Prediction of Energy Consumption from Renewable Solar Resources in a Smart Home using Markov Chain

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Abstract
Everything in the modern era is designed to be smart and a home is not an exception. A smart home is a home where all the devices are smart devices and are connected to a central point of access. Home automation expects energy efficiency. Energy generation and energy consumption are the momentous two sides of energy management. Hence prediction of energy usage from renewable resource becomes a dynamic option. In this paper the Markov Chain principle is used to forecast the amount of energy used from the solar energy generators across seasons. Markov Chain proves apt in handling random variables and it does not brood on historical data. It considers the present data alone to forecast the future. The dataset for this work is taken from Austin, Texas. A single home data is taken and the various seasons in Austin are considered as the state space. The energy consumption from solar is segregated based on the various seasons in Austin. Using these seasons as space state, a transition matrix is built and the future data is simulated. After the simulation of future data, Markov Chain is used to predict the amount of energy used from the solar generators during various seasons in the forth-coming year. Here forecasting is done for six years (2014 -2019) and the RMSE is calculated for each year. The loglikelihood is taken as a measure to prove that Markov Chain principle gives higher value than Bayesian and Markov Bootstrap therefore a better option.

Keywords:
Smart Home, Energy Efficiency, Transition Matrix, Markov Chain.

1. Introduction

Now a days, everybody is fascinated by the word smart and the whole world is turning out to be a smart one. The house that we live is also becoming a smart home. A smart home is a home in which all the appliances are smart and are connected and accessed from a central point which may be any device like mobile, laptop etc.,. Electric energy has become one of the highly prioritized requirements in today's world. A smart home is also designed in such a way that it is made to think. When smart home is considered, efficiency in energy usage becomes one of the most important area of concern. When energy is managed efficiently it helps in reducing the usage of energy from the grid and this leads to reduce the pricing. Excess energy can also be given to the grid which can be used by the utilities to use during outages and natural calamities. In a smart home solar energy, wind energy and biomass energy can be generated on their own from energy sources like sun, air and organic matters respectively. Since a smart home is able to generate energy on its own through the various renewable resources, forecasting of energy consumption from these sources will help greatly in using the energy more efficiently. When energy generation from renewable resources are considered, solar energy plays an important role. The generation of energy from solar greatly relies on various seasons. Seasons are the most important criteria when solar energy generation is considered.

The solar energy generation during various seasons are random and inconsistent as it is affected by various parameters like global warming, intensity of heat from the sun, the location of the house, the area of the house, number of panels used etc., Researches in this area is booming as this is of great help to the utilities as well as the consumers. This paper focuses on predicting the amount of energy usage in a smart home from solar during various seasons in the upcoming year. Since the energy consumption faces uncertainty, traditional forecasting techniques like SVM, ARIMA and ANN will not prove that very good [1]. Hence a technique that suits well for this uncertainty is the Markov Chain principle. Markov Chain is a principle that is often referred to as the memoryless principle as it does not consider the previous historical data but considers only the present to predict the future. This is a technique which proves good in dealing with uncertainity. This rest of the paper is organized as follows: Section II deals with the various research activities that is carried out in this area, Section III elaborates on the preliminaries that are needed to understand this work, and Methodology of this work is dealt in Section IV. The results are discussed in Section V and the paper is concluded with the future work in Section VI.

2. Review of Literature

Prediction of renewable solar energy generation and usage has become an important area of research. Researches are carried out in this area and many authors have given their contribution towards this area of research. Goh T.N and Tan K.J have proposed a model using stochastic time series methodology to present the statistical properties of solar radiation data [2]. Mohamed Abuella and Badrul Chowdhury have forecasted solar power using Artificial Neural Networks model and has shown the comparison with

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multiple linear regression [3]. Vikas Pratap Singh et.al have proposed a solar power forecasting model using soft computing techniques like ANN and GNN [4]. Annette Hammer et.al have proposed a short term forecasting model for solar radiation using the satellite data [5]. Mariam Alkandari and Imitiaz Ahamed have proposed a hybrid model using ML algorithms and statistical methods to forecast the solar power generation.[6].Nurul Nnadiah Zakaria et.at have proposed a forecasting tool to assess the air pollution level in long term using Markov [7]. Soumyadip Gosh et.al has proposed new techniques using Markov Chain for customers demand response and probability distributions for long term-pricing [8]. S.Elgharbi et.al have forecasted the production and usage of electricity in Morocco based on historical data using Grey-Markov, which is a combination of grey and Markov Chain models [9]. Wayes Tushar et.al has used Markov Chain to propose a stochastic model for the generation of solar energy [10]. Kishore Kumar Senapati has implemented first order hidden Markov model using Viterbi algorithm to present a framework for predicting demand in household electricity by taking climatic conditions, population and financial capability [11]. The related works indicate that Markov Chain is not used in predicting the energy usage from solar resource in a smart home. Since Markov Chain handles random variables well, this principle is taken for prediction in this paper.

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3. Preliminaries

3.1. Markov Chain

Markov Chain is a probabilistic stochastic process which deals greatly with random variables and uncertainties. This is also said to be memoryless as it does not bother about the sequence of previous data but considers only the present data to predict the future data. Markov Chain works on the state space. From the state space the initial state is considered and the transition between states are calculated. After knowing the states, the transition matrix is constructed and future data is simulated [9]. Using this simulated data prediction is done. Since there is a change in the weather every day, it affects the seasons which in turn affects the generation of energy from the renewable resources. Hence Markov chain is useful when prediction of energy usage from solar is considered to predict the energy usage during various seasons.

3.2. Problem Definition

In a smart home efficiency in the usage of energy is of great importance as all the appliances in a smart home are made to think and work based on the peak hours and the pricing related to the use of energy. Since energy is generated in a smart home through various renewable resources, the price can be reduced and the amount of energy drawn from the grid can also be reduced. This energy generation greatly depends upon various seasons. Based upon this, the energy from various resources can be used accordingly. When solar energy is considered, the generation of energy will be the highest during summer and lowest during winter. So, energy usage from solar during various seasons will differ. Hence there comes the need for prediction of energy usage from solar during various seasons in a year. This will help the consumers to know more on when to use the energy from the solar and on to reduce the energy drawn from the grid. This will help to reduce the price and it can also help the utilities to get more energy from the smart home.

3.3. Notations

Let Se, So are the parameters that indicate the amount of energy from solar that is used during different seasons.

Let f (Se, So) be the function of the variables that are used as inputs to build the transition matrix.

The transition matrix for energy usage from solar during various seasons is built based upon the following steps se

$$T_{(m,n)} = P\,[q_{t+1} = m \mid q_t = n\,]$$

Where q_t is the state at time t

q_{t+1} is the state at time t+1

m, n = States

Pattern pre-estimation is identified using

$$P\,[\underbrace{X(t_{j+1}) = n}_{\text{Future}} \mid \underbrace{X(t_1) = 1, X(t_2) = 2, \ldots X(t_s) = m}_{\text{Present}}]$$

$$P\,[\underbrace{X(t_{j+1}) = n}_{\text{Future}} \mid \underbrace{X(t_s) = m] = p_{m,n}(t-s)}_{\text{Present}}$$

where X is the states

m, n are the initial states

t is the state at time t

t+1 is the state at time t+1

The steady state probability vector is identified using

$$\pi\, T = \pi$$

where π denotes the steady state probability vector for power usage.

3.4. Loglikelihood

The fitness of a statistical model built for a particular dataset is measured using Loglikelihood. The data is generated based on sample date in statistical models. The value of the loglikelihood indicates the efficiency of the parameter considered for prediction. The higher the value of loglikelihood the probability of the sample data taken for observation is maximized.

4. Methodology

Generally, the generation of solar energy relies on various seasons. So, the consumption of energy from the solar generators will also vary. During summer season, the solar energy can be generated more and during winter the energy generation will be less. Since there is fluctuation in the amount of energy consumed from the solar generators during various seasons, prediction of energy usage from solar during various seasons has become important. This prediction will help the consumers to know when to use the energy from the solar and when to give the excess energy generated from the solar to the grid. This also helps the consumers as well as the utilities to know how much of energy from grid will be needed to meet the need of energy in a smart home. Since there is no regularity in energy usage from solar traditional forecasting techniques does not prove as good as the statistical approach. Hence a statistical approach will increase the accuracy of predicting the amount of energy used from solar during various seasons. In this work Markov Chain is used as it proves good for variables that are random and which are not linear. A real time solar energy consumed by various smart devices in a smart home from Pecan Street, Austin, USA for the years 2013 to 2019 is taken as the data set to forecast the energy used from solar in a smart home during different seasons using Markov Chain. Two variables namely season and energy usage from solar are taken into consideration as per the availability of the dataset to predict the amount of energy used from solar during various seasons. The energy usage is a function of input variables, f (Se, So) where Se and So are assigned to each input variable. The usage of energy from solar in a smart home from the months January to December is taken as the input. The energy used from solar is aggregated according to various seasons and these seasons are considered as the state space which helps to build the transition matrix. The transition matrix is built to identify the probability of the future state. Based on this transition matrix the energy usage from solar during various seasons for the future year is predicted by using the Markov Chain principle. In this work prediction is done for six years and the RMSE is calculated for each year based on the actual value and the predicted value. The efficiency of this work is highlighted by calculating the loglikelihood and comparing it with other Markovian techniques like Bayesian and Bootstrap. R tool is used to implement this work.

4.1. Input Parameters

Input parameters are the ones that influences the energy usage during different seasons. Hence the following input parameters are taken for this work:

1. Seasons
2. Energy Usage from Solar

4.1.1. Seasons

Energy usage from solar greatly depends on various seasons. Based on various seasons the solar energy generation will vary and this in turn will affect the amount of energy usage by the household appliances in a smart home. Hence prediction of energy usage from solar is affected by the seasonal changes. A real time data set of a smart home located in Austin; USA is taken for this work. Austin has four seasons and each season exists for three months. The various seasons in Austin are Winter (December – February), Spring (March – May), Summer (June – August) and Autumn (September – November).

4.1.2. Energy Usage from Solar

A smart home gets its energy from electrical grid, solar, windmill, organic waste etc., Solar energy is taken for this work and the dataset shows that the energy used from solar varies based on different seasons. Since solar energy greatly depends on the sun, it is clearly seen that the smart home uses the energy from solar to its maximum during summer and it is used least in winter. Hence the energy used from solar varies according to the time structure of the seasons.

4.2. Building of Transition Matrix

The seasons and the energy usage from solar is taken as the input and the average amount of energy used by various smart appliances in Kw is calculated for different seasons based on the average energy usage during different months. Table I demonstrates values to show the average usage of solar energy in kw during various seasons for the years 2014 to 2019.

Table I: Average Energy Usage from Solar in KW

Year	Winter	Spring	Summer	Autumn
2014	1.6	2.8	3.1	2.1
2015	1.6	2	3	2
2016	1.8	2.3	2.8	2
2017	1.5	2.3	2.6	2
2018	1.2	2.2	2.5	1.4
2019	1.4	2.4	2.7	1.6

The data in the table clearly indicates that the maximum amount of energy from solar is used during summer and the least is during winter. Considering these values, a transition matrix for each year is constructed and the seasons are taken as the state space. Here Winter is represented as Wi, Spring as Sp, Summer as Su and Autumn as Au. The probability of transition from one state to the other is simulated based on this transition matrix. The transition matrix is constructed following a basic rule which indicates that the sum of each row should be 1. A sample transition matrix is given below which is constructed using the 2014 data.

$$
\begin{array}{c|cccc|}
 & Wi & Sp & Su & Au \\
Wi & 0.12 & 0.28 & 0.30 & 0.20 \\
Sp & 0.05 & 0.10 & 0.51 & 0.34 \\
Su & 0.2 & 0.12 & 0.4 & 0.28 \\
Au & 0.17 & 0.28 & 0.42 & 0.13
\end{array}
$$

After simulating the future data, the probability of the future state is calculated based on the amount of energy used from solar during different seasons. The diagrammatic representation is given below with the help of a transition diagram. The transition diagram based on the dataset of 2014 is shown in Fig 1.

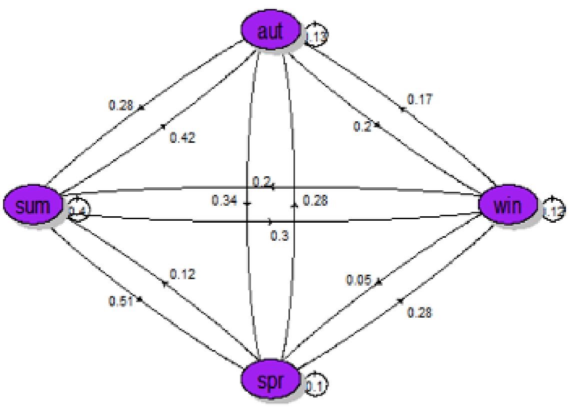

Fig 1. Transition Diagram for various states based on the year 2014

The energy usage from Solar during various seasons for the forthcoming year is predicted by using Markov Chain. Similarly, the energy usage for six years (2014 – 2019) based on seasons are calculated and the results are given in Table II.

4.3. Pictorial Representation

Fig 2 represents the conceptual diagram of this work. The energy usage from solar during different seasons are considered to predict the amount of energy usage for the forthcoming year. Markov Chain is used to predict the future based on the present year data.

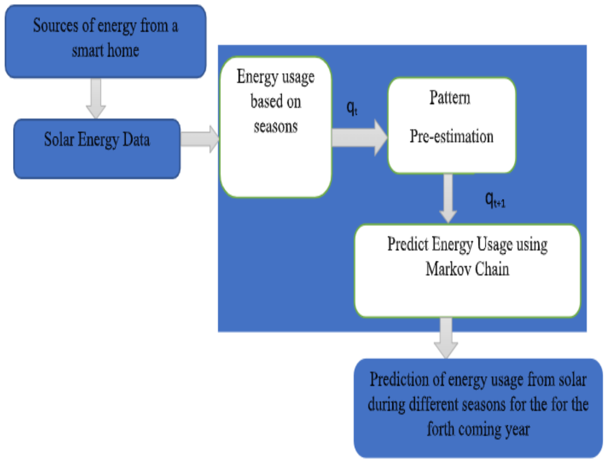

Fig 2. Conceptual Diagram

4.4. ALGORITHM TO PREDICT ENERGY CONSUMPTION DURING VARIOUS SEASONS BY USING MARKOV CHAIN

Step 1: Read the Variables Se, So

Step 2: If (Se $\wedge$ *So* $\neg$ *= NULL)*

Then Go to Step 3

Else

Check the dataset

Step 3: Construct the Energy Usage Transition matrix between Seasons based on Current Data

$T_{(m,n)} = P\,[q_{t+1} = n \mid q_t = m\,]$

Where q_t *is the state at time t*

m,n are the states

Step 4: Compute the Pattern pre-estimation

$P\,[X_{j+1} = n \mid X_0 = x_{0,\ldots.}\ X_{j-1} = x_{j-1},\ X_j = m]$

$P\,(X_{j+1} = n \mid X_j = m) = P(m_{j+1,}\ n_j)$

For all $x_{0,\ldots.}\ X_{j-1},\ m,\ n \in D$, *and* $j \geq 0$.

where D is the state space of the Markov chain

Step 5: Compute the steady state probability vector, which uses the stationary distribution,

$\pi = T\pi$

where π *denotes the steady state probability vector for energy usage.*

Step 6: Predict the Energy usage,

$P = So * \pi$

Step 7: Stop

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5. Result

Markov Chain is a technique that is used when random variables are considered. It considers only the present to predict the future. Based on this technique prediction is done in this work for six years from 2014 to 2019 using the dataset of a house in Austin, USA. To predict the energy usage from solar for the year 2014, the data from 2013 alone is taken and executed according to the methodology that is discussed in the previous section.

Similarly, prediction is done for six years. The actual energy usage and the predicted energy usage from solar is used to find the RMSE and the result is given in Table II. From the result shown in the table it is found that the RMSE is very less for the year 2014 and for 2017 it is the highest. The actual and predicted amount of energy usage from solar during different seasons for the years 2014 to 2019 is graphically given from Fig 3.1 to Fig 3.6 respectively. The accuracy of using Markov Chain for this dataset proves better when the loglikelihood is compared with other Markovian techniques like Bayesian and Bootstrap. The values of the loglikelihood for six years (2014-2019) is given in Table III.

TABLE II: Actual and Predicted Values of Average Energy Consumption and RMSE

Year		Win.	Spr.	Sum.	Aut.	RMSE
2014	Actual	1.6	2.8	3.1	2.1	0.33
	Predicted	1.5	1.9	4.1	2.3	
2015	Actual	1.6	2	3	2	0.48
	Predicted	1.5	1.3	4.8	2.2	
2016	Actual	1.8	2.3	2.8	2	0.46
	Predicted	1.7	1.4	4.4	2.3	
2017	Actual	1.5	2.3	2.6	2	0.5
	Predicted	1.5	1.5	4.4	2.4	
2018	Actual	1.2	2.2	2.5	1.4	0.41
	Predicted	1.7	2.2	3.9	2.1	
2019	Actual	1.4	2.4	2.7	1.6	0.45
	Predicted	1.9	2.2	4.1	1.6	

Fig 3. Graphical representation of the actual and predicted values for six years (2014 – 2019)

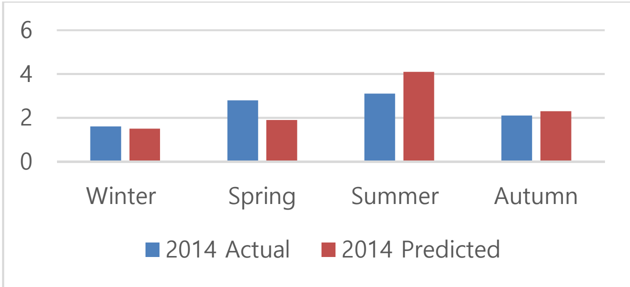

Fig 3.1. Graphical representation for the year 2014

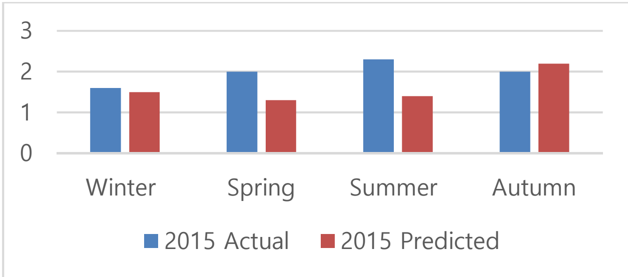

Fig 3.2. Graphical representation for the year 2015

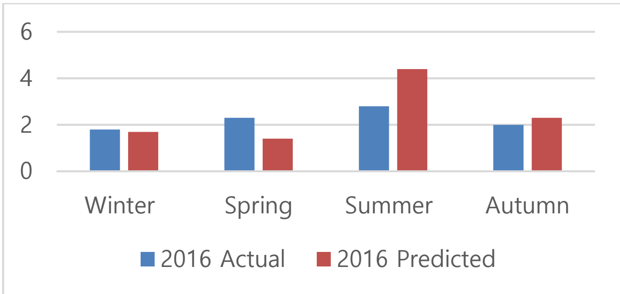

Fig 3.3. Graphical representation for the year 2016

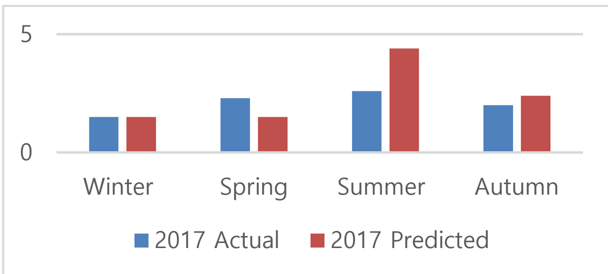

Fig 3.4. Graphical representation for the year 2017

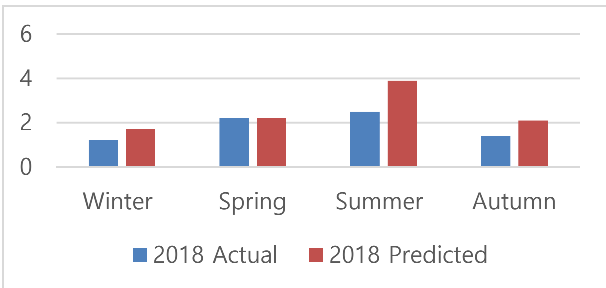

Fig 3.5. Graphical representation for the year 2018

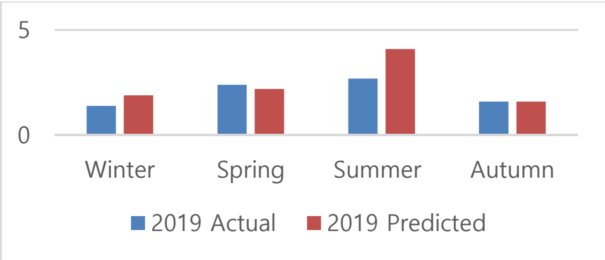

Fig 3.6. Graphical representation for the year 2019

TABLE III: Loglikelihood Values

Year	Markov Chain	Markov Bayesian	Markov Bootstrap
2014	-13145.25	-15147.56	-15147.25
2015	-12506.37	-15508.37	-15507.37
2016	-12851.5	-15853.35	-15852.65
2017	-12850.21	-15852.37	-15851.25
2018	-13316.25	-16318.45	-16317.86
2019	-13312.50	-16311.24	-16316.35

6. Conclusion

This work uses Markov Chain to predict the amount of energy usage from solar in a smart home during various seasons Based on the result obtained it can be concluded that Markov Chain can be used for prediction when there is non-linearity in data and it proves better when random variables are taken as the input. The accuracy is also high based on the RMSE value obtained in this work. The accuracy of this work is also compared by comparing the loglikelihood of Markov Chain with other Markovian techniques like Bayesian and Bootstrap. This work has considered only the amount of energy usage from solar. In future energy consumption from smart grid and solar can be combined to predict the amount of energy consumed during various seasons. The individual appliance energy consumption can also be predicted so that the devices can be scheduled in such a way that the price can be reduced and to get uninterrupted power supply at the time of natural calamities and crisis.

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