ISSN (Online) 2394-2320

International Journal of Engineering Research in Computer Science and Engineering (IJERCSE)

Vol 5, Issue 2, February 2018

A Pattern Prediction on Electricity Consumption using Hidden Markov Model

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Abstract - **The present era is the digital era and digital technologies are many impacts on human life as well as societies. Starting from Smart city design to social networking peoples are now using digital technologies. As the use of technologies grows the demand for its source that is electricity grows. Predication of electricity demand is a crucial problem and providing a solution through statistical rules is a big challenge. Present day Electricity demand pattern is considered to play a crucial role in the modernization of community. So, forecasting of household energy consumption precisely is essential due to the fluctuating demand –response of energy. It is also considered very significant for energy planning, development mechanism and economic success. In this paper, Statistical technique model is used to predict future consumption demand of electrical consumption rate. The prediction with output likely sequence works significantly by the implementation of Hidden Markov Model (HMM) using the Viterbi Algorithm with emphasis is given to forecasting future energy consumption demand where data pattern changes monthly and shows non-linear trends. This paper uses an extensive data sample of author's working university database. The final forecasted outcome is tested and compared with actual data. Experimental results show an aggregate of 0.0366 error rate showing non–linear trends of household electricity consumption with respect to factors concerning such as population, climatic conditions and financial strength. The prediction model based on small-scale fraction of households summarizing for most likely aggregate consumption response. The proposed model helps in recognizing future electricity consumption pattern which will be used in smart city design and provide a solution for electrification of urban and rural as well as any planning in government and non-government organizations for electricity consumption.**

Index Terms: Electricity, Consumption, pattern, Hidden markov model, Viterbi algorithm, Design, forecast, Demand, Smart city.

1. INTRODUCTION

Forecasting electricity consumption has been one of the challenging hurdles to overcome the transmission and distribution losses of electrical power. The objective of predicting research has been majorly beyond the extent of traditional research which has primarily focuses on developing intelligent systems. In recent years the developing countries endure with the crisis of shortage of electricity supplement [18]. So, energy prediction leads to a cost effective and energy planning such as energy distribution, generation, planning. Global energy consumption is expected to rise 56% by 2040 with a changing composition of energy sources, with China and India driving the rate increase far more than the rest of the world [18]. India is world's 6th largest energy consumer, accounting for 3.4% of global energy consumption according to the report of energy survey of India [1]. But Electricity losses in India during transmission and distribution are extremely high, about 28.44%as per as the report of (2008-09) [1]. The authentic role of a co-ordinated market for electricity (like the energy exchange or the energy pool) is to couple with the supply and demand of electricity to determine efficient way of electrical energy usage. Primal to any energy planning and control system is the statistical forecast. In this paper, focus is on developing and estimating a model of electricity consumption depending on several factors concerning that can be used to evaluate alternative energy designs. This model focuses on the heterogeneity in households' demand elasticity's, their relation to other consumption characteristics and how they predict household consumption responses to (nonlinear) geographical and environmental changes. The model developed also illustrates the influence of the energy input variables in the prediction. The future regional demand was estimated by escalating historical data, and the regional supply was determined by stacking up existing and announced generation units in some wise order of their variable operating costs [2]. There is large range of predictive techniques available, varying from a more complex and advanced techniques to a simpler average techniques such as classical artificial neural network (ANN) [3] models and a Box Jenkins [2]. Statistical technique such as regression models [1] are often used to predict random demand for products, but the prediction process works satisfactory on HMM statistical technique. The proposed model is based on statistical model. The main advantages of HMM-based systems are the statistical representations of the stochastic processes that capable of modelling sequential data.

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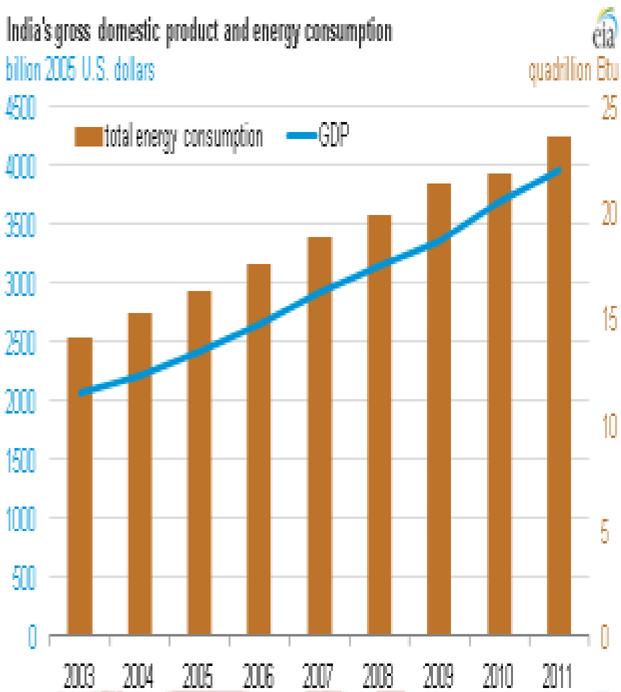
There are many approaches considered for forecasting electricity demand, including multiple regression models [4][5], time-varying splines [6], and artificial neural networks [3]. However, HMM methodology is increasingly applied to many complex predictive applications, processes, and researches.

Fig.1 Shows the figures of India's gross demand product with respect to the energy consumption [19].



2. BACKGROUND

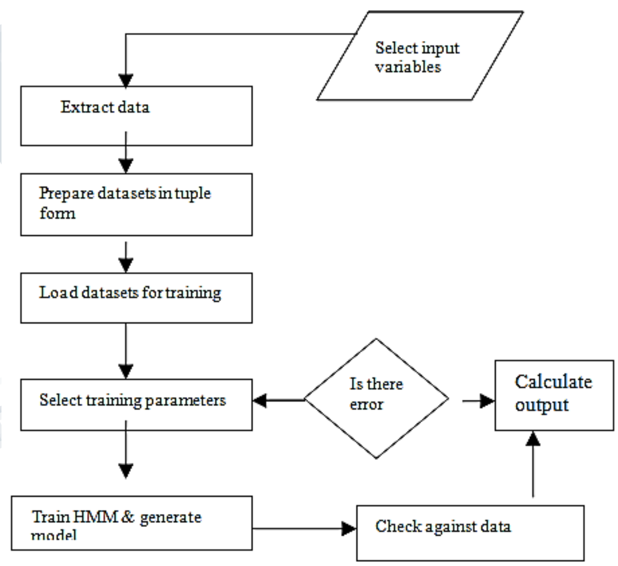
2.1. Some related works

Some methods have been formulated in the past as well as in the recent years. Mohammad Anwar Rahman et. al (2012) performed the prediction of electricity consumption by computing Bayesian model and then comparing the result with classical ANN [2]. Hideitsu Hino et. al (2013) presented a model to extract electricity consumption pattern based on Gaussian distribution and then applied generalized Kullback-Leibler divergence distance metric to find an optimal cluster [1]. J.P.S Catal˜ao et. al. (2006) proposed a neural network approach for forecasting short-term electricity prices by implementing a three-layered feed forward neural network, trained by the Levenberg-Marquardt algorithm for forecasting next-week electricity prices [7]. S.B. Nugroho, A. Fujiwara et al. developed a model of household energy consumption based on in-home and out-home activities [8].

3. DIAGRAMMATICAL EXPLANATION OF THE PROPOSED MODEL

Steps in optimizing electrical consumption using HMM techniques.

• The first step involves electrical metrics to be involved in an efficient algorithm to find the predicted data.
• The second step starts with evaluation of prediction accuracy to produce final prediction.
• The final prediction is validated against the real data to find an optimized value.
• This can be shown by data flow analysis given below -



4. PROPOSED ALGORITHM

A real-time series University data of household electricity demand is used to develop the HMM model through Viterbi algorithm and compare. Generally, electricity demands are not smooth and greatly varying over the season and various included factors. Conventionally predicting methods are not suitable enough to forecast such demand that has rapid growth and large fluctuations. Application here is to observe the performance of HMM model, comparing the forecast and ordinary dynamic linear methods.

Considering the extent of regulation of the parameters on power demand specifically household electricity demand and depending on the availability of related data three variables have been selected as the input parameters to model the HMM. Selected parameters are integrated with three input variables, (1) climatic conditions, (2) urban household size, and (3) urban household income. The household electricity demand is a function of input variables, f(x1, x2 …x3), where x1, x2 …x3 is assigned to each input variable. The time series dataset from 2014 are used for developing the forecasting models and dataset from 2014 are used to test the efficiency of the models and compare.

4.1. Notations and Problem Definition

Let x1, x2 and x3 are three parameters influencing the electrical demand.
Let f(x1, x2, and x3) is the function of three input variables to the algorithm.
According to algorithm using a dynamic programming trellis to store probabilities that the HMM is in state j after seeing the first t observations, for all states j which is calculated by

$$V_t(j) = \max_{1 \le i \le N-1} v_{t-1}(i) a_{ij}\, bj(o_t)$$

Where,
i= The previous state.
j= The current state.
t=no of observation.
a_{ij} = state transition from previous state to current state
b_j =state observation likelihood from previous state to current state.
O_t = {O1, O2, O3……..On) is the observation sequence.
$V_{t-1}(i)$ = The Viterbi output path.

4.2. Input parameters

Considering the influence of variables on power demand specifically in the environment and depending on the availability of related data, three variables have been selected as the input parameters to model the HMM.
The proposed model based on selected parameters and tested on three input variables such as:

- (1) Climatic conditions
- (2) Urban household size
- (3) Urban household income

4.2.1. Climatic conditions

Climatic conditions are also one of the major influencing factors. During hotter seasons the power consumption increases as temperature surges but during the rainy season consumption of electricity decreases with increase in rainfall. There are reasons behind this occurrence of un-uniformity. Firstly, heavy rainfall declines the use of air cooling equipment. So, the demand of electricity declines due to heavy rainfall.

4.2.2. Urban household income

Household income is one of the important factors related to increment or decrement of electricity consumption. A good financial household may have spent or may possess more appliances, electrical goods like refrigerator, washing machines, air conditioners etc. which are major factors of high rated consumption of power whereas an average income household may not possess as much as electrical appliances and hence leads to a lower electrical consumption.

4.2.3. Urban Household Size

With the passage of time, several variables increase in quantity or their influence increases that cause greater demand of electricity. Examples of such variables include growth of population, advancement in technology, industrialization, number of households under the coverage of electricity supply etc. Increase in population raises demand and consumption of electricity. Wider coverage of households under electric supply obviously demands more electricity to transmit.

4.2.4. Output parameter

Here the resulting output is the predicted monthly power demand which is computed in terms of Megawatt (MW) and the number of resulting output variable is one. The developed algorithm forecasts the predicted power consumption.

4.3. Algorithm

The following algorithm is incorporated in the data set to find the best sequence observation.

```
IS: input sequence of an array, length ` len'
 S: array of states, length `k` (start and end states omitted for clarity)
 V: observations, length `b`
ST (k, k): state transition probability distribution
 OT (k, b): observation probability distribution
Start
function_Observation(IS, S, ST, OT)
VT = zeros (len, k)
for j in 1: len
for s in 1:k
```

```
VT(j, s) += VT(j-1, o) * ST(o, s)
end
VT(j, s) = VT(j, s)*OT(s, IS(j))
end
end
return max(VT(len))
end
```

5. RESULT AND MODEL COMPARISON

Electricity consumption will increase drastically in winter and summer due to the weather condition and will remain moderately consumed during rainy season. Some of the months show gradual decrease in power consumption due to holidays and events due to which there is low electricity consumption.

Table 1. Power Demand prediction for the year 2017 by the modeled HMM

Month	Actual demand (MW)	*HMM demand (MW)*
January	516.9	489.43
February	458.7	439.5
March	434.64	452.4
April	454.8	432.86
May	352.65	322.01
June	304.2	321.54
July	373.4	328.4
August	436.83	441.32
September	488.6	432.6
October	371.6	352.06
November	449.82	465.3
December	449.82	412.8

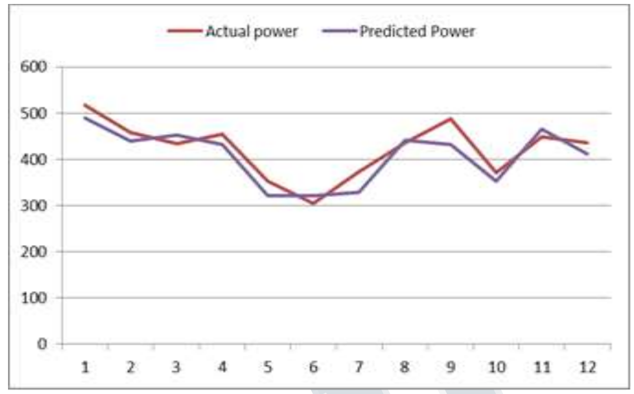


Fig 2. Shows the fluctuations in the actual and the predicted power consumption in University.

Table 2. Error rate of Demand forecast for the year 2017 by the modeled HMM

Month	Error rate	*% error rate*
January	+27.47	+0.05
February	+19.2	+0.04
March	-17.76	-0.04
April	+21.94	+0.04
May	+30.64	+0.08
June	-17.34	-0.05
July	+45	+ 0.12
August	-4.49	-0.01
September	+56	+ 0.11
October	+19.54	+0.05
November	-15.48	-0.03
December	+37.02	+0.08

A public domain software package Mathematical laboratory (MATLAB) and JAVA programs is used to generate feasible sample in minimum computational time. The configuration of the system on which the proposed model worked are processor is Pentium (r) dual-core CPU, installed memory is 2.00 GB, system type is 32-bit operating system, speed of the system is 2.20 GHz, RAM is 4 GB, Hard disk used is of 298 GB, operating system is windows 7 and IDE is JAVA runtime environment jre 7.

6. CONCLUSION

The proposed algorithm predicts the electricity consumption with minimum amount of error rate of 0.0366 percent. In this paper, experimental results conclude that the proposed model is better than other predicting model and performs with a better output resemblance towards actual consumption. This paper presented a frame work for application of Hidden Markov technique on Linear Model with an illustrative problem of predicting household electricity demand in a developing region. It is also necessary to apply this model to other universities database of electric consumption and various other scenarios resembling to universities to get more evidence on the estimation results. The proposed algorithm based on one-year data but this can be improve on working of the model by increasing the size of the training pool and training window. A larger data set could be made applicable which can be decided by a dynamic programming approach. The proposed model is applied only on first order HMM but further higher order HMM can also be applied. The application of the Hidden Markov Model to one single demand time series, more specifically since different electricity consumption predictive time series have different characteristics, different parameters can be taken up to consideration.

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