Development of an Enhanced Bayesian Model Averaging Technique for Weather Forecasting

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ABSTRACT

This study has been undertaken to investigate Weather Forecasting using an Enhanced Bayesian Model Averaging Technique. Seventy (70%) percent of data in Ibadan was retrieved from OpenWeatherMap Application Programming Interface (API) online data repository which was used for training and the remaining thirty percent (30%) was used for the testing process. The EBMA was developed by introducing the operators of Ant Colony Optimization Algorithm (ACO). The Max-Min Ant System (MMAS) technique was used for feature normalization. Evaluation of the developed EBMA technique was investigated by benchmarking its performance with BMA using Mean Square Error (MSE) and Mean Absolute Error (MAE). The developed EBMA has effectively reduced the problems of poor weather forecasting with associated high accuracy in weather forecasting.

Keywords: Enhanced BMA, Numerical Weather forecasting, Ant Colony Optimization

INTRODUCTION

Weather forecasts are generated by collecting quantitative data about the state of the atmosphere and using a scientific understanding of atmospheric process to extrapolate how the atmosphere will evolve. This can also be defined as a scientific estimate of the weather conditions at subsequent time, conveyed in terms of temperature, precipitation, wind etc. It is generally achieved through three major steps: i) observation and data collection, ii) assimilation, processing and analysis and iii) extrapolation to predict the future state of the atmosphere. The totality of observations, analysis, and model constitute a forecast system.

Weather forecasts have always played an important role to humankind in their everyday life activities. For example, forecasts help people determine what to wear or what activities to do on a given day; whether the weekend will permit an outing, rally, school bash, or an outdoor for a wedding reception and whether or not to put on a coat or carry an umbrella. People can also know and be aware of atmospheric changes through variables such as temperature, wind speed and direction, humidity, sunshine, cloudiness and precipitation. Variations in these parameters describe weather the state of the atmosphere at a particular time. However, different terminologies are used to describe weather in terms of sets of fundamental quantities and various characterizations proposed and employed in weather forecasting.

Need Of The Study

Impacts of global warming on the climate and weather conditions that occur at these days are unstable and fluctuate. This causes many environmental problems and social issues which directly impact livings. Therefore, forecasting techniques to predict weather with diverging outputs are necessary; such method which output is mapped into each coordinate of a region presenting detailed information on the status of the weather. Presently, accurate weather forecasting has been a major problem in Nigeria. Some methods have met many unresolved challenges which have become a major concern for the Meteorology Department in Nigeria. The task is complicated in the field of meteorology because all decisions are made within a visage of uncertainty associated with the weather system. Chaotic features associated with atmospheric phenomenal has also attracted the attention of modern scientist.

RESEARCH METHODOLOGY

The methodology section outlined the plan and method of how the study is conducted. This includes Data and sources of data, Data pre-processing, Data cleaning, Data selection.

Data and Sources of Data

In the data processing, 70% of the total Countries data in the world was used for training and the remaining 30% was used for the testing process. The dataset employed are weather data that are obtained from OpenWeatherMap Application Programming Interface (API) and API. The data collected are data that are passed as preprocessing data. The data collected are data that are passed as preprocessing data. Historical data and Classification data are required. Historical data acquired are the weather data at some geographical points of the city's districts Nigeria. The collection comes from a raw data list which was retrieved from the site of the OpenWeatherMap Application Programming Interface (API) server. The next data sources are sorted and stored in a database application. Preprocessing consists of two stages; namely Data cleaning and Data selection. Then subsequently these data are entered into the forecasting process consisting of several stages of training data normalization, determining activation function process, calculating on each weight difference, and calculating on net weight and output. The testing process are performed.

Theoretical Framework

Variables of the study contains dependent and independent variable. The study used pre-specified method for selection of variables.

Enhanced Bayesian Model Averaging is a method that is capable to predict the best model based on the weighted average of all models. Enhanced BMA evenly averages the posterior distribution of all the possibly formed models. The purpose of the Enhanced BMA is to combine uncertain models to get the best model. The estimation result includes all models that may have formed so they can get a better estimation (Montgomery and Nyhan, 2010). Since the data has undergone a series of pre-processing, the data are then stored as initial data used in the forecasting process. There is a chronology of the forecasting process using Enhanced Bayesian Model Averaging (EBMA).

Ant Colony Optimization (ACO) is based on the natural behavior of ant colonies and their individual worker ants. When ants forage, they naturally seem to find a “logical” and “effective” route between their nest and the food source; in other words, they seem to determine an optimum route. Ant Colony Optimization (ACO) employs artificial ants that corporate to find good solutions for discrete optimization problems. These software agents mimic the foraging behavior of their biological equal in finding the shortest path to the source of the food (David et al., 2007).

The Max-Min Ant system (MMAS) algorithm controls the maximum and minimum pheromone amounts on each trail. Only the global best tour or the iteration best tour are allowed to add pheromone to its trail. To avoid stagnation of the search algorithm, the range of possible pheromone amounts on each trail is limited to an interval [τmax,τmin]. All edges are initialized to τmax to force a higher exploration of solutions. The trails are reinitialized to τmax when nearing stagnation.

Statistical tools and Econometric Models

This section elaborates the proper statistical/econometric/models which are being used to forward the study from data towards inferences. The detail of methodology is given as follows.

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Descriptive Statistics

Descriptive statistics has been used to find the maximum, minimum, standard deviation, mean and normally distribution of the data of all the variables of the study.

Linear Regression Model of Bayesian Model Averaging

The implementation of BMA, which was first proposed by (Leamer, 1978), for linear regression models is as follows. Consider a Linear Regression model with a constant term, β0, and k potential explanatory variables x1, x2, . . . ,xk,

$y = \beta 0 + \beta 1\ x1 + \beta 2\ x2 + \cdots + \beta k\ xk + \varepsilon$ (1)

Given the number of regressions, we will have 2k different combinations of right hand side variable indexed by Mj for j = 1, 2, 3, . . . , 2k . Once the model space has been constructed, the posterior distribution for any coefficient of interest, say βh, given the data D is

$\Pr(\beta h|D) = \sum Pr(\beta h|Mj)\ Pr(Mj|D)\ j{:}\beta h \in Mj$ (1.2)

BMA uses each model's posterior probability, $Pr(Mj|D)$, as weights. The posterior model probability of Mj is the ratio of its marginal likelihood to the sum of marginal likelihoods over the entire model space and is given by

$Pr(Mj|D) = Pr(D|Mj)\ Pr(Mj)\ Pr(D)$

$Pr(D|Mj)\ Pr(Mj) \sum 2k\ i{=}1\ Pr(D|Mj)\ Pr(Mi)$ (1.3)

Where: $Pr(D|Mj) = \int Pr(D|\beta j, Mj)\ Pr(\beta j, Mj)\ d\beta j$

and βj is the vector of parameters from model Mj, Pr (βj, Mj) is a prior probability distribution assigned to the parameters of model Mj, and Pr (Mj) is the prior probability that Mj is the true model. The estimated posterior means and standard deviations of β^ = (β^0, β^1, . . . , β^k) are then constructed as:

$E[\beta\hat{}|D] = \sum 2k\ j{=}1\ \beta\hat{}\ Pr(Mj|D)$,

$V[\beta\hat{}|D] = \sum 2k\ j{=}1\ (Var[\beta|D, Mj] + \beta\hat{}\ 2)\ Pr(Mj|D) - E[\beta\hat{}|D]\ 2$ (1.4)

Performance Evaluation

The system was assessed based on its overall accuracy and other characteristics of the system using the performance metrics stated below:

Mean Square Error (MSE)

This is defined as Mean or Average of the square of the difference between actual and estimated values of dataset. The error value was known at Minimum temperature which was rated and Maximum temperature was also rated. Meanwhile, the error value of Minimum humidity was rated and the error value of Maximum humidity was rated. After all, the forecasting error rate of wind speed was also rated.

$$\mathrm{MSE} = \frac{1}{n}\sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2. \qquad (3.1)$$

n = number of data points

Yi = Observed values

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Y ^ i = Predicted value

Mean Absolute Error (MAE)

This is calculated by taking the mean of the absolute Differences between the actual values (also called y) and the predicted values.

$$MAE = \frac{1}{n}\sum_{i=1}^{n} |y_i - \hat{y}_i| \qquad (3.2)$$

n = total number of data points

yi = Prediction

y ^ = True value

RESULTS AND DISCUSSION

The new system was improved by adding the Max-min Ant System (MMAS) feature which has a default value of 'MSE' i.e. Mean Square Error which is the function to measure the quality of a split and changing it to 'MAE' which stands for Mean Absolute Error, adding and setting the bootstrap value which has a default value of True to False. The activation function for the weather forecasting process is the bipolar threshold activation function. The modification of the threshold function has three output values, Rangeley -1, 0, or 1. Calculating the value of each node activation function is by setting with a random value that outputs the value of -1, 0, or 1.

In the prediction process, 70% of the data was used for training and the remaining 30% was used for the testing process. The respective dataset was imported into Visual Studio Code (VS-code) environment using JavaScript Object Notation (JSON) library. The dataset was analyzed and pre-processed using JavaScript Object Notation (JSON) library, visualized using Matplotlib and Numpy packages libraries and subsequent prediction result was gotten. This result gives an insight into the prediction carried out and the metrics for performance evaluation. The weather data retrieved from the OpenWeatherMap server which has been stored in the database earlier. Forecasting the weather data begins by opening the Weather forecasting application on the browser page. Then on the same page, system requires users to input the city location to forecast the weather.

Table 4.1. Weather Forecasting Results for Existing system

	A	B	C	D	E	G	H	K	P	Q
1	City Name	Date/time	Max Temp	Min Temp	Normal Temp	Heat Index	Precipitation	Wind Speed	Relative Humidity	Conditions
2	Ibadan, Oyo	10/01/2021	30.4	22.1	26.2	35.7	31	12	81.33	Rain, Partially cloudy
3	Ibadan, Oyo	10/02/2021	31	30.1	30.7	35.9	0	14.8	63.94	Overcast
4	Ibadan, Oyo	10/03/2021	25.4	22.4	24.4		9	9.4	97.04	Rain, Overcast
5	Ibadan, Oyo	10/4/2021	27.6	25	26.5	31.2	2	27.7	86.71	Rain, Overcast
6	Ibadan, Oyo	10/05/2021	28	26	27	32.7	0	9.4	89.01	Partially cloudy
7	Ibadan, Oyo	10/06/2021	30.2	26.6	28.4	37.8	0	11.2	85.39	Overcast
8	Ibadan, Oyo	10/07/2021	32	26	29	37.9	0	9.4	69.09	Partially cloudy
9	Ibadan, Oyo	10/08/2021	33.1	24	27.7	38.9	0	11.2	80.84	Partially cloudy
10	Ibadan, Oyo	10/09/2021	25	24	24.7		0	5.4	96.13	Overcast
11	Ibadan, Oyo	10/10/2021	25.6	25.6	25.6		0	11.2	87.66	Overcast
12	Ibadan, Oyo	10/11/2021	31.1	31.1	31.1	38.3	0	11.2	71.76	Overcast
13	Ibadan, Oyo	10/12/2021	32.1	26	30.7	40.6	0	9.4	70.43	Partially cloudy
14	Ibadan, Oyo	10/13/2021	31	24.9	27.6	37.7	0	11.2	80.53	Overcast
15	Ibadan, Oyo	10/14/2021	32	27	29.3	36.8	0	22.3	71.74	Partially cloudy
16	Ibadan, Oyo	10/15/2021	32.1	25	29.2	40	0	40.7	77.3	Partially cloudy
17	Ibadan, Oyo	10/16/2021	34	32.1	33	40.6	0	13	50.55	Partially cloudy
18	Ibadan, Oyo	10/17/2021	31.4	24.1	28.6	38.3	0.9	16.6	73.9	Rain, Overcast
19	Ibadan, Oyo	10/18/2021	31.6	27	29.2	38.4	0	11.2	73.35	Partially cloudy
20	Ibadan, Oyo	10/19/2021	31.7	23	27	35.5	0	16.6	80.06	Partially cloudy
21	Ibadan, Oyo	10/20/2021	27	23.1	25	30.1	0	9.4	91.54	Partially cloudy
22	Ibadan, Oyo	10/21/2021	30	25	27	35.1	0	11.2	84.41	Partially cloudy
23	Ibadan, Oyo	10/22/2021	31	24.4	26.5	36.5	0	11.2	84.23	Overcast
24	Ibadan, Oyo	10/23/2021	24.1	23	23.3		0	0	98.05	Overcast
25	Ibadan, Oyo	10/24/2021	31	25	28	35.5	0	11.2	76.97	Partially cloudy
26	Ibadan, Oyo	10/25/2021	28.1	24	25.4	33.8	0	18.4	93.32	Partially cloudy
27	Ibadan, Oyo	10/26/2021	25.7	24	24.8		0	11.2	92.52	Partially cloudy
28	Ibadan, Oyo	10/27/2021	32	24.2	28.6	36.8	15	9.4	73.78	Rain, Overcast
29	Ibadan, Oyo	10/28/2021	32	24.6	28.9	36.8	0	14.8	74.82	Partially cloudy
30	Ibadan, Oyo	10/29/2021	33	24	27.2	39.3	3	27.7	81.1	Rain, Partially cloudy
31	Ibadan, Oyo	10/30/2021	26.6	24	24.5		0	14	94.17	Partially cloudy
32	Ibadan, Oyo	10/31/2021	29.4	26	27.2	33.8	0	18.3	87.59	Partially cloudy

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Table 4.2. Weather Forecasting Results for Enhanced system

1	City Name	Date/time	Max Temp	Min Temp	Normal Temp	Heat Index	Precipitation	Wind Speed	Relative Humidity	Conditions
2	Ibadan, Oyo	10/01/2021	33.4	24.1	27.2	36.7	33	13	82.33	Rain, Partially cloudy
3	Ibadan, Oyo	10/02/2021	32	31.1	31.7	37.9	0	14.8	63.94	Overcast
4	Ibadan, Oyo	10/03/2021	24.4	24.4	24.4		9	9.4	97.04	Rain, Overcast
5	Ibadan, Oyo	10/04/2021	27.6	25	26.5	31.2	2	27.7	86.71	Rain, Overcast
6	Ibadan, Oyo	10/05/2021	28	26	27	32.7	0	9.4	89.01	Partially cloudy
7	Ibadan, Oyo	10/06/2021	30.2	26.6	28.4	37.8	0	11.2	85.39	Overcast
8	Ibadan, Oyo	10/07/2021	32	26	29	37.9	0	9.4	69.09	Partially cloudy
9	Ibadan, Oyo	10/08/2021	33.1	24	27.7	38.9	0	11.2	80.84	Partially cloudy
10	Ibadan, Oyo	10/09/2021	25	24	24.7		0	5.4	96.13	Overcast
11	Ibadan, Oyo	10/10/2021	25.6	25.6	25.6		0	11.2	87.66	Overcast
12	Ibadan, Oyo	10/11/2021	31.1	31.1	31.1	38.3	0	11.2	71.76	Overcast
13	Ibadan, Oyo	10/12/2021	32.1	26	30.7	40.6	0	9.4	70.43	Partially cloudy
14	Ibadan, Oyo	10/13/2021	31	24.9	27.6	37.7	0	11.2	80.53	Overcast
15	Ibadan, Oyo	10/14/2021	32	27	29.3	36.8	0	22.3	71.74	Partially cloudy
16	Ibadan, Oyo	10/15/2021	32.1	25	29.2	40	0	40.7	77.3	Partially cloudy
17	Ibadan, Oyo	10/16/2021	34	32.1	33	40.6	0	13	50.55	Partially cloudy
18	Ibadan, Oyo	10/17/2021	31.4	24.1	28.6	38.3	0.9	16.6	73.9	Rain, Overcast
19	Ibadan, Oyo	10/18/2021	31.6	27	29.2	38.4	0	11.2	73.35	Partially cloudy
20	Ibadan, Oyo	10/19/2021	31.7	23	27	35.5	0	16.6	80.06	Partially cloudy
21	Ibadan, Oyo	10/20/2021	27	23.1	25	30.1	0	9.4	91.54	Partially cloudy
22	Ibadan, Oyo	10/21/2021	30	25	27	35.1	0	11.2	84.41	Partially cloudy
23	Ibadan, Oyo	10/22/2021	31	24.4	26.5	36.5	0	11.2	84.23	Overcast
24	Ibadan, Oyo	10/23/2021	24.1	23	23.3		0	0	98.05	Overcast
25	Ibadan, Oyo	10/24/2021	31	25	28	35.5	0	11.2	76.97	Partially cloudy
26	Ibadan, Oyo	10/25/2021	28.1	24	25.4	33.8	0	18.4	93.32	Partially cloudy
27	Ibadan, Oyo	10/26/2021	25.7	24	24.8		0	11.2	92.52	Partially cloudy
28	Ibadan, Oyo	10/27/2021	32	24.2	28.6	36.8	15	9.4	73.78	Rain, Overcast
29	Ibadan, Oyo	10/28/2021	32	24.6	28.9	36.8	0	14.8	74.82	Partially cloudy
30	Ibadan, Oyo	10/29/2021	33	24	27.2	39.3	3	27.7	81.1	Rain, Partially cloudy
31	Ibadan, Oyo	10/30/2021	25.6	24	24.5		0	13	94.17	Partially cloudy
32	Ibadan, Oyo	10/31/2021	28.4	26	27.2	32.8	0	18.3	86.59	Partially cloudy

Performance Evaluation Results

Forecasting error for Existing system is calculated by Mean Square Error (MSE) diverging at 0.85% of Minimum Temperature parameter, 0.198% of Maximum Temperature parameter, 0.073% of Normal Temperature parameter, 0.178% of Humidity parameter, 0.244% of Wind Speed parameter, 0.277% of Precipitation parameter and 0.189% of Heat Index parameters respectively. Forecasting error for Enhanced system is calculated by Mean Square Error (MSE) diverging at 0.75% of Minimum Temperature parameter, 0.196% of Maximum Temperature parameter, 0.070% of Normal Temperature parameter, 0.168% of Humidity parameter, 0.144% of Wind Speed parameter, 0.257% of Precipitation parameter and 0.179% of Heat Index parameters respectively. Mean Square Error (MSE) is a method for measuring Forecasting Error. In this method, each error or residual is squared, then summed or divided by the number of observations. Table 3.2 shows the Mean Square Error (MSE) calculations and Averaged Absolute Forecast Error against its actual data. Error calculation results using the Mean Square Error (MSE) are provided.

Forecasting error for Existing system is calculated by Mean Absolute Error (MAE) diverging at 0.322% of Minimum Temperature parameter, 0.261% of Maximum Temperature parameter, 0.0867% of Normal Temperature parameter, 0.143% of Humidity parameter, 0.37% of Wind Speed parameter, 0.27% of Precipitation parameter and 1.0333% of Heat Index parameter respectively. Forecasting error for Enhanced system is calculated by Mean Absolute Error (MAE) diverging at 0.21% of Minimum Temperature parameter, 0.141% of Maximum Temperature parameter, 0.002% of Normal Temperature parameter, 0.011% of Humidity parameter, 0.25% of Wind Speed parameter, 0.18% of Precipitation parameter and 0.021% of Heat Index parameter respectively. Mean Absolute Error (MAE) is a method for measuring Forecasting Error. In this method, each error or residual is squared, then summed or divided by the number of observations.

Forecasting error for Existing system is calculated by Mean Square Error (MSE) diverging at 0.85% of Minimum Temperature parameter, 0.198% of Maximum Temperature parameter, 0.073% of Normal Temperature parameter, 0.178% of Humidity parameter, 0.244% of Wind Speed parameter, 0.277% of Precipitation parameter and 0.189% of Heat Index parameters respectively. Forecasting error for Enhanced system is calculated by Mean Square Error (MSE) diverging at 0.75% of Minimum Temperature parameter, 0.196% of Maximum Temperature parameter, 0.070% of Normal Temperature parameter, 0.168% of Humidity parameter, 0.144% of Wind Speed parameter, 0.257% of Precipitation parameter and 0.179% of Heat Index parameters respectively. Mean Square Error (MSE) is a method for measuring Forecasting Error. In this method, each error or residual is squared, then summed or divided by the number of observations. Table 3.2 shows the Mean Square Error (MSE) calculations and Averaged Absolute Forecast Error against its actual data. Error calculation results using the Mean Square Error (MSE) are provided.

Forecasting error for Existing system is calculated by Mean Absolute Error (MAE) diverging at 0.322% of Minimum Temperature parameter, 0.261% of Maximum Temperature parameter, 0.0867% of Normal Temperature parameter, 0.143% of Humidity parameter, 0.37% of Wind Speed parameter, 0.27% of Precipitation parameter and 1.0333% of Heat Index parameter respectively. Forecasting error for Enhanced system is

calculated by Mean Absolute Error (MAE) diverging at 0.21% of Minimum Temperature parameter, 0.141% of Maximum Temperature parameter, 0.002% of Normal Temperature parameter, 0.011% of Humidity parameter, 0.25% of Wind Speed parameter, 0.18% of Precipitation parameter and 0.021% of Heat Index parameter respectively. Mean Absolute Error (MAE) is a method for measuring Forecasting Error. In this method, each error or residual is squared, then summed or divided by the number of observations.

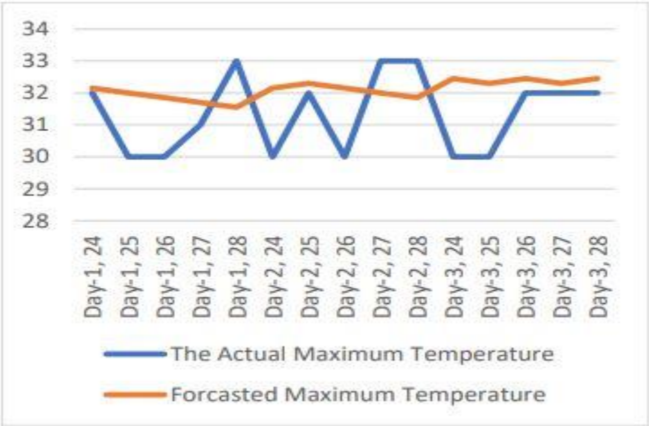

Figure 4.1: Real time-forecasting for Maximum Temperature

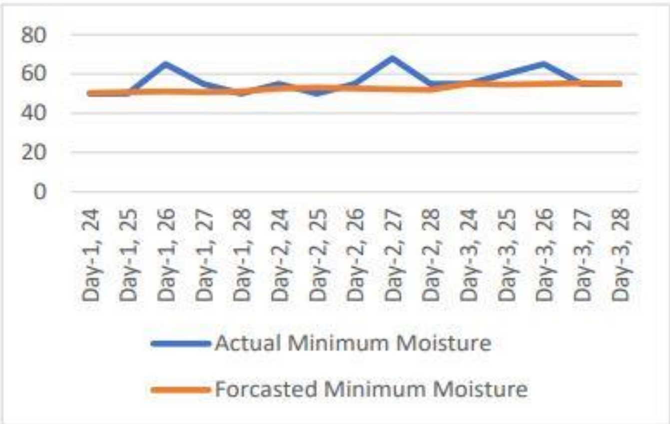

Figure 4.2: Real time-forecasting for Minimum Humidity

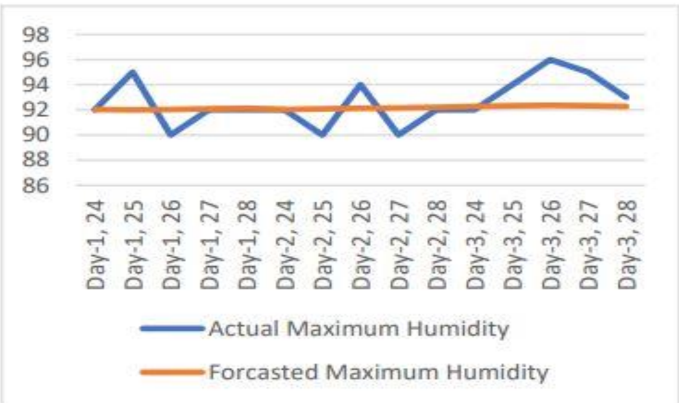

Figure 4.3: Real time-forecasting for Maximum Humidity

Figure 4.1 shows the real time-forecasting chart parameters of Minimum temperature which is 24 degrees Celsius. From the chart, three days (Day 1, Day 2 and Day 3) weather forecasting was implemented with the respective days. Figure 4.2 shows the real time-forecasting chart parameters of Maximum temperature which is 32 degrees Celsius. From the chart, three days (Day 1, Day 2 and Day 3) weather forecasting was implemented with respective days. Figure 4.2 shows the real time-forecasting chart parameters of Minimum humidity which is 50g/kg. From the chart, three days (Day 1, Day 2 and Day 3) weather forecasting was implemented using the respective days. Figure 4.3 shows real time-forecasting chart parameters of Maximum humidity which is 92g/kg. From the chart, three days (Day 1, Day 2 and Day 3) weather forecasting was implemented using the respective days. Figure 4.4 shows Actual-forecasting chart of wind speed which is 23 km/h. From the chart, three days (Day 1, Day 2 and Day 3) weather forecasting was implemented using the respective days.

Figure 4.4: Actual-forecasting chart of wind speed

CONCLUSION

According to Weather Forecasting system using an Enhanced Bayesian Model Averaging, forecasting error values generated by the Existing system yielded Mean Square Error diverging at 0.85% of Minimum Temperature parameter, 0.198% of Maximum Temperature parameter, 0.073% of Normal Temperature parameter, 0.178% of Humidity parameter, 0.244% of Wind Speed parameter, 0.277% of Precipitation parameter and 0.189% of Heat Index parameters respectively. The result of the Enhanced Weather Forecasting System yielded Mean Square Error (MSE) diverging at 0.75% of Minimum Temperature parameter, 0.196% of Maximum Temperature parameter, 0.070% of Normal Temperature parameter, 0.168% of Humidity parameter, 0.144% of Wind Speed parameter, 0.257% of Precipitation parameter and 0.179% of Heat Index parameters respectively. The Existing system has higher error value of Mean Square Error (MSE) and Mean Absolute Error (MAE). However, the Enhanced system has lower error value for Mean Square Error (MSE) and Mean Absolute Error (MAE). The lower the value of MSE and MAE shows the more optimal in forecasting accuracy. Therefore, the Enhanced system performed better than the Existing system in all the performance evaluation metrics used.

In the future study, we would like to do forecasting using our classification engine such as Distributed Adaptive Neural Network and improved by using fast learning algorithm.

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APPENDICES

1. **Html And Boostrap**:

```
<!DOCTYPE html>

<html lang="en">

<head>

<meta charset="utf-8" />

<meta name="viewport" content="width=device-width, initial-scale=1.0" />

<title>Weather in App</title>

<link rel="stylesheet" href="https://cdn.jsdelivr.net/npm/bootstrap@5.0.0-
```

```
beta1/dist/css/bootstrap.min.css" integrity="sha384-

giJF6kkoqNQ00vy+HMDP7azOuL0xtbfIcaT9wjKHr8RbDVddVHyTfAAsrekwKmP1"

crossorigin="anonymous" />

<link rel="stylesheet" href="style.css" />

</head>

<body>

<div class="container my-5">

<h1 class="text-center title">Weather in</h1>

<form class="search-location">

<input type="text" name="city" placeholder="what city?" autocomplete="off" class="formcontrol text-muted
form-rounded p-4 shadow-sm" />

</form>

<div class="card rounded my-3 shadow-lg back-card">

<div class="card-top text-center">

<div class="city-name my-3">

<p class="text-white text-black">Abuja</p>

<span class="text-white text-black">...</span>

</div>

<img src="img/night_image 3.jpg" alt="" class="card-img-top time" />

</div>

<div class="card-body">

<div class="card-mid row">

<div class="col-8 text-center temp">

<span>30&deg;C</span>

</div>

<div class="col-4 condition-temp">

<p class="condition">Thunder Storm</p>

<p class="high">30&deg;C</p>

<p class="low">27&deg;C</p>

</div>
```

```
<div class="icon-container card shadow mx-auto">

<img src="img/Cloud 3.png" alt="" />

</div>

<div class="card-bottom px-5 py-4 row">

<div class="col text-center">

<p>30&deg;C</p>

<span>Feels like</span>

</div>

<div class="col text-center">

<p>55%</p>

<span>Humidity</span>

</div>

</div>

</div>

</div>

</div>

<script src="request.js"></script>

<script src="index.js"></script>

</body>

</html>

</div>
```

2. Cascaded Styling Sheet (Css)

```
@import url('https://fonts.googleapis.com/css2?family=Raleway:wght@100;400;700&display=swap');

body {

font-family: 'Raleway', sans-serif;

background: #e0e0e0;

color: #707070;

margin: 0;

padding: 0;
```

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```
}
.container {
max-width: 400px;
min-width: 400px;
}
.title {
font-weight: 700;
font-size: 50px;
}
.form-rounded {
border-radius: 2em;
}
.back-card {
border-radius: 40px !important;
}
.city-name {
position: absolute;
width: 100%;
}
.city-name p {
font-size: 16pt;
font-weight: 400;
}
.city-name span {
font-weight: 400;
font-size: 36pt;
font-family: 'Times New Roman', serif;
position: relative;
top: -60px;
```

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```
}

.temp span {

font-weight: 100;

font-size: 5em;

letter-spacing: -5px;

white-space: nowrap;

}

.card-mid {

line-height: 0.5;

}
```

3. Javascript

```
const searchForm = document.querySelector('.search-location');

const cityValue = document.querySelector('.search-location input');

80

const cityName = document.querySelector('.city-name p');

const cardBody = document.querySelector('.card-body');

const timeImage = document.querySelector('.card-top img');

const cardInfo = document.querySelector('.back-card');

const spitOutCelcius = (kelvin) => {

celcius = Math.round(kelvin - 273.15);

return celcius;

}

const isDayTime = (icon) => {

if (icon.include('day')) {

return true;

} else {

return false;

}

}

updateWeatherApp = (city) => {
```

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```
console.log(city);

const imageName = city.weather[0].icon;

const iconSrc = `http://openweathermap.org/img/wn/${imageName}@2x.png`

cityName.textContent = city.name;

cardBody.innerHTML = `

<div class="card-mid row">

<div class="col-8 text-center temp">

<span>${spitOutCelcius(city.main.temp)}&deg;C</span>

</div>

<div class="col-4 condition-temp">

<p class="condition">${city.weather[0].description}</p>

<p class="high">${spitOutCelcius(city.main.temp_max)}&deg;C</p>

81

<p class="low">${spitOutCelcius(city.main.temp_min)}&deg;C</p>

</div>

</div>

<div class="icon-container card shadow mx-auto">

<img src="${iconSrc}" alt="" />

</div>

<div class="card-bottom px-5 py-4 row">

<div class="col text-center">

<p>${spitOut Celcius(city.main.feels_like)}& deg;C</p>

<span>Feels like</span>
```

4. Request. Js

```
const key = '918609eb25f4c18a84b3811104429460';

// const base URL =

'http://api.openweathermap.org/data/2.5/weather?q=Lagos&appid=918609eb25f4c18a84b381110442
9460'

// fetch(base URL)
```

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```
//.then ((data) => {console.log ('response', data. json ())})

//.catch ((error) => {

// console.log(error);

// });

const request City = async(city) => {

const base URL = 'http://api.openweathermap.org/data/2.5/weather'

const query = `?q=${city}& appid=${key}`;

//Make fetch call (promise call)

const response = await fetch (base URL + query);

//Promise data

const data = await response. json();

return data
```