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DESIGN OF A RENEWABLE ENERGY OUTPUT PREDICTION SYSTEM FOR 1000mW SOLAR-WIND HYBRID POWER PLANT.

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Abstract
Problems associated with non-renewable energy sources such as fossil fuels make it necessary to move to cleaner renewable energy sources such as wind and solar. But the wind and sun are both intermittent sources of energy therefore accurate forecasts of wind and solar power are necessary to ensure the safety, stability and economy of utilizing these resources in large scale power generation. In this study, five meteorological parameters namely Temperature, Rainfall, Dew Point, Relative Humidity and Cloud Cover were collected for the year 2012 and used to predict wind and solar power output in Jos, Nigeria. The study used prediction algorithms such as Regression techniques and Artificial Neural Networks to predict the output of a 1000mW Solar-Wind Hybrid Power Plant over a period of one year. Individual prediction techniques were compared and Isotonic Regression was found to have the highest accuracy with errors of 40.5% in predicting solar power generation and 35.4% in predicting wind power generation. The relatively high levels of error are attributed to several limitations of the research work.

Introduction
All human cultures require the production and use of energy. Energy is used for transportation, heating, cooling, cooking, lighting, and industrial production. Fossil fuels account for more than 90 percent of global energy production but they are considered problematic resources. They are non-renewable, which means they can be depleted, also their use causes air pollution. There is a global need to increase the use of renewable energy resources. Renewable alternatives such as waterpower (using the energy of moving water, such as rivers), solar energy (using the energy from the sun), wind energy (using the energy of the wind or air currents), and geothermal energy (using energy contained in hot-water deposits within the Earth's crust) are efficient and practical but largely underutilized because of the ready availability of inexpensive, non-renewable fossil fuels in industrial countries and also due to the unreliable and/or unpredictable nature of most renewable energy sources. This study centres on the potential of Wind, Solar and Hydro power to become major sources of electrical energy generation. The author explores methods by which the output of these renewable energy sources can be accurately predicted and how the effects of instability in power generation can be managed. This work proposes a solution to the problem of intermittency and unreliability of renewable energy sources with a view to making the option of renewable energy more viable, efficient and cost-effective.
The major limitation of renewable energy sources is intermittency. Most renewable sources like wind, solar and hydro have variable and sometimes unpredictable periods of availability. This leads to a large degree of uncertainty and instability in the output of the power grid which makes renewable energy integration a difficult task. There is need for a reasonably accurate Output Prediction System (OPS) to provide advance knowledge of the production capacity of renewable energy sources like solar, wind and hydro in order to adjust the output of other power sources accordingly and stabilize the overall output of renewable energy power plants. This study seeks to produce a system for predicting the output of Solar and Wind energy in order to provide forehand knowledge of instability and fluctuations in electrical generation and effectively manage the variability in renewable energy output. And also to design and propose the structure and operation of a hypothetical 1000mW Solar-Wind Hybrid power plant model which would utilize the output prediction model to balance the overall output of the solar and wind generators by making use of Grid Energy Storage Systems.
A solar-wind hybrid power plant is essentially an electricity generating plant which employs the use of both the sun (solar energy) and wind (wind power) to produce electrical energy. This kind of setup provides a unique advantage in the deployment of renewable energy as a viable power source. One reason which makes the pair – solar and wind - very practical is the fact that they are mutually complementary. Wind and solar power individually are quite intermittent in their output but combined, they both provide the opportunity to balance out their individual deficits. In most parts of the world, solar power can only be harvested during the day when the sun shines which means that at night, vast photovoltaic arrays become useless. This is where wind power complements the system, with the wind blowing all through the day in most climate regions thereby producing power virtually through-out the day, albeit in variable levels. Generally, wind speeds reach their highest levels at night when the sun is not shining which allows the wind turbines to fill-up the shortage in solar energy.

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To facilitate successful exploration for the best prediction model, reliable techniques are required for combining different regression algorithms, creating ensembles, model testing etc. It is called meta-learning or ensemble learning research (Jankowski, 2008). Historical solar data are key elements in solar power prediction systems. Computational Intelligence (CI) holds the key to the development of smart grid to overcome the challenges of planning and optimization through accurate prediction of Renewable Energy Sources (Hossain *et al.*, 2013).
Hossain *et al*, (2013) proposed a hybrid prediction method for solar PV output prediction based on heterogeneous ensemble techniques using a pool of regression algorithms. In their research work, the three most accurate regression algorithms were selected based on experimental results. Feature selection was then carried out on the selected regression algorithms to reduce the error of individual local predictors.
Chen *et al*, (2013) took a unique approach to short-term prediction of wind power by applying Gaussian Processes (GPs) to the outputs of a Numerical Weather Prediction (NWP) model. The predicted wind speed from an NWP model was corrected using a GP. Then a Censored Gaussian Process (CGP) method was applied to build the relationship between corrected wind speed and wind power. Finally, Automatic Relevance Determination was used for feature selection in order to improve generalization performance.Wind speed and Temperature variables were found to affect the NWP model the most therefore these two were used as the input for the GP correction process. This method of combining CGPs and NWP was found to have 4.84% to 11% improvement in accuracy when compared to an MLP-CSpeed model.

Materials and method

The weather equipment used in gathering meteorological data for this research work are:
1. Anemometer
2. Thermometer (minimum and maximum)
3. Hydrometer
4. Rain gauge
5. Solar panel (for radiation intensity)

Methodology

Meteorological data of six weather parameters namely; Temperature, Humidity, Dew point, Sky Cover and Rainfall was collected from National Meteorological Agency (NiMet) synoptic centre at Jos Airport, Haipang, Plateau State. One-year hourly values of the mentioned weather parameters were taken from January to December, 2012. In addition to the five weather parameters mentioned above, daily values of Solar Intensity and Wind speed were also collected over the duration of one year from January to December, 2012. The calculations and analysis in this research work were done using the one-year meteorological data collected.
In this research, the correlation between each of the five parameters and both Solar Intensity and Wind speed was investigated using graphs and regression techniques. Scatter graphs were plotted separately with each of the five parameters against both Solar Intensity and Wind Speed individually in order to observe and analyze how Solar Intensity and Wind speed relate with the weather parameters in question.
The correlation coefficient was obtained from these graphs using Linear Least Squares Regression method. The correlation coefficient gives a measure of how each of the weather parameters is related to Solar Intensity and Wind speed. It gives an idea of how much these two quantities depend on the values of each weather parameter used. After regression analysis, the correlation coefficients corresponding to each of the five (5) weather parameters in relation to both Solar Intensity and Wind speed were analyzed to determine the most relevant data for the prediction of Solar Intensity and Wind speed.
The selected parameters were then fed into the data mining software, WEKA v. 3.6, and run through each of the machine learning algorithms for the prediction process. The Mean Absolute Percentage Error (MAPE) was computed for each of the algorithms and the most accurate algorithm was determined for both Solar Intensity and Wind speed prediction.

Data collection and analysis

Meteorological data of six weather parameters namely; Temperature, Humidity, Dew point, Sky Cover and Rainfall was collected from National Meteorological Agency (NiMet) synoptic Centre at Jos Airport, Haipang, Plateau State. One-year hourly values of the mentioned weather parameters were taken from January to December, 2013. In addition to the five weather parameters mentioned above, daily values of Solar Intensity and Wind speed were also collected over the duration of one year from January to December, 2013. The calculations and analysis in this research work were done using the one-year meteorological data collected.
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Determination of optimum solar-wind ratio

The optimum ratio of solar power to wind power for the proposed 1000mW solar-wind hybrid power plant was determined using a novel formula. It was found that a typical wind turbine will produce, on average of about 30% of its theoretical maximum output over the course of a year; this is known as the load factor (Cell Energy International, 2015). Due to this reason, 30% was taken as the effective capacity of any given wind farm within the test region. The solar capacity was therefore chosen in such a way as to cover the difference between 30% of the wind capacity and the overall nominal capacity of the solar-wind hybrid power plant. The wind turbine capacity was also the same as the power plant nominal capacity (1000mW), therefore the solar capacity is given by the formula:

Solar capacity = 1000mW – (0.3 × wind capacity) (1)

Determination of storage capacity

The storage capacity of the proposed 1000mW solar-wind hybrid power plant is determined by using the day with the lowest value of Wind power output in the year. The rationale behind this method was the fact that the lowest value of Wind power output indicates the highest capacity of stored power that would be required to cover the shortage at any particular point throughout the year given the fact that wind is available throughout the day while the sun is only available during the daytime.

The Wind power output (which represents the lowest daily wind power output throughout the year) was then subtracted from the Nominal Capacity and the difference was taken as the proposed value of the Storage Capacity for the power plant.

Storage capacity = Nominal Capacity – (Lowest Wind Power Output) (2)

Estimation of wind and solar output potential

In estimating the total energy output potential of a 1000mW solar-wind power plant throughout the year 2012, the monthly average values of Solar Intensity and Wind Speed were used.

For wind power, the average value of the Wind Output for the month of November (with the lowest average Wind Speed) was used to estimate the power output for the whole year. The average value for November was simply multiplied by 12 to represent the months of the year. The product was then multiplied by the total number of hours in the year and the result was taken as the Total Wind Energy Output for the whole year.

$$\text{Total wind energy output} = \text{Average output of lowest month} \times 12 \times \text{Hours} \quad (3)$$

To calculate solar power potential, the required capacity of the solar array as previously determined was multiplied by the total number of daylight hours in the year using an estimation of nine daylight hours per day and the results was taken as the total estimated solar energy output for the whole year.

$$\text{Total solar energy output} = \text{solar array capacity} \times \text{no. of daylight hours} \quad (4)$$

Finally, the Total Annual Energy Potential for a 1000mW solar-wind hybrid power plant built in the research area of Jos; Plateau State was determined by adding the Total Solar Energy Output and the Total Wind Energy Output.

Total Annual Energy Potential = (Total Solar Energy Output) + (Total Wind Energy Output) (5)

Power plant models

Proposed structure and operation of 1000mW hybrid plant

In this research work, a hypothetical model for a 1000mW solar-wind hybrid power plant is designed which utilizes the prediction system in its operation in order to balance the fluctuations in the output of wind and solar power. The structure and operation of the proposed 1000mW hybrid plant is as follows.

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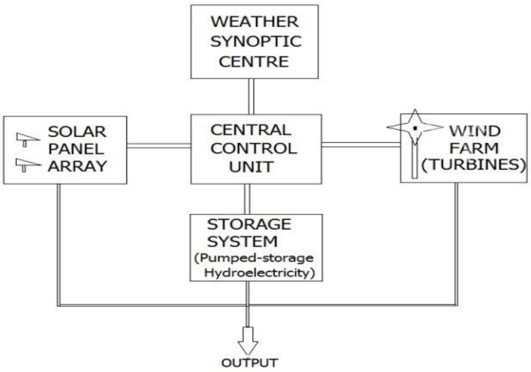

Figure 1: Schematic of the proposed 1000mW Solar-Wind Hybrid Power Plant

Weather synoptic centre

The weather synoptic Centre is a meteorological station located within the grounds of the power plant or very close to its vicinity. The proximity improves the relevance of the weather data gathered by the weather equipment. The weather synoptic Centre gathers hourly readings of the relevant parameters (i.e. Temperature, Solar Intensity, Wind Speed, etc.) and automatically transmits the collected data to the Central Control Unit of the power plant.

The Weather Synoptic Centre serves as the primary source of information to the Central Control Unit. The operation of the power plant depends on the accuracy of weather data collected and transmitted by the Weather Synoptic Centre. The Central Control Unit uses the information from the weather synoptic Centre to predict power output of both the solar array and the wind farm. It also helps the Central Control Unit to make decisions regarding the output levels of the solar array and wind farm dedicated to the Storage System.

Solar panel array

The solar panel array consists of a large collection of photovoltaic modules. The total capacity of the solar panel array was gotten from the formula used to determine the solar-wind ratio.

Solar capacity = 1000mW – (0.3 × wind capacity) (6)

The solar panel array represents the solar power capacity of the power plant. Due to the fact that the sun does not shine during the night, the solar panel array is virtually useless at night. But during the day, the solar panel array complements the output of the wind farm and contributes to the overall output of the power plant. The solar panel array is connected to the Central Control Unit and the Storage System. The Central Control Unit controls the output of the solar array and diverts the correct level of output to either the Storage System or the Output.

Wind farm

The wind farm consists of a large collection of wind turbines. The total capacity of the wind farm is equal to the nominal capacity of the Hybrid Power Plant i.e. 1000mW. The wind farm represents the wind power capacity of the power plant. The output of the wind farm depends on the wind speed and wind direction. One advantage of the wind farm is the fact that damage to a few wind turbines is isolated and will not drastically affect the overall output of the power plant. The wind farm is connected to the Central Control Unit and the Storage System. The Central Control Unit controls the output of the wind farm and diverts the correct level of output to either the Storage System or the Output.

Central control unit

The Central Control Unit (CCU) is a computerized and largely automated system which controls the operation of the various sections of the power plant. The Output Prediction System is integrated into the CCU which carries out the prediction of the projected solar and wind power output and makes decisions based on these predictions. The CCU is directly connected to the weather synoptic Centre and all predictions and decisions are made based on the weather data collected.

The CCU uses the weather data to predict power output using the most accurate prediction algorithm determined by this research work. The CCU makes decisions in three major situations:

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- When the predicted total output is below nominal capacity, the CCU deploys the Storage System to supply the exact amount of power needed to raise the overall output level to the nominal capacity.
- When the predicted total output is above nominal capacity, the CCU maintains output at the Nominal Capacity and diverts excess power to the Storage System to be stored for future use.
- When predicted total output is equal to nominal capacity, the CCU deploys the total output to the overall output power.

The CCU carries out the decisions at the very point when the event is predicted to take effect e.g. if the total output is predicted to drop below Firm Capacity in the next 20 minutes, the CCU takes decision to deploy the power deficit from the Storage System in 20 minutes time. All predictions and decisions are made in real time. The CCU also constantly monitors the amount of stored energy in the Storage System and factors the efficiency of the Storage System in the operation of the power plant.

Storage system

The Storage System serves the purpose of reserving excess energy when total output is above Nominal Capacity and supplies the deficit when total output is less than Nominal Capacity. The Storage System should have the capacity of being deployed within a short interval. The preferred form of Grid Energy Storage for the 1000mW hybrid plant is Pumped-Storage Hydropower. Pumped-Storage Hydro is a clean energy source with 70% - 75% efficiency and has the capacity to come online within a relatively short time, about 20 seconds.
The Storage System is controlled by the CCU based on information collected from the weather synoptic Centre. The Storage System is activated when the power plant output is below Nominal Capacity and the exact level of the power output is controlled and specified by the CCU. Conversely, during periods of output below Nominal Capacity, the CCU switches off the Storage System and positions it for charging.

Design of small-scale model

For the purpose of this research work, an electrical circuit was designed as a small scale demonstration of the proposed structure and operation of the 1,000mW hybrid power plant. In the circuital representation, a 12V DC power source (i.e. three 4V Li-Ion Batteries) was connected in series with three potentiometers (i.e. variable resistors) which were used to represent the Solar Array, Wind Array and Storage System respectively. The 12V DC source and the potentiometers were connected in series to a basic Voltage Indicator Circuit.

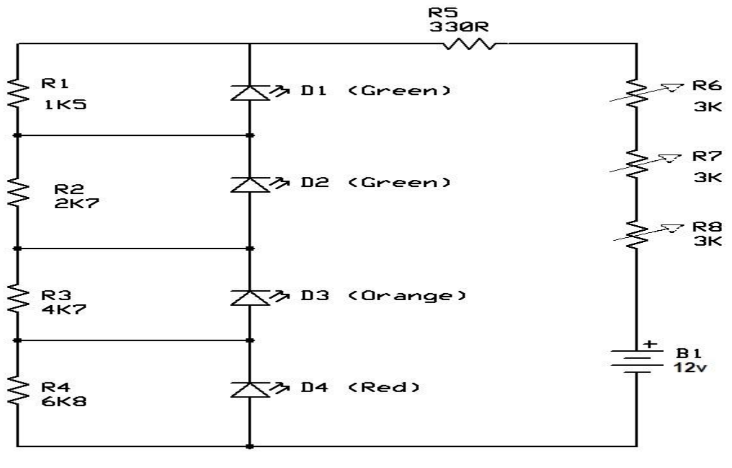

Figure 2: Schematic of the Small-Scale Power Plant Model Circuit

By Ohm's law:

$$V = I \times R \tag{8}$$

Therefore, varying the resistance of each of the three potentiometers will change the voltages across each potentiometer and also the voltage across the Voltage Indicator Circuit.

$$P = I \times V \tag{9}$$

This means that a change in the voltage across a section of the circuit implies a change in the electrical power expended in that section of the circuit. Therefore, varying the three potentiometers made it possible to alter the voltage and hence the power reaching the Voltage Indicator Circuit in order to illustrate variations that take place in an actual Solar-Wind Hybrid Power Plant.

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This process demonstrates what happens in the actual 1,000mW power plant. An increase in the output of the Solar Array, Wind Farm or the Grid Storage will yield a corresponding increase in the overall output of the power plant, and vice versa.
The Voltage Indicator section of the circuit was composed of five resistors and four LEDs of different colours. Two green, one orange and one red LED were used as voltage indicators in the circuit. The circuit was designed to indicate differences in the voltage produced by the DC sources by switching on the appropriate LED at the right voltage level. The circuit was designed to indicate voltage variations in the following way:

1. Switch on the first green LED when the voltage across the circuit is 7.5V
2. Switch on the second green LED when the voltage across the circuit is 6.5V
3. Switch on the orange LED when the voltage across the circuit is 5.5V
4. Switch on the red LED when the voltage across the circuit is 4.5V

For a simple simulation of the Power Plant, the circuit was made to behave in a manner similar to a real life 1000mW Solar-Wind Hybrid Power Plant. The natural variations in Wind Power and Solar Power were emulated and demonstrated by adjusting the individual potentiometers (labelled *solar, wind* and *storage* respectively) by the right amount to bring about the desired variation.
For this simulation, it is assumed that the output of the small-scale model of the power plant is above Nominal Capacity when the voltage in the circuit reaches 7.5V and the first green LED is on. When the voltage is at 6.5V, the second green LED comes on and the model is now at Nominal Capacity. When the individual potentiometers are adjusted such that the voltage drops to 5.5V, or 4.5V, the circuit automatically switches on the orange and red LEDs respectively. In either of the two cases, the variable resistor labelled *Storage* is adjusted so as to raise the voltage (and hence the power output) back to the Nominal Capacity (6.5V) and switch the green LED back on.
This shows what is obtainable in a real life situation at the hybrid plant where Solar and Wind output vary randomly but the Plant is able to maintain a steady output by deploying the required amount of power from the Grid Storage to cover the shortage at the appropriate time as estimated by the Output Prediction System. In this simulation, the operator of the circuit essentially performs the task of the Central Control Unit (CCU) which automatically makes the decision to vary the output of the Storage System according to fluctuations in the Solar and Wind supply in the actual 1000mW Solar-Wind Hybrid Power Plant.

Data analysis and results

Using the formula below, the Solar Capacity was determined to be 700mW. As stated in the methodology, the wind turbine capacity is the same as the power plant nominal capacity i.e. 1000mW. From equation (2);
Solar capacity = 1000mW – (0.3 × wind capacity) = 700mW
Hence, for the proposed 1000mW hybrid power plant, the total solar capacity would be 700mW and the total wind capacity would be 1000mW.

Minimum output profile

November showed the lowest average value for wind speed at 9.8 ms^{-1} while August showed the lowest average value for solar radiation at 104 watt m^{-2}. The power graphs for the two months were plotted separately and then superimposed by adding the daily values and plotting a third graph. This was done to derive a worst case scenario or the minimum output profile of the proposed hybrid power plant.
Hypothetically, a 48m^2 solar panel at 20% efficiency will produce 1kW when solar radiation is 104 watts/m^2. Therefore a solar array capable of producing 700mW at 104 watts/m^2 solar radiationwill consist of a total of 33.6million m^2 of solar panel surfaces i.e. 3360 hectares. The output of each of the 31 days of august was computed using the hypothetical output of 3360 hectares of solar panel with 20% efficiency.

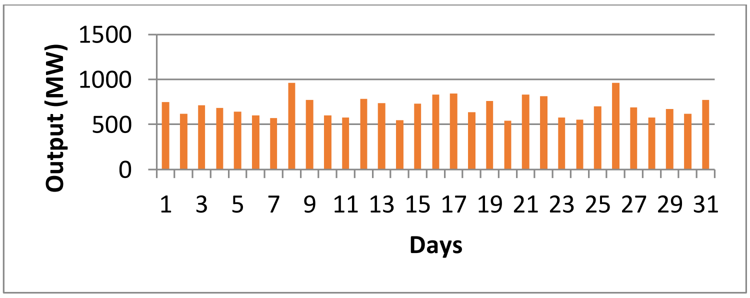

Figure 3: Solar Output of power plant in August, 2012.

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For the wind output, the power curve of a standard 3mW wind turbine (*Alstom ECO 110*) was used. For the total power plant wind capacity of 1000mW, the wind farm must contain at least 334 units of the *Alstom ECO 110*3mW wind turbine. The power graph for the wind output was computed by multiplying the daily outputs of the 3mW wind turbine by 334 units

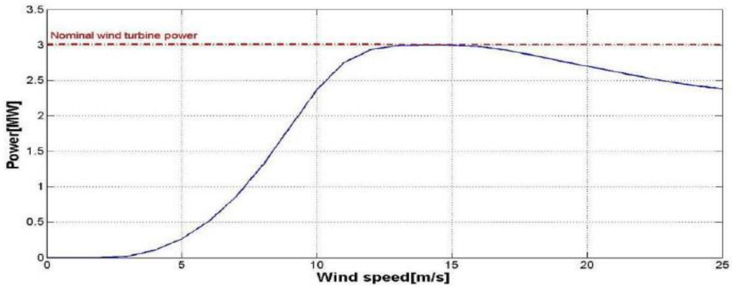

Figure 4: 3mW Wind Turbine Power Curve, type Alstom ECO 110

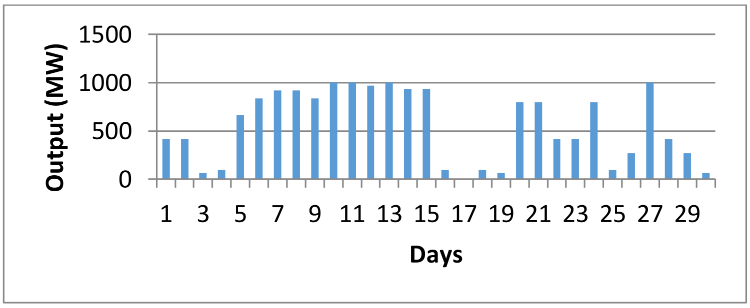

Figure 5: Wind Output of power plant in November, 2012.

Both graphs were then superimposed by adding the daily values and plotting a third graph as shown below.

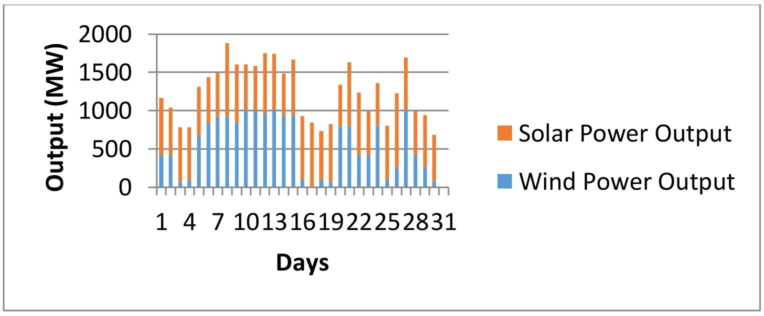

Figure 6: Total Output of power plant within a 30-day period.

Therefore, the graph above represents the minimum output level expected to be produced from the proposed hybrid power plant. Therefore, according to the operation of the power plant, whenever power output rises above 1000mW, the excess is deployed to the storage system. Also, whenever the output drops below 1000mW, the shortfall is covered-up using the stored energy in the Grid Storage System

Storage capacity
From equation 3,Storage capacity = Nominal Capacity – (Lowest Wind Power Output) = 1000mW.
The lowest wind power capacity in the month of the year was found to be 0mW obtained on the 17th of November as shown in Figure: 8 above. Therefore, the Grid Storage System of the proposed 1000mW Solar-Wind Hybrid Power Plant must have a minimum capacity of 1000mW to be able to balance the overall output at any point in time.

Wind and solar output potential

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Solar Output Potential was gotten as the product of the solar array capacity and the number of daylight hours in the year. From equation (5);
Total solar energy output = 2305800 mWh.
Wind Output Potential was gotten by multiplying the average value of wind output for the month with the lowest average windspeed (i.e. November) by 12 and then by the total number of hours in the year. From equation (4);

$$\text{Total wind energy output} = \text{Average output of lowest month} \times 12 \times \text{Hours}$$

Total wind energy output is ≅ 58501092 mWh.

Regression and correlation analysis

The relationship between Solar Radiation, Wind speed and five other weather parameters was investigated using correlation graphs and their correlation coefficients (R^2) were computed as illustrated below.

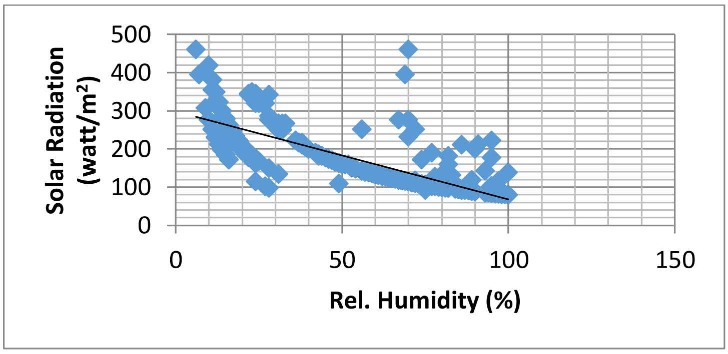

Figure 7: Correlation graph of Solar Radiation against Relative Humidity, Correlation coefficient, R^2 = 0.617

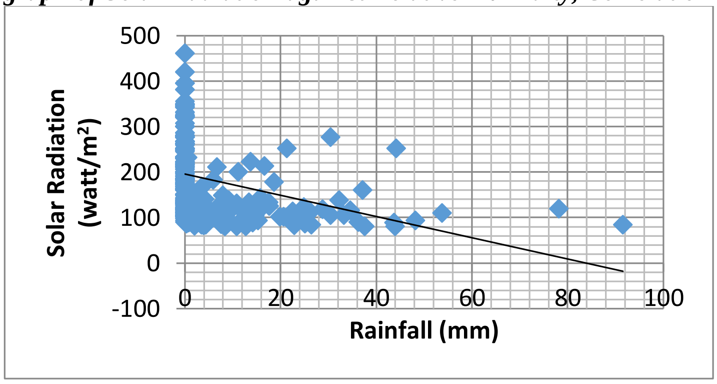

Figure 8: Correlation graph of Solar Radiation against Rainfall, Correlation coefficient, R^2 = 0.0867

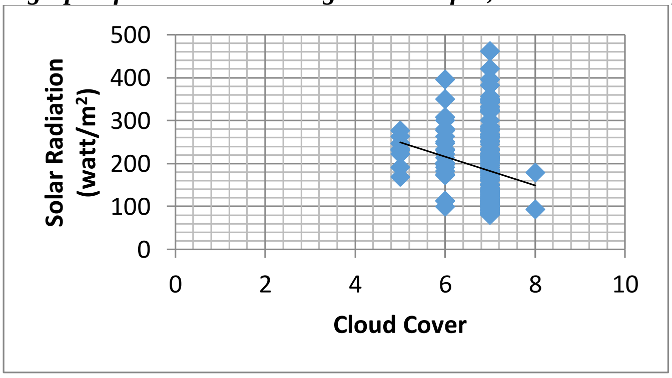

Figure 9: Correlation graph of Solar Radiation against Cloud Cover, Correlation coefficient, R^2 = 0.0272

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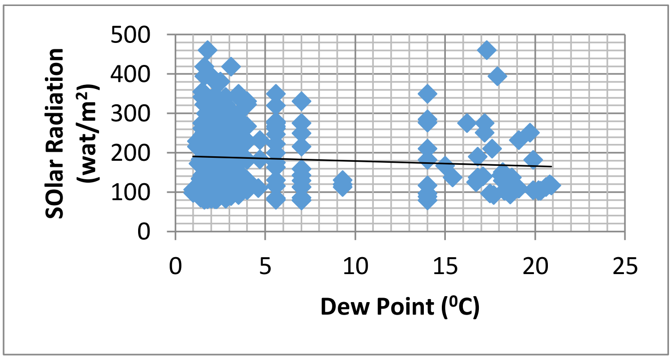

Figure 10: Correlation graph of Solar Radiation against Dew Point, Correlation coefficient, R^2 = 0.0061

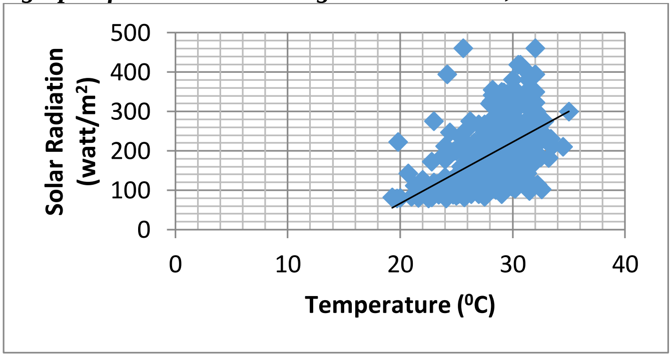

Figure 11: Correlation graph of Solar Radiation against Temperature, Correlation coefficient, R^2 = 0.3021

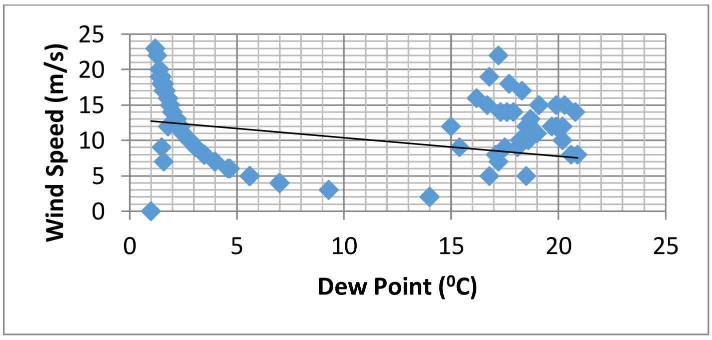

Figure 12: Correlation graph of Windspeed against Dew Point, Correlation coefficient, R^2 = 0.0061

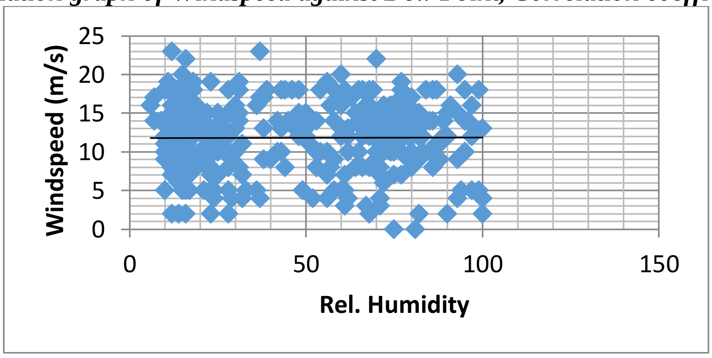

Figure 13: Correlation graph of Windspeed against Relative Humidity, Correlation coefficient, R^2 = 2E-05

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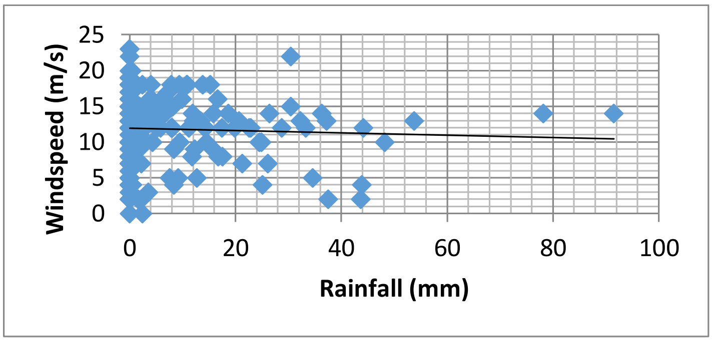

Figure 14: Correlation graph of Windspeed against Rainfall, Correlation coefficient, R^2 = 0.0015

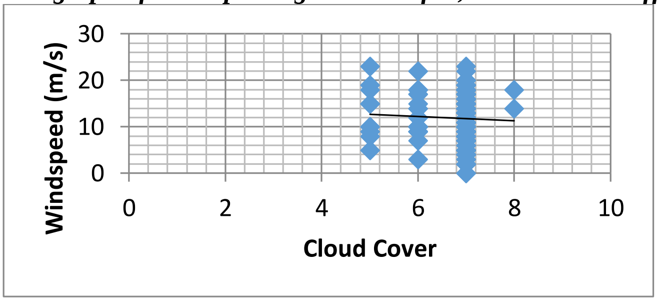

Figure 15: Correlation graph of Windspeed against Cloud Cover, Correlation coefficient, R^2 = 0.0017

The graphs above show the relationships between Solar Radiation, Windspeed and five other weather parameters in order to pick the parameter which is most relevant to Solar Radiation and Windspeed. The correlation coefficient (R^2) is a measure of the relationship between two parameters. The parameters with the highest correlation coefficients are most related and relevant to the concerned variables (i.e. Solar Radiation and Windspeed) and are therefore chosen for the prediction process.
From the correlation coefficients of these relations, it was observed that Solar Radiation has its highest correlation with Relative Humidity (R^2 = 0.0617), while Windspeed has its highest correlation with Dew Point (R^2 = 0.0061) when compared with other parameters.It is also important to note that Solar Radiation has a significantly high correlation with Temperature as well, although it does not have the highest correlation coefficient among the five parameters.

Error and comparative analysis
Using the data analysis software, WEKA v3.6, the weather data was organized and analyzed to produce predictions for both Solar Radiation and Wind Speed. From the above graphs, the weather parameter with the highest correlation coefficient was selected each for Solar Radiation and Windspeed. These were used as the sole variables for the prediction in each case.
Five prediction techniques were used out of several others available on the WEKA 3.6 software platform, they are:

- Gaussian Process (GP)
- Least Median Square (LMS)
- Linear Regression (LR)
- Isotonic Regression(IR)
- Multi-Layer Perceptron (MLP) neural network

Each one of these techniques also has three possible modes namely;

Training set: In this mode, the prediction is tested on the same data set that the classifier is trained on.
Cross validation (10-fold): In this mode, the classifier performs an n-fold cross-validation, in this case 10-fold.
Percentage split: In this mode, the classifier trains on a percentage of the data and tests on the remainder. In this case 70% is used for training while 30% is used for testing.
The prediction is carried out using each of the five techniques under each one of the three modes which results in 15 rounds of prediction for both Solar Radiation and Windspeed. The table below shows an analysis of the Mean Absolute Percentage Error (MAPE) associated with the predictions gotten from each of the techniques.

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Table 1: Mean Absolute Percentage Errors of five different prediction techniques

Techniques	GP			LMS			LR			IR			MLP		
Modes	1	2	3	1	2	3	1	2	3	1	2	3	1	2	3
Solar Radiation	48.5	48.8	46.1	50.9	50.4	43.3	51.0	51.3	46.7	42.4	44.7	40.5	49.7	52.9	86.1
Windspeed	64.3	65.9	71.9	367.8	375.2	382.1	96.4	96.6	95.6	35.4	35.6	41.5	43.9	77.6	101.3

Where the modes 1, 2, 3 represent
1. Training Set
2. Cross Validation (10-Fold)
3. Percentage Split

Conclusion
Five meteorological parameters were used to predict the values of Solar Radiation and Windspeed in Jos, Plateau State. Five prediction techniques were used with Isotonic Regression showing the best accuracy level for both Solar Radiation and Windspeed prediction. The results showed fair correlation between actual and predicted values with errors of 40.5% for Solar Radiation and 35.4% for Windspeed. The result shows that Solar Radiation and Windspeed can indeed be predicted using other related weather parameters.

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