Energy Prediction for Smart Solar Remote Monitoring System

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***Abstract*— The solar energy is a clean and renewable energy. Solar Photovoltaic renewable sources proving to be most beneficial with low-cost, so that number of PV plants is significantly growing. Today's solar plants are highly localized and unstructured. Around 14% of solar system face major fault every year therefore the management of photovoltaic systems is important for increase their efficiency.**

The system is implemented in two phases first one is monitoring followed by prediction which helps to reduce the energy loss. The solar monitoring phase collects and analyzes several constraints being evaluated by using sensors to calculate its panel level performance. Smart Monitoring system maintains track of electricity generation contents and regional temperature. The experimental results forecast the mistake finding as well as the panel's dead state with time parameters. Phase two deals with analyzing time-series of solar energy data for prediction using Hidden Markov Model (HMM). The model decides a prediction considering probabilistic relationship of the first value to next value in series. The predicted output is then compared with real-time output to increase accuracy of prediction.

Keywords— Solar radiation, Prediction, Time-series, Forecasting, Modeling, Solar Energy, Internet of Things (IoT).

I. Introduction

Non-renewable energy sources are reducing day by day. Considering other renewable energy resources, the solar energy is one of most ideal energy at the current time. For developing world economies importance of solar energy is increasing. Recent Technology develops Photovoltaic (PV) panels more competent and reasonable. This result has topmost energy compactness in sustainable environment. From that scenario PV market will experience an amazing growth in future [1]. The number of PV plants is significantly growing but today's solar plants are highly unstructured and localized therefore the need for management of these plants is becomes essential. It is possible by proper performance monitoring and maintaining the robustness of PV panels. Actual and reliable valuations of PV system presentation are important for good PV industry [2]. For study and analysis, it is necessary to classify and recognize the future requirements. Aging of panels is also plays important role in measuring and calculating the parameters of smart monitoring of PV plants.

Internet of things (IOT) based application is really helpful for monitoring system at lower cost. Performance of solar panels is highly depends on the weather conditions therefore with the help of sensors we can directly collect details about weather conditions like temperature and humidity of that particular location. The real-time monitoring system shows current status of energy level, temperature, humidity and details of dead panels by using IoT. On the other hand financial investments in solar plant are still considerably high but forecasting helps for better operating solar panels by reducing energy loss. Solar energy generation is the major parameter of solar engineering problems such as electrical or thermal chapters. Therefore it can be said that accurate prediction is of very important for solar engineering studies [3].

A smart solar plant system requires accurate PV power forecasting for energy management procedure. Accurate forecasting can states better future electric power needed to the electricity network which helps to trim down the supplementary costs associated with general volatility. The disordered nature of environmental conditions and the unexpected weather circumstances like sunny, cloudy, dust and rainy makes accurate solar power prediction tremendously complicated [4].

Common solar prediction modeled using different approaches. Arithmetic approaches are depending on historical measured records to predict solar power in timely sequence. Next is Artificial Intelligence (AI), these approaches utilize advanced techniques, to construct models of solar forecasters. Some substantial models are depends on satellite pictures or numerical weather prediction (NWP) which helps to predict total solar irradiance and PV power generation. Lastly, hybrid approach which is grouping of the all three abovementioned approaches [5].

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There are many methods works for prediction. Support Vector Machines (SVM), Maximum power point tracking (MPPT), Hidden Markov Model (HMM), ARIMA, Neural Networks (NN), linear filters used for solar irradiance and power generation prediction. Hidden Markov Model (HMM) can decide a prediction according to probabilistic relationship of the last values to the next value in series. The existing systems work on either monitoring or prediction here we collect real time data by using IOT and then use it for prediction with the help of machine learning strategies.

II. Related Work

Recent work in the area of Energy Prediction for Smart Solar Monitoring System has been divided into following: A. Solar plant monitoring system. B. Solar energy prediction System.

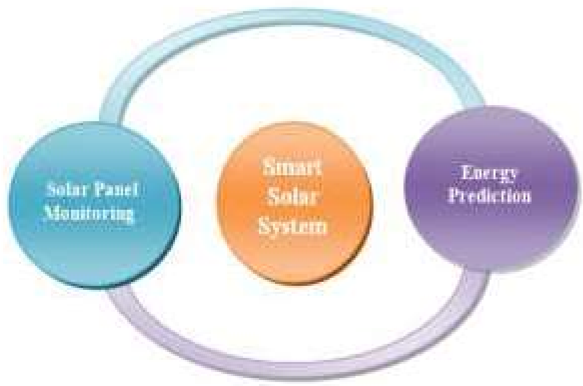

Fig. 1: General diagram of Smart Solar System.

A. *Solar plant monitoring system*

The major components of monitoring system are following: monitored parameter, sensing modules, data acquisition, data pre-processing mechanism and monitoring technique. Author Siva Ramakrishna Madeti and S.N.Singh [6] make the classification and comparison of temperature, voltage, current, solar radiation measurement based on different working principle using costly sensors. On the other hand, Bruno Ando [1] suggested a system where apply a low-cost multi-sensor at spread architecture. This estimates the PV plant effectiveness at the PV panel stage. The paradigm build up for the automatic analysis of effectiveness loss at the PV panel stage and that system intended for the abnormal aging recognition of PV panels.

PV panels connected for the purpose of monitoring, which presents supervision plus fault recognition of the PV systems incorporated in the similar environment. The fault finding procedure helps for the recognizing diagnosis of the solar plant

TABLE I.
Different Methods for Prediction

Reference	Author	Method
[6]	A. Chikh and A. Chandra	Maximum Power Point Tracking (MPPT)
[7]	F. O. Hocaoglu and F. Serttas	A Novel Hybrid (Mycielski-Markov) Model
[8]	Y. Jiang, H. Long, Z. Zhang, and Z. Song	A Markov Switch Approach
[10]	C. Wan, J. Zhao, S. Member, and Y. Song	Artificial Neural Networks, ARIMA
[11]	M. J. Sanjari and H. B. Gooi	Higher-order Markov chain (HMC)
[12]	J. Prasanth Ram and N. Rajasekar	Maximum Power Point Tracking (MPPT)

system, which depends on the study of voltage and current parameter estimated from monitored data of a PV generator [7]. Performance of the sustaining communication structure, in form of latency, redundancy and virtual security, will find out the activity of all structure of WAM based security [8].The benefits assign the core responsibility of wide area monitoring (WAM) when component is developing the flexibility of power schemes beside strained circumstances and conflict wide area, not the separation of individual errors.

B. *Solar energy prediction*

Prediction of solar power renewable energies is strongly connected with weather forecast predictions. For ensure efficient utilization of energy, it becomes supportive to forecast the info of energy generation. The correct forecasting of solar irradiance deviation increases the excellence of process with improving PV energy managing situation [9].

Maximum power point tracking (MPPT) technique for PV system helps for prediction by measuring voltage and estimating current. The Adaptive Neuro-Fuzzy (ANFIS) model use solar radiation and PV cells temperature with a wavelet denoising model to get filtered parameters. MATLAB is helpful to study the processing of the MPPT algorithm [10].

To calculate the short-term predictions of solar radiation authors F. O. Hocaoglu and F. Serttas used novel hybrid (Mycielski-Markov) model. This method had chosen an hourly predictor of solar radiation forecasting as appliance. Using of only past solar radiation records and not using any further factors it is achievable to predict latest solar radiation record section exactly. Repeated records can directly able to take suitable outcomes from the algorithm [3].

By Yu Jiang [5] Day-ahead Forecasting as a Bi-hourly solar radiance with help of Markov Switching Approach (MSA), the suggested method exercises a regime switching method in the direction of assigning the growth of the solar radiance sequence. The Gaussian process regression (GPR) model, the Autoregressive (AR) model, Neural Network (NN) model and Perseverance model be the four solar radiance predicting models. Which are calculated as base models for authenticating the MSA. The analysis depend on mathematical research results shows that simply, a MSA model is better than other allied models in category of day-ahead time sequence prediction.

III. Proposed System

Energy prediction using IoT based monitoring makes a smart system and it starts with monitoring of plant at panel level. Voltage and current values are sensed by PV panel and, a temperature of the location is sensed by sensor. Monitoring smart solar system displays the generating energy power and temperature at certain time intervals. This scheme is able to employ in smart grid for powerful outcome. The section provides system architecture of a Smart Solar Energy Monitoring.

Projected monitoring system of solar energy is developed with the help of IoT. Solar panel stores the generated energy in the battery which is connected with the middleware micro controller. The micro controller is a middle observing structure at cheap cost therefore it reduces cost of the system. As we know python is a largely used, advanced, interpreted, high-level, dynamic programming language so we uses python programming to complete this task. Monitoring parameters are uploaded on cloud using python program. Flask is work as light-weight framework, which is written in Python. The Flask uses stretchy cast off to read the sensor values. We consider DHT-11 as well as LM-35 sensor for generating the weather data from real-time situations. The system utilizes the multiple solar panel which having the heterogeneous configuration.

The fig. 3 shows detailed system architecture of proposed system. In the fig. 3, it can observe how data will traverse from a sensor to microcontroller. In a microcontroller module, there is Raspberry pi which is responsible to store data into global dataset, after preprocessing. Internet helps to display all the statistics on the web pages then it stores on the cloud, we use cloud with public access. Another objective of proposed system is to predict solar energy generation and Reinforcement learning is useful for prediction. To improve adaptive forecast technique we are using Hidden Markov Model (HMM) which works as time-series prediction.

IV. Prediction Methodology

In the proposed system HMM helps to find the most expected time series by estimating the probability of state transition and observation sequences for every condition which results correctness in prediction.

The system initially takes the input from database like power reading in voltage and temperature in degree Celsius. A Hidden Markov Model is used for prediction and classifications. Markov chain property is that the possibilities of each following state depend only on previous state [16]. The HMM has N states, labeled $s_1, s_2, \dots, s_N$ where distinct time slots $t = 0,1,\dots$ At each and every time slot the system is in the state which one is free and accessible i.e. N states. The states at time t is define as Q_t, with $Q_t \in \{s_1, s_2, \dots, s_N\}$. At each time-slot, state Q_t is creating, one resultant symbol according to their Observation or Emission Probabilities allotment.

We get hidden states as well as observed states, named state probability vector Π, inter-state transition probability matrix A with emission probability matrix B. Markov chain converts measured data into the multiple numbers of states, so the sequence of hourly energy generation values is converted into the states.

i.e. State transition probabilities $\{s_1, s_2, \dots, s_N\}$

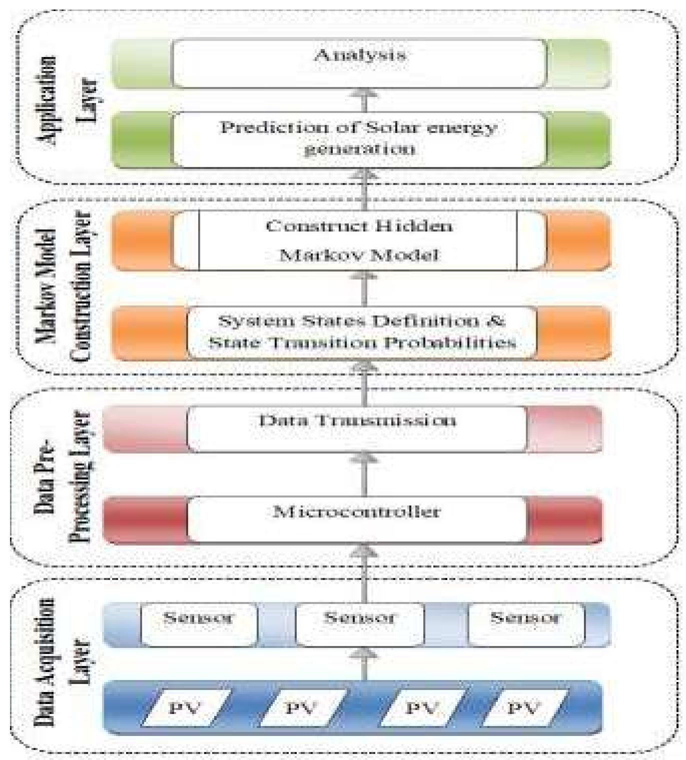

Fig 2: Proposed smart solar system architecture.

This represents probability between one state to another state as state transition probability matrix

$$A = (a_{ij}), \qquad a_{ij} = \mathrm{P}(s_i|s_j)$$

Where i is number of rows and j is number of columns. The observation probability allotment represent for state j is $Vm, m = 1, \ldots, M$ in the state s_j

$$B = (b_i(v_m)), \qquad bi(v_m) = \mathrm{P}(v_m|s_i)$$

As the number of symbols are two that is $m = 2$
And vector initial probability matrix

$$\Pi = (\Pi_i), \qquad \Pi_{\mathrm{i}} = \mathrm{P}(s_i)$$

Finally, Model is expressed by $\lambda = (A, B, \Pi)$

The objective of energy prediction is learning a Hidden Markov Model from observed time series. Here Maximum likelihood estimation approach evaluate λ^* that maximizes a likelihood of sample training series, $OTs = \{OTs_t\}_{t=1}^{T}$ by means of enhancement in $\mathrm{P}(OTs|\lambda)$.

Independent and ideally scattered samples of, $OTs = \{OTs_t\}_{t=1}^{T}$ are strained from the probability allotment $\mathrm{P}(OTs|\lambda)$. The goal is to find out value of λ which formulates OTs_t to $\mathrm{P}(OTs|\lambda)$ as probable as likely.

$$OTs_t \cong \mathrm{P}(OTs|\lambda)$$

The probability modification process specified with known $\lambda = (A, B, \Pi)$, recalculate λ for all steps using likelihood probability of incidence of state s_j after state s_i. This adaptation step is repeats till convergence for the duration of which $\mathrm{P}(OTs|\lambda)$ not at all diminishes.

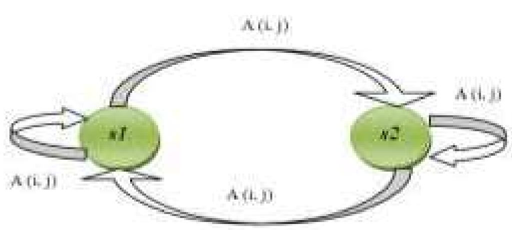

Fig. 3. A simple two-state Markov chain example.

Step 1: Observe Time series in sequence

$$OTs = \{0's, \quad 1's\}$$

Step 2: Fix the different observation symbols for states *N*

$$V = \{0, \quad 1\}$$

Step 3: Estimate values of Markov model to maximize probability $\mathrm{P}(OTs|\lambda)$

$$\lambda = (A, B, \Pi)$$

Step 4: Predict Energy power generation based on history of observation time series

$$P(OTs, 1|\lambda) < P(OTs, 0|\lambda) \; then \; S(t+1) = 0$$
$$\mathrm{P}(OTs, 1|\lambda) \geq \mathrm{P}(OTs, 0|\lambda) \; then \; S(t+1) = 1$$

Step 5: Compare the recorded data with same evidences

$$RMSE = \sqrt{\frac{1}{n}\sum_{t=0}^{n}(yi - xi)^2}$$

Step 6: Generate predicted observation time series of energy for $t = T + 1 \; to \; 2T$

$$POTs = \{OTs\}_{t=T+1}^{2T} \quad \text{using} \quad \{OTs\}_{t=1}^{T}$$

The above algorithm first it will read all records from data table and spite the each attribute. In step 2, it will provide the each attribute separate symbols i.e. $0's$ and $1's$. The sampling approach has used from HMM model by step 3. The next step can perform prediction of observation time series as moving ratio based on desired samples. In the algorithm step 5 calculate value of RMSE where n is the total number of samples in series, xi corresponds the value of the actual generated value meant for hour $= i$, and yi denotes the predicted value for the similar hour. Finally shows prediction output.

V. Result and Discussions

As a result system displays dashboard of monitoring PV panels which show energy level. As we know the results of prediction are depend on the site and climate therefore monitoring system also shows temperature, humidity of that location.

Solar energy generation vary according to harness of solar irradiance, figure 4 shows hourly day wise ratio of solar energy generation.

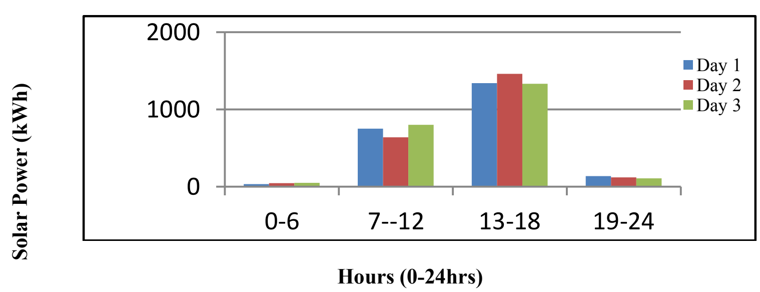

Fig. 4: Power Generation ratio based on hours.

We used graphs to highlight the data in more significant and standard way for representing detailed information to the users. Graphs plot for temperature and generated solar energy rate with current time and date as shown in figures 5 and 6 respectively. These graphs are available on internet from anywhere and anyplace. Once connection to server is successful, the information is continuously pass via solar panel to the web server for monitor parameters of solar Power Conditioning Unit (PCU). The collected information may be examined at anytime and everyplace. By considering the graphs we know the extreme entities created by solar PCU. The monthly and yearly status also states by the system which shows average wise ratio of energy generation as shown in fig 7. System also forecast the mistake finding as well as the panel's dead state with the immediate notification of the PCU.

For prediction model, A Hidden Markov Model is used which predict solar energy generation. We used real-time data collected by monitoring model for better results. Prediction accurateness by Root Mean Square Error (RMSE) metric has been calculated per time period. If a value of RMSE is nearby zero, then we get superior outcome at the low error rate between predicted and actual values.

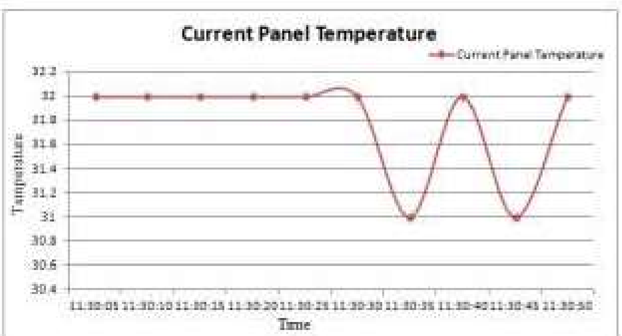

Fig 5. Current monitoring status of Temperature.

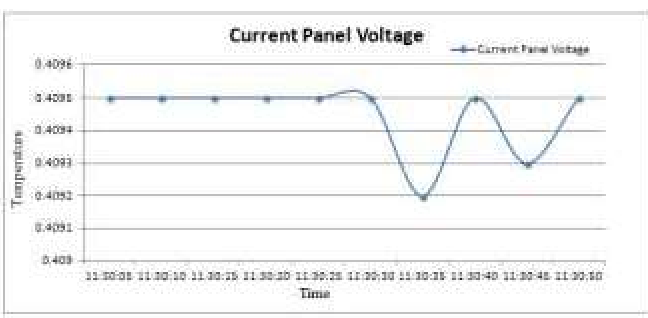

Fig 6. Current monitoring status of PV Panel's Voltage.

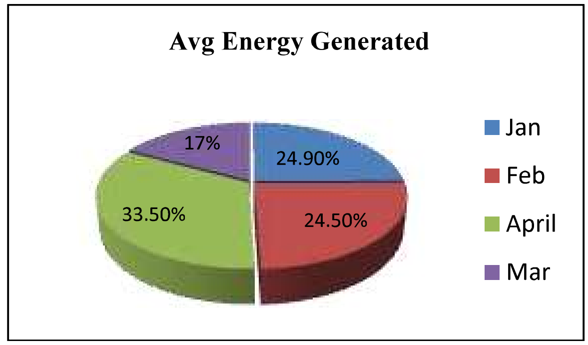

Fig 7. Monthly average energy generation status of PV Panel.

VI. CONCLUSION

This paper presents research work on developing PV with IoT based monitoring and solar power prediction system. Internet of Things is experimentally skillful which gives accurate results of monitoring parameters. The planned system monitors the solar PV PCU, forecast the mistake finding and the panel's dead state with time parameters. It maintains the resultant reports according to the requirements. For example estimation entity plot and create full amount entity produced for every month. It stores all the details over the cloud with respect to time parameters; this will helpful to calculate the circumstance of many parameters of system. Monitoring directs the user for analysis of renewable energy consumption which used to describe the characteristics of solar prediction. Hidden Markov model can predict solar energy generation data in time series samples accurately by using historical solar energy generation data. This system is cost effective therefore the use of renewable energy is reliable and sustainable.

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