when required. The data captured are sent continuously, via the Internet transmission system, to applications devised for calculating the stream-flow and quantifying the spatial distribution of flood risk for each controlled watershed. The calculated risks, along with data obtained from other sources (sensors, cameras, emergency services and public), are analysed by a diagnostic decision system. The system provides risk-alert scheduling strategy that can diagnose the condition of the supervised environment and defines specific alarm levels for each potential region. Eventually, the computed risks are used for to generate dedicated alerts to all citizens (ubiquity) present in each selected area only (alerting locality).

According to the World Risk Report [17], Mauritius Island is the 18th country which is most susceptible to climate change among the 171 countries. Additionally, several reports produced by: the United Nations Environmental Programme (UNEP, 2014) [18]; the Government of Mauritius [19], [20]; Intergovernmental Panel on Climate Change [21] and [22]; and United Nations Framework Convention on Climate Change [23] (UNFCCC, 2014); and which deal with livelihoods, potential impacts on communities, and the economy at large have already highlighted the scary challenges in store for Mauritius in the near future together with a projection on climatic situations. The alterations which can be observed in the parameters defining climatology, such as: rise in sea level and intensity of tropical cyclones; instability of rainfall patterns; amongst many more, have already struck the communities and people of Mauritius and neighbouring Island: Rodrigues. Lately, Mauritius has experienced the aftermaths of life-taking flash floods without the capacity of prediction with conventional meteorological infrastructure in place currently on the island [24]. Hence, in this research a framework for implementing a real-time cloud based weather forecasting system for Mauritius is proposed. The system proposed will be able to predict weather conditions over small regions and small intervals of time. Moreover, it will have the ability to send timely alerts to all end users via a cloud connection.

The remainder of this paper is organised as follows. Section 2 gives an overview of the climate profile in Mauritius and the existing weather forecasting system. Section 3 gives a detailed overview of how real-time cloud based weather forecasting is performed as well as the algorithms used in predictive analytics. Section 4 presents the proposed framework for real-time weather forecasting in Mauritius. Finally Section 4 concludes the paper.

2. Climate profile in Mauritius and the existing weather forecasting system

Mauritius Island has an area of about 1844 km^2 and located in the Indian Ocean at approximately 20^{0}S and 57^{0}E on the globe as depicted in Fig. 1. The structure of the island is a central hill and flat terrain also known as the caldera. The general characteristics of its climate can be categorized as a pleasant and moderate tropical one. According to statistics, the usual annual rainfall is about 2120 mm with average annual temperatures of about 22^{0}C. The small size of the island does not make it indifferent to the significant alterations in the features of the climate such as rainfall caused by variations in the parameters: distance from coast, elevation, windward-leeward locations apart from the influences from cold fronts, irregular storms and Inter Tropical Convergence Zone (ITCZ) (Padya, 1989). In contrast to other countries across the globe, there are only two seasons which are observed

in Mauritius which are: summer (wet and warm) from November to April and winter (dry and cold) from May to October (Fowdur, Rughooputh, Cheeneehash, Boojhawon, & Gopaul, 2014).

Figure 1: Location of Mauritius [27].

In addition to the general annual climatic characteristics of the island, each of the four regions have different specificities. For instance, the northern region experiences dry conditions from August to October while wet conditions from November to April. Approximately 70% of the average annual rainfall is accounted by these wet months. The western region experiences the result exhausting water vapour on the windward slopes and descent of air on the leeward slopes. As a matter of fact, July to September are the driest months while in the summer months November to April. 78% of the rainfall in the west occurs. The rainfall patterns of the eastern and southern parts share some similarities. They are hit by the moisture-containing oceanic air almost throughout the year and benefit from the forced uplift as a result of its passage over the sloping lands and hills (Padya, 1989), (Fowdur, Rughooputh, Cheeneehash, Boojhawon, & Gopaul, 2014).

The three main life-threatening incidences which have openly struck the Mauritian communities are: rise in sea level; flash floods and tropical cyclone. Some other connected natural occurrences which have been witnessed are: wave surges; forest fires; coral bleaching; landslides; and droughts (Chun, 2015). The location of Mauritius Island make it extremely vulnerable to powerful tropical cyclones which cause blasts of wind with speeds beyond 260 km/h, along with torrential rain occurrences which frequently go above the 400 mm mark. These types of tropical cyclones are accountable for severe damages to private and public structure, loss of human lives, farming and agriculture, erosion of beaches due to wave surges amongst others (Ministry of Environment and Sustainable Development, and Disaster and Beach Management, 2013). Current historical archives have shown that stronger cyclones with much longer life-span are born in the South-west Indian ocean area (Mauritius Meteorological Services, 2016). Over the past decades, extremely strong tropical cyclones having a more extended diameter and average surface winds beyond 212 km/h have been witnessed. Examples of these cyclones are: Bansi and Eunice in 2015 (Meteorological Services, 2008).

The long term annual average rainfall of 2,010 mm (measured between 1971 to 2000) is expected to decline according to the Mauritius Meteorological Services (MMS) (Mauritius Meteorological Services, 2016) and IPCC (2007) (United Nations Environment Programme (UNEP), 2014) and Mauritius is already facing sparse distribution of rainfall from 4,000 mm on the Central Plateau to 900 mm in the western region. Previous reports of the MMS have demonstrated a rise in the frequency of droughts over the years as well as an extreme lack of rainfall in the years: 1983 to 1984; 1998 to 1999; and 2011 to 2012. Particularly, it is estimated that the mean annual rainfall will experience a degradation by 8% (Intergovernmental Panel on Climate Change, 2007) with a rise in the frequency of flash floods. 30th March 2013 marked history in Mauritius with the life-taking flash flood which occurred in the capital city of Port Louis killing 11 people with the 152 mm of rain falling in a very short

lapse of time (Government Information Service Newsletter, 2013). Places such as La Butte, Montagne Ory, Quatre Soeurs and Chitrakoot experience landslides during heavy rainfalls.

The rise in the level of sea is forecasted to be between 18 and 59 cm by the year 2100. The average tidal gauge records from 1950 to 2001 reveal a rise of 7.8 cm in the sea level around Mauritius and 6.7 cm around Rodrigues Island (Mauritius Meteorological Services, 2016). This trend would ultimately lead to erosion of the beaches, loss of bays and irreversible damages to built-up regions around the coast. The rise in sea level has stressed the influences of storm flows which are threats to the lovely littoral landscape (Ministry of Environment and Sustainable Development, 2013), (United Nations Framework Convention on Climate Change, 2014), (Ministry of Environment and Sustainable Development, and Disaster and Beach Management, 2013).

The Mauritius Meteorological Services (MMS) is a Government Institution which operates under the Prime Minister's Office (PMO) with the aim of executing meteorological and other connected tasks deemed as the duty of the State by the Government. This responsibility is undertaken to support the security, safety and general well-being of the people and to accomplish the global duties under several United Nations treaties, more precisely, the World Meteorological Organization. The MMS encompasses 5 temperature stations (including 2 synoptic stations, ECV) in Mauritius, 23 rainfall stations, 3 stations including 2 synoptic stations in Rodrigues, one in Agalega and one in St Brandon. Figure 2 depicts the scatterings of the weather stations in Mauritius (Goolaup, 2016).

Table 1 gives an overview of the observation network of the MMS.All material on all pages should fit within an area of A4 (21 x 29.7 cm), 2.8 cm from the top of the page and ending with 2.4 cm from the bottom. The left and right margins should both be 2.4 cm.

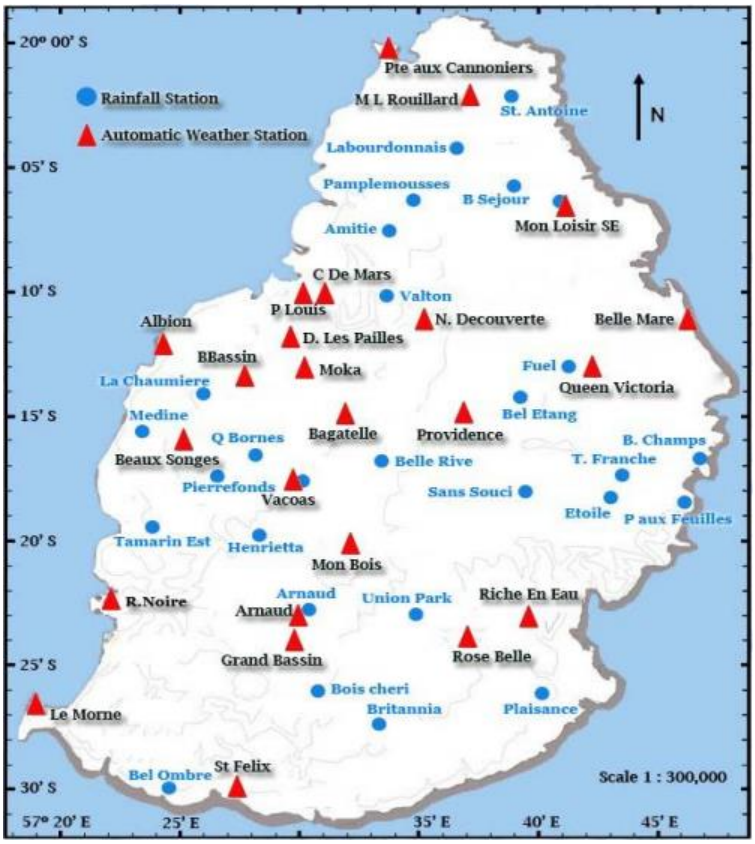


Figure 2: Rainfall and Automatic Weather Stations in Mauritius (Goolaup, 2016).

Table 1: Observation Network of MMS (Goolaup, 2016).

Element	No. of Observation Sites	Length of Records (years)	Remarks
Rainfall	200	Over 100 years at some stations	Excluding AWS
Temperature	26	Over 40 years	Excluding AWS
Atmospheric Pressure	19	Over 40 years	Including Rodrigues and Outer Islands
Wind	35	Over 40 years	9 Dynes, 22 AWS + 4 Outer Islands
Relative Humidity	20	Over 40 years	Excluding AWS
Bright Sunshine	23	Over 40 years	
Evaporation	21	Over 40 years	

3. Real-Time Weather Forecasting Systems and Prediction Algorithms

A typical WSN based real-time weather forecasting system that is connected to the cloud is shown in Fig. 3 (Yawut & Kilaso, 2011).

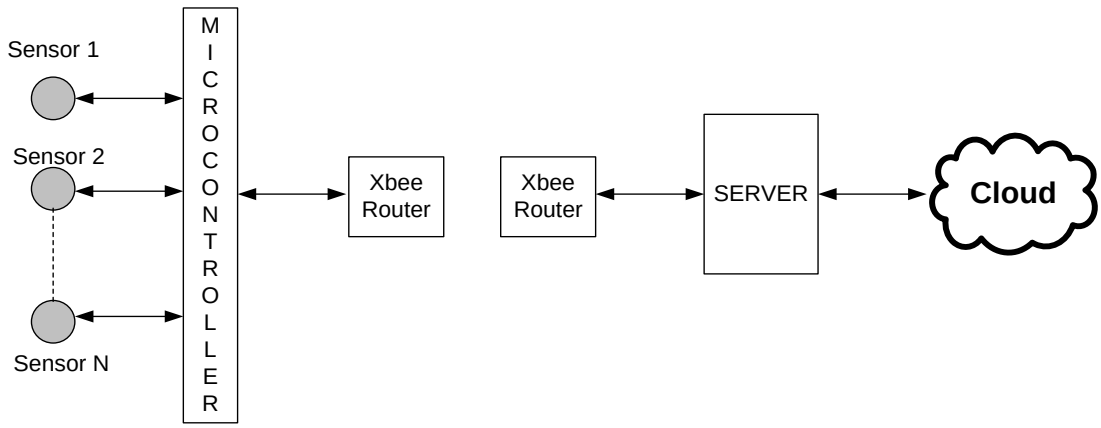


Figure 3: WSN based weather forecasting system.

In this system there are N wireless sensors that are placed in a given location to record weather data such as temperature, wind speed, rainfall, moisture etc. The C language is used to program the wireless sensor nodes if an Arduino UNO board is used as micro-controller or it can be programmed in Java for other micro-controllers such as Raspberry-Pi. The micro-controller remains in standby mode. It awaits requests of data sent from the server. When it receives the request for data, the microcontroller reads the data from different sensors and sends the data back to the server. The wireless communication is ensured by an XBee device which is used to build up a ZigBee/IEEE 802.15.4 (Zigbee Alliance, 2011) network reference standard. XBee functions can be divided by network topology in different ways including the Coordinator / Server, Router and End Device / Sensor (Yawut

& Kilaso, 2011). The server can either process the weather data locally using forecasting algorithms or send the data to be processed by a cloud computing facility. This is normally required for real-time processing of large amounts of data and when it is important to send alert messages to end users. An overview of the forecasting algorithms that can be used with this system is given next.

(i) Regression Model

Suppose the amount of rainfall, Y, is to be predicted based on values obtained for the water velocity, x_1 and water level x_2, both recorded for a given amount of time, T, by the WSN network. Then, Y is given by the following equation (De Castro, Salistre, Byun, & Gerardo, 2013):

$$Y = a + b_1 x_1 + b_2 x_2 \tag{1}$$

Where,

$$b_1 = \frac{(\sum x_2^2)(\sum x_1 Y) - (\sum x_1 x_2)(x_2 Y)}{(\sum x_1^2)(x^2) - (\sum x_1 x_2)^2} \tag{2}$$

$$b_2 = \frac{(\sum x_1^2)(\sum x_2 Y) - (\sum x_1 x_2)(x_1 Y)}{(\sum x_1^2)(x^2) - (\sum x_1 x_2)^2} \tag{3}$$

(ii) Artificial Neural Networks

An ANN is composed of a large number of highly interconnected processing elements (neurons) to solve specific problems. It is an information processing paradigm which models the way biological nervous systems, such as the brain, process information. The main component of this paradigm is the novel structure of the information processing system. In biological systems, learning involves making adjustments to the synaptic connections between the neurons. Neural networks have a wide range of applications in real world problems. They have even been successfully deployed in many industries (Dastorani, Afkhami, Sharifidar, & Dastorani, 2010), (Santhanam & Subhajini, 2011). The configuration of the neural network is highly problem dependent. It is up to the designer to determine the appropriate number of input, output and hidden layer nodes. A generic model that can be used for example to predict temperature in weather forecasting is given Fig. 4 (Hayati & MOhebi, 2007).

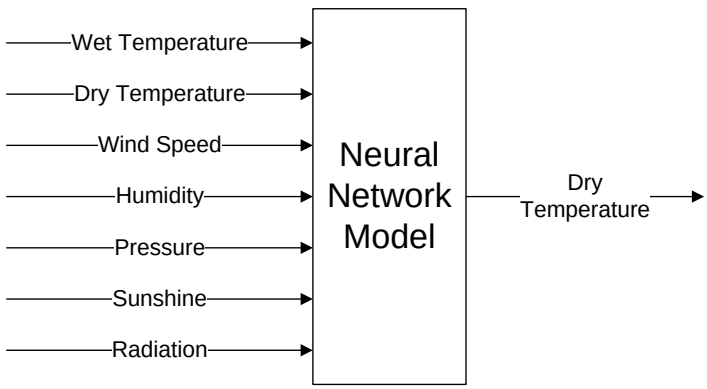


Figure 4: General Structure.

Here there are several weather data that are captured and fed to the ANN based forecasting system which will process the data and generate a forecast of the temperature.

Typically, a neural network consists of layers. A single layered network has an input layer of source nodes and an output layer of neurons. A biological neuron is a unique piece of equipment that transmits information to another neuron in the chain of networks. An artificial neuron tries to perform these functions and their specific process of learning (Fausett, 1994). An artificial neuron is shown in Fig. 5 (Zurada, 1992).

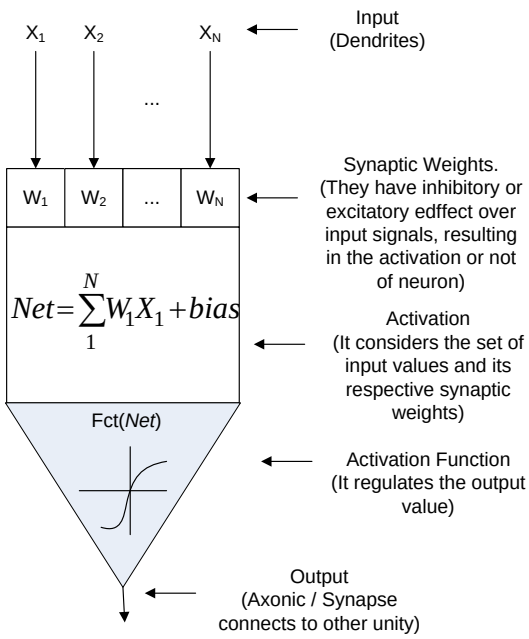
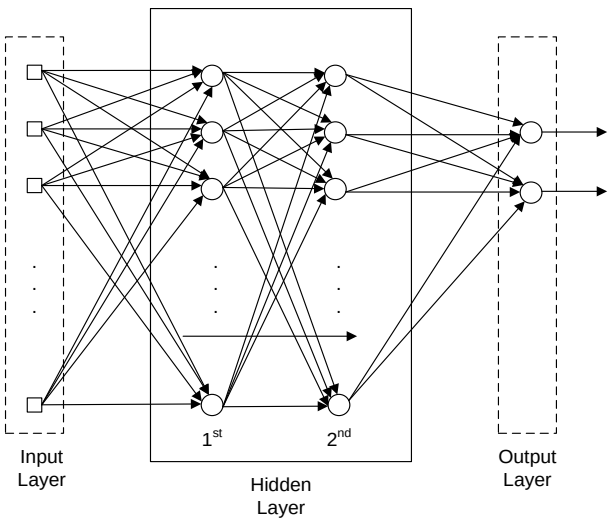


Figure 5: Artificial Neuron.

A multi-layer as shown in Fig. 6 network has in addition one or more hidden layers. Additional hidden neurons increase the network's ability to extract higher order statistics from the input data. A network termed as being fully connected if every node in each layer of the network is connected to every other node in the adjacent forward layer (Khan & Coulibaly, 2010). The network "learns" by adjusting the interconnections (called weights) between layers. A valuable property of neural networks is that of generalization, whereby a trained neural network is able to provide a correct matching in the form of output data for a set of previously unseen input data (Haykin, 1994). When the network is sufficiently trained, it can generalize relevant output for a set of input data.



.**Figure 6:** Multi-Layer Neural Network

(iii) Time Series Analysis

Time series analysis and forecasting is a useful tool in numerous hydro-meteorological applications to analyse trends and variations in variables such as temperature, streamflow, rainfall, humidity, and several other weather elements (Machiwal & Jha, 2006), (Shamsnia, Shahidi, Liaghat, Sarraf, & Vahdat, 2011). There are several time-series analysis techniques for example Moving Average, Weighted Moving Average and Autoregressive Integrated Moving Average (ARIMA) which are sometimes also called Box-Jenkins models (Box & Jenkins, 1976). An autoregressive model of order p is conventionally classified as AR (p) and a moving average model with q terms is known as MA (q). A combined model that contains p AR-terms and q MA-terms is called an ARMA (p, q) model (Badhiye, Wakode, & Chatur, 2012). To make a generally non-stationary time-series stationary time-shifted (by dlags, whereby in most cases d=1) differences are computed before further processing. Such a model is then classified as ARIMA (p, d, q), where the symbol "I" signifies "integrated" (Monsell, 2002).

For climate data which usually follows a seasonal, i.e. an annual cycle, it is more appropriate to use a seasonal ARIMA (p, d, q) (P, D, Q)S model, whereby P is the order of the seasonal AR-model; D is the order of the seasonal differencing (for monthly data, usually, D= 12) and Q is the order of the seasonal MA-model and s is the number of periods in the season (s=12, for an annual cycle) (Acurite, 2010 - 2015).

(iv) KNN for weather forecasting

The k-nearest neighbour algorithm (k-NN) is one basic instance-based learning method that is widely used due to its simplicity and its remarkably good performance and accuracy. K-NN is a non-parametric technique used to categorise or classify different samples (Lammertsma, 2000). It is deployed in cases where anomalies are required to be detected in unknown data sets. The K-NN factor is the metric which is computed based on Mahalanobis distance or Euclidean distance. The Euclidean distance for a two-dimensional data set can be computed using the formula:

$$Euclidean\ distance = \sqrt{\sum_{i=1}^{k}(a_i - b_i)^2} \tag{4}$$

Where,

a and b are coordinates composed of k features such that $a = \{a_1, a_2, \dots, a_k\}$ and $b = \{b_1, b_2, \dots, b_k\}$.

K-NN does not learn a specific mapping function from the training data set. It uses the training data itself during the testing phase for making predictions. The drawback lies in the large number of computations in order to find the K-nearest neighbours for each data point. Therefore, the performance of this technique is highly dependent on the set of records input for training.

With a view to make real-time weather predictions, the work of (Barde & Patole, 2016) presents weather forecasting models using Multi-layer Perceptron, K-Nearest Neighbours and Naïve Bayes techniques. It has been observed that K-NN can have an accuracy of 100% at the expense of increasing execution time with increasing data sizes.

4. Proposed framework for real-time weather forecasting in Mauritius

There are several ways for setting up the prototype of the cloud-based localised weather forecasting system. The set-up greatly depends on the cloud platform to be used to achieve the goal. In this work, the cloud platform to be used is the IBM Bluemix Platform as a Service (PaaS) which has the required services in terms of Internet of Thing ready, Watson APIs for analytics, Databases, Mobile Applications and Services and many more. The IoT architecture with respect the IBM Bluemix platform is shown in Fig. 7. The proposed block diagram for the cloud-based localised weather forecast is shown in Fig. 8.

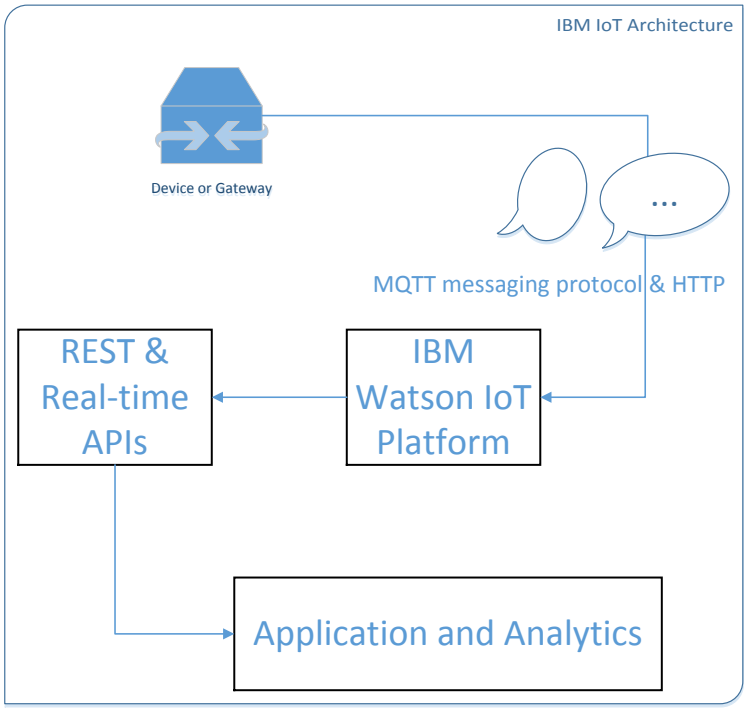


Figure 7: IBM Internet of Things Architecture (IBM, Watson Internet of Things on Bluemix, 2016).

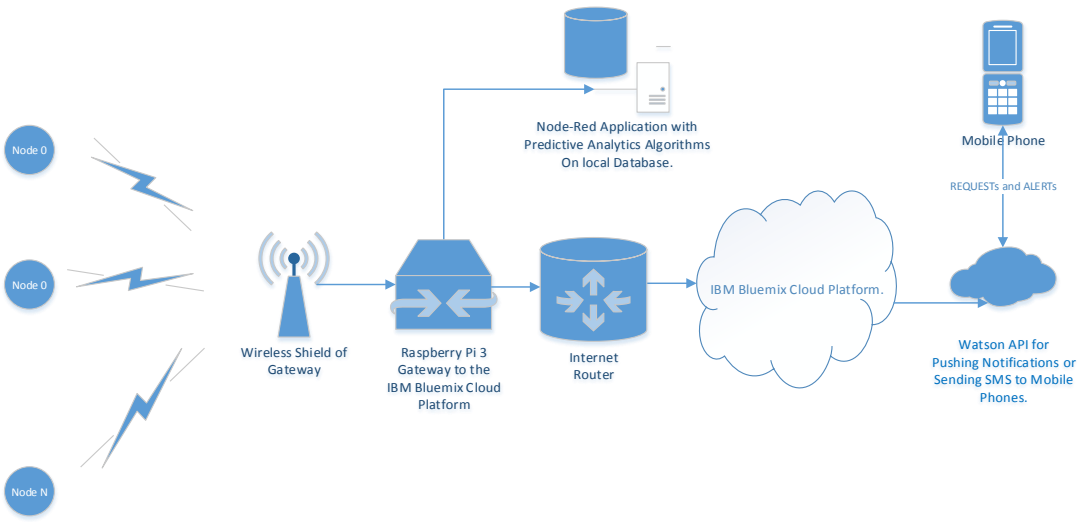


Figure 8: Proposed Architecture for localised cloud-based weather forecast system.

Watson Internet of Things Platform is a fully managed, cloud-based service which eases the derivation of value from Internet of Things (IoT) devices (IBM, Watson Internet of Things on Bluemix,

2016). The IoT device can be a sensor, a mobile, a gateway or something else. By making use of the recipes available on Bluemix, the device can be connected and start sending data securely to the cloud using the open, lightweight MQTT messaging protocol. From there, devices can be setup and managed using the online dashboard or the available secure APIs so as to enable the applications to access live as well as historic data at very high speed. Further to the data access, analytics can also be performed using powerful APIs available on Bluemix (IBM, Watson Internet of Things Platform, 2016).

The different parts of the system have to be set-up independently in order to come up with the complete operational system as shown in Fig. 8. The nodes shown are IoT devices in a wireless sensor network, specifically Arduino microcontrollers with sensors for weather measurements connected and configured, and Wi-Fi shields to communicate data collected to the gateway. The gateway is a Raspberry-PI 3 with the Raspbian Jessie operating system installed. The Raspberry-Pi 3 is a powerful microcontroller with built-in Wi-Fi modules to allow the collection of data being transmitted from the sensor nodes. The data is aggregated and sent over to the IBM Bluemix cloud platform through the Internet by making use of the Ethernet port to connect to an Internet Router. Being equipped with high compute capabilities, local processing of data can also be performed on the Raspberry-PI 3. Once live data is collected on Bluemix, they can be stored on a NoSQL database. The data can then be accessed to perform several operations like Map Reduce tasks or Predictive Analytics. The results obtained from the analytics can then be pushed on mobile applications or send SMSs to specific users. A detailed explanation on each part of Fig. 2 is given in the following sub-sections.

4.1. Sensor Nodes

The sensor nodes need not have high compute capabilities. The requirements for the sensor nodes are as follows:

1. Arduino micro-controllers, as shown in Figure 9.
2. Weather meters: Wind vane, Cup anemometer and Rain Gauge, as shown in Figure 10.
3. Atmospheric Sensors: Temperature Humidity and Barometric Pressure, as shown in Figure 11.
4. XBee and Wi-Fi modules, as shown in Figure 12.

Additional electronic materials such as: bread-boards, connecting wires, power cables and resistors.

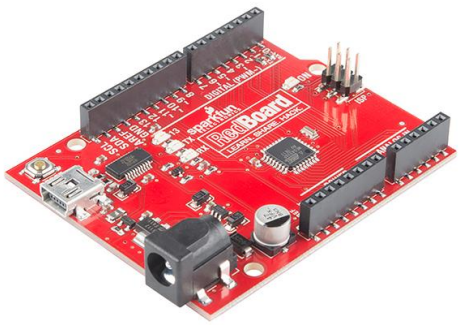


Figure 9: Arduino Micro-controller (Sparkfun Electronics, 2016).

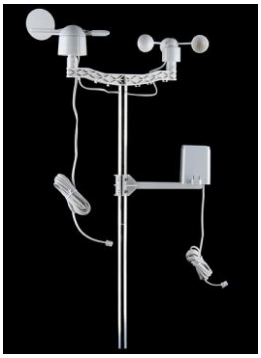


Figure 10: Weather meters (Sparkfun Electronics, 2016).

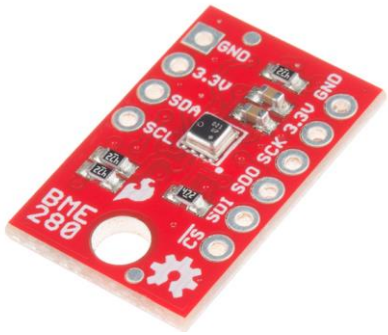


Figure 11: Atmospheric Sensors (Sparkfun Electronics, 2016).

Figure 12: XBee and Wi-Fi module (Sparkfun Electronics, 2016).

The Arduino is programmed in C language to collect the data obtained from the weather and atmospheric sensors. Using the XBee and Wi-Fi module, the data collected is sent over the more compute intensive Raspberry-Pi microcontroller.

4.2. Raspberry-Pi

The Raspberry-Pi is intended for high compute needs and acting as gateway by consolidating data before reporting to the cloud platform. The Raspberry Pi 3 is the third generation Raspberry Pi which has: A 1.2GHz 64-bit quad-core ARMv8 CPU, 802.11n Wireless LAN, Bluetooth 4.1, Bluetooth Low Energy (BLE), 1GB RAM, 4 USB ports, 40 GPIO pins, Full HDMI port, Ethernet port, Combined 3.5mm audio jack and composite video, Camera interface (CSI), Display interface (DSI), Micro SD card slot (now push-pull rather than push-push),and VideoCore IV 3D graphics core. Figure 13 shows the Raspberry-Pi 3.A power supply is needed to operate the Raspberry-Pi. Additionally, a MicroSD card is required to act as the hard drive of the Raspberry-Pi for holding the Operating System and the applications created. Typically, 8 GB or more is recommended for the MicroSD card. The OS which is used on the Raspberry-Pi is the Raspbian Jessie OS which is a linux distribution and comes with Node-Red. In order to transfer the OS to the MicroSD card, a MicroSD adapter or a MicroSD USB adapter is required. The initial set-up of the Raspberry-Pi requires to have a monitor with HDMI input, HDMI cable, and USB keyboard and mouse. During the OS installation, I2C, which is a multi-device pass used to connect other devices such as SenseHAT or the Arduino, needs to be enabled. In order to prevent latencies in the transmission of the collected data to the cloud platform, an Ethernet cable will be used to connect to an internet router instead of Wi-Fi which is already in use to collect data from the Arduino-based sensor nodes. A local application can be built using the Node-Red on the OS to make predictions on the small local dataset and push notifications to mobile devices through Wi-Fi.

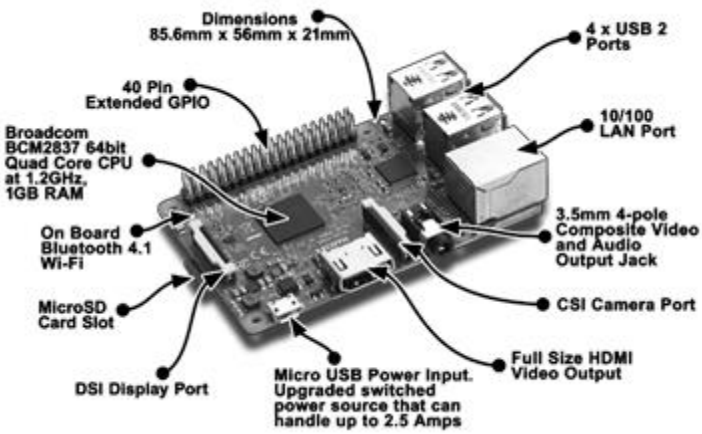


Figure 13: Raspberry-Pi 3 (App Developper Magazine, 2012 - 2016).

4.3. IBM Bluemix Cloud Platform

IBM Bluemix is the cloud platform which is powered by the world's most powerful open source project to accelerate the pace of innovation, take advantage of existing IT and to build systems which use data to understand, reason and learn (IBM, What is Bluemix?, 2016). Several methods and programming languages for building applications on the IBM Bluemix platform are available. In this work, the Node-Red flow using the IBM Watson IoT service running on the Bluemix will be used. The data from sensor nodes (Raspberry-Pi 3 in conjunction with Arduinos and sensors) arrive into Bluemix where it can be saved on the Cloudant database which is a NoSQL database already bound to the application upon creation. The "ibmiot" node in Node-Red is used to get the data from the Raspberry-Pi using the MAC-Address as unique identifier. The data will be in JSON format so as to ease handling and processing. Once the data is available on the cloud platform, analytics can be performed as per the requirements of the application and notifications as well as SMSs can be sent to mobile devices using the "MQTT", "Twilio" and "ibmpush" nodes.

Historic Data can initially be populated to the Cloudant Database so as to perform analytics and look for trends in the data and then perform testing on live data for predictive analytics. The application running in IBM Bluemix has a rich set of services which can be pulled into the application. The services which are not available in Node-Red can be replaced using the API libraries or REST APIs so as to plug-in to the rest of the services from a Node-Red environment. Node-Red is basically a Node.js application and the files can be viewed and modified on Bluemix such that there is the option to extend the application using JavaScript codes. Flows can thus mi mixed which is useful for the incorporation of mathematical modifications to existing algorithms or devise new algorithms and apply to the application.

Additionally, there exists APIs on the IBM Bluemix platform which allow to build a mobile application. Nodes can be added to the Node-Red flow to push notifications to mobile devices through Wi-Fi or send SMSs. In order to achieve this, the "Twilio" node can be used for sending SMS and the "ibmpush" node can be used to push notifications to mobile nodes. Another useful node is the "rbe (report by exception)" node which prevents being notified every time of the same situation. It allows notifications only when there is a change. A sample flow diagram on Node-Red in Bluemix can be as shown in Fig. 14.

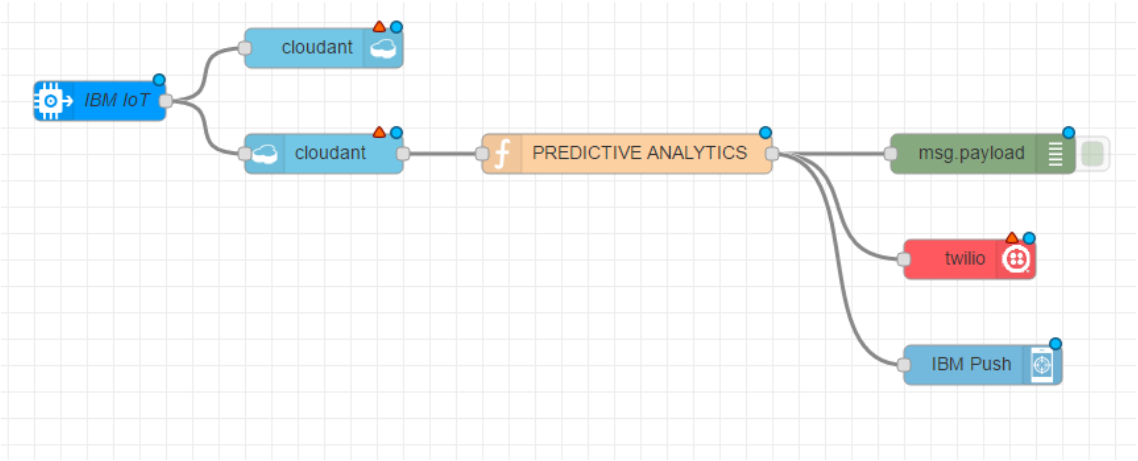


Figure 14: Sample Flow Diagram in Node-Red on Bluemix Cloud Platform.

CONCLUSION

In this paper an in depth analysis of real-time weather forecasting systems has been carried out. Additionally a framework for implementing a real-time weather forecasting system in Mauritius has been proposed. The proposed system will be developed with a WSN based on Arduino and Rasberry-PI3 microcontrollers. It uses the IBM Bluemix cloud platform for predictive analytics and is very effective as it will be able to execute in real time. It does not require any special clearance from authorities. Its complexity is low and no database is needed to predict as compared to traditional methods. It consumes very less amount of time to be implemented unlike other techniques that consume a lot of time to process very huge database and further finding patterns of hidden knowledge in order to produce predictions. The method costs very less as the sensors used are of low cost and the micro-controller board is programmed easily. The same board can even be used for different purposes. The proposed system has the potential to support emergency managers e.g. fire services / Police and SMF and the general public in severe weather events by promptly providing them with potentially life-saving information. As future work, the proposed system will be implemented and tested in different regions of Mauritius.

12. References

[1] Acurite, "5 - in - 1 Weather Sensor," 2010 - 2015. [Online]. Available: http://www.acurite.com/learn/weather-stations/acurite-5-in-1-sensor. [Accessed 11 June 2016].

[2] App Developper Magazine, "Raspberry Pi 3 Model B Offers Built-in Wireless LAN and Bluetooth," 2012 - 2016. [Online]. Available: https://appdevelopermagazine.com/3688/2016/2/29/Raspberry-Pi-3-Model-B-Offers-Built-in-Wireless-LAN-and-Bluetooth/.

[3] B. C. Monsell, "An Update on the Development of the X-12-ARIMA Seasonal Adjustment Program," in Proceedings of the 3rd Internat. Symposium on Frontiers of Time Series Modeling, Tokyo: Institute of Statistical Mathematics, Japan, 2002.

[4] B. M. Padya, Weather and Climate of Mauritius (1st Edition), Moka: Mahatma Gandhi Institute, Mauritius, 1989.

[5] BBC News, 1 January 2011. [Online]. Available: http://www.bbc.com/news/world-asia-pacific-12102126. [Accessed 2016 December 2016].

[6] C. Yawut and S. Kilaso, "A Wireless Sensor Network for Weather and Disaster Alarm Systems," in International Conference on Information and Electronics Engineering, IPCSIT, Singapore, 2011.

[7] D. G. Huber and J. Gulledge, "EXTREME WEATHER & CLIMATE CHANGE: UNDERSTANDING THE LINK AND MANAGING THE RISK," December 2011. [Online]. Available: http://www.c2es.org/docUploads/white-paper-extreme-weather-climate-change-understanding-link-managing-risk.pdf. [Accessed 13 December 2016].

[8] D. Machiwal and M. K. Jha, "Time Series Analysis of Hydrologic Data for Water Resources Planning and Management: A Review," Journal of Hydrology and Hydromechanics, vol. 54, no. 3, pp. 237 - 257, 2006.

[9] G. E. P. Box and G. M. Jenkins, Time Series Analysis: Forecasting and Control. Revised Edition, San Francisco, CA: Holden-Day, 1976.

[10] Government Information Service Newsletter, "Eleven die in flash floods," March 2013. [Online]. Available: http://gis.govmu.org/English/Documents/News%20March%202013.pdf. [Accessed 14 December 2016].

[11] IBM, "Watson Internet of Things on Bluemix," IBM, 2016. [Online]. Available: http://www.ibm.com/cloud-computing/bluemix/internet-of-things/. [Accessed 11 June 2016].

[12] IBM, "Watson Internet of Things Platform," 2016. [Online]. Available: http://www-03.ibm.com/software/products/en/internet-of-things-platform. [Accessed 12 June 2016].

[13] IBM, "What is Bluemix?," IBM, 2016. [Online]. Available: http://www.ibm.com/cloud-computing/bluemix/what-is-bluemix/. [Accessed 11 June 2016].

[14] Intergovernmental Panel on Climate Change, "Impacts, Adaptation and Vulnerability. Contribution of Working Group II to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change," Cambridge University Press, Lipton, 2007.

[15] J. M. Chun, "Migration, Environment and Climate Change: Policy Brief Series," International Organisation for Migration, vol. 1, no. 11, 2015.

[16] J. M. Zurada, Fundamental of Neural Networks, Saint Paul Minnesota: West Publishing Company, 1992.

[17] J. T. De Castro, G. M. Salistre, J. Y. C. Byun and B. D. Gerardo, "Flash Flood Prediction Model based on Multiple Regression Analysis for Decision Support System," in Proceedings of the World Congress on Engineering and Computer Science, San Francisco, USA, 2013.

[18] L. Fausett, Fundamental of Neural Networks, New York: Prentice Hall, 1994.

[19] M. Hayati and Z. MOhebi, "Application of Artificial Neural Networks for Temperature Forecasting," International Journal of Electrical, Computer, Energetic, Electronic and Communication Engineering, vol. 1, no. 4, pp. 654 - 658, 2007.

[20] M. S. Khan and P. Coulibaly, "Assessing hydrologic impact of climate change with uncertainty estimates: Back propagation neural network approach," Journal of Hydrometeorology, vol. 11, pp. 482 - 495, 2010.

[21] M. T. Dastorani, H. Afkhami, H. Sharifidar and M. Dastorani, "Application of ANN and ANFIS models on dryland precipitation prediction," Journal of Applied Science, vol. 10, no. 20, pp. 2387 - 2394, 2010.

[22] Mauritius Meteorological Services, "Climate Change," 2016. [Online]. Available: metservice.intnet.mu/climate-services/climate-change.php. [Accessed 16 December 2016].

[23] Meteorological Services, "Technical Report CS 28 Cyclone Season of the South West Indian Ocean 2006-2007," January 2008. [Online]. Available: http://metservice.intnet.mu/pdfs/technical-note-on-cyclone-season.pdf. [Accessed 14 December 2016].

[24] Ministry of Environment and Sustainable Development, "Maurice Ile Durable: Policy, Strategy and Action Plan," May 2013. [Online]. Available: http://www.govmu.org/portal/sites/mid/file/full%20report%20midpolicy.pdf. [Accessed 13 December 2016].

[25] Ministry of Environment and Sustainable Development, and Disaster and Beach Management, "National Climate Change Adaptation Policy Framework for the Republic of Mauritius," 30 July 2013. [Online]. Available: http://environment.govmu.org/English/Climate_Change/Pages/Climate-Change.aspx. [Accessed 14 December 2016].

[26] N. C. Barde and M. Patole, "Classification and Forecasting of Weather using ANN, k-NN and Naïve Bayes Algorithms," International Journal of Science and Research (IJSR), vol. 5, no. 2, pp. 1740 - 1742, 2016.

[27] National Climatic Data Center, "State of the Climate: Global Analysis for May 2011," June 2011. [Online]. Available: http://www.ncdc.noaa.gov/sotc/global/201105. [Accessed 13 December 2016].

[28] P. Goolaup, "Mauritius Meteorological Services - Capabilities for the provision of climate services at national level," 14 March 2016. [Online]. Available: http://www.gfcs-climate.org/sites/default/files/Mauritius.pdf. [Accessed 14 December 2016].

[29] P. Lammertsma, "K-Nearest Neighbor Algorithm," 2000.

[30] S. A. Shamsnia, N. Shahidi, A. Liaghat, A. Sarraf and S. F. Vahdat, "Modeling Of Weather Parameters (Temperature, Rainfall And Humidity) Using Stochastic Methods," in International Conference on Environment and Industrial Innovation, IPCBEE, Singapore, 2011.

[31] S. C. Fowdur, S. D. D. V. Rughooputh, J. Cheeneehash, R. Boojhawon and A. Gopaul, "Rainfall analysis over Mauritius using Principal Component Analysis," Environmental Management and Sustainable Development, vol. 3, no. 2, pp. 94 - 108, 2014.

[32] S. Haykin, Neural Networks: A Comprehensive Foundation, New York, Macmillan: Prentice Hall, 1994.

[33] S. S. Badhiye, B. V. Wakode and P. N. Chatur, "Analysis of Temperature and Humidity Data for Future Value Prediction," IJCSIT, vol. 3, no. 1, pp. 3012 - 3014, 2012.

[34] Sparkfun Electronics, "SparkFun Atmospheric Sensor Breakout - BME280," 2016. [Online]. Available: https://www.sparkfun.com/products/13676. [Accessed 17 December 2016].

[35] Sparkfun Electronics, "SparkFun RedBoard - Programmed with Arduino," 2016. [Online]. Available: https://www.sparkfun.com/products/12757. [Accessed 17 December 2016].

[36] Sparkfun Electronics, "Weather Meters," 2016. [Online]. Available: https://www.sparkfun.com/products/8942?_ga=1.249437381.333494973.1462356297. [Accessed 17 December 2016].

[37] Sparkfun Electronics, "XBee WiFi Module - PCB Antenna," 2016. [Online]. Available: https://www.sparkfun.com/products/12568?_ga=1.15568246.1908961372.1461466768. [Accessed 17 December 2016].

[38] T. R. Karl, G. A. Meehl, C. D. Miller, S. J. Hassol, A. M. Waple and W. L. Murray, Weather and Climate Extremes in a Changing Climate Regions of Focus: North America, Hawaii, Caribbean, and U.S. Pacific Island. A rep[ort by the U.S. Climate Change Science Program and the subcomittee on Global Change Research, Washington, D. C., USA: Department of Commerce, NOAA's National Climatic Data Center, 2008.

[39] T. Santhanam and A. C. Subhajini, "An Efficient Weather Forecasting System using Radial Basis Function Neural Network," Journal of Computer Science, vol. 7, no. 7, pp. 962 - 966, 2011.

[40] United Nations Environment Programme (UNEP), "Emerging issues for small Island Developing States. Results of the UNEP Foresight Process," United Nations Environment Programme (UNEP), Nairobi, Kenya, 2014.

[41] United Nations Framework Convention on Climate Change, "Chapter 3: Vulnerability and Adaptation," 2014. [Online]. Available: http://unfccc.int/resource/docs/natc/maunc1/chap3/chapter3.htm. [Accessed 13 December 2016].

[42] Zigbee Alliance, "Zigbee Technology," 2011. [Online]. Available: http://www.zigbee.org/About/AboutTechnology/ZigBeeTechnology.asp. [Accessed 11 June 2016].