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Time-Series Energy Prediction using Hidden Markov Model for Smart Solar System

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***Abstract*—Solar energy is a one of the cleanest renewable energy resource, it does not affect greenhouse atmosphere. Presently, the photovoltaic solar energy characterizes as a third-biggest resource of renewable energy following to the hydro energy and wind energy. It results solar energy is fastest growing source of energy in the world. The management of photovoltaic systems is essential to increase the efficiency of solar system. The proposed system implemented in two phases, first is a panel level monitoring system and second is a solar power prediction system. We used Internet of Things for supervising solar power generation, it significantly enhance the performance, monitoring and maintenance of the solar plant. The solar monitoring system collects several constraints being evaluated by sensors to analyze the panel level performance. Monitoring system keeps track on solar power generation with environmental conditions, like temperature and humidity of particular location. This monitoring system forecast the faults as well as the panel's dead state with time parameters. Second phase works on the solar power prediction with the help of Hidden Markov Model. It gives accurate prediction considering correlation of the first value to next value in time-series. The output is then compared with existing prediction module that shows proposed module provides good accuracy of prediction.**

Keywords*— *Solar Energy; Internet of Things (IoT); Time-Series; Solar Energy Prediction;

I. INTRODUCTION

Solar energy is accessible from everywhere; it gives outstanding growth in the photovoltaic market over the last few years. Figure 1 show yearly growth of the solar system in India [1].The global investment in photo-voltaic solar systems increased because of transformation in favorable government polices and compensation in rate of the solar systems. There are other renewable sources are also available but PV (Photovoltaic) resource has more efficient than thermal power, hydropower and wind power.

There are various techniques used for prediction, table I shows different existing methods of prediction. In this paper we are considering Hidden Markov Model (HMM), it finds the probabilistic connection of the past values to the future value in data series.

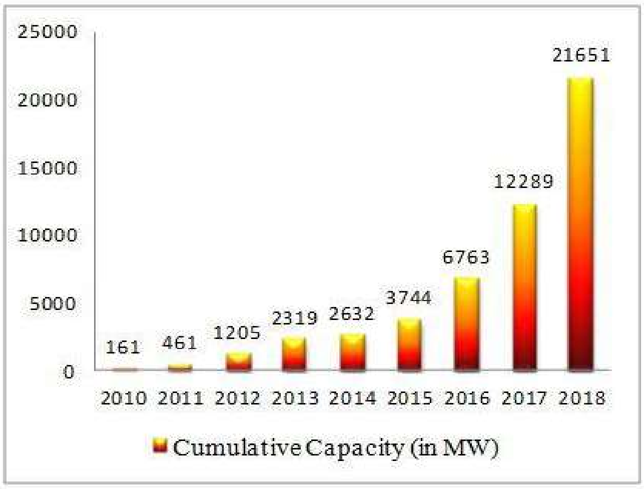

Fig. 1. Yearly development in solar system of India.

All the existing methods perform either monitoring or else prediction, however projected method gather the real-time monitored data and consequently use it for accurate prediction. The goals of this proposed system are to monitor as well as to predict the solar energy generation. System work as a web application, by assembling a solar panel, IoT devices, and Gateway which permits the communication in different smart plugs and web server. Then prediction helps the user to operate accordingly to use of renewable energy resources. To develop the smart reliable PV systems, it have to use the resources with superier technologies that are clean, adequate, reliable and cheap in cost [2].

The paper is organized as follows: Section II focused on the implimatnation details that describes IoT based monitoring method and machine learning based prediction algorithms for power forecasting. Section III is discussion on result analysis, and lastly conclusion is mentioned in Section IV.

TABLE I. EXISTING METHODS FOR PREDICTION.

Author	Reference	Method
F. O. Hocaoglu and F. Serttas	[4]	A Novel Hybrid (Mycielski-Markov) Model
Y. Jiang, H. Long, Z. Zhang, and Z. Song	[5]	A Markov Switch Approach
C. Wan, J. Zhao, S. Member, and Y. Song	[6]	Artificial Neural Networks, ARIMA
A. Chikh and A. Chandra	[7]	Maximum Power Point Tracking (MPPT)
M. J. Sanjari and H. B. Gooi	[8]	Higher-order Markov Chain (HMC)
J. Prasanth Ram and N. Rajasekar	[9]	Maximum Power Point Tracking (MPPT)
Simone Sperati , Stefano Alessandrini, Luca Delle Monache	[10]	Neural Network
Mashud Rana, Irena Koprinska, Vassilios G. Agelidis	[11]	Neural Networks, Support Vector Regression
Hong-Tzer Yang, Chao-Ming Huang, Yann-Chang Huang, Yi-Shiang Pai	[12]	Hybrid Method
A. Aybar-Ruiz, S. Jime´nez-Ferna´ndez, L. Cornejo-Bueno, C. Casanova-Mateo, J. Sanz-Justo, P. Salvador-Gonza´lez, S. Salcedo-Sanz	[13]	Grouping Genetic Algorithm (GGA)
Michelangelo Ceci, Roberto Corizzo, Fabio Fumarola, Donato Malerba and Aleksandra Rashkovska	[14]	ANN, Regression Trees
Luis Martı´n , Luis F. Zarzalejo a, Jesu´ s Polo a, Ana Navarro a, Ruth Marchante b, Marco Cony b	[15]	Neural Networks and ANFIS
Arash Asrari, Thomas Wu and Benito Ramos	[16]	ANN, Shuffled Frog Leaping Algorithm (SFLA)

The devices used to monitor the system are cheap in cost. It is essential for a monitoring system that the customers must know the potential and practical boundaries of devices, operational deviations and objective wise data analysis. To fulfill the requirement of our objective, finest monitoring devices are selected. Important devices, which are used for developing the projected system and to calculate the important parameters with good precision and accuracy, are shown below:

TABLE II. HARDWARE SPECIFICATION

Hardware	Specifications
Raspberry pi-3	• System-on-Chip:-Broadcom BCM2837 • Memory:- 1 GB LPDDR2-900 SDRAM • CPU: -1.2 GHZ quad-core • Network: -Bluetooth 4.0, 802.11n Wireless LAN ,10/100 MBPS Ethernet • 4 USB ports
DHT11 Sensor	• Voltage Supply:- +5 V • Temperature limit :-0 to 50 °C • Humidity :- 20 to 90%
MCP 3204	• 12-bit resolution • -40 to +85°C temperature range
Solar Panel	• Cell type - Crystalline Silicon • Operating Temp:-20°C ~ +60°C

Sensors and PV panels are connected with Raspberry Pi 3 as shown in figure 2. We used DHT 11 sensor, it measure temperature and humidity of particular location. The RPi and sensor are cheap in cost so it reduces the system cost. The collected data stored on the cloud. We used that data to construct the HMM. The HMM defines states and probabilities to get accurate prediction of energy generation.

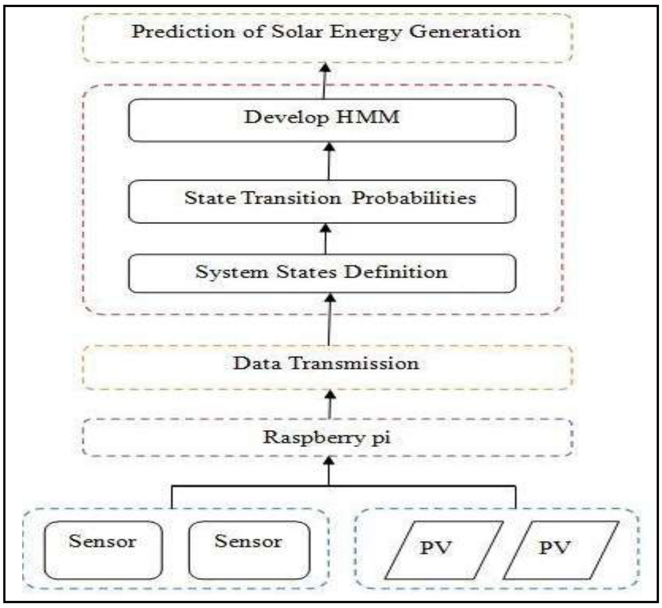

Fig. 2. Architecture diagram of proposed system.

In the proposed system, we used HMM to find the most probable time-series. The time-series prediction is calculated by estimating probability of state transition and observation sequences for the predetermined state which gives precision in prediction. HMM used historical data of power as a input. The Markov chain property states that the possibility of every successive state depends on past state [15].

HMM contain N number of states, called $s_1, \ldots, s_N$ at time-period $t = 0, 1, \ldots$ At every time-period, the system is in the free and available states, known as N states. The state at time slot t is recognize as Q_t, by $Q_t \in \{s_1, \ldots, s_N\}$. On every time-period state Q_t produces a symbol considering distributed Observation and Emission Probabilities.

We get the hidden as well as observed states, known as state probability vector $\boldsymbol{\Pi}$, inter-state transition probability matrix $\boldsymbol{A}$ along with emission probability matrix $\boldsymbol{B}$. Markov chains convert the considered information into number of states.

i.e. State transition probabilities - $\{s_1, \ldots, s_N\}$

It shows possibility from state to next state, called as state transition probability matrix

$$A = (a_{ij}),\ a_{ij} = \mathrm{P}(s_i|s_j) \qquad (1)$$

Where, i and j stand for row and column respectively. The observation probability distribution represents for j be $Vm,\ m = 1, \ldots., M$ in the state s_j

$$B = (b_i(v_m)),\ bi(v_m) = \mathrm{P}(v_m|s_i) \qquad (2)$$

Amount of symbols are shown as $m = 2$

And vector initial probability matrix

$$\Pi = (\Pi_i), \qquad \Pi_\mathrm{i} = \mathrm{P}(s_i) \qquad (3)$$

Then, Model represented as $\lambda = (A, B, \Pi)$.

Objective of prediction system is testing a HMM from observed sequence. The likelihood assessment method evaluate λ^*, that maximizes a likelihood of training sequence, $OTs = \{OTs_t\}_{t=1}^{T}$ for advancement in $P(OTs|\lambda)$. Independent and enormously distributed sequences of, $OTs = \{OTs_t\}_{t=1}^{T}$ are strained from possibility allocation $P(OTs|\lambda)$. We get a significance λ, it initiate OTs_t to $P(OTs|\lambda)$ as probable sequence.

$$OTs_t \cong \mathrm{P}(OTs|\lambda) \qquad (4)$$

The possibility modification identified as $\lambda = (A, B, \Pi)$. Re-evaluated λ for every step, consider likelihood sequence of state s_j to state s_i. Repeat the step until union for duration of $P(OTs|\lambda)$ not condenses.

Algorithm for Prediction:

Input: Historical monitored data.
Output: Predicted data of next hour.
Steps:

1. Observe and examine the Time-Series Sequence
$$OTs = \{0's, 1's\}$$
2. Assign as unique observation digits for states *N*
$$V = \{0, 1\}$$
3. Calculate appropriate values of Markov model to maximize probability $\mathrm{P}(OTs|\lambda)$
$$\lambda = (A, B, \Pi)$$
4. Predict output considering historical observations
$$\mathrm{P}(OTs, 1|\lambda) < P(OTs, 0|\lambda)\ then\ S(t+1) = 0$$
$$\mathrm{P}(OTs, 1|\lambda) \geq \mathrm{P}(OTs, 0|\lambda)\ then\ S(t+1) = 1$$
5. Produce predicted observation time-series for $t = T + 1\ to\ 2T$
$$POTs = \{OTs\}_{t=T+1}^{2T} \quad \text{using} \quad \{OTs\}_{t=1}^{T}$$

The algorithm initially observes historical the report from the database and spites every attribute. In step 2, it separates attribute as a unique symbol to $0's$ or $1's$. In next step the sampling approach develop using help of HMM model. In step 4 perform prediction of observation time-series as moving ratio on desired samples. In conclusion step 5 returns the prediction output. This procedure is specified as an observer Markov Model. The HMM is a fundamental edition of Markov method, yet HMM is an autonomous process. Here, number of states communicates with a collection of similar probability allotment of observation. While working on this algorithm we found two challenging problems that are mention below:

A. The Forward Algorithm

The initial problem is to calculate the maximum likelihood sequence of a distinct observation series that is a new observation sequence and a set of models. It finds a model which gives the best sequence. The best possible sequence linked with known observations using state sequence and Observed Time-Series

$$\mathrm{P}(OTs|Q) = \Pi\,\mathrm{P}(OTs|\ s_i) \times \Pi\,\mathrm{P}(\ s_i|\ s_{i-1}) \qquad (5)$$

Therefore we used a competent algorithm known as the forward algorithm. This algorithm is a dynamic programming algorithm. It calculates the observe likelihood probability with adding probabilities of all probable hidden-states that could produce the observation series.

B. *Viterbi Algorithm*

HMM contains hidden variables, the challenge is to determine which sequence is the underlying source of some series of observations. It is known as a the decoding task. Decoder finds the best hidden sequence, this problem solved by the Viterbi algorithm [17]. It is possible to alter the model constraint $\lambda = (A, B, \Pi)$ to maximize $P(OTs|\lambda)$. Viterbi Algorithm achieve supreme score from the a exact path at initial time t observations, trim with state s_i, presented as:

$$\delta(i) = max\mathrm{P}(s_1, s_2, \ldots, s_N = i, OTs|\lambda) \quad (6)$$

III. Result and Discussions

In result, the system displays a status control panel of monitoring PV with power generation intensity. As we recognize the consequences of energy prediction are associated to environment situations and location of PV plant. This system able to monitors the temperature in degree celsius and humidity in the percentage of panel's location.

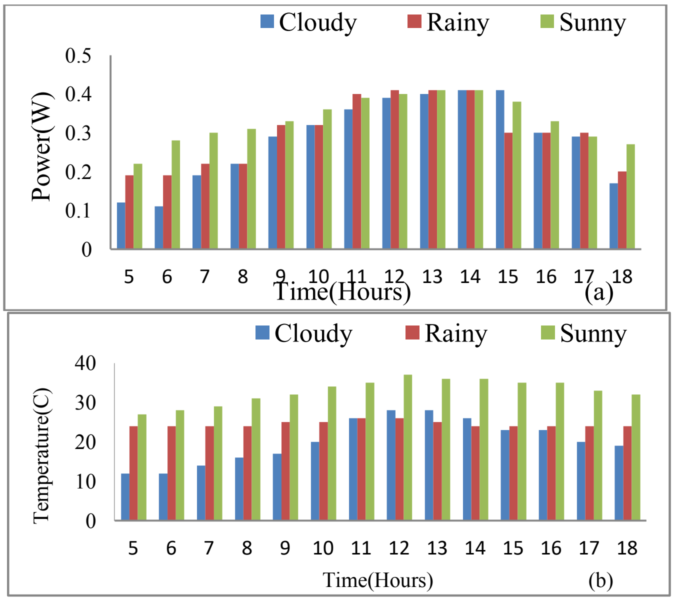

Fig.3. Seasonal (a) Power and (b) Temperature of system.

Solar energy differs by environmental seasons [18-23], the above graphs shows hourly temperature and solar energy generation in sunny, cloudy and rainy days as shown in figure 3. The system used graphs for analyzing the performance in a standard method to provide the understandable view of information to the users.

These graphs are accessible to the users from anywhere and anyplace. If the one-time server connection is successful, then the real time status of the monitoring is persistently passed on the web server of Power Conditioning Unit (PCU). A graph helps to examine the intense values generated by solar PCU.

The system can analyze precedent average ratio of solar power generation monthly and yearly. Figure 4 and 5 shows actual with predicted PV generation data in a different months and days. It forecast the panel's dead status as well as error finding via sending the alert note of PCU whenever the power ratio is zero for a particular time period.

An advanced HMM predicts PV power generation ratio. Considering real-time data calculated by monitoring system it gives most probable results. Truthfulness of prediction is measured by Mean Absolute Percentage Error (MAPE) and Root Mean Square Error (RMSE). If ratio of predicted and actual values is nearby zero in terms of RMSE, then we have a better outcome. Figure 6 illustrate the actual and predicted values compared with linear regression model for few hourly sample cases.

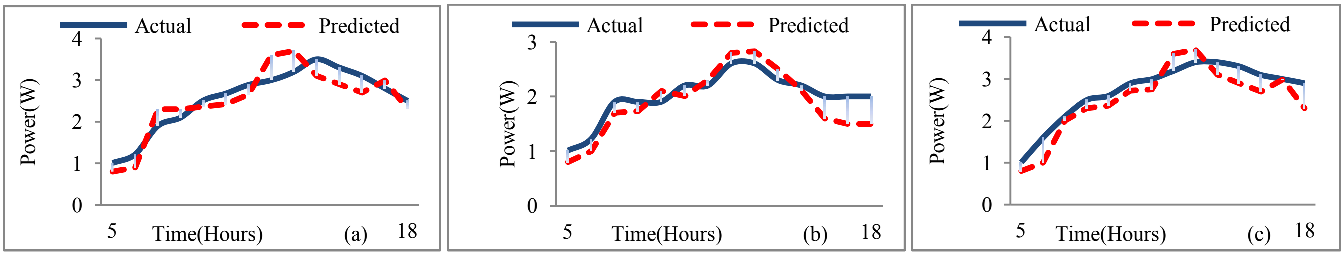

Fig.4. Actual and Predicted PV power generation in (a) Cloudy, (b) Rainy and (c) Sunny Month.

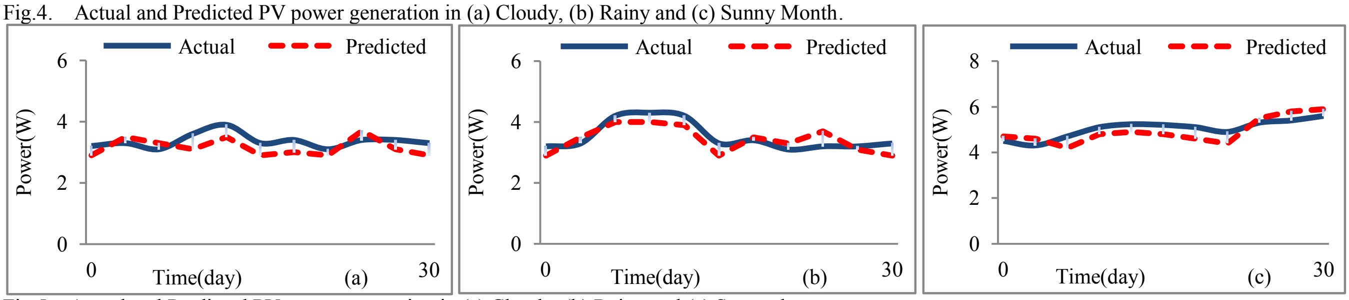

Fig.5. Actual and Predicted PV power generation in (a) Cloudy, (b) Rainy and (c) Sunny day.

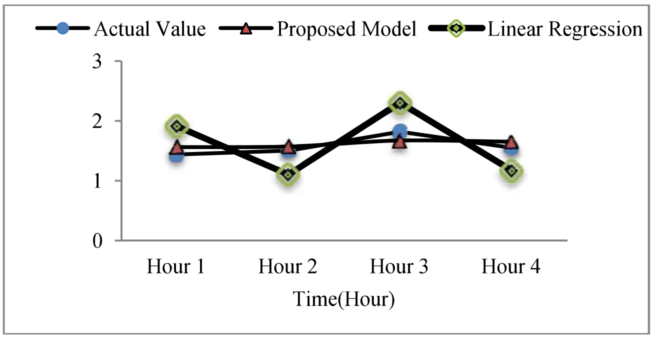

Fig.6. Comparison of Actual and Predicted PV power generation.

TABLE III. COMPARISON BETWEEN PROPOSED METHOD AND LINEAR REGRESSION METHOD

Methods	**MAPE**	**RMSE**
Proposed Method	8.442	0.642
Linear Regression	13.440	1.501

IV. CONCLUSION

Solar energy is green and reliable hence the consumption of this system is consistent and cost-efficient. The proposed system comprises both Monitoring and Prediction. Internet of Things offers practically proficient methods that give accurate outcome. We consider parameters like Temperature, Humidity and Solar Power with the help of Internet of Things (IoT) for monitoring the solar. The planned system monitors the PCU and finds faults at the panel level. We can examine the weekly and monthly performance ratio of monitoring system. For prediction we used a Hidden Markov Model to forecast the solar power. We have developed an hourly prediction system. HMM Considers historical data to predict the accurate power generation in time- series. Statistical outcome shows that the proposed model gets superior prediction accuracy as compare to simple Linear Regression model.

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